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Multi-Source Data Fusion

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INFORMATION SECURITY AND MULTISENSOR DATA PROCESSING

This issue of *Information & Security* is dedicated to one of the most promising areas of contemporary research and development – Multisensor Data Fusion (MSDF). The research community has already adopted common MSDF models and terminology. System developers have reached consensus on main engineering directions, and many commercial off-the shelf data fusion tools are now in use. Why are we focusing our attention on something so closely interrelated with the human cognition practice, and not self-evidently connected with the problems of information security?

As it is well known, the main amount of problems concerning information security arise from the area of signal, data and knowledge processing practice. The emergence of the information society has been inevitably followed by a rapid increase in the implementation of information processing systems. The ascending flood of equipment and sophisticated information systems applications has produced a lack of security for all levels of data processing. The information vulnerability of command and control (C^2) systems became of prime importance. Many system developers started to complain about the insufficient knowledge and expertise. Numerous conferences and symposia on this theme are dedicated to seemingly an endless discussion. But from our point of view, these events are not focused on the exact issue. What is generally neglected is that the essence of all fundamental ideas about information operations and information warfare is the disruption (the protection) of information processing in opposing Command, Control, Communications, Computing and Intelligence (C^4I) systems. The core of the information attacks is to produce attrition in the adverse Observe-Orient-Decision-Act (OODA) cycle by affecting the performance of C^4I systems characteristics. The information processing, and more precisely - the multisensor data fusion process, became the "center of gravity" of information operations.

There are two ways to protect our own C^4I system from adversary invasion. The first one is to shield the information processing hardware and software, giving all responsibility to the "fire-walls". The second is to utilize robust data processing algorithms, providing a new level of sustainability and survivability of the whole system. The first way has been widely discussed in the last decade. Based on this discussion an opinion was formed that the information security will be implemented in C^4I systems "from outside" - in the form of coding, ciphering or compressing technologies and respective tools. The second approach was left to the C^4I system designers and engineers. It became their responsibility to assure robustness, sustainability and survivability of the whole information system, in the way they seem appropriate. We do not deny this generic division of the information security problems. We think that now is the right time to include the second approach to C^4I system protection in the flow of discussions, i.e., to consider information security as development of new sophisticated techniques and algorithms for data and information processing.

It is well known that the processing of ‘bad’ information will contribute to the creation of a bad common picture of situations and threats under consideration. There is no sense to protect poor data, obtained from obsolete sources. Everyone is eager to utilize advanced sensors. They are impressively effective but often vulnerable. The use of multiple sensors, especially those having the capability to measure different physical phenomena (infrared, acoustic, electromagnetic, etc), will improve the robustness of the common picture synthesis and assessment. Thus, the efficient use of multiple sensors can defeat enemy attempts to use jammers, deception or camouflage as components of information operations. Additionally, multiple sensor data fusion provides opportunities to correct errors, produced by each individual source. It is easy to demonstrate that the use of correct models of target behavior and adequate modeling of jamming can significantly improve the robustness of situation assessment processes.

It is clear, that there is no perfect set of techniques and algorithms, which would be optimal under all circumstances. In reality, the mathematical assumptions upon which many of these algorithms are formulated are rarely satisfied. This is one of the main directions of information attacks. They are often successful, because any sophisticated algorithm will produce very poor results, when the input data does not meet the required conditions. So, the effectiveness of the C^4I systems is sharply dependent on the available a priori knowledge. Unfortunately, the issue of its adequate collection, processing and storing is rarely discussed in the context of information security. We consider this area of contemporary research and development as a promising source for the increase of information security.

Algorithm development for some important applications such as automatic target recognition or identification "friend-foe-neutral" often utilizes specific flow of signals. Based on the specific spectrum patterns, the algorithms are trained to recognize the known targets based on the features extracted from the signals. But today it became obvious, that a thorough discussion on this theme is needed, because for new "stealth" targets there are never enough signals to satisfy the requirement for statistical significance. Besides the numerous methods, which provide the necessary synthetic training data, other techniques must be used to obtain significance for "stealth" pattern recognizers.

Of course, there are many information processing problems related to C^4I systems resistance to information attacks. Generally speaking, all users seek to improve the security of contemporary C^4I systems by improving their functional ability to estimate position, velocity, and identity/characteristics of entities. A very promising way to do this is to combine information using multiple target behavior models.

The applications of sensor’s data fusion range from situation and threat assessment to smart weapons, automatic target recognition, identification "friend-foe-neutral", and intelligence. Fusion techniques for all these applications are drawn from such advanced disciplines as space-time adaptive signal and image processing, multiple model statistical estimation, neural net pattern recognition, and decision-level artificial intelligence processing methods. It is beyond the scope of this issue of I&S to present all successful multiple sensor data fusion approaches and implementations, related to information security. Our intention is only to illustrate common problems in data fusion and how they are avoided or mitigated in particular systems implementation.

We believe this issue will accomplish its mission if two important conclusions about MSDF will appear after acquaintance with the proposed selection of papers. The first one is that in the theoretical and applied considerations of Information Warfare the development of the new sophisticated techniques has to be included. New robust and sustainable algorithms for moving target indication, multiple target tracking, artificial neural network pattern recognition, early warning, genetic algorithms, hybrid intelligent systems for situation and threat assessment, and virtual reality agents and robot control, have to be utilized. The second conclusion is that the knowledge engineering technology becomes of prime importance. It is well known that knowledge is mind's eye in the intelligence, and that the Information Warfare concept is build around the model of the human intuition and decision-making process. No doubt that today this branch of research becomes of a vital importance for the information warfighting concept.

The brief look on proceedings of latest MSDF conferences and workshops, organized by the Information Fusion International Association, shows lists of key research programs for design and development of numerous new technologies and tools. Correct identification of these research areas is crucial for information security in the 21st century. The basic purpose of this effort is not only "to create explicit, formal catalogs of knowledge that can be used by new data processing systems", but also to create a comprehensive vision for the information security in the 21st century. It is clear that the developed methods and algorithms are not only creative tools and means, but also parts of the emerging new military warfighting instruments. In this interpretation these methods and algorithms could be considered as smart "weapons", which mission is not only to possess signals, data and knowledge, generating real-time battlefield situation and threat assessments. They are also intended to generate friction in the enemy’s C^4I system, blocking its attempt to do the same. Having this in mind, we believe that the multiple sensor data fusion concept gives general-purpose (i.e. universal) understanding of social security and future warfare. Only the joint interpretation of relations between MSDF and Information Security will form the necessary conceptual frame of reference for understanding the 21st century environment.

In our attempt to illustrate our vision about information security and multiple sensor data fusion, we compiled this set of articles, which we consider only a representative sample of the huge number of publications. What we are trying to accomplish with this volume is not so much to present particular problem solutions in depth, as to mark the diversity and interdisciplinarity of the research area.

The first article in this edition is devoted to the problem of optimization of the Multi-Source Data Fusion system for Integration on the Canadian Patrol Frigate. Halifax Class Canadian Patrol Frigates and CP-140 (Aurora) fixed wing aircraft are planned to be upgraded within the next decade to be able to deal with far more demanding threat and mission environments of today and the future than when these platforms were designed. All levels of data fusion, resource management and imaging decision support capabilities, and their integration within a generic real-time knowledge base system are considered. The paper describes the efforts towards restructuring and optimizing the proof-of-concept MSDF algorithms to build and demonstrate a real-time prototype which will be ready for integration on the existing platforms and can perform real-time tracking and identification by the end of the year 2000. This paper is an excellent example of successful implementation of MSDF technology for overall information security increase in a large complex system.

In the next paper the integration of topographical and topological data in the estimation of the actual traffic situation on airports is studied. The automatic estimation of actual traffic situation on airports has become more and more important with the increase of the security of traffic flow. A method to model and to integrate the airport topography and topology into the traffic situation estimation process is presented in the paper. A filtering algorithm based on the advanced Interacting Multiple Model approach to hybrid systems estimation is proposed. It performs better than the known solutions, and provides an opportunity to rise the public safety in the complex airport area situations. This paper shows how MSDF can improve the security of air traffic control.

The next two papers treat the relation between human decision making and the fusion of information from multiple sources. The authors of the first of the two papers use the concept of integration of information processing functions by humans (instinctual behavior, intuition, motivational and emotional effects, rational decision making) as an useful paradigm to be followed by designers of MSDF architectures and algorithms. The resulting concept of computational intelligence provides for a holistic approach to design and integration of methods and algorithms for information fusion. The authors describe the application of computational intelligence to the fusion of data and information in two studies of early warning. The emphasis is on the power of soft-computing methods in designing early warning architectures pertinent to forecasting events in complex dynamical systems. The parallel with human decision making is found useful in dealing with incomplete and imprecise information on processes on which we have no or limited a priori knowledge.

The second of the two papers threats human intuition from a different perspective. It compares human intuition with computer based decision-making systems. The authors study performance of humans and computer algorithms in the task of classifying airborne targets according to their threat status and the appropriate response from an Integrated Air Defense System. Their results show that partial disclosure of the deterministic algorithm used to classify targets made the classification task even more difficult, contrary to intuition. The inadequacy of intuition is considered as a compelling reason for using specialized methods to design decision support systems.

The last paper in the first group presents an IMMPDA filtering algorithm for radar management and tracking maneuvering targets in the presence of false alarms and Standoff Jammer. The performance of the designed algorithm is evaluated by Monte Carlo simulation. The obtained results demonstrate that the tracking filter satisfies the performance restriction on a maximum allowed track loss posed by the benchmark problem. The reported results provide a glimpse on ongoing studies in this area, as well as on directions of further investigation. When you get acquainted with this paper you will realize how MSDF technology could be successfully utilized in Electronic Warfare.

The second group of papers presents Bulgarian MSDF R&D program and activities. A brief historical view, chosen strategy and achievements in the field of MSDF, and current joint R&D projects are presented.

The first paper of authors form the Central Laboratory for Parallel Processing at the Bulgarian Academy of Sciences presents an effective Doppler-filtering algorithm using higher-order statistics.

An algorithm for moving target selection in the presence of clutter and wideband jammer is presented. The algorithm performance is investigated by the means of Monte Carlo simulation analysis. The obtained result shows how the information included in the reflected signal could be effectively exploited for development of robust algorithms.

Tracking filters for radar systems with correlated measurement noise is the subject of consideration in the next article. Tracking filter for systems with colored measurement noise is developed. A new technique for adaptive evaluation of the algorithm parameters is proposed. The realized algorithm is incorporated into Interacting Multiple Model schemes for tracking maneuvering objects. A substantial improvement in velocity and acceleration estimation is achieved. Obviously, the robustness and security of such algorithms will be higher because of their capability to work in uncertain environment.

An Interacting Multiple Model algorithm for stochastic systems control is presented in the next paper. The overall system control is synthesized as a probabilistically weighted sum of the control processes from separate regulators working in parallel. These regulators are synthesized for each model from the uncertainty domain. The simulation results demonstrate that the IMM control algorithm provides better results in the presence of abrupt changes in the parameters than the already utilized similar algorithms. Because of the sustainability and survivability of data processing in conditions of random perturbations, this kind of algorithms is very promising for an increase in information processing security.

Multiple hypothesis tracking using Hough transform track detector is proposed and evaluated in the next paper. Uncertainty in the measurements is managed by the usage of asynchronous multiple hypothesis algorithms. At the cost of delayed track detection, this algorithm shows remarkable good performance and noise resistance. The inclusion of this paper in the issue has been motivated by the successful implementation of the multiple hypothesis approach. This approach is one of the most important instruments for fighting uncertainty in hostile environment (jammers, false alarms, closely spaced targets, crossing trajectories, etc.). By using the a priori information about the situations and threats that will appear, multiple hypothesis approach gives an opportunity to raise the reliability, and thus the security, of data processing. An interesting feature of the study is the combined use of multiple hypothesis tracking with Hough transform track initiator.

Maneuvering ship tracking, especially ship collision avoidance, is a problem of a great practical and theoretical interest. Real-world tracking applications meet a number of difficulties caused by the presence of different kinds of uncertainty due to the unknown or not precisely known system model and random processes’ statistics or because of their abrupt changes. These problems are especially complicated in the marine navigation practice, which needs a high level of security of the vessels traffic control. A solution of these problems is presented in the paper. A new ship model is derived after an analysis of basic hydrodynamic models. This model is implemented in a new version of the Interacting Multiple Model tracking algorithm - the most cost-effective multiple model algorithm for hybrid estimation. The performed Monte Carlo simulation shows that the model fits available data excellently. The obtained good estimation performance demonstrates that this algorithm could be successfully implemented in collision avoidance system for reliable real-time data processing.

For readers, interested to learn more about MSDF, four fundamental books are presented in this volume: *Multisensor Data Fusion* by Edward Waltz and James Llinas, *Information Warfare Principles and Operations* by Edward Waltz, *Bayesian Multiple Target Tracking* by Lawrence Stone, Carl Barlow, Thomas Corwin, and *Multitarget/Multisensor Tracking: Applications and Advances (Volume III)* by Yaakov Bar-Shalom and William Blair. The fifth book - *Sensors for Peace: Applications, Systems and Legal Requirements for Monitoring in Peace Operations* edited by Jurgen Altmann, Horst Fisher and Henny van der Graaf - provides a multidimensional study of the connection between sensor system technologies and important international security issues such as the efficiency of peacekeeping operations. We find these books very useful not only for students and Ph.D. applicants, but also for specialists who are not familiar with the foundations of MSDF, but are interested in further applications and have a good mathematics background. For the beginners, a small set of information fusion terminology is given. Additionally, a short list of introductory publications is proposed. For more information and references a sample of Internet links is provided, as well as a schedule of events of the International Society of Information Fusion.

We hope this issue will help to develop new interrelations within different areas of science community. The common interest in solving Information security problem using MSDF technologies could provide new opportunities for fruitful cooperation and consideration of future joint R&D projects.

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OPTIMIZATION OF THE MULTI-SOURCE DATA FUSION SYSTEM FOR INTEGRATION ON THE CANADIAN PATROL FRIGATE

Elisa SHAHBAZIAN, Louise BARIL and Jean-Rémi DUQUET

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1. Introduction

Since 1991, the Research and Development (R&D) group at Lockheed Martin Canada (LM Canada) has been developing and demonstrating Level 1, 2, 3 and 4 data fusion, resource management and imaging technologies which will provide Observe-Orient-Decide-Act (OODA) decision making capabilities/tools in Naval and Airborne Command and Control (C2) for application on Canadian Patrol Frigates (CPF) and Canada's CP-140 (Aurora) fixed wing aircraft. Over the last three years LM Canada, in collaboration with Canada's Defence Research Establishment Valcartier (DREV), has also established a generic expert system infrastructure and has demonstrated that it is suitable for integrating these decision making technologies into real-time Command and Control System (CCS). The Multi-Source Data Fusion (MSDF) technology is the most mature among these decision making technologies and is likely to be integrated onboard a currently fielded CCS the soonest. Over the last two years the LM Canada R&D team has started the effort towards re-structuring and optimizing the proof-of-concept MSDF algorithms to establish a prototype which will be ready for integration on the existing platforms, specifically the CPF, and that can perform real-time tracking and identification by the end of the year 2000. This restructuring and optimization is occurring in phases.

First the existing proof-of-concept MSDF system was broken down into very basic modular and independent components within the generic expert system infrastructure. Each MSDF process (alignment, association, kinematic estimation, identification, etc.) consists of one or more of these basic components. This architecture is designed to enable independent modification and evaluation of each component. It is also ideal for ensuring future growth for adding additional decision support capabilities, with minimal impact on the already implemented and demonstrated system.

Next these components are analyzed, optimized and evaluated in terms of their performance, given the characteristics and amount of input sensor data and information. Initially, this is done using simulated data, and the optimization is iterated until the performance of the overall MSDF system is able to process peak loads of data with higher operational performance than the current CPF.

In the third phase, recorded data at sea will be used to validate and further optimize the MSDF system. It is clear that the behaviour of some of the algorithms will be different with this data, and this will be the most challenging aspect of this phase. At the end of this phase the MSDF system will be ready for integration on CPF. It will not only be able to process all data available on CPF, producing high quality kinematic and identification estimates, but will also be open for future evolution to more sophisticated sensor data processing, fusion of additional sources of data, higher level fusion processing, etc.

At the current time, the first two phases of this effort are close to completion. This paper includes the details, lessons learned and results of the first two phases, and describes the specific research activities envisaged in the third phase. It also describes some earlier and parallel proof-of-concept efforts towards demonstrating the future growth of this system.

2. KBS Architecture Based MSDF Design

The details of the MSDF prototype,[1,2] as well as the KBS architecture, have been published earlier.[3,4,5,6]

The KBS architecture developed at LM Canada was designed right from the start as an architecture that could support a large real-time application through all phases of its development life-cycle, from early analysis and prototyping phases to the final deployment. As such, it had to incorporate several key features to give maximum flexibility to the developers without adversely impacting performance. As a minimum, the KBS shell must provide the following:

a. *Speed*: The key advantage of this system is pure execution speed, as a result of its implementation as a compiled system (C++) rather than an interpreted one, and because of its optimized blackboard controller.

b. *Small Overhead*: Because of its streamlined design, the KBS scheduling and activation mechanisms introduce very little overhead in the system. The difference between "Total Agent CPU" and the "user CPU" has been shown to be less than 5 %.

c. *Linearity*: The blackboard controller design incorporates a critical mechanism, similar to the so-called RETE algorithm, which directly links each agent to its associated data types, thereby avoiding costly loops each time an agent-data pair needs to be activated. This mechanism, coupled with a design which avoids lists searches in the internal controller, ensures from a theoretical point of view that the processing time of a given system of agents will scale linearly with the number of rules and data instances present in the system, thereby allowing system scaleability (provided of course that the agents themselves are linear). This linearity has been demonstrated with run-time benchmarking of Level 2, 3 data fusion algorithms in a previous study[6] (similar to MSDF in terms of software complexity and CPU needs) with up to 1000 tracks.

These features illustrate that the KBS-based implementation will not handicap the run-time performance of the MSDF system.

Other major benefits of this architecture include modularity and the possibility of modifying each component independently, without affecting the rest of the system, as well as the ability for integrating algorithmic and rule-based decision support within the same infrastructure

Although Level 1 data fusion does not require rule-based reasoning, it is clear that the architecture is ideal for future growth into higher level fusion implementations.

Therefore the first step towards optimization of the MSDF prototype was to decompose it into agents. Figure 1 shows a high level diagram of how MSDF was decomposed into agents within the KBS architecture. It illustrates the fact that the MSDF system can be viewed as a small number of independent domains, consisting of a number of sequential steps:

a. Data reception, preparation and buffering

b. Data processing (i.e., the fusion processes)

c. Track management

d. Data output mechanism (not represented in Figure 1).

The end result of this first step was a new prototype, Data Fusion on Blackboard (DFBB).

The designer can use three potential options to make optimal use of the processor (and other system's resources) to obtain a faster execution, and ultimately guarantee real-time performance of the system within this infrastructure.

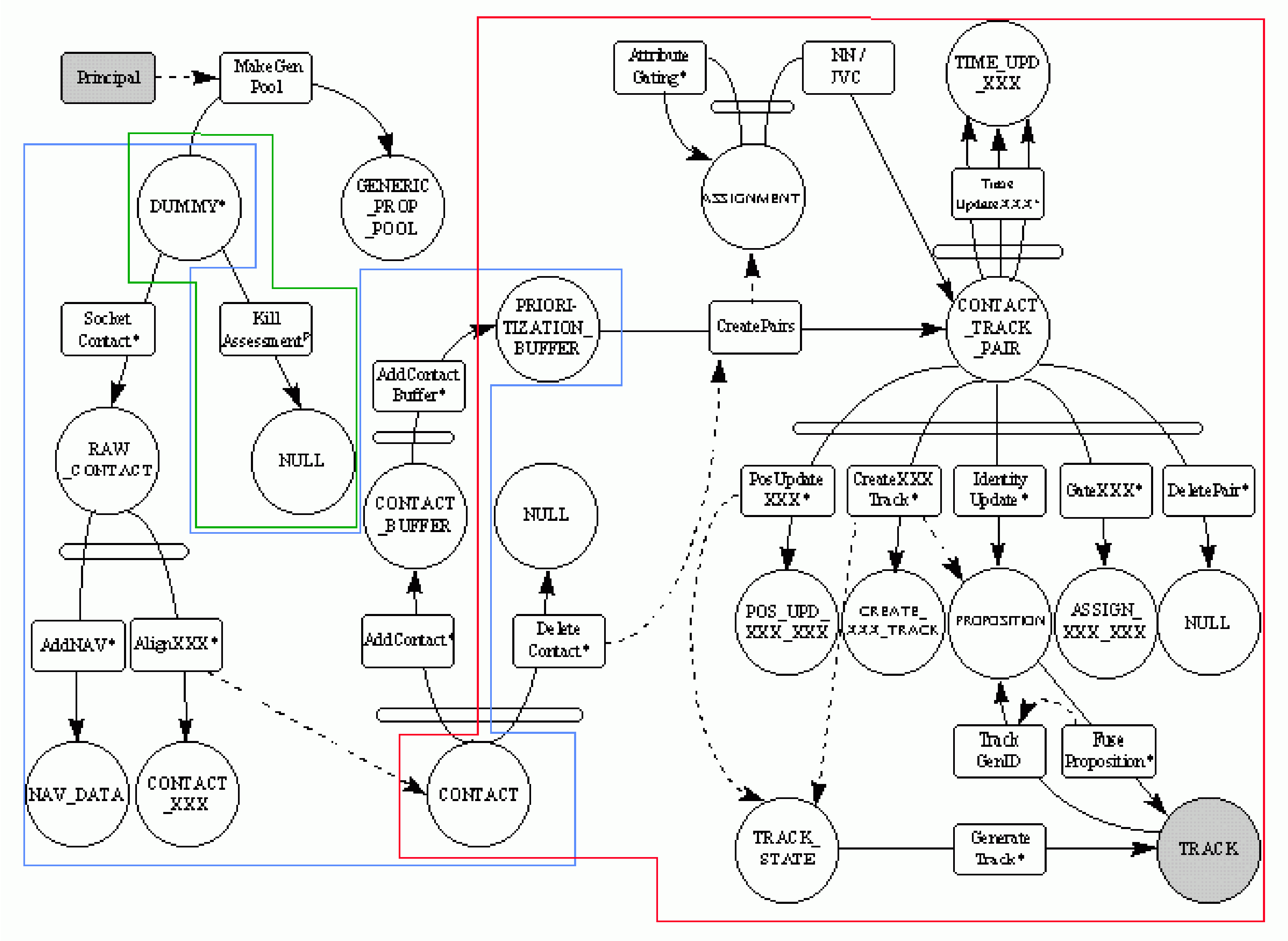

Figure 1: High-Level Data Flow Diagram of Agents Present in the MSDF System. Circles represent data types present on the KBS, while squares represent the agents that act on the data. Symbols XXX are used when agents/data types are present under several flavors depending on the context of operation (e.g. sensor name, track and contact types, etc.)

The first is intrinsic to the KBS and involves the regular blackboard scheduler together with the fine granularity of each individual agent; the second deals with agents multithreading, which is very robust and user-friendly on the KBS; and the third uses the real-time features of the operating system, which are still available to the developer through the KBS layer. Because of the nature of Data Fusion algorithms, and also because the timing constraints are not too stringent, our efforts will focus on the first method, namely run-time optimization of individual agents.

3. Initial Optimization Efforts

The first necessary condition that has to be met by any real-time application is run-time efficiency, that is, it has to ensure at least average real-time performance. This step involves the optimization of the DFBB to support real-time processing of all data available on a platform, specifically the CPF.

The four domains of MSDF are more or less independent and could in principle be suitable for process prioritization schemes and real-time scheduling. However, initial review of the DFBB code shows that three domains out of four are low consumers of CPU resources, and the remaining one (Data Processing) consists of a relatively small number of sequential steps which would benefit very little from a sophisticated scheduling mechanism. Moreover, CPF real-time constraints on input data (typically several tenths of a second) do not justify the use of hard real-time features (or even a strict real-time operating system). For these reasons, before real-time scheduling and prioritization issues are even considered, code optimization must be pushed to the limit to increase run-time performance as much as possible.

The code optimization is done by iteratively profiling the software, evaluating the bottlenecks and re-designing/re-coding to remove/reduce CPU utilization by such components, taking advantage of the various intrinsic facilities of the KBS architecture and other methods.

3.1. DFBB Benchmarking

The initial DFBB system processed a 100 seconds scenario in about 100 seconds (i.e., average real-time) for 100 targets, while the 200-targets scenario requires about 3.5 times the amount of CPU to process a scenario of the same duration.

This is not surprising, since a few agents are clearly expected to behave in a non-linear way. In fact, all the agents participating in updating tracks, the application of the Kalman filter and the identity update are expected to show a linear behaviour (i.e., linear against the number of tracks), while those performing the gating are expected to behave roughly as "Ntr2", since the gating process involves "Ntr" x "Nir" pairs (where "Nir" is the average number of input reports in a data set which is proportional to "Ntr").

Those expectations are confirmed by a closer inspection at code profiling results for the individual agents. Several tools are available for this task, depending on the level of investigation taking place. Standard profiling tools are available on Unix, such as gprof, giving various degrees of details about the internal calls performed in each agent, with various timing accuracies as well. For the time being, a minimally intrusive way of probing the cumulative CPU used by each agent is of interest. For this investigation, a timing tool is available on the KBS to monitor the user process time spent between the start and the end of each agent with minimal overhead, using C "Times" functions. The nominal precision on each agent execution (time / call) is 1 millisecond.

Results are presented in Table 1 for most agents involved in the fusion process in DFBB.

Table 1. DFBB Benchmark Results on a 450MHz Pentium Processor running under Solaris 2.6. A very large fraction of the CPU is used by only 6 agents (highlighted).

Scenario :	50 Targets		100 Targets		200 Targets	
Agent Name :	num. of calls	Total Time (secs)	num. of calls	Total Time (secs)	num. of calls	Total Time (secs)
AddContact	14171	0.070	26808	0.230	51214	0.260
AlignIFFContact	4389	0.170	8454	0.480	16307	0.900
AlignSG150Contact	4663	0.240	8760	0.600	16629	0.980
AlignSPS49Contact	5119	0.210	9594	0.550	18278	0.990
AttributeGating	**7120**	**0.760**	**8831**	**2.190**	**9358**	**7.760**
CreatePairs	**7142**	**1.510**	**8854**	**3.620**	**9370**	**10.310**
CreateRBTrack	59	0.010	117	0.010	248	0.010
DeleteContact	14171	0.100	26808	0.300	51214	0.700
DeletePair	**55984**	**0.660**	**153937**	**1.640**	**550216**	**6.640**
ExtAdap KalmanRB_RB	**14112**	**2.170**	**26691**	**4.050**	**50966**	**7.490**
FuseProposition	2534	0.110	4870	0.180	9472	0.410
GateRB_RB	**41813**	**3.700**	**127129**	**11.690**	**499002**	**46.870**
GenerateTrack	14171	0.230	26808	0.490	51214	0.770
IdentityUpdate	14112	0.320	26691	0.600	50966	1.370
NearestNeighbour	7120	0.520	8831	0.720	9358	1.270
Principal	1	0.130	1	0.140	1	0.140
SocketContact	7143	0.580	8855	0.930	9371	1.620
TimeUpdateRBTrack	**55925**	**5.290**	**153820**	**14.630**	**549968**	**54.720**
TrackGenID	1615	0.620	2516	0.910	3174	1.310
CPU agent total time		**17.42**		**43.98**		**144.52**
User CPU time (sec):		18.67		46.07		152.46
System CPU time (sec):		1.27		2.89		6.00
Execution Time (min):		0:20.40		0:49.36		2:38.85
Overall CPU use (%):		97.7 %		99.1 %		99.7 %

The following observations follow directly from the data displayed in Table 1:

a. A very large fraction of the CPU time (above 90% for 200 tracks) is spent in six agents. These agents are all on the critical path and cannot be pushed aside or executed out of sequence by some process scheduling scheme. In order to reduce average run-time comfortably below the 100-second duration of the scenario, the first step is clearly to optimize those agents to increase execution speed and, if possible, linearize them with respect to the number of tracks "Ntr" to reduce their impact on the worst-case scenario and improve scaleability (for Ntr > 200).

b. The most time-consuming agents, as identified in Table 1, are all (except one) agents that show a non-linear execution time against the number of tracks processed by the system. The non-linear agents are: *TimeUpdateRBTrack*, *GateRB_RB*, *CreatePairs*, *DeletePair*, *AttributeGating*; Among those, we can identify two categories:

    1. The number of calls to the agent is roughly constant, but the agent internal algorithms involve input data of the type "Ntr" x "Nir" (e.g., track-input report pairs), and requires a processing time roughly proportional to "Ntr2 ". The agents falling in this category are "AttributeGating" and "CreatePairs".

    2. The agent execution time is roughly constant, but the number of calls to

the agent increases like "Ntr2". This category includes DeletePair, GateRB_RB and TimeUpdateRBTrack.

From the preliminary analysis and observations above, taking each agent independently, the following optimization strategy to reach average real-time performance was selected:

a. *TimeUpdateRBTrack:* This agent is the most demanding in the whole system, thanks to both internal processing needs and a large number of calls. It is used both for the gating process and the positional track update process (as part of the Kalman filter process); these processes can be analyzed separately:

    1. Track update: At the end of the fusion process, each contact is used to update the state vector of one of the tracks in the system. The track is time-updated in the process, resulting in ~50 000 calls to TimeUpdateRBTrack for the 200 seconds scenario. The number of calls is linear with Ntr and does not cause abusive overhead in this process.

    2. Position update: before the gating process, the MSDF algorithm selects a sample of tracks, and propagates their state vector to the time of each contact received to form a contact-track pair. This translates into a number of calls of order "Ntr^2", for a total of ~480 000 agent calls to TimeUpdateRBTrack during the 200 second scenario. This latter number could be reduced by a factor of ~6 if the tracks were time updated to an average time instead of the individual times of the input reports, thereby making the number of calls to the agent linear with "Ntr"

    3. Once this agent has been linearized, another quantum leap in speed will be gained by the use of XY coordinates for tracking, instead of the current RB coordinates. The current agent TimeUpdateRBTrack spends significant processing time converting the RB track state to an intermediate XY state vector, and back to RB.

b. *GateXY_XY* will replace the current RB_RB version. This by itself will do little to improve run-time performance since the gating agents do not require RB to XY conversions. However, in the current implementation, all gating agents compute their statistical distance via a call to a single, generic method that performs several complex matrix operations (i.e., matrix reduction, transposition, multiplication and inversion). This improves code readability but only at the expense of significant CPU overhead. It is hard to predict the cumulative gain expected by all these optimizations; a factor of 2 is certainly an underestimation and a factor or 5 is not out of reach.

c. *ExtAdapKalmanRB_RB* is a linear agent, but suffers both from time-consuming RB to XY conversions and from extensive use of matrix operations used to calculate the Kalman gain and the resulting track state update. This agent is already linear in "Ntr" and should drop by a (very conservative) factor of 2 at least in the final implementation.

d. A significant speed increase can be achieved just by implementing a better object creation strategy in the MSDF system. Most of the dynamic memory allocation can be replaced by the use of persistent objects created upon system initialization, for instance by replacing contact-track pair objects by a single, persistent pair list. An immediate effect would be the disappearance of the agents *DeletePair* and *DeleteContact*, two of the major - non-linear - CPU contributors identified above. This would result in an immediate gain of about 40 seconds out of 320, for the 200-targets scenario. Similar object creation is also hidden inside other agents (e.g., *ExtAdapKalmanRB_RB*, which instantiates a new TrackState object for each track update) and can be improved, with significant gains in terms of run-time performance.

The sole implementation of about half of the strategies stated above decreased significantly the CPU time needed by those processes, prior to performing any deeper investigation to streamline and optimize the individual agents (e.g. through internal code profiling). After a change of coordinate system, and with most generic matrix operations expanded, one gets the figures presented in Table 2, where the results of benchmarking before and after optimization are shown side-by-side for 200-targets scenario.

Even though object creation/deletion strategies and agents linearization still remain to be applied, overall CPU needs of DFBB agents has already been divided by three, allowing the system to achieve average real-time performance on the presented scenario. Further optimization is expected to bring the current figure down by another factor of two.

Table 2. Comparison of DFBB before and after the first round of optimisation for a 100-seconds, 200-targets scenario on a 450MHz Pentium Processor, showing the main CPU-demanding agents.

Scenario :	Before Optimisation (R-B Tracking)		After Optimisation (X-Y Tracking)	
Agent Name :	num. of calls	Total Time (secs)	num. of calls	Total Time (secs)
ExtAdapKalman	50743	8.100	50764	7.510
TimeUpdate Track	891431	102.140	895377	17.000
Gate	840688	101.040	844613	12.400
CreatePairs	9326	22.350	9326	21.950
DeletePair	891681	10.110	895606	9.940
AttributeGating	9315	12.770	9315	2.510
total main 6 agents		*256.51*		*71.31*
% of total agent CPU		*95 %*		*85 %*
total all other agents		*15.04*		*14.01*
Total Agents CPU		**271.55**		**85.32**

4. Supporting R&D and Future Plans

In parallel with this real-time performance optimization efforts, there are a number of projects at LM Canada which look at the optimization of algorithm performance, development of alternate algorithms which have higher performance, development of strategies for fusion management (level 4 fusion) to activate different algorithms depending to different context, etc.

The KBS architecture is ideally suited for supporting all of these concurrent activities, permitting iterations of algorithmic and real-time optimization indefinitely, until the desired performance is achieved of each individual platform.

The next step for the CPF is to use recorded data at sea and use it to validate and further optimize the MSDF system. It is clear that the behaviour of some of the algorithms will be different with this data, and this will be the most challenging aspect of this phase. In this phase too, the algorithmic developments of the parallel research efforts will be very useful, as a variety of algorithms to perform each MSDF task will be available for experimentation. At the end of this phase the MSDF system will be ready for integration on CPF.

Acknowledgements

The authors would like to thank the DREV DFRM research team and the rest of LM Canada’s R&D team, all of whom had significant contributions into decision support technologies research and demonstrations for Canada’s defence platforms since 1990, and specifically the application of these technologies to CPF.

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Optimization of the Multi-Source Data Fusion System for Integration on the Canadian Patrol Frigate

Elisa Shahbazian, Louise Baril and Jean-Rémi Duquet

Canada's Halifax Class Canadian Patrol Frigates (CPF) and CP-140 (Aurora) fixed wing aircraft are planned to be upgraded within the next decade to be able to deal with far more demanding threat and mission environments of today and the future than when these platforms were designed. Over the last ten years Lockheed Martin Canada (LM Canada), in close collaboration with Canada's Defence Research Establishment Valcartier (DREV), has been developing and demonstrating Level 1, 2, 3 and 4 data fusion, resource management and imaging decision support capabilities, and their integration within a generic real-time KBS BB architecture. The Level 1 data fusion or Multi-Source Data Fusion (MSDF) technology is the most mature, and is likely to be integrated onboard a currently fielded Command and Control System (CCS) the soonest. This paper describes the efforts towards re-structuring and optimizing the proof-of-concept MSDF algorithms to build and demonstrate a real-time prototype which will be ready for integration on the existing platforms and can perform real-time tracking and identification by the end of the year 2000.

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INTEGRATING TOPOGRAPHICAL AND TOPOLOGICAL DATA IN THE ESTIMATION OF THE ACTUAL TRAFFIC SITUATION ON AIRPORTS

Christoph MEIER

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1. Introduction

The main necessary functions to manage the traffic on the movement area and the airspace around an airport are surveillance, control, routing and guidance.[1] Routing is often also termed planning. Today these functions are carried out manually by the controller in the tower and in the apron. But automatic assistance is becoming more and more important with increase of traffic flow in order to reduce the controllers' workload from routine work. The basis for assisting systems is normally a system to estimate the actual traffic situation.

The task of assessing the traffic situation is done today mainly by means of visual observation. The second information source is the voice communication between pilots and controllers. The pilot says where he actually is. Technical systems that help the controller are TV cameras looking at areas not directly seen from the controller, approach radar (Airport Surveillance Radar ASR) and airport radar (Surface Movement Radar SMR). These sources present their information in various ways - visual (TV), aural (Voice), from different points of view (all), with clutter (SMR) and synthetic (ASR). The controller fuses all this information in his head in order to estimate the actual traffic situation.

2. Concept for an automatic airport surveillance

In a future system the task of traffic situation estimation could be performed by an automatic system. As the traffic objects are partly non-cooperative and partly cooperative also two types of sensors have to be used. Non-cooperative sensors are necessary to detect obstacles and vehicles not equipped with transponders. Cooperative sensors are necessary to identify objects. In order to present an unambiguous traffic situation on a synthetic display to the controller a data fusion process is necessary to fuse at least the information of these two sensor types. But also non-sensor information should be taken into account as presented in Figure 1.

Internal sensors are those installed for traffic situation assessment. Examples for sensors actually under development are:

- SMR with digital target extraction
- Near range Radar Network NRN [2]
- TV or infrared cameras with image processing

- SSR Mode S multilateration [3]
- D-GPS with automatic downlink
- Fiber Optical Sensor FOS [4]
- Aircraft Registration Mark Identification [5]

Of cause further sensors are possible. When such a multi sensor system is applied to an airport the types and locations of the sensors have to be selected according to the needs of the airport in order to optimize the cost / benefit ratio.

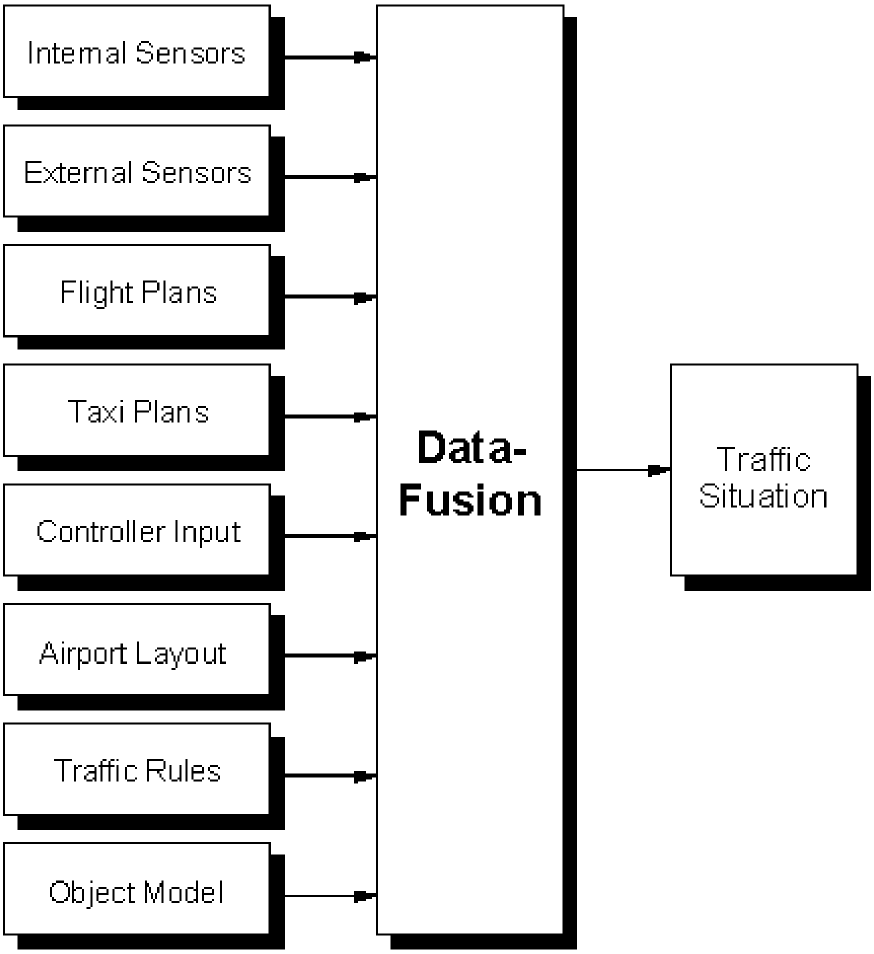

Figure 1: Data Fusion Concept

External sensors are those already installed for different purposes. Often an ASR for airspace surveillance around the airport is available. External sensors as well as flight plans give valuable hints on expected traffic objects. This information can be used, e.g., for identification purposes. Taxi plans might be available from an automatic routing system. They define with a certain probability the future route and future actions of a traffic object on the airport. Controller inputs such as guidance instructions also define the future behavior of traffic objects. The use of this information would require reliable speech recognition. More realistic is the use of controller inputs concerning the object identity (optional manual labeling). The airport layout defines in most cases all possible routes a traffic object can take on an airport. Heavy aircraft are not able to taxi beside the taxiways. Furthermore, traffic rules limit the number of probable routes for a traffic object. Finally a physical object model is of course used to integrate the knowledge that traffic objects do not jump from one place to another.

The advantage of integrating this a priori information is that it can be quite easily obtained and that it requires little maintenance. The problem of integrating such assumptions, i.e., that traffic objects use exclusively the taxiways or that they respect all traffic rules all the time, includes the risk that the traffic situation estimation could fail if these assumptions are violated. So, methods have to be developed and used that cope with these risks.

3. Modeling the airport layout

3.1. Purpose of the model

A model is always a simplified representation of the main characteristics needed by the user of the model. In this case the data fusion process is the user of the model and therefore defines the requirements to this model. Before modeling the airport layout it has to be defined what tasks the data fusion process has to perform using this model.

1. Positional sensor information normally refers to x-y coordinates. If the data fusion wants to use the airport layout, it has to find out which part of the airport is actually used by a traffic object. This is the mapping from mathematical 2D (or even 3D) space to a part of the airport.
2. The inverse conclusion from the usage of a certain part of the airport to mathematical coordinates is necessary at least for output purposes.
3. Inference on the probable future behavior of a traffic object derived from the type of the airport part the object is using might also be useful (e.g. high accelerations are probable on runways).
4. It should be possible to conclude from the usage of a part of the airport to the usage of further parts of the airports. This is a prerequisite to find possible routes on the airport.

3.2. Modeling approach

The airport layout is modeled in two parts:

- topography
- topology

The topography describes the physical location of segments of the airport. Especially the boundaries or *shapes* of these segments are part of the topography. Shapes are defined as sets of topographical *points*. The definition of these shapes is done in such a way that each point of the mathematical 2D space belongs exactly to one topographical shape. Therefore the shapes are defined mutually exclusive, they do not overlap as shown in figure 2. The segments are carrying references to the topological elements of the airport.

Topological elements are *nodes* and *links*. Nodes are referencing also topographical points - each node is associated with one physical point. This point is normally defined on the edge of a topographical shape. The only exceptions are the ends of taxiways in the apron area. Links are connections between two nodes. Normally exactly one link is referencing a topographical shape. The exceptions are junctions of taxiways where several links reference the same topographical shape. Links are wearing additional attributes to define the operational meaning of that part of the airport, used types are „Runway", „Taxiway", „Apron", „PushBackGate", „DriveThroughGate", ApproachArea", „Grass", „Hangar", „Terminal" and „Street". Further attributes describe whether the nodes are connected in a straight line or with an arc.

Figure 2 shows the defined shapes, nodes, links and attributes for a small part of an airport. With this model the statement „traffic object at position P_1" can be unambiguously translated into the statement „traffic object inside shape S_1" and further into „traffic object following link L_1" or further into „traffic object on runway 27R".

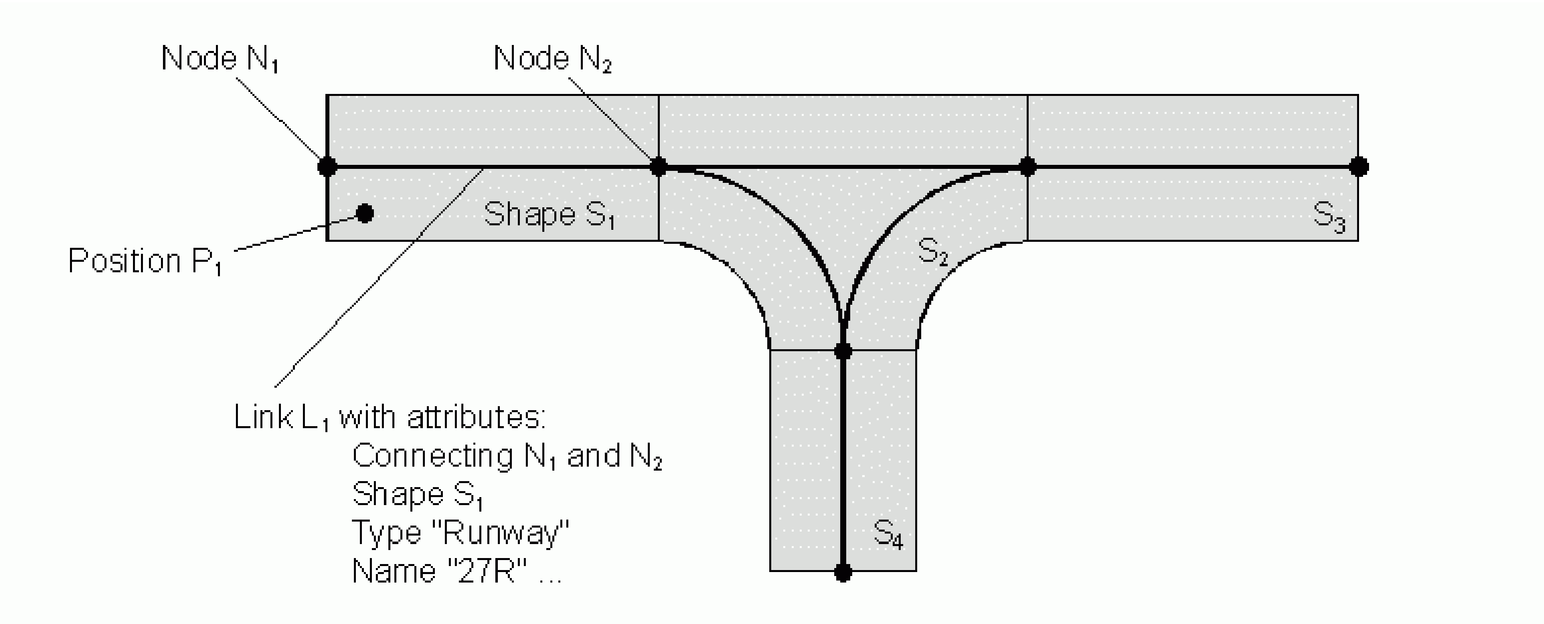

Figure 2: Model of a runway exit

This translation will only be reliable, if the position is not uncertain. If the traffic objects position P_1 has an error of e.g. 10 m, it would be possible that a wrong shape is selected and that all further conclusions based on this shape assumption become also wrong. Furthermore, the conclusion from one single position P_1 to the statement „traffic object following link L_1" is very fragile, the object might just cross the runway. These aspects have to be taken into account when using the model in the state estimation process.

3.3. Application to a specific airport

There are several ways to obtain the described airport model. For airports where no reliable maps are available the best approach might be an analysis of satellite images. Another way is the digitalization of paper maps that is very time consuming. But in most cases larger airports today have already an airport map in electronic form. This can be further processed by a CAD system. The processing steps in this case are:

1. Check the validity of the map data, do not trust anything
2. Pick up the relevant topographical points on edges of taxi- and runways, centerlines etc.
3. Construct further points, e.g. centerpoints for arcs
4. Define shapes connecting topographical points
5. Declare some topographical points to be also topological nodes
6. Connect the topological nodes with straight and arc links
7. Give attributes to the links
8. Let the topological elements reference the topographical ones

4. Using the airport model in the state estimation process

4.1. Searching a topographical shape

When a new traffic object becomes tracked, it is normally not possible to decide immediately which part of the airport it is using. A search phase is necessary. At least one should take into account the direction of movement - the object might just cross a topographical shape - and perhaps the type of the object - a car cannot be on final approach. Because the observation process in the sensors are normally subject to additive noise a soft decision method should be used to find the correct topographical shape. For example, numerical integration of the assumed position error distribution in the limits of the considered shape gives a probability that the object is actually within the shape. Doing this - in the worst case with all shapes - one gets a discrete probability distribution on some shapes. To filter this over time a Bayesian framework can be used. The requirement that the shapes must be mutually exclusive avoids the necessity to apply Dempster-Shafers evidence theory. In the search phase a standard Kalman filter - state vector x, y, vx, vy and additive white gaussian process noise - is used to filter the kinematic sensor data in world coordinates. The search phase is only terminated if a topographical shape is found with a certain high probability or the object leaves the surveillance area.

4.2. Following a route

If a topographical shape is found, the conclusion to the used link is done. The link is extended by adjacent links in both directions until a junction or a leaf of the node-link-network is found. The sequence of links now represents an assumed route the object is following. Another Kalman filter is created filtering the kinematic sensor data in route coordinates. X represents the progress on the route, y the deviation to the left side, vx the speed along the route and vy the speed across the route. The Kalman filter from the search phase is not destroyed, it represents the hypothesis that the object is not following a route. So two Kalman filters run in parallel. To avoid divergence of their state estimates a Interacting Multiple Model (IMM) algorithm is used to make continuously a soft decision between the two hypotheses - using the network or not. At junctions further Kalman filters, each representing a feasible route, are created and integrated into the IMM. Route hypotheses are generated when they become possible and are destroyed when they become implausible. Too large deviations from the route make them implausible, the same applies to too high curve accelerations. The first Kalman filter is never destroyed in order to cope with situations where a traffic object leaves the taxiway.

4.3. Experiments

To demonstrate the behavior of the proposed method it is tested with simulated sensor data as follows. An object is moving at a constant speed of 10 m/s on the airport shown in figure 3 (Braunschweig airport). It starts on the DLR apron and taxies via F and C. Two fictive sensors observe the moving object. They only deliver positional sensor plots. The characteristics of the two sensors are:

	Sensor 1	Sensor 2
accuracy in x (1s)	15 m	3 m
accuracy in y (1s)	3 m	15 m
update interval	1,25 sec	0,95 sec

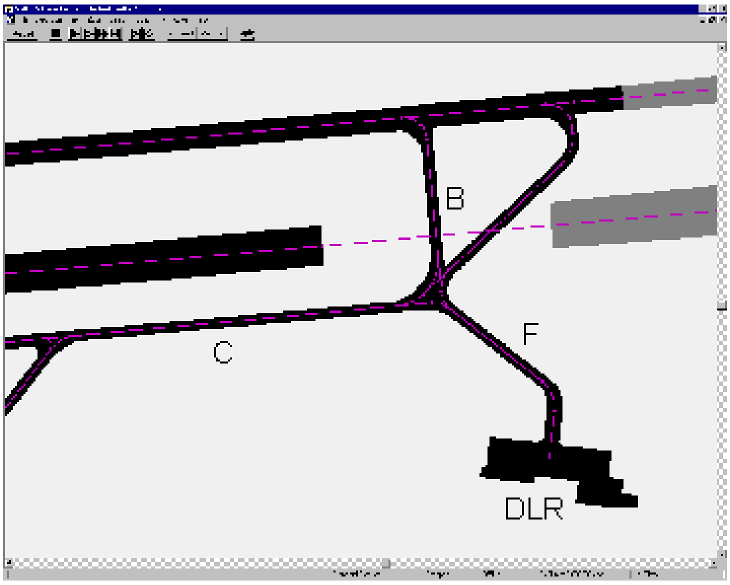

Figure 3: Layout of the Braunschweig airport

First a standard Kalman filter is tested for comparison purposes. The state vector is composed of x, y, vx and vy. Random accelerations in x and y direction with a 1 s value of 0,5 m/s² represent the process noise. Figure 4 shows the result. The gray line represents the true object position. The gray crosses represent the plots of the two sensors and the black solid line the estimates of the Kalman filter.

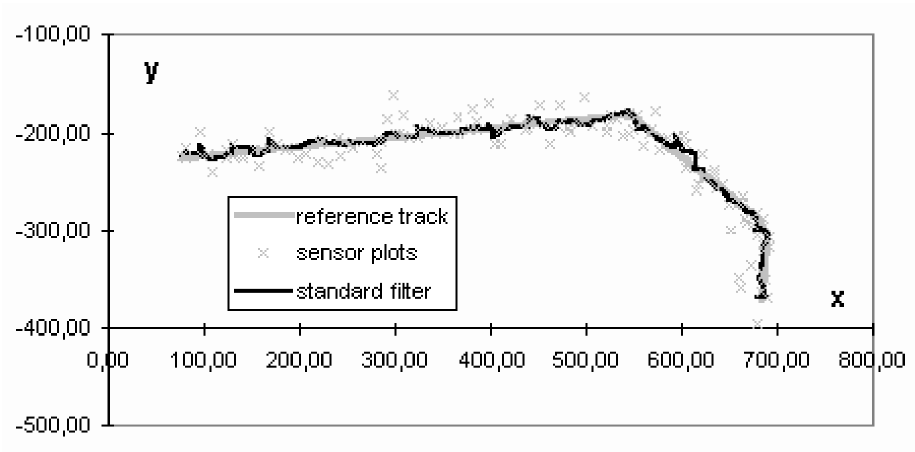

Figure 4: Filtering with a standard Kalman filter in world coordinates

Figure 5 shows that an improvement can be achieved when filtering in route coordinates instead of world coordinates. That requires the knowledge of the correct route. Figure 6 presents what can happen in the worst case, if the route assumption is wrong (DLR-F-B) - the filter diverges!

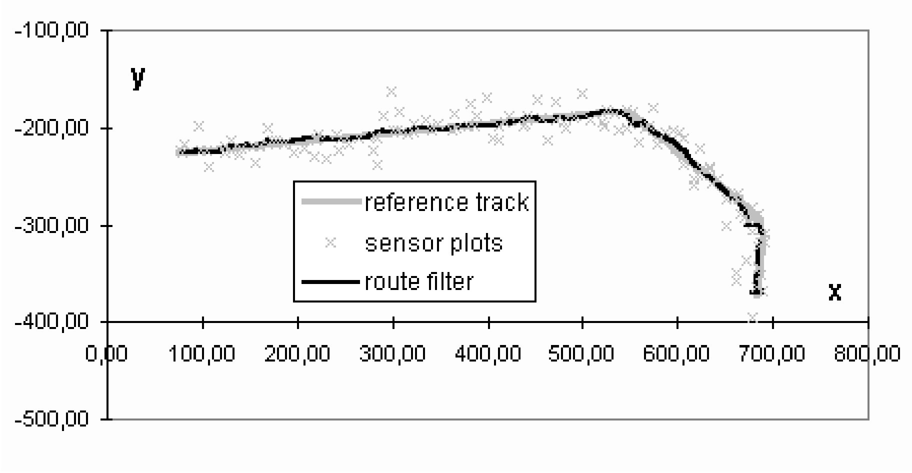

Figure 5: Filtering in route coordinates, assuming the correct route (DLR-F-C)

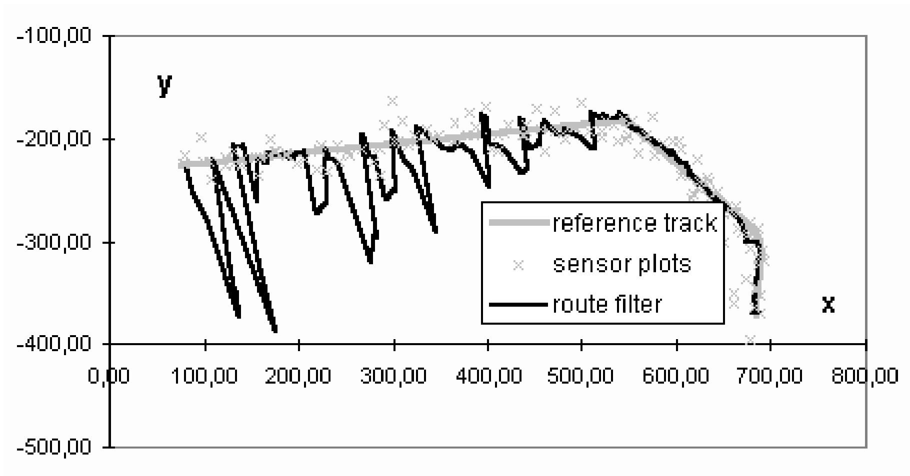

Figure 6: Filtering in route coordinates, assuming the wrong route (DLR-F-B)

Finally, figure 7 shows the filtering with the proposed IMM method that searches and maintains the correct route automatically.

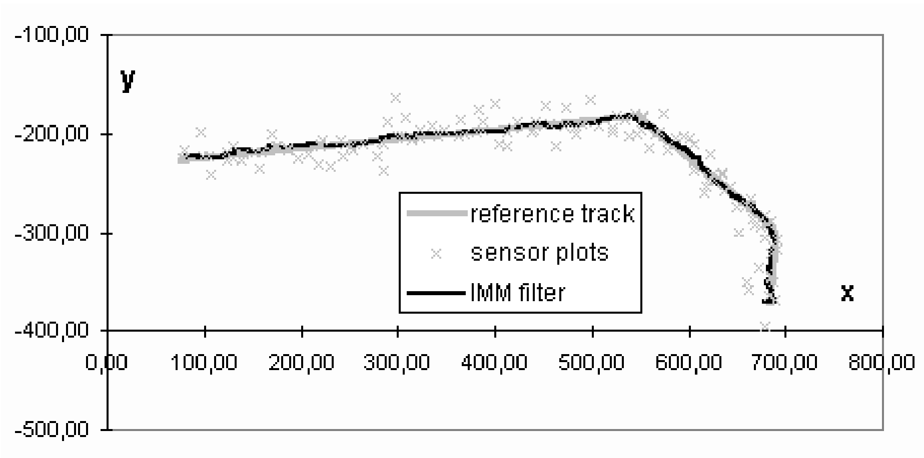

Figure 7: Filtering with the proposed IMM method

The main advantages of the proposed method are:

- The filter predicts the object motion „around the corner". Therefore, less systematical errors occur when the object is following a curve. This might also be useful for a data association process to enhance the track continuity.

- The relationship of the traffic object to the airport is permanently estimated. This is part of the data fusion function „situation assessment". Following subsystems, e.g., Routing, require such higher level data representation.

The disadvantage is a higher computational complexity. Three Kalman filters integrated in one IMM are approximately as expensive as four stand alone Kalman filters.

5. Summary

A method to model and to integrate the airport topography and topology into the traffic situation estimation process has been presented. It performs better than standard Kalman filter solutions. A certain abstraction of the state description of a traffic object from mathematical coordinates to higher level functional airport elements is obtained as a positive side effect. The proposed method is computationally more complex than standard solutions.

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Integrating Topographical and Topological Data in the Estimation of the Actual Traffic Situation on Airports

Christoph Meier

Keywords: Data Fusion, Topographical and Topological Data Estimation**,** Kalman Filtering

The automatic estimation of the actual traffic situation on airports is becoming ever more important with the increase of traffic flow. A method to model and to integrate the airport topography and topology into the traffic situation estimation process is presented in the paper. A certain abstraction of the state description of a traffic object from mathematical coordinates to higher level functional airport elements is obtained as a positive side effect. A filtering algorithm, based on the advanced Interacting Multiple Model approach to hybrid systems estimation is proposed. It performs better than standard Kalman filter solutions. The proposed method is computationally more complex than standard solutions.

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COMPUTATIONAL INTELLIGENCE IN MULTI-SOURCE DATA AND INFORMATION FUSION[1]

Todor TAGAREV and Petya IVANOVA

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I. Introduction

The rapid development of information technologies in the last decades of the twentieth century created opportunities to increase the effectiveness in practically every area of human activity. The use of ever more powerful computers contributed to a better understanding of the nature of many social, economic, physical and physiological phenomena. Somewhat surprising was the discovery that the increase of data collection and information processing power does not necessarily increase our ability to define cause-effect relationships and to predict the development of real-world processes. Computers helped us to discard certain paradigms and to reveal some characteristics of nonlinear behavior and complex interaction. Nevertheless, our abilities to analyze, model, and predict is still rather limited. A number of methods have been proposed that combine the power of computer processing with attempts to imitate biological processing and human intellect. A new framework recently emerged – computational intelligence (CI). The application of CI methods to the problem of fusing data and information from multiple sources has significant potential, not yet fully discovered.

Rapid developments in sensor and computing technologies allow to combine data and information from multiple sources. The advantages of combining outputs from a number of sources to increase performance has been long recognized in such diverse areas as political economy models, financial management, weather and climate prediction, estimation and prediction of physiological condition, diagnostics. The implication of effective fusion for the purposes of monitoring, situation assessment, early warning, and other security related issues is crucial. A small sample of examples includes:

- The impact of the explosion of information technologies on the capabilities for political and military early warning, including the capabilities for detection and collection of threat indicators, the dissemination of potential warning signals and threat assessments, the interpretation of collected signals and patterns, the capabilities to understand, interpret and respond to collected warnings;[2]
- The impact of sensor and information processing technologies on organizations and systems for monitoring in peace-keeping, arms control and humanitarian operations;[3]
- Design and implementation of measures and systems for information security, information warfare and critical information protection;[4]
- Design of reliable and safe systems for individual landmine detection based on using ground penetrating radar with integration of multiple microwave-sensor technologies and development of multi-sensor data fusion, feature extraction and object classification methods and algorithms.[5]

Since the mid-80s, *MultiSensor Data Fusion* (MSDF) emerged as a powerful technology for handling large amounts of data and decision support. Data fusion is examined as the integration and application of both traditional disciplines and new areas of engineering to achieve the fusion of data. These areas include computer science, expert systems, communication and decision theory, epistemology, estimation theory, digital signal processing, fuzzy logic, and neural networks. Methods for representing and processing data (signals) are adapted from each of these disciplines to perform data fusion.

Rapid developments in the field of information technology created opportunities for qualitative increase in data storage, processing power, and presentation. On that basis, the MSDF processes, including collection of data from multiple sensors, association, aggregation, and merging of data to increase the understanding of past and current situations, provided new opportunities. Ultimately, the output from a data fusion system is aimed at supporting a human decision process. The usefulness of a fusion system is measured by the extent to which the system supports the intended decision process.

In the process of decision making most people can not process rationally large quantities of data rapidly and accurately. But, as a rule, people deal well with situations, characterized by incomplete, imprecise, and uncertain information. Therefore, to adequately support the decision process, we need 'technologies' that, while processing increasing amounts of data, exploit the human tolerance for imprecision, uncertainty, and partial truth. Such a technology is *computational intelligence*.

In the current paper, we examine potential applications of computational intelligence methodologies to support decision making by fusing data and information from multiple sources. In section II we briefly describe the well known data fusion and decision support system architecture for command and control, based on the SHOR decision making model. Section III presents this model in the framework of a new view on *information space*. Section IV outlines basic ideas of computational intelligence, and section V - its application in developing systems and algorithms for data and information fusion and decision support. As an example, in section VI we describe the application of CI methodologies in two ongoing projects. We conclude by emphasizing the potential for expanding traditionally military technologies and their contribution to increasing stability and security.

II. MSDF and Decision Support in Military Applications

The decision making model proposed by Wohl in studying command and control is depicted on Figure 1.[6] The SHOR model comprises four dynamically interacting elements:

- Stimulus - The initiation of the decision making process to provide information on the current situation and the associated uncertainties;
- Hypotheses - A set of perception alternatives explaining the real-world situation;
- Options - Response alternatives made available to the decision maker;
- Response - The selected action to be taken.

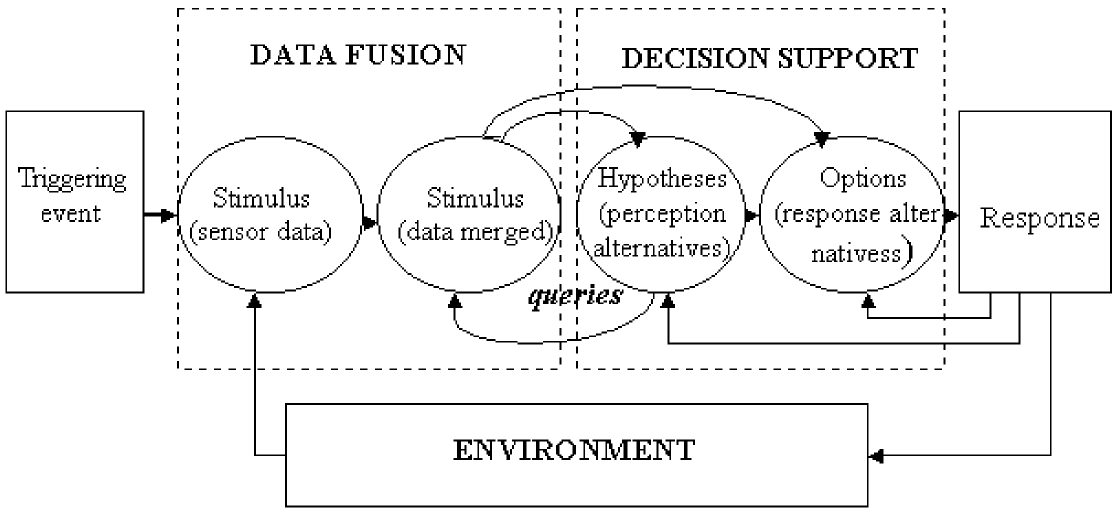

Figure 1: Data fusion and decision support in the SHOR model

Waltz and Buede divide the 'information' part of the model into two distinct subsystems for data fusion and decision support.[7] *Data fusion* collects information from various sensors and sources in order to develop the best possible perception of the situation. The situation is described by friendly and enemy orders of battle, locations and movements of weapons and equipment, events, and intelligence as it relates to past, present, and predicted behavior of the enemy. In the fusion process the authors include collection, association, aggregation, and merging of data to create and display current and past situations. The *decision support* function creates and evaluates alternative estimates of the real situation and the responses available to the commander. Both functions are performed interactively, and the results of the military response are included in the model through a feedback loop.

III. MSDF vs Multisource Information Fusion

In 1986, Prof. Arapov published an overview of the developing information technologies and their societal impact.[8] For that purpose he proposed a model of the information space. Twelve years later a modified version of his model was announced, called *Stratified Information Space Model*.[9] Both models allow to study IT developments and influence in three strata: data and signals, knowledge, and culture. Accordingly, we propose a modification of the SHOR model, depicted in Fig. 2.

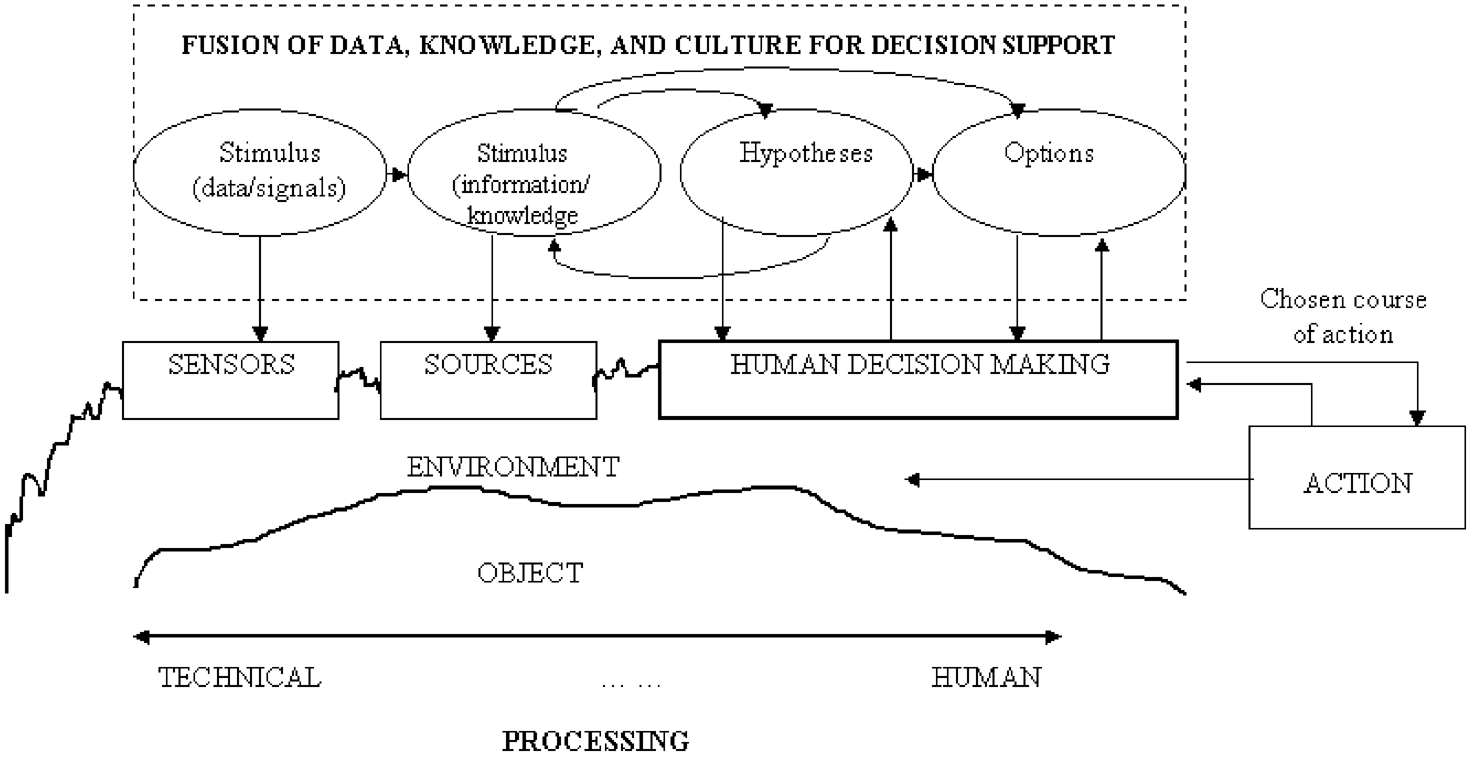

Figure 2: MultiSource Information Fusion (MSIF) for decision support

This modification allows for a better representation of the information strata *Data-Knowledge-Culture* and gives a preference to the term *source*, examining *sensors* as just one type of sources. Respectively, the type of processing along the information strata changes from exclusively technically oriented to increasing human participation.

The MSIF model represents the intersection between the MSDF framework[10] and the information space paradigm.[11] There are two main differences between the classic SHOR model and the MSIF model:

1) We examine the term information more broadly to include not only technologically acquired data from the object under study and its environment, but also:

- inputs based on expert analysis, i.e., intelligence forecasts;
- criteria-type inputs for the decision making process based on value systems, doctrine, education and training, etc.

2) Instead of response we propose the use of term action. The difference is not just linguistic but in the essence. The term response assumes reactive attitude while, as in the cases under examination in section VI, we aim at taking preventive measures.

The outlined differences are not crucial. Nevertheless, they have methodological implications and, in our opinion, the MSIF model will help to expand the application of proven MSDF techniques to diverse problem areas. And although in many cases there is an overlap between various strata of the information space and variety of combinations between roles of technology and experts, this model allows for a unified framework clearly separating *functions* in the system from *methods* dealing with partial, uncertain, and imprecise information.

At this juncture, several approaches to MSDF were proposed in order to deal with incompleteness and ambiguousness both in the available data and in the preferences of decision makers. In terms of methodology, a minimal representative sample includes contributions from fuzzy set theory, neural networks, probabilistic reasoning, and multiple-criteria decision making under uncertainty:

- Waltz and Buede use the term *soft decision data* - representation of uncertainty using probabilities, possibilities, or fuzzy rules - as opposed to hard decisions (declarations). Hard decisions are reported as single statements, and soft decisions are provided as multiple hypotheses, each with its own representation of the uncertainty associated with the hypothesis.[12] When fuzzy rules are used, uncertainty is reflected both in the fuzzy character of the *if-then* rules and the fuzzy presentation of the input information through membership functions.
- Studying the approaches to identity declaration in MSDF, Hall examines the potential for application of adaptive neural networks (NNs) for pattern recognition.[13] On the next level of the MSDF system - *decision level identity fusion* - he examines the use of classical inference, Bayesian inference, Dempster-Shafer method, generalized evidence processing theory and heuristic methods for association/fusion of identity declarations from different sources.
- Rao studies the capacity of neural networks to fuse data and information when the error densities of the separate sources are

unknown.[14] Many of the existing information integration techniques are based on maximum a posteriori probabilities of hypotheses under a suitable probabilistic model. However, in situations where the probability densities are unknown (or difficult to estimate) such methods are ineffective. Therefore, as opposing to early methods (many of which required even independence of the errors of the sources), he envisions NN schemes that extract/infer fusion rules on the basis of empirical data and employ suitable training algorithms. Furthermore, Rao proves that for a certain class of continuous functions a feedforward neural network infers fusion rules that provide empirical risk minimization.

- Decision making involves choosing some course of action among various alternatives. In almost all decision making problems, there are several criteria for judging possible alternatives. The main concern of the decision maker is to fulfill his or her conflicting goals while satisfying the constraints of the system. Milakooti and Zhou formulate the multiple criteria decision making problem and use an adaptive NN to rank the set of discrete alternatives where each alternative is associated with a set of conflicting and noncommensurate criteria.[15] Examining decision making problems under certainty, they consider discrete sets of alternatives with the assumption that there exists a multiple attribute utility function (MAUF) that can represent the preferences of the decision maker. They demonstrate that adaptive NNs can represent a more general and flexible MAUF than other generally used types of MAUFs. Adaptive NNs for representing various MAUFs enable the decision maker to rank alternatives and choose the most desirable ones. The authors show that the NN approach to solve multiple criteria problems is versatile yet robust approach to quantification and representation of the preferences of the decision maker: First, it does not assume any particular structure or property of MAUF; secondly, the NN method generates a completely assessed function; and, third, it can adjust and improve its representation as more information from the decision maker becomes available.

The cited works provide but a glimpse at the power of fuzzy logic and neural networks to deal with complex processes in the lack of certainty and precision and to learn by example. Even more promising is their combined implementation, integrated with powerful optimization techniques in a probabilistic framework.

IV. Computational Intelligence and Soft Computing Methodologies

Recently, the term 'computational intelligence' is gaining influence in analysis, modeling and control of complex processes. It describes a concept for synergistic implementation of information processing methods in parallel with levels of human information processing. Figure 3 depicts this parallel. On the left side is the 'biological' processing according to the idea of the "triune brain".[16] It envisions a cortex organized in three layers responsible respectively for instinctual behavior, motivational and emotional influences, and rational influences on decision making. The parallel with computational intelligence is presented on the right side of Fig. 3. The three respective layers involve implementation of quantitative statistical methods, soft-computing, and rule-based approaches of the symbol-processing kind.[17]

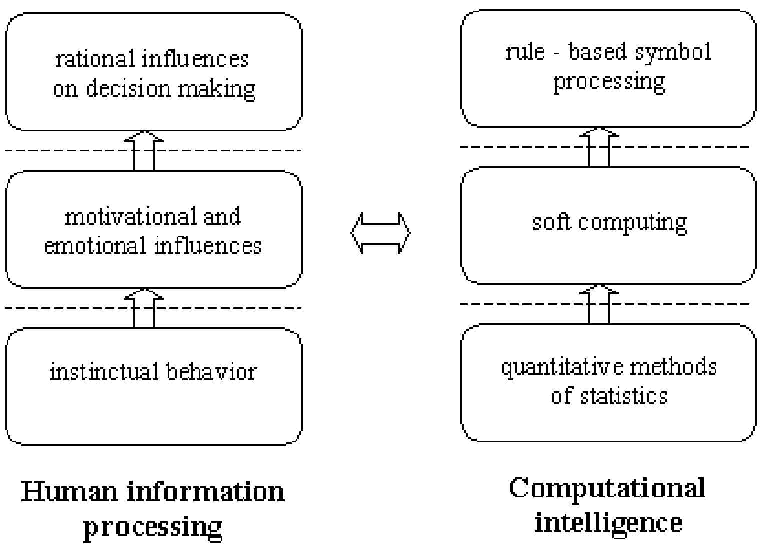

Figure 3: Parallel between human and computational intelligence

Guiding principle of the implementation of soft computing is the exploitation of the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost. In 1994, Prof. Zadeh considered as main components of soft computing fuzzy logic, neural network theory, and probabilistic reasoning, the latter including parts of evolutionary computation, parts of learning theory, belief networks, and chaos theory.[18] Of these, the first principal component is primarily concerned with imprecision of data and information, the second - with learning, and the third - with uncertainty. Soft computing is not a single methodology but rather a consortium of methodologies. At this juncture, fuzzy logic, neural networks, probabilistic reasoning and genetic algorithms are considered as principal constituents of soft computing. In many applications it is advantageous to exploit the synergism of these methods by using them in combination rather than alone. Examples of combined use include neuro-fuzzy, neuro-genetic, neuro-probabilistic, fuzzy-probabilistic, genetic-fuzzy and neuro-fuzzy-genetic systems.[19]

V. Soft Computing in MSIF and Decision Support

The focus of the Berkeley group led by Prof. Zadeh is on the development of techniques for combined implementation of fuzzy, neural, genetic, and probabilistic methods in the design of *autonomous systems*.[20] We study the application of soft computing methodologies in MSIF for decision support. Accordingly, we transform the SHOR model (Fig. 2) to a MSIF model (Fig. 4) that presents *functional* problems in MSDF[21] as problems of information fusion in the face of imprecision, uncertainty, high complexity, and change.

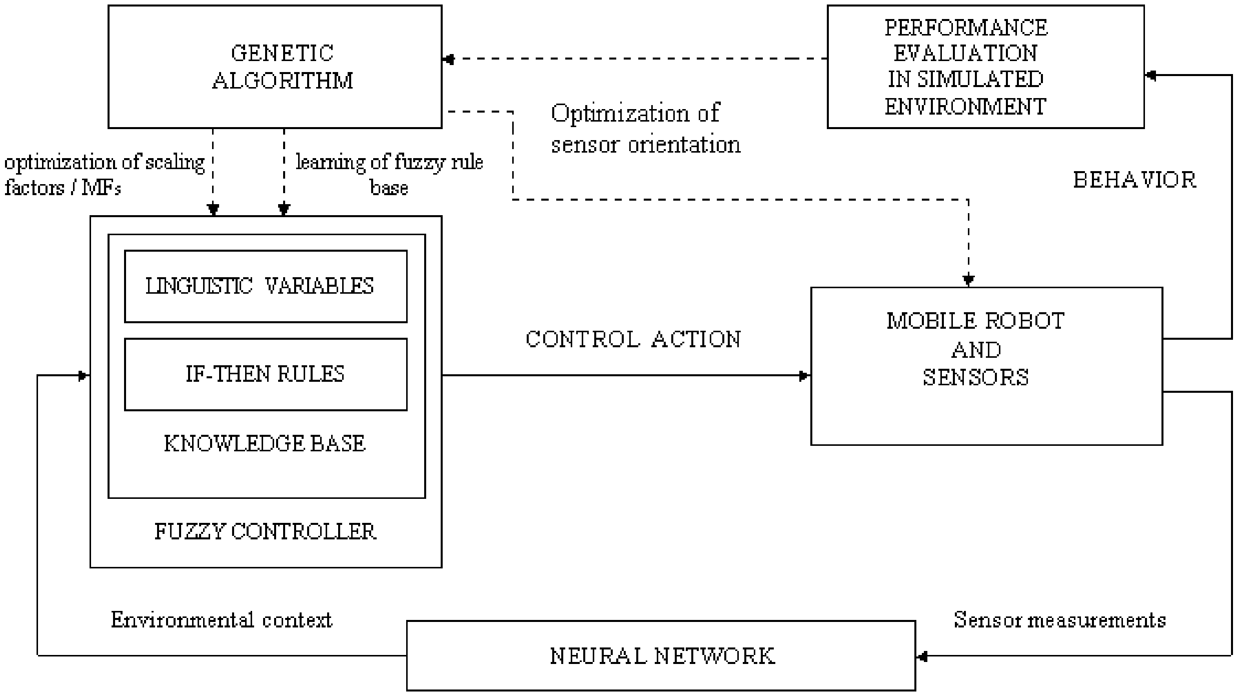

Figure 4: MSIF in the Information-decision-Action (IDA) loop

In this dynamical framework, principal tasks in fusing information from multiple sources are:

- Classification - placing the current situation in a class of typical *behavior*. This goal is achieved when we have *a priori* (usually expert) knowledge of the types of behavior allowing to implement supervised learning methods. If such knowledge is not available, solving the task involves formation of classes via unsupervised learning;
- Modeling - finding a description that accurately captures features of the long-term dynamical behavior of the system;
- Characterization - determining fundamental properties of the system with little or no a priori knowledge;
- Forecasting - accurately predicting the short-term evolution of the system.

These tasks are overlapping but not necessarily identical. They serve as building blocks for *event forecasting* (Fig. 5), which we regard as the basis for decision support. Details are provided in the next section.

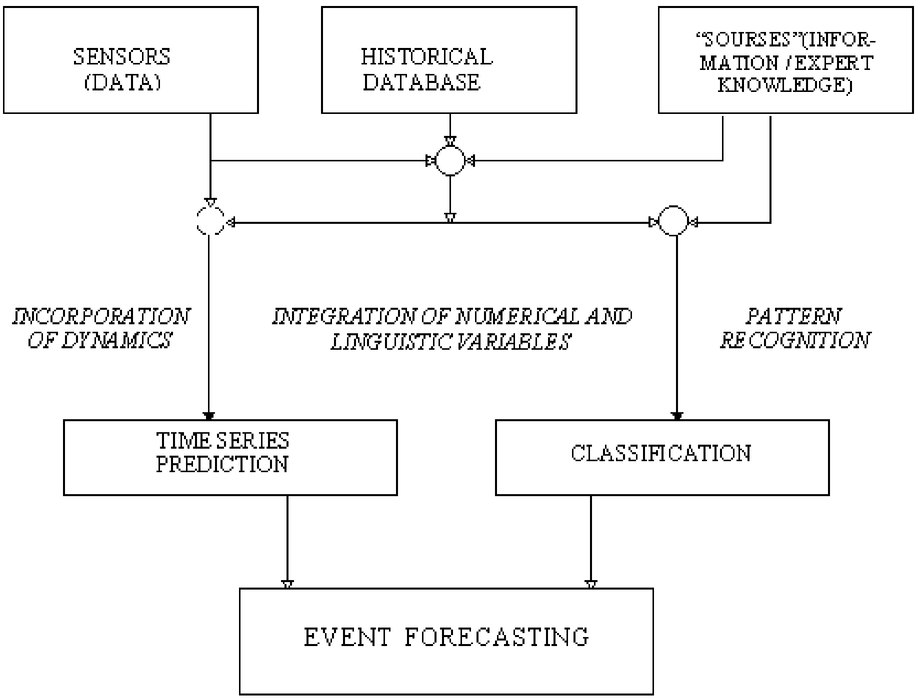

Figure 5: Functional tasks in event forecasting

VI. Computational Intelligence for Early Warning

Soft-computing methodologies are applied in two ongoing projects at the Space Research Institute of the Bulgarian Academy of Sciences.

6.1. Classification of physiological condition for advance warning

Multisource fusion of physiological information is a promising venue in the analysis and forecasting of biological and psychological processes. A R&D group at the Space Research Institute designed the 32-channel system "NEUROLAB-B". The system, used on the "Mir" space station, records four channels of ECG, four channels of EMG, two channels of EOG, blood pressure, pulse wave, breath frequency, two channels body temperature, skin conductance level, dynamometric probe and somatosensor stimulation, and is working on a Holter system for 24-hour recording.[22] Up to now, data is being processed by traditional statistical and signal processing techniques. However, recent research results convincingly ascertained the nonlinearity of many physiological processes and the complex interaction of variety of factors.[23] On the basis of this multisource information the research group started the development of novel nonlinear methods and algorithms to forecast physiological condition of an operator working under external conditions.

6.2. Early warning through classification of security situations

Effective prevention of crisis or moderation of their impact requires advance warning. The application of traditional statistical and knowledge-based approaches to early warning did not prove sufficiently powerful for the purposes of early warning. That is not surprising if we account for the highly nonlinear character of triggering mechanisms and the levels of uncertainty caused both by the imprecise and partial information and by the inherently complex dynamics of security processes.[24]

In the quest for efficiency, the use of artificial NNs has been suggested. After transforming the expert knowledge into a representative set of indicators in a form suitable for NN processing, they are fed into an NN recognition scheme, trained on a historical data base. Thus, advance warning is issued when a particular security situation is recognized as a preconflict situation.

Both studies are aimed at providing advance warning. Although to a different degree, the resulting systems must support decisions in the face of poorly defined situations, with poorly measured variables, incomplete and inaccurate data, and incomplete theoretical understanding. We aim at a new quality both in the accuracy of prediction and in presenting information in the language used by decision makers through combined application of computational intelligence as follows.

6.3. Computational intelligence on the implementation stage

To classify certain situation as a potential pre-crisis situation we apply a combination of fuzzy logic, NNs and probabilistic computing. Fuzzy representations of the input information reflect the symbolic nature of the expert opinion. The use of fuzzy sets allows to employ a mode of approximate reasoning, to describe knowledge by linguistic concepts, and to make decisions based on imprecise and incomplete information in a way similar to human beings. However, the sheer amount of information precludes the inference of a complete set of fuzzy rules. Therefore, we take advantage of the learning capabilities of NNs. The combination of a particular form of neural network, i.e. multilayer perceptron (MLP), with the transparent knowledge representation of fuzzy systems, produces a model with the ability to learn from real world observations and whose behavior can be described naturally as a series of linguistic humanly understandable rules.

Furthermore, instead of seeking a single optimal event forecasting model, we envision the use of several potential predictive models, which may lead to different inferences. Intuitively, ambiguity over the model should dilute information about predictions. A promising technique for properly accounting for this source of uncertainty, as well as for interpretation of the output of the classification scheme (type of expected crisis) is the Bayesian model averaging. Of considerable importance is the fact, that the treatment of the neuro-fuzzy system from a Bayesian perspective leads to practical procedures for estimating the confidence in the predictions.

Finally, it is possible that not a single configuration of inputs points to an upcoming crisis, but the way in which a configuration evolves in time. Hence, we need to build a warning system with inherent dynamic behavior. But MLPs are purely static and incapable of processing time information. Several approaches for incorporation of the dynamics in classification and forecasting schemes have been successfully applied:

- One way to extend MLPs to time processing is by creating a time window over the input configurations to serve as memory of the past. This leads to the so called time-delay NNs;
- Alternatively, recurrent NNs may be applied. The latter, however, are not guaranteed to be stable and they cannot be trained with standard back-propagation. These problems are avoided in a scheme known as partially recurrent network;[25]
- A third approach, devised by one of the authors[26] involves design of nonlinear predictive models of the dynamics of some input variables and the use of the parameters of the model as potential features in the input space of the classification scheme. A similar approach, involving global dynamical models of the data, was used successfully to classify high noise signals, such as actual open ocean acoustic data.[27]

6.4. Computational intelligence on the design stage

One of the goals in design is to develop methods that account for prior knowledge of data and exploit such knowledge in reducing search and that, in the same time, are robust against uncertainty and missing data problems. Bayesian methods and decision analysis provide a basic foundational framework. This framework is successfully supplemented by contributions of chaos theory and genetic algorithms in the definition of an informative input space, the choice of the structure of the forecasting model, and the calibration of its parameters (the learning phase).

Design of input space. Chaos theory is applied to estimate the dimension of possible attractors in the situational dynamics. The estimated attractor dimension is used to initialize the number of input indicators of the classification scheme. Then, the genetic algorithm technique is used to precisely configure the indicator space so that it accounts for both dimensional and time (memory-type) factors.[28] At this stage the dimensionality of the input data is reduced and deficiencies such as missing input values or incorrect target values are eliminated.

Structure of the forecasting scheme. Requirements for tractability (overcoming the curse of dimensionality) and model generalization (expanding the predictive power of the classification scheme to previously unseen situations) give significant advantage to parsimonious models. Furthermore, such models provide for a qualitative insight into the behavior of the system in the form of fuzzy rules. Therefore, we formulate the design as an optimization problem. The genetic algorithms are well suited for optimization in high-dimensional, nonlinear and noisy problems. They offer a means to systematically and efficiently explore the space of forecasting architectures. Also, they allow to optimize concurrently the NN topology, its parameters, as well as the parameters of the learning algorithm.

An alternative is provided by the Bayesian approach. Using only the training data, it allows different models to be compared in an objective and principled framework for dealing with the issues of model complexity. Also, estimations of the relative importance of different inputs can be automated. Choices can be made as to where in input space new data should be collected in order that it be most informative (such use is known as *active learning*).

Learning. Many algorithms exist for optimizing the values of the parameters in the network, in other words, for training the network. Successful solutions of various problems apply latest developments in machine intelligence allowing to mimic the ability of the human mind to effectively employ modes of reasoning that are approximate rather than exact, to learn from past experience, and to adapt to environmental changes.[29] In most cases, we have expert-defined pairs "input configuration of indicators - class of situation." Then we apply algorithms for *supervised learning*, closely approximating available pairs (training examples). Examples for such algorithms in NN learning are back-propagation and simulated annealing.

When expert knowledge is lacking or insufficient, *unsupervised learning* techniques are applied for data clustering. Central data clustering, also called vector quantization, and pairwise data clustering are two classes of combinatorial optimization methods for data grouping which extract hidden structure from data. The main issues in algorithm development are to determine appropriate quality measures for the evaluation of clusters and to limit the complexity of the cluster set. Several models for data clustering exist, e.g., K-means clustering, selforganizing feature maps, the neural gas algorithm and complexity optimized vector quantization. Respective algorithms to estimate the cluster parameters have been derived in the maximum entropy framework which has been proven to be optimal for stochastic optimization. Clustering models for proximity data have also been introduced. Proximity data characterize items by their mutual relationship and not by coordinates in a vector space.[30]

Data issues. For most applications before training the classification/forecasting scheme it is necessary to transform the data into some new representation. Because of the very few assumptions in using computational intelligence methods, this problem is alleviated to some extent and less emphasis has to be placed on careful optimization of pre-processing than would be the case with simple linear techniques, for instance. Nevertheless, in most practical applications pre-processing of available data has a significant influence on the performance of the final system. Computational intelligence methods find successful applications in:[31]

- Input normalization;
- Input encoding;
- Dimensionality reduction: feature selection,[32] feature extraction;
- Pre-filtering, removal of outliers;
- Dealing with missing data;
- Integration of domain specific knowledge.

Similarly, CI methods are used for post-processing to provide required output data.

VII. Conclusion

The application of computational intelligence in our studies extends the potential of ‘traditional’ MSDF. The discipline of multisensor data fusion appeared as a particular technology to support command and control. Thus, our extension of MSDF may be examined as a special type of convergence of *soft* ‘military technologies’ to non-military applications.

Of particular interest is the application of modern information technologies to increase international stability. Early warning through close international cooperation has a great potential to defuse crisis and conflict even before they appear. The monitoring of security situations for the purposes of early warning is such application calling for all-source data and information fusion, analysis, assessment and decision making support.[33] Therefore, through development of architectures for multisource information fusion, the application of computational intelligence may contribute to increasing stability and security.

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Computational Intelligence in Multi-Source Data and Information Fusion

Todor Tagarev and Petya Ivanova

Keywords: Computational Intelligence, Soft Computing, Neural Networks, Fuzzy Logic, Genetic Algorithms, Pattern Recognition, Forecasting, MSDF, Decision Support

A model of MultiSource Information Fusion (MSIF) is proposed. It expands the application of proven MSDF techniques to diverse problem areas. This model allows for a unified framework clearly distinguishing processing functions from methods dealing with partial, uncertain, and imprecise information. The concept of computational intelligence provides for a holistic approach to design and integration of methods and algorithms for information fusion. We describe the application of computational intelligence to the fusion of data and information in two studies of early warning. The emphasis is on the power of soft-computing methods in designing early warning architectures pertinent to forecasting events in complex dynamical systems.

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HUMAN INTUITION AND DECISION-MAKING SYSTEMS (II)

Linda ELLIOTT and Andrew BORDEN

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1. Background

One of the authors of this paper has developed a canonical design method for designing Situation Assessment strategies in the form of very efficient decision trees.[1,2] This method uses the mathematical theory of information, developed by Claude Shannon in the 1940's, to reduce uncertainty (Entropy) most efficiently.[3] The method applies when:

- There is a data base containing a statistical description of the objects in the Frame of Discernment;
- There is a capability to measure at least some of the parameters in the data base;
- There may be a differential cost, usually in time, for making parameter measurements;
- High confidence, on-time classifications are important.

Specifically, the program, called the Situation Assessment Evaluation Tool (SAET) produces a decision tree by selecting the most efficient entropy-reducing parameter to expand each node. When the decision tree is complete, the program provides a report card covering performance. The report card contains statistics which include reliability and response time. The program can also run a simulation and provide very detailed information about the performance of the run-time algorithm.

The motivation for developing the SAET was the task of designing an efficient Radar classification Algorithm for use in Radar Warning Receivers in combat aircraft. The Radar Warning Receiver makes measurements of radar parameters on demand. Each measurement has a cost in time. There is a strategy for fetchng the measurements and comparing them to the data base in order to produce a confident, on-time identification of the radar. Appropriate warning is given to the aircrew using an alpha-numeric cockpit display and audible tones.

This task is typical of many Situation Assessment tasks. Another such task is the design of Indications and Warning (I&W) programs. In I&W, parameters are collected and evaluated according to an efficient strategy in order to determine the probable activities and intentions of an adversary. In one of the previous studies,[2] the SAET was applied to several Situation Assessment tasks. A preliminary examination of the data bases suggested that the tasks were approximately comparable in difficulty. However, one of the assessments turned out to be two orders of magnitude more difficult than another. An I&W designer relying on intuition could easily be led astray if the perception of the relative difficulty of the design tasks was so far from being correct.

In the present task, airborne target threat assessment, a similar finding occurred. Data that (intuitively) should be helpful to a human decision maker actually degraded the capability to make confident, on-time decisions. In this paper, a description of the threat assessment study is given and the non-intuitive finding is explained.

2. The Target Classification Study

In a study being conducted by the Air Force Research Laboratory, Brooks AFB, Texas, the performance of human observers in learning to classify airborne threats is being investigated. In this study, a deterministic algorithm classifies targets using a point-scoring system. The lowest scores indicate that a target being seen by a radar is friendly without doubt. The highest scores mean that a target is hostile without doubt and represents a threat to friendly forces.

Nine parameters are used by the observers in making their assessments. In some cases, a partial presentation of five of these parameters is given. The parameters are visually coded so that the effects of shape, size and color of the presentation can be determined. The nine parameters are:

1. Type of IFF (transponder) return
2. Speed
3. Flight path relative to the radar
4. Size
5. Position relative to known airway corridors
6. Altitude
7. Range to the radar

8. ESM indications (type of airborne radar)
9. Change in altitude

Each parameter is scored as "Zero", (Mimimal threat) to "Two" (Maximal threat). Before being summed, the parameter scores are processed to reflect weight of importance and pairwise interactions. Since IFF is relatively important, its score is doubled, giving possible weights of "0", "2" or "4". The remaining eight parameters are grouped in pairs. The score for the pair is the product of the scores for the two parameters in the pair. For example, if a target received a score of "2" for speed and "0" for flight path, the score for the pair would be "0". After processing the scores for IFF and for the remaining pairs of parameters, the numbers are added. A high score corresponds to "Defend" and a low score correspond to "Ignore". Intermediate scores match the categories of "Monitor", "Review", "Warn", "Ready" or "Lock-on".

A large number of human trials were conducted. The subjects were told the meaning of the visual and other cues and were told generally that a high score corresponded to a more serious threat. They were not given the specific algorithm used for scoring, but they were told which parameters were to be considered pairwise. In some cases, they had only five of the nine parameters to consider. In other cases, time constraints were introduced.

The human responses have been analyzed and are currently being compared with the results produced by the ideal decision maker provided by the SAET. The remainder of this paper will consider the performance of the ideal decision maker, not the human subjects.

3. Results

The initial reaction of the investigator to the results of this experiment was that the SAET had worked hard to produce a poor result. Based on the relative frequency of outcomes in the Frame of Discernment, the initial Entropy is about 2.1 bits (The amount of Entropy associated with all the possible outcomes of two (three) tosses of a fair coin is two (three) bits). Each of the nine parameters, if used first, would reduce the Entropy by about 0.25 bits. After the optimal decision tree runs, about 1.47 bits of uncertainty remain.

The SAET was run to the 50 % confidence level, then forced to make a decision based on the highest probability, even if lower than 50 %. The correct classification was made 56 % of the time and the mean error was 0,58 categories. That is, a result of "4" would, with very high probability be between "3" and "5".

"Max Nodes" are the possible combinations of parameters that could be encountered. The program only had to generate a small fraction of these combinations to design the decision tree. Generating more nodes would not have improved the result.

The second run (parameter dependencies considered) produced a slightly worse result. Each parameter, if used first, would reduce Entropy by only 0.14 to 0.19 bits. The remaining Entropy after running the optimal decision tree was 1.48 bits.

The forced decision was right 54 % of the time and the mean error was .62 categories. The investigator’s reaction was that this result was not consistent with intuition and could be an error in the program. Since the data base for the second run was based on partial execution of the "ground truth" algorithm, the result should have been better.

Table 1. Performance of the optimal decision-maker compared to the "Real-World" (algorithmic) solution.

CONDITION	ENTROPY (INITIAL/FINAL)	PROBABILITY OF CORRECT DECISION	MEAN ERROR	MAX NODES	NODES USED
DEPENDENCY RULES NOT USED	2.1/1.47	0.56	0.58	19,683	353
DEPENDENCY RULES USED	2.1/1.48	0.54	0.62	1024	325

4. Discussion Of Results

The statistical distributions of the parameter measurements were almost identical. Only the first measurement (IFF) was slightly different from the others. This was true in both the nine parameter and the five parameter cases. There was a great deal of noise (overlap) in the probabilities for each parameter. In other SAET investigations, one or more parameters had minimum overlap, at least for several of the classifications being predicted. As a result, a classification of "4" for example, could be quite far from a result of "3" or "5". The program finds these productive parameters and uses them first to reduce uncertainty more efficiently. This property of the data base enables the SAET to prune the resulting decision tree very quickly.

In the present situation, results of "3", "4" and "5" are statistically quite close. It is difficult for the SAET to distinguish them with high confidence. Therefore, the performance of the SAET is reasonable in this very difficult decision-making task. The mean error of a classification was acceptably small. There is probably little operational importance to an error of one category. If a high threat target "7" were classified as friendly "1" that would be very serious, but this would occur rarely if at all.

The relatively poor performance of the combined (five) parameter case is also reasonable, but it seemed difficult to understand how partial execution of the scoring algorithm can actually be a handicap in predicting the threat category. The SAET is based on the assumption that any two parameters are either conditionally independent or correlated. The rule for combining parameter measurements in this investigation, however, is to multiply the scores for the two parameters and use the result. Thus, if one parameter was a "2" (high threat indication) and the other was a "0", (low threat), the result would be "0" for the combined parameter. The impact of this method is that one parameter can negate another, thereby reducing the information bandwidth by discarding data that should produce real information. Parameters are neither conditionally independent nor correlated. This part of the investigation was studied very thoroughly. It appears correct that informing the human observers, in part, of how the scoring algorithm works actually degrades their decision-making ability.

5. Comment

It is the peculiar strength of the SAET that it surpasses human intuition and sometimes produces surprising, but correct results. The investigator noted a similar result in doing Indications and Warning experiments in which some problems turned out to be much harder to accomplish than other. Only a meticulous examination of the data base revealed why this was so. The current project seems to be another case in which the mathematical theory of information beats intuition.

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Human Intuition and Decision-Making Systems (II)

Linda Elliott and Andrew Borden

A canonical design method was applied to the task of building a system to classify airborne targets according to their threat status and the appropriate response from an Integrated Air Defense System. The nature of the data base made the classification task (understandably) difficult. However, partial disclosure of the deterministic algorithm used to classify targets made the classification task even more difficult, contrary to intuition. The inadequacy of intuition is a compelling reason for using canonical methods to design for decision making systems.

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AN IMMPDAF SOLUTION TO BENCHMARK PROBLEM FOR TRACKING IN CLUTTER AND STANDOFF JAMMER

Donka ANGELOVA, Emil SEMERDJIEV, Ludmila MIHAYLOVA and Xiao RONG-LI

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1. Introduction

Multiple target tracking is a very important and rapidly developing area. The formulation of a clearly defined standard or benchmark problem for evaluation and comparison of the various existing algorithms is necessary. Researchers have established such a unifying general problem that imposes different and contradictory requirements in the face of the first benchmark problem (BP) defined in [4] and further extended in [6]. The first benchmark problem considers only aircraft tracking and pointing/ scheduling of a phased array radar. The second benchmark problem[6,7] involves the presence of False Alarms (FA) and Electronic Countermeasures (ECM) and requires radar resources management. The tracking filter performance criterion is the minimization of a weighted combination of a radar time and energy at the cost of a maximum 4 % tracks' loss.

Previous results devoted to this problem have shown that the Interacting Multiple Model (IMM) filtering algorithm[8] is the most efficient and cost-effective tool for tracking highly maneuvering targets.[3,9,10] Additionally the presence of FA and ECM requires sophisticated data association approaches such as Probabilistic Data Association (PDA) or Multiple Hypothesis Tracking.[3]

In the present paper a solution to the benchmark problem based on the combined IMM estimator and PDA technique is proposed. An IMMPDA tracking filter satisfying the benchmark performance criteria is designed. It is realized by using appropriate Extended Kalman Filters (EKF) in the IMM configuration, adaptive scheme for track formation and adaptive radar beam pointing control in order to maximize the revisit interval.

The complete solution to the BP requires the development of the neutralizing techniques for ECM, in particular against a Standoff Jammer (SOJ). The IMMPDA filtering approach has been naturally extended in [11] to accomplish this task. When the jammer influence is taken into account, the detection threshold and the radar waveform are adaptively selected to ensure a constant false alarm rate and a predetermined target detection probability. This methodology is implemented in the work.

The paper is organized as follows. Section 2 concisely summarizes the idea of the IMMPDA filtering approach to hybrid system estimation. In Section 3, the concrete implementation of the IMMPDA filter for BP solution is described. The SOJ neutralizing technique is briefly described in Section 4 and the simulation results are given in Section 5.

2. IMMPDA Filtering of Hybrid Systems

The behavior of a maneuvering target can be adequately described in the terminology of the stochastic hybrid systems. The base state vector $x(k) \in R^{n_x}$ of the discrete hybrid system

$$x(k) = f(M(k), x(k-1)) + G[M(k)]v(k-1, M(k)) \qquad (1)$$

$$z(k) = h(M(k), x(k)) + w(k, M(k)), \; k = 1, 2, \ldots \qquad (2)$$

is estimated, where $z(k) \in R^{n_z}$ is the measurement vector, $v(k) \in R^{n_x}$ and $w(k) \in R^{n_z}$ are respectively the system and measurement noises, assumed to be white and mutually uncorrelated, with zero means and variances, respectively $Q(k)$ and $R(k)$. The system (1)-(2) at time *k* is among *r* possible modal states (models), depending on the parameter $M(k) \in \{1, 2, \cdots, r\}$, where $M(k) = i$ denotes that the *i*-th system mode is in effect during the sampling interval *T* ending at time *k*. The mode sequence $\{M(k)\}_{k=1,2,\ldots}$ is assumed to be a Markov chain with known initial mode probabilities $\mu_i = P\{M(0) = i\}$ and transitional probabilities $p_{ij} = P\{M(k) = j / M(k-1) = i\}$, $i, j \in M$, where $P\{.\}$ is the notation for probability .

In the presence of clutter several measurements are received from the sensor at time *k*, *i.e.* $Z(k) = \{z_i(k)\}_{i=1}^{m(k)}$. The aim of the hybrid estimation is to provide the system state and modal state estimates on the basis of the cumulative set of measurements $Z^k = \{Z(k)\}_{k=1}^{k}$. In general, suboptimal Bayesian procedures are applied and the final estimate is a weighted sum of the estimates generated by *r* working in parallel Kalman filters. In the absence of model uncertainty, the single model minimum variance estimate of the state is computed by the PDA filter[1]:

$$\hat{x}(k/k) = \sum_{i=0}^{m(k)} E[x(k)|\theta_i(k), Z^k] P\{\theta_i(k), Z^k\}$$

where $\theta_i(k)$ is the event that $z_i(k)$ is the correct measurement from the target at *k* and $\theta_0(k)$ - the event that none of the measurements is correct. $E\{.\}$ is the mathematical expectation operator. When both model uncertainty and measurement origin uncertainty are present, the state estimate is given within the framework of the IMM filtering approach by the total probability theorem:

$$\hat{x}(k/k) = \sum_{j=1}^{r} \{\sum_{i=0}^{m(k)} E[x(k)|\theta_i(k), M_j, Z^k] \; P\{\theta_i(k)|M_j, Z^k\}\} P\{M_j|Z^k\}$$

or $\hat{x}(k/k) = \sum_{j=1}^{r} \hat{x}^j(k/k)\mu_j(k)$

where $\hat{x}^j(k/k)$ is the output of the *j*-th PDA filter based on the *j*-th model and $\mu_j(k) = P\{M_j|Z^k\}$, *j=1,…,r* is the conditional posterior probability of mode *j*. The associated with the estimate error covariance $P(k/k)$ takes into account the effect of the model and measurement origin uncertainties.

3. IMMPDA Filter for BP Solution

A number of mutually connected tasks for precise target tracking are posed in the benchmark formulation.[6] Their optimum solution minimizes both the radar time and energy. *The tracking algorithm* involves *track formation* and *maintenance*, as well as the *choice of target revisit interval*. One solution to these tracking problems is presented here.

The IMMPDA filter is an algorithm for tracking that can realize simultaneously track formation and maintenance. It provides a quantitative assessments for track termination and tracking capability in clutter. In the present work IMMPDA filter is implemented only for track maintenance. The track termination is determined here according to the criterion for lost tracks suggested in [7]. A simplified version of track formation is accomplished in view of the specific benchmark problem features. As a result the computational load and the radar energy are reduced.

3.1. Track formation

The track formation is a difficult task in the presence of FA. On the basis of the sequence of measurements with a high signal-to-noise ratio (SNR), a track is formed by the Least-Squares (LS) method. This technique provides the initial target state estimates and the associated covariance matrix. The estimation accuracy, however, greatly depends on the target ranges which vary from 20 to 100 *km* in the considered benchmark trajectories. For this reason the number of the measurements and sampling intervals in the LS procedure are determined according to the measured range to the target. In addition, the highest energy waveform is used for the remote fast targets.

3.2. Track maintenance

The suitable choice of motion models, covering well the whole range of target flight modes, is *the first important task* in the IMMPDA filter design. The hardest target maneuvers require lateral accelerations up to 7 *g* and longitudinal accelerations up to 2 *g*. The targets maneuver mainly through turns with the highest intensity (7 *g*). That is why it is proposed here a nonlinear approximate turn model to be used for the maneuvering segments.[2] As the angular rate of the turns is not known and varies in a wide range, it is included in the state vector and is estimated by the filter.

The following set of models is suggested for the IMM track maintenance algorithm:

a. No target model (M_1) takes into account an *undetectable* or "false" target. It is usually selected as a second order model[1] with low noise level, corresponding to the uniform motion, with a target detection probability $P_D = 0$. Its posterior mode probability can be used as a criterion for track termination. According to (1), $f[M(k),x(k-1)] = f[M_1,x(k-1)] = Fx$, where the state space vector $x = [x,\dot{x},y,\dot{y},z,\dot{z}]^T$ contains the target positions and velocities in a Cartesian coordinate frame and the matrix *F* has the form described in [1] (pp. 228).

b. A second order model (M_2) considers the nearly *constant velocity (CV) motion* of a nonmaneuvering target. It is usually selected with low noise level and $P_D \neq 0$, given by the target's expected SNR. For the state space vector $x = [x,\dot{x},y,\dot{y},z,\dot{z}]^T$, the CV target motion model is linear. According to (1), $f[M(k),x(k-1)] = f[M_2,x(k-1)] = Fx$, where the matrix *F* is the same as in a.

c. A maneuver model (M_3), ($P_D \neq 0$) takes into account the *on-going maneuvers*. It is a nonlinear coordinated turn model[2] with unknown angular rate ω, incorporated into the state vector $x = [x,\dot{x},y,\dot{y},z,\dot{z},\omega]^T$. According to the eq. (1) $f[M_3,x(k-1)] = f(x)$, where

$$f(x) = \left[f_1^T(x) \;\; f_2^T(y) \;\; f_3^T(z) \;\; f_4^T(\omega)\right]^T,$$

$$f_1(x) = \left[x + T\dot{x} - \frac{T^2}{2}\dot{y}\omega,\ \dot{x} - T\dot{y}\omega - \frac{T^2}{2}\dot{x}\omega^2\right],$$

$$f_2(y) = \left[y + T\dot{y} + \frac{T^2}{2}\dot{x}\omega,\ \dot{y} + T\dot{x}\omega - \frac{T^2}{2}\dot{y}\omega^2\right]$$

$$f_3(z) = [z + T\dot{z}, \dot{z}], \qquad f_4(\omega) = \omega.$$

d. A maneuver start / termination model (M_4) ($P_D \neq 0$) for *transitional flight segments* (between constant speed and turns), necessary for tracking highly maneuvering targets. It is selected as a second order model with a high level of noise:

$f[M(k), x(k-1)] = f[M_4, x(k-1)] = Fx$, where $x = [x, \dot{x}, y, \dot{y}, z, \dot{z}]^T$ and the transition matrix *F* is the same as in the models a. and b.

The second task of the IMMPDA filter design comprises the selection of prior parameters: the process noise variance and the Markovian transition matrix. In view of the dynamics of the simulated in the BP targets, the standard deviations of the process noise components for the four models are chosen as:

$$M_1: \quad \sigma_{v_1} = 2.8\, m/\sec^2;$$

$$M_2: \quad \sigma_{v_2} = 2.8\, m/\sec^2;$$

$$M_3: \quad \begin{cases} \sigma_{v_3 x} = \max\{10, \min[abs(-\dot{y}\omega), 70]\}\ m/\sec^2 \\ \sigma_{v_3 y} = \max\{10, \min[abs(\dot{x}\omega), 70]\}\ m/\sec^2 \\ \sigma_{v_3 z} = 15\ m/\sec^2 \\ \sigma_{v_3 \omega} = 0.064\, rad/\sec \end{cases}$$

$$M_4: \quad \sigma_{v_4} = min\{\, 50T, 70\,\}\, m/sec^2,$$

where $\ddot{x} = -\dot{y}\omega$ and $\ddot{y} = \dot{x}\omega$ are the accelerations in the "coordinated turn" model. The matrix $G[M(k)] = G$ from (1) has the usual form[1] in the four models.

The elements of the transition matrix can be chosen as follows[2]:

$$p_{ij}(T) = \begin{cases} exp(-T/\tau_i) & if \quad j = i \\ p_{ij}[1 - p_{ii}(T)] & if \quad j \neq i \end{cases}$$

where τ_i is the expected sojourn time of the *i*-th mode. In the present IMM implementation, however, the following constant values are assigned to the transition probabilities in order to reduce the computational time:

$$p = \begin{bmatrix} 0.94 & 0.02 & 0.02 & 0.02 \\ 0.02 & 0.83 & 0.13 & 0.02 \\ 0.02 & 0.09 & 0.86 & 0.03 \\ 0.02 & 0.08 & 0.20 & 0.70 \end{bmatrix}.$$

The initial mode probabilities are set to : $p_1^0 = 0.1; p_2^0 = p_3^0 = p_4^0 = 0.3;$

3.3. Measurement model

Since the radar measurements are received in a spherical coordinate system, the measurement vector *z* comprises the range *r*, the bearing *b* and elevation *e* angles, i.e. $z = (r \quad b \quad e)^T$. The measurement equation (2) has the form:

$$h(x) = \left[\sqrt{x^2 + y^2 + z^2}, \quad \tan^{-1}\frac{y}{x}, \quad \tan^{-1}\frac{z}{\sqrt{x^2 + y^2}} \right]^T.$$

The nonlinearity in the relationships $f(x)$ and $h(x)$ imposes the Extended Kalman Filters application in the IMM configuration.

3.4. Adaptive sampling

An adaptive computation of the sampling interval is needed when the radar resources have to be saved. It is achieved by using a short sampling interval during maneuvers and a long one during nonmaneuvering trajectory segments. Here, the sampling interval selection scheme, suggested in [11], is adopted:

- a set Δ of fixed sampling intervals *T* is determined;
- for the largest *T*, the predicted positions and innovation covariances from the IMM filters are combined, by using IMM predicted mode probabilities;
- the combined innovation standard deviations σ_k^b, σ_k^e in bearing and elevation are compared with the antenna beamwidth in bearing B_k^b and elevation B_k^e, respectively:

  $$\sigma_k^b \le B_k^b / K_b \text{ and } \sigma_k^e \le B_k^e / K_e,$$

  where K_b and K_e are threshold parameters;
- if any of these angle deviations exceeds the threshold, the test is repeated for the next shorter *T*;
- if no measurements are received, the sampling interval *T* is assumed to be equal to 0.1 sec.

In our implementation the following set of sampling intervals is accepted:

$$\Delta = \{\ 0.1, 0.5, 0.9, 1.3, 1.7, 2.1, 2.5, 2.9, 3.3, 3.7\ \}.$$

At first the threshold $K_b = K_e = K$ is selected equal to $K = 4.2$. If the target is not detected, the threshold K is augmented to the value of 6. During the next subsequent scans, the sampling interval increases to its maximum value $T = 3.7$ *sec*, (according to the described above logic), and then K is returned to its ordinary base value of 4.5.

4. Neutralizing the SOJ

The neutralizing technique for The SOJ, presented in[11], is realized in the paper. The SOJ motion parameters are estimated by EKF based on angles only measurements, received at the radar in passive mode. The jammer tracker using azimuth and elevation angles, their derivatives and a 2.0 *sec* update rate is implemented[7] to predict the jammer position. The predicted estimate of the jammer power level is used for an adaptive selection of the detection threshold in order to maintain a constant false alarm rate. To maintain the predetermined target detection probability, the radar waveform is also adaptively selected by an additional assessment of the target radar cross section.[11]

5. Simulation results

The algorithm performance is evaluated over six standard BP test scenarios.[7] The well known criteria for filter performance are used: the energy and radar time costs,[7] position and velocity root-mean-square errors (RMSE), computational requirements, percentage of lost tracks.[7]

The number of tracks lost is a key performance indicator for a filter, operating in a cluttered environment and ECM. The main measures of performance, concerning the energy and radar time costs have the form[7]:

$$C_i = \overline{E}_{ave} + \alpha_i \overline{T}_{ave}, \quad i = 1,2\ ; \quad \alpha_1 = 10^3; \quad \alpha_2 = 10^5,$$

where $\overline{E}_{ave}$ is the average radar energy per second, $\overline{T}_{ave}$ is the average radar time per second and α_i is a given weighting parameter.

The results obtained for 200 Monte Carlo runs in the presence of FA and SOJ are shown in Table 1. The average values of the parameters C_1 and C_2, computed over the six scenarios by taking into account the respective parameters of target 1 two times (as is required in [7]), are given in the last row of Table 1. It can be seen from the results that the realized IMMPDA algorithm version satisfies the BP requirements for all six target scenarios.

Figures 1 through 6 illustrate the results obtained for the most difficult scenario 6. The waveform adaptation, corresponding to the selected detection threshold can be seen in Figure 1. The waveform peaks follow the changes in the acceleration magnitude and the SOJ influence. The sampling interval (Figure 2) is larger during nonmaneuvering phases of motion ($\approx 3 \div 3.6$ *sec*) in comparison to the maneuvering periods of flight (≈ 1.5 *sec*). Therefore, the IMM innovation standard deviations give a good measure for the confidence of the predicted state estimates. The evolution of the IMM mode probabilities for one run is presented in Figure 5. The posterior mode probabilities correctly identify the true system mode for all target scenarios. The rapid response to the changes in the target behavior ensures acceptable RMS Errors. The average position and velocity RMSE are shown in Figures 3 and 4, respectively. The peak RMS position errors do not exceed 500 m; the top velocity RMSE are of the order of 250 *m/s*. The average estimated value of the angular rate, which is a state component of the maneuvering model, is presented in Figure 6. It is obvious from the simulation results that the performance of the proposed tracking algorithm is comparable to the performance of the algorithm derived in [11]. The average sampling interval (2.85 s) and the average power (8.24 W) are approximately the same as the respective parameters (2.71 s and 8.6 W) in [11].

Table 1: IMMPDAF performance in the presence of FA and SOJ

Target	**Sample Period (s)**	**Ave. Power (w)**	**Pos. RMSE (m)**	**Vel. RMSE (m/s)**	**Cost C_1**	**Cost C_2**	**Lost Tracks (%)**
1	2.91	7.28	115.0	50.27	7.63	41.65	0
2	2.88	6.16	100.3	52.18	6.51	40.84	0
3	2.87	10.36	148.7	79.15	10.71	45.18	0
4	2.91	3.07	45.81	36.55	3.42	37.37	0
5	2.77	15.91	171.4	74.49	16.27	51.94	0
6	2.71	7.62	114.8	72.44	7.99	44.48	1
Ave.	2.85	8.24	-	-	8.60	43.31	-

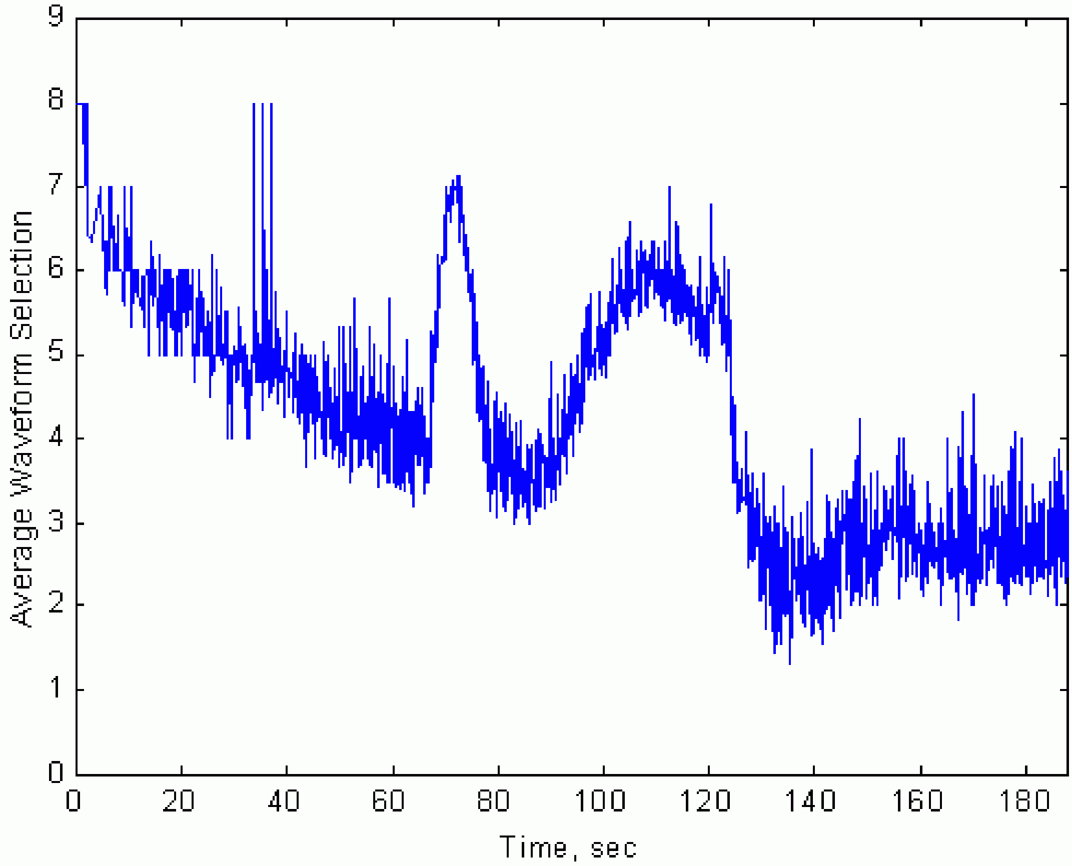

Figure 1

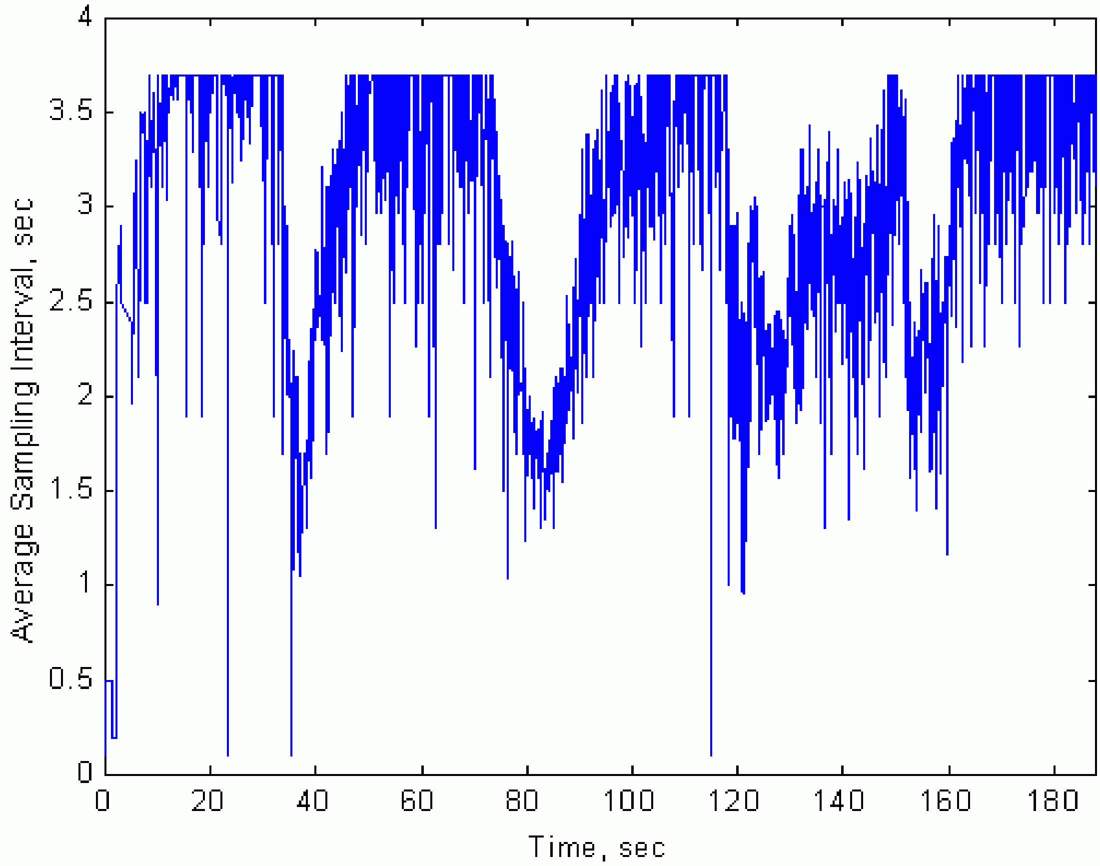

Figure 2

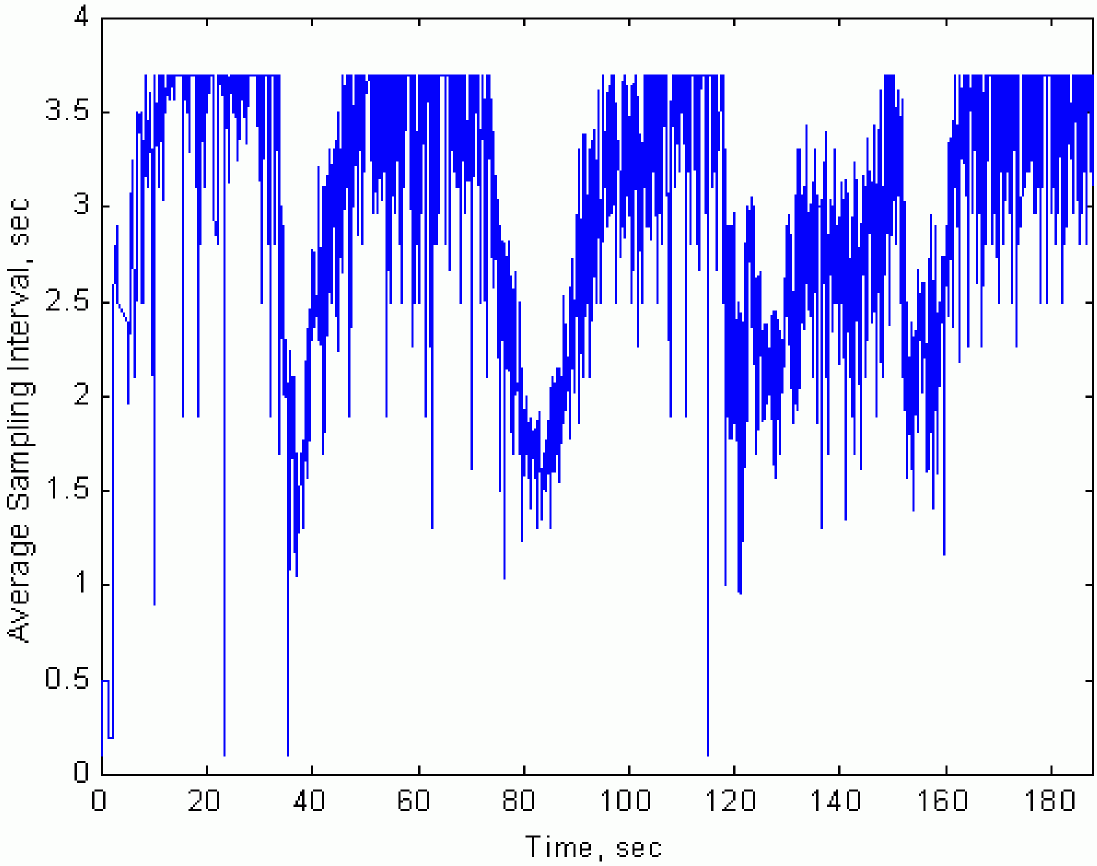

Figure 3

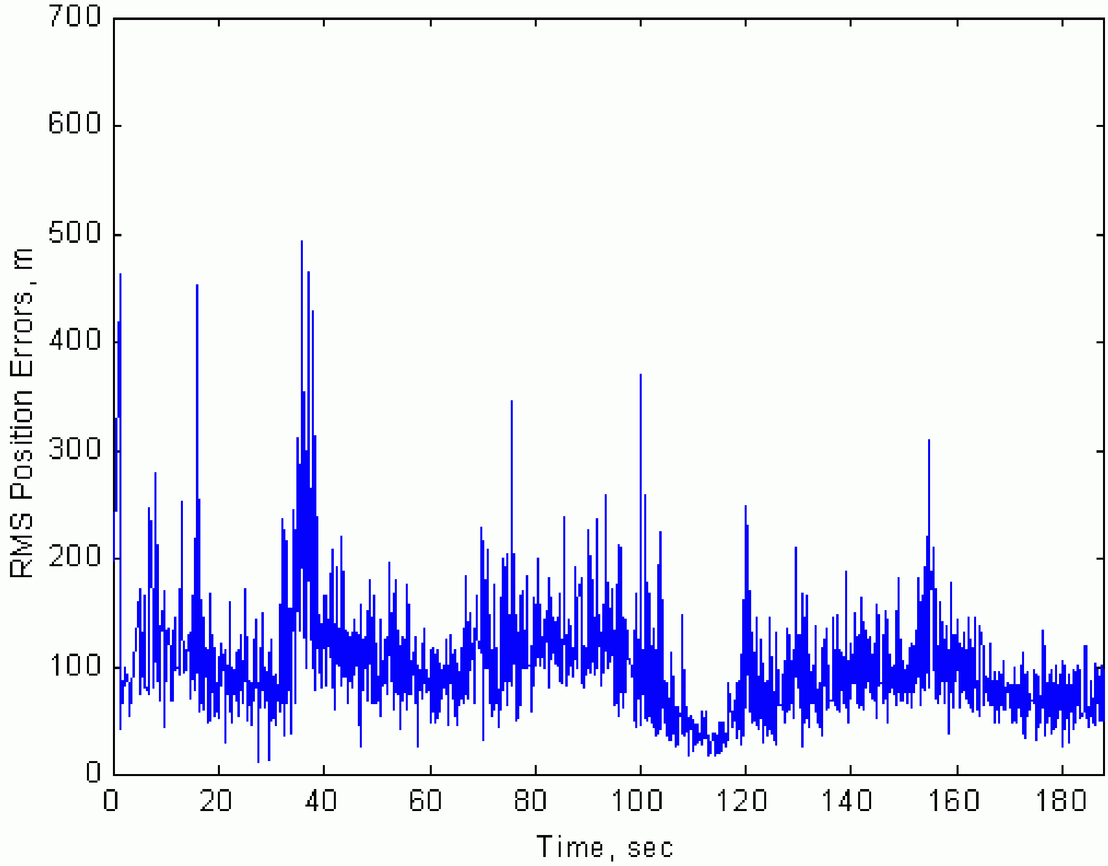

Figure 4

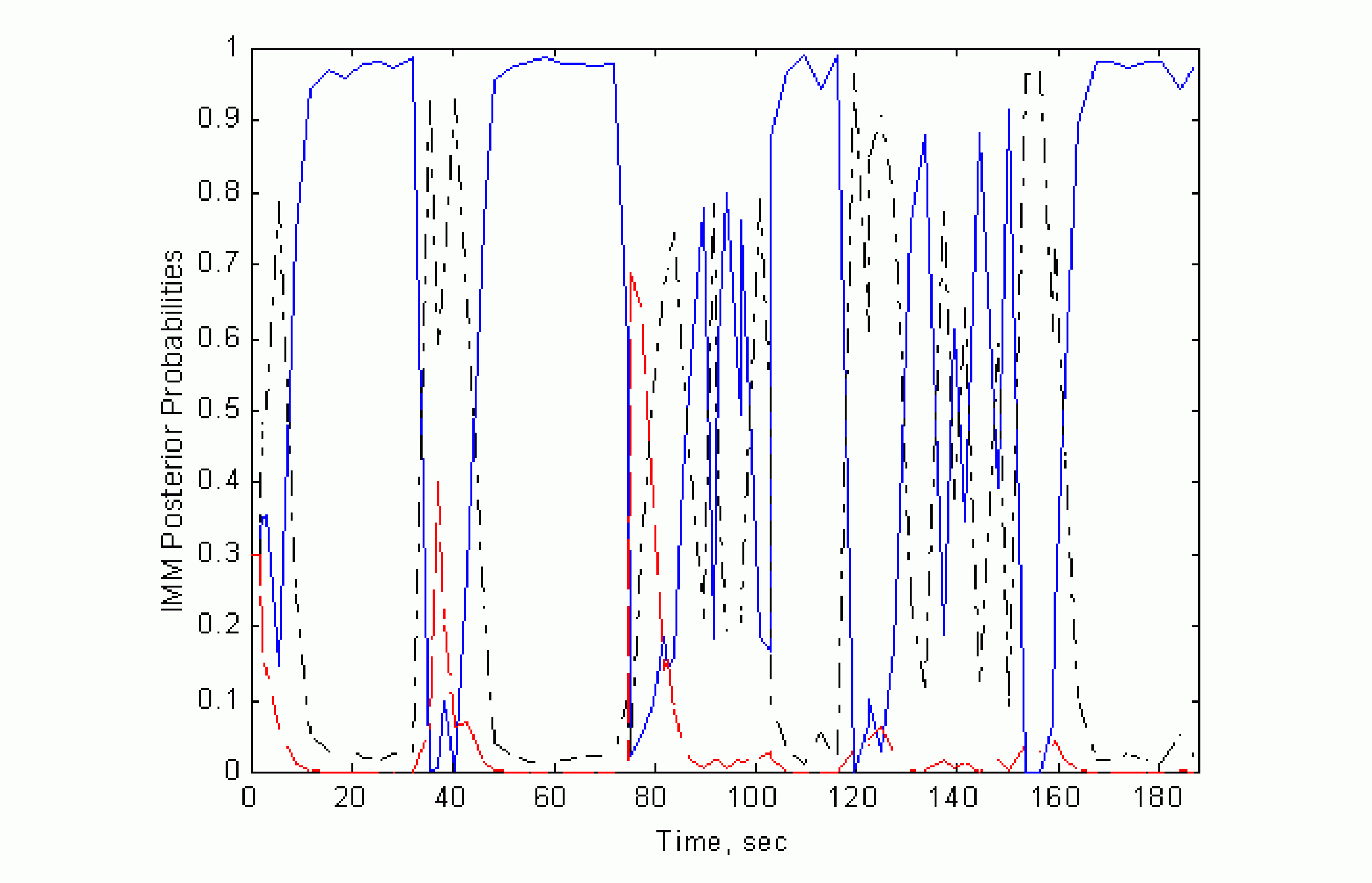

Figure 5

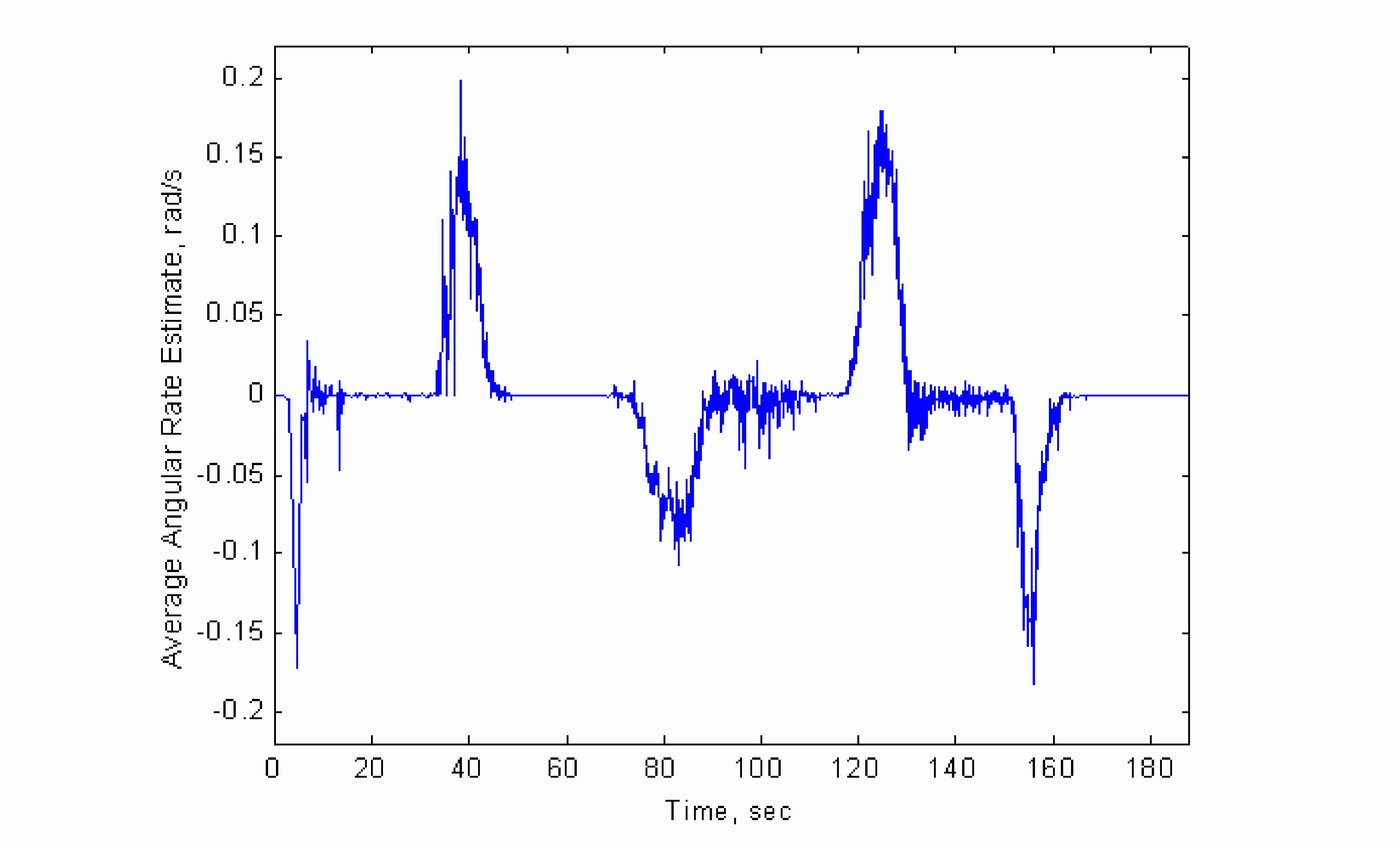

Figure 6

6. Conclusions

Preliminary results of an ongoing study are reported in the paper. An algorithm is proposed for radar management and tracking of maneuvering aircraft in the presence of clutter and Standoff Jammer. It is based on the advanced IMMPDA filtering approach for hybrid system estimation. The performance of the designed algorithm is evaluated by Monte Carlo simulations. Results obtained over six standard benchmark test scenarios are given. They show that the tracking filter characteristics satisfy the benchmark restrictions and they are close to the performance of the algorithms, recently published in the literature.

The further investigation comprises:

- implementation of the idea of the optimal initialization, described in [12];
- replacement of the PDAF with IPDAF for track formation, confirmation and termination;
- replacement of the PDAF with Probabilistic Strongest Neighbor Filter or Interacting 2-model PDAF[5];
- implementation of the Decomposition and Fusion Method for handling Range Gate Pull-Off ECM.

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An IMMPDA Solution to Benchmark Problem for Tracking in Clutter and Stand-off Jammer

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Keywords: hybrid system estimation, target tracking, radar data processing

An IMMPDA filtering algorithm is presented for radar management and tracking maneuvering targets in the presence of false alarms and Standoff Jammer. The performance of the designed algorithm is evaluated by Monte Carlo simulation. The results obtained over six benchmark test scenarios demonstrate that the tracking filter satisfy the performance restriction on a maximum allowed track loss of 4 %, posed by the benchmark problem. The achieved average sampling interval is approximately 2.85 sec and the average power is about 8.24 W. The paper reports preliminary results of an ongoing study and further investigation is under way.

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BULGARIAN MSDF R&D NATIONAL PROGRAM AND ACTIVITIES

Emil SEMERDJIEV and Tzvetan SEMERDJIEV

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1. Introduction

The Bulgarian National MSDF R&D program was established more than twenty years ago. Bulgarian electronics and Bulgarian military industry were specialized in development and serial manufacturing of sea and river radars. Driven by increasing demands for better quality, faster production and minimum costs, MSDF R&D projects have been constantly developed by research institutes and laboratories of Bulgarian industry and Bulgarian Academy of Science. The Bulgarian military branch has been especially interested in keeping abreast of the latest advances in this important field to ensure the highest standards and quality for military electronic systems modernization and upgrade. A number of young men have been educated in leading Soviet and East European military academies, civil technical universities and research centers, obtaining fundamental qualification. Since the mid 80’s, the increased capabilities of computer performance provided a reliable base for direct implementation of scientific methods, previously considered as too expensive from computational point of view. Since then it was realized that the MSDF theory is an independent scientific branch requiring special attention and significant scientific efforts. Following this direction, a Multiple Sensors Data Fusion Department was founded in 1988 at the Bulgarian Academy of Sciences, as R&D Laboratory named "SIGNAL". The most of research activities in Bulgaria in MSDF have been redirected from the industrial research centers toward this new unit. The major part of research activities in Bulgaria in this field were concentrated and accomplished in it. The Laboratory specialized in solving scientific and real-world problems involving signal, image and other type of data processing, with focus on the Bulgarian industry. It has become a leader in the design, development and evaluation of algorithms and application software for radar data processing and tracking systems. A number of R&D product implementations, mainly in the field of multiple target tracking algorithms (MTT) and related to it fields of simulation, guidance and control, have been accomplished:

- MTT algorithms and software implemented in meteorological radars (in serial manufacturing until 1990);

- MTT algorithms and software implemented in a parallel processor system for coastal radars (in serial manufacturing since 1990);
- mathematical models of signal and data processing systems for Complex Radar CAD systems (in use since 1988).
- Specialized Mathematical Library for radar data processing systems design and performance evaluation (in use since 1989);
- mathematical models and application software for Radar Simulators (in use since 1988)
- algorithms and software for unmanned ships collision avoidance systems.

A considerable scientific knowledge and experience has been accumulated in MSDF and especially in MTT during its eight-year history. In all these years, constant efforts for transition from defense-developed technologies to civilian government and commercial markets have been made, too.

2. The Current Strategy

The economical situation in Bulgaria after the Currency Board implementation two years ago became stabile and the success of the reforms is obvious. During this time it has been recognized that the further association of Bulgaria to the Western political, financial, and especially industrial, transport and military structures requires experts familiar with cutting-edge technologies (such as MSDF) capable to transfer knowledge and experience in Bulgaria and to participate in joint projects. That is the reason the general strategy of the most of research centers in Bulgaria has changed. The number and staff of the institutes and laboratories in industry and Bulgarian Academy of Science has been minimized. The strategy of their professional existence has been changed, too. A serious revision of the purpose and directions of the research activities has been made.

In the area of MSDF, the following directions of activity have been recognized as basic:

- preservation of existing scientific knowledge in the field of MSDF and accumulation of new one on a level that keeps the ability of nation to renovate technologically its industry;
- provision of experts in such rapidly changing (in technological sense) fields as transportation, military armaments and other fields related to the MSDF technologies;
- transfer of new technologies in the mentioned fields supporting the process of transition of the Bulgarian industry towards western standards and structures.
- education of new generation highly qualified young experts and specialists for the needs of Bulgarian industry, administration and private business.

Applying these considerations in practice, some important steps have been accomplished:

- the *laboratory has been reorganized* and associated as a department named *"Mathematical Methods for Sensor Data Processing"* at the *Central Laboratory for Parallel Processing* at the Bulgarian Academy of Science, to provide a strong connection with researchers working in the field of mathematics (mathematical statistics and Monte Carlo methods) and computer science (parallel and distributed computer architectures);
- the *research activities* have been concentrated (but not restricted) *in the field of MTT*;

- some *education courses*, concerning the implementation of MSDF theory and practice in Air-Traffic Control, Strategic Leadership and Decision Making, DoD Science, High-Technologies & Innovations Management have been developed from the department's staff and are in progress in Technical University in Sofia, Sofia's Business University, Rakovski War College and other schools;
- another area of activity is the participation in *international research projects*. Having experience in this field, based on successfully accomplished three R&D projects in MTT field for foreign customers (ELTA Ltd. - Israel Aircraft Industry), the Department management considers this area as strategic.

3. The Team

In 1999 the department personnel consists of 13 researchers: two full professors with D.Sc. degrees, two associate professors and eight senior researchers with Ph.D. degrees. All specialists have broad knowledge and experience in:

- application of theoretic and systems approaches for solving the problems in tracking radars;
- developing and applying effective sensor data processing approaches and methods;
- base physical properties of large number of sensors and observed (air, sea and land) moving objects;
- fields of scenario generation and use of real data for performance testing, and in the operator-machine interfaces testing & evaluation and training.
- With classical scientific training and knowledge of advanced computer tools, software design and state-of-the-art technologies, the team provides the best solutions to customer problems.

4. MSDF Research & Development

The field of MTT is an area where future joint fruitful collaboration is promising. Our achievements in this field relate mainly to tracking methods, algorithms and software development.

Generally speaking, the observed dynamic objects in our research studies are considered as hybrid stochastic systems. Such systems are characterized by continuous state and discrete set of unknown control, statistical or other parameters. A number of algorithms overcoming different kinds of uncertainty about the observed systems behavior and the ambiguity in the measurement sources, have been developed and their performance has been evaluated. These algorithms can be separated in five groups:

1. Recursive Pseudo-Bayesian algorithms estimating the hybrid state of a single object, based on the multiple model (MM) approach.
2. Recursive Pseudo-Bayesian algorithms associating measurements originating from multiple objects.
3. Data association algorithms using batch-processing techniques.
4. Recursive data classification & association algorithms using attribute measurement data.
5. Multisource data association algorithms.

The algorithms from the first group include Interactive MM algorithms (IMM)[1-10] with fixed structure (FS)[1-3] or with variable structure (VS)[4-10] and Generalized Pseudo-Bayesian algorithms (GPB).[14] Recently, the FS algorithms are considered well studied, but we have succeeded in developing precise models of some commonly observed dynamic systems, improving their overall performance, as well as the performance of the VS algorithms.[1-3,6,7] The development of different adaptive mechanisms, providing on-line adjustment of the unknown parameters in the IMM VS algorithms is a second perspective R&D direction.[4-10]

The *"bootstrap"* (*BS*) approach is another promising hybrid state estimation tool, alternative to the above mentioned ones. Implementing the MM approach in it, a BS-IMM algorithm was developed.[11,12] It processes in real time an immense number of simulated data to identify and refine the *pdf* of the observed system state. The algorithm demonstrates good estimation accuracy.

Our further efforts in the above mentioned fields are directed mainly towards generalization of the developed methods and their application in fault detection, robotics and other fields.[6,32]

The second group of algorithms comprises versions of the Probabilistic Data Association (PDA) approach and of the Multiple Hypotheses Tracking (MHT) algorithm. The developed PDA-IMM and BS-IMM-PDA versions[13,21] demonstrate significant stability in dense clutter environments.

The developed versions of an object-oriented MHT algorithm are the core algorithms of the second group.[14-21] Applying the MM approach,[14,15] the Hough transform (HT),[17,18] applying some heuristic techniques,[15] and incorporating information about measurement features[19,20] an overall improvement of MHT algorithm performance has been achieved. The results have been implemented in software CAD package, evaluating the algorithm performance through Monte Carlo simulations (see figures 1-4).

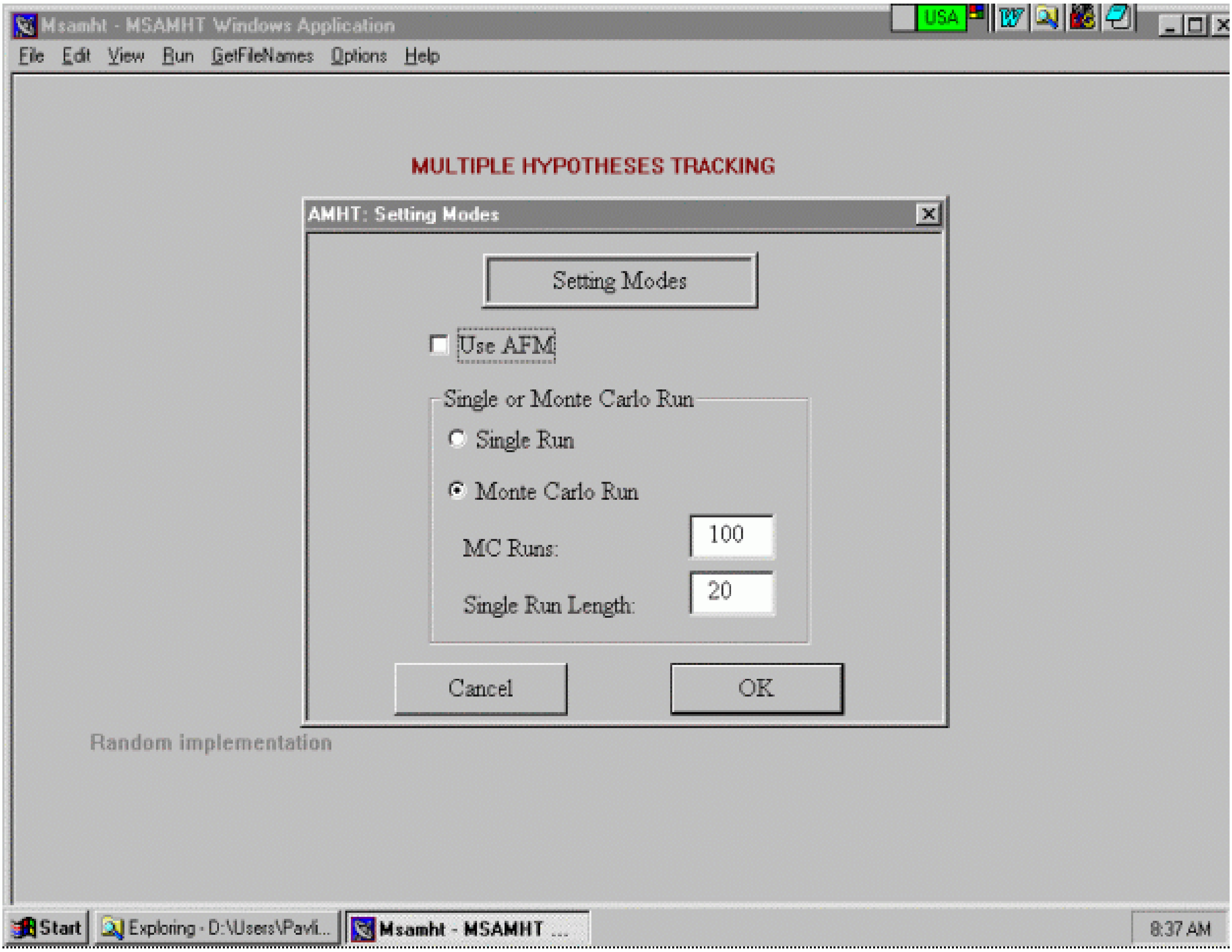

Figure 1: Dialog Setting Box

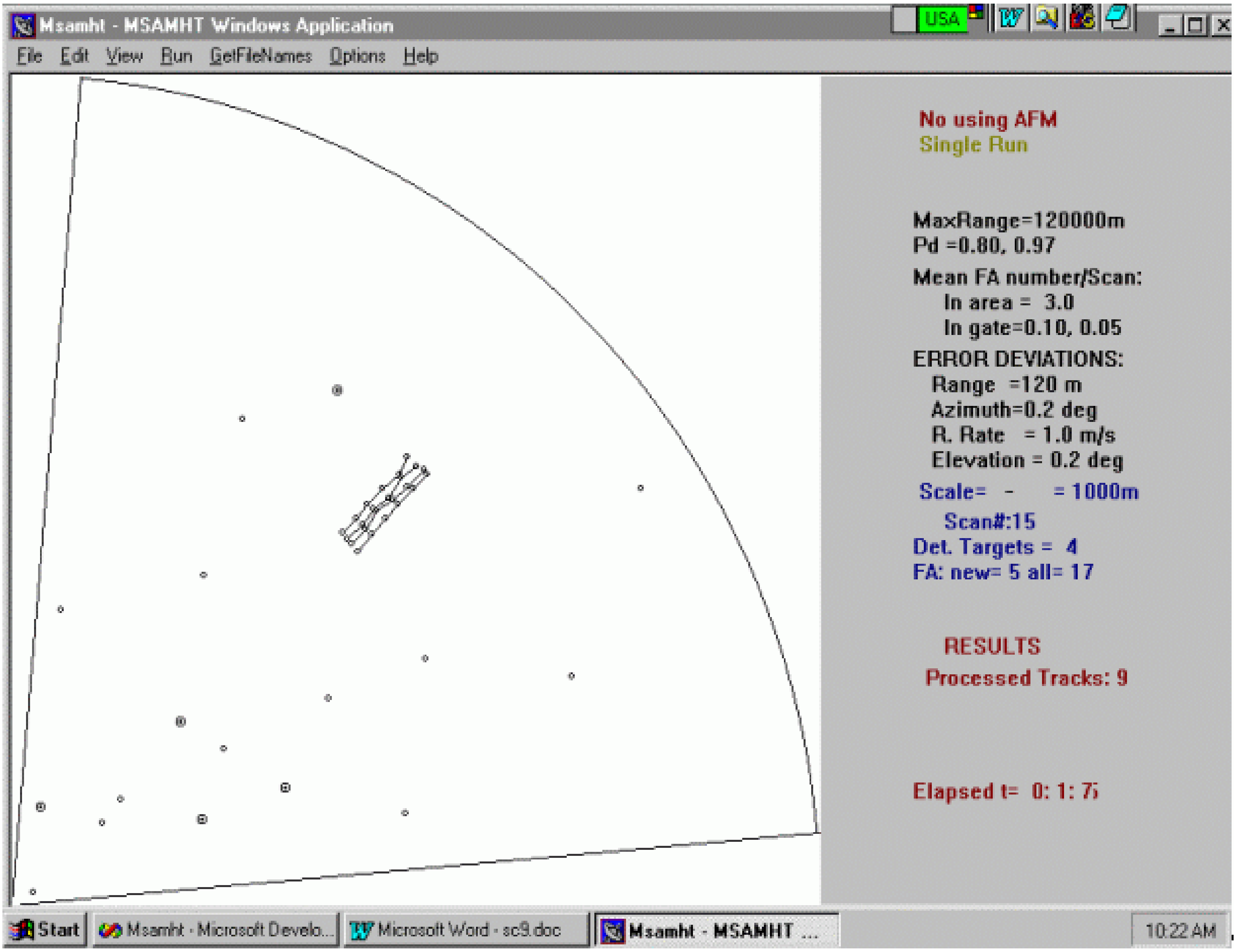

Figure 2: Graphical results visualization in a Single mode

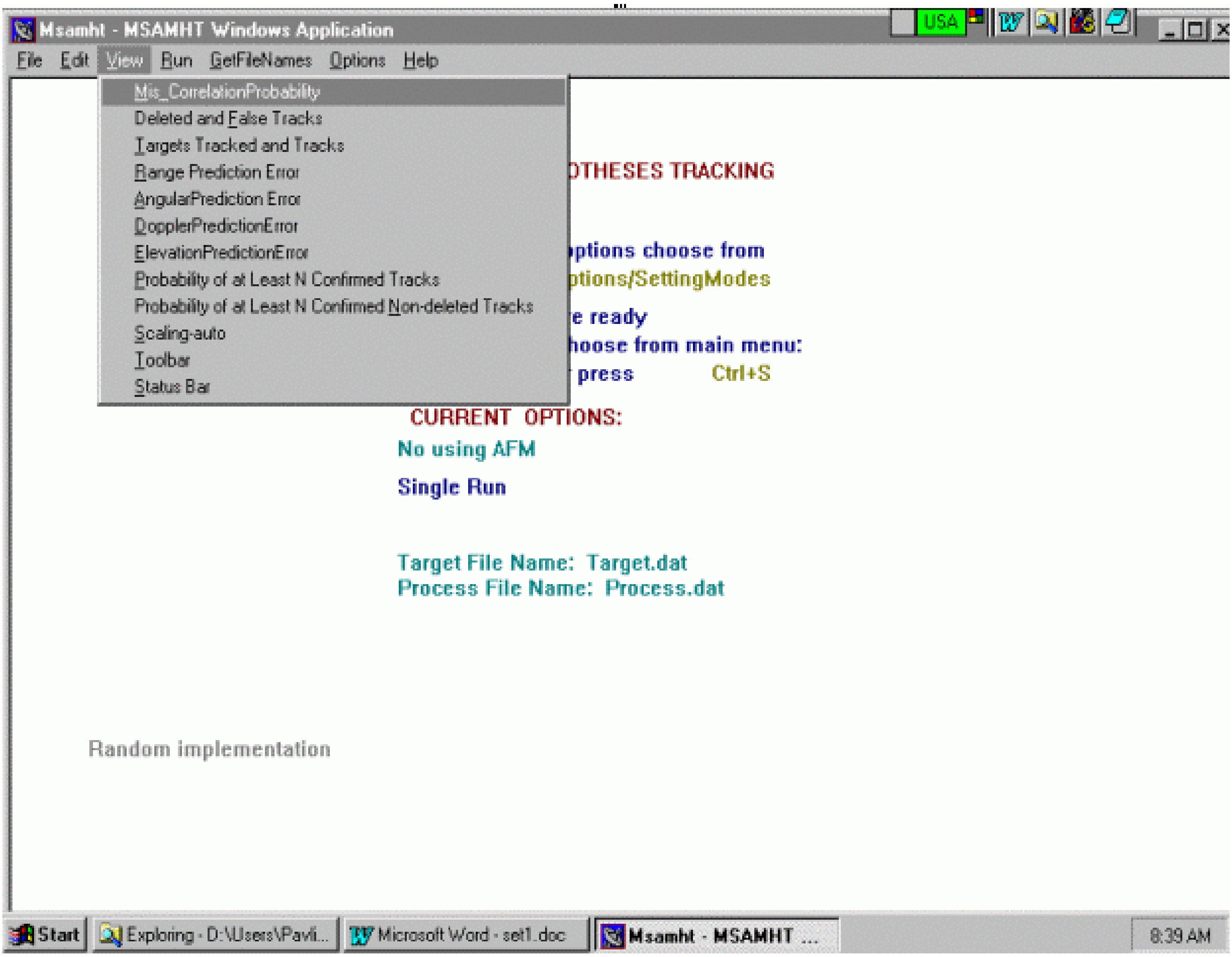

Figure 3: Measures of performance - the Control menu

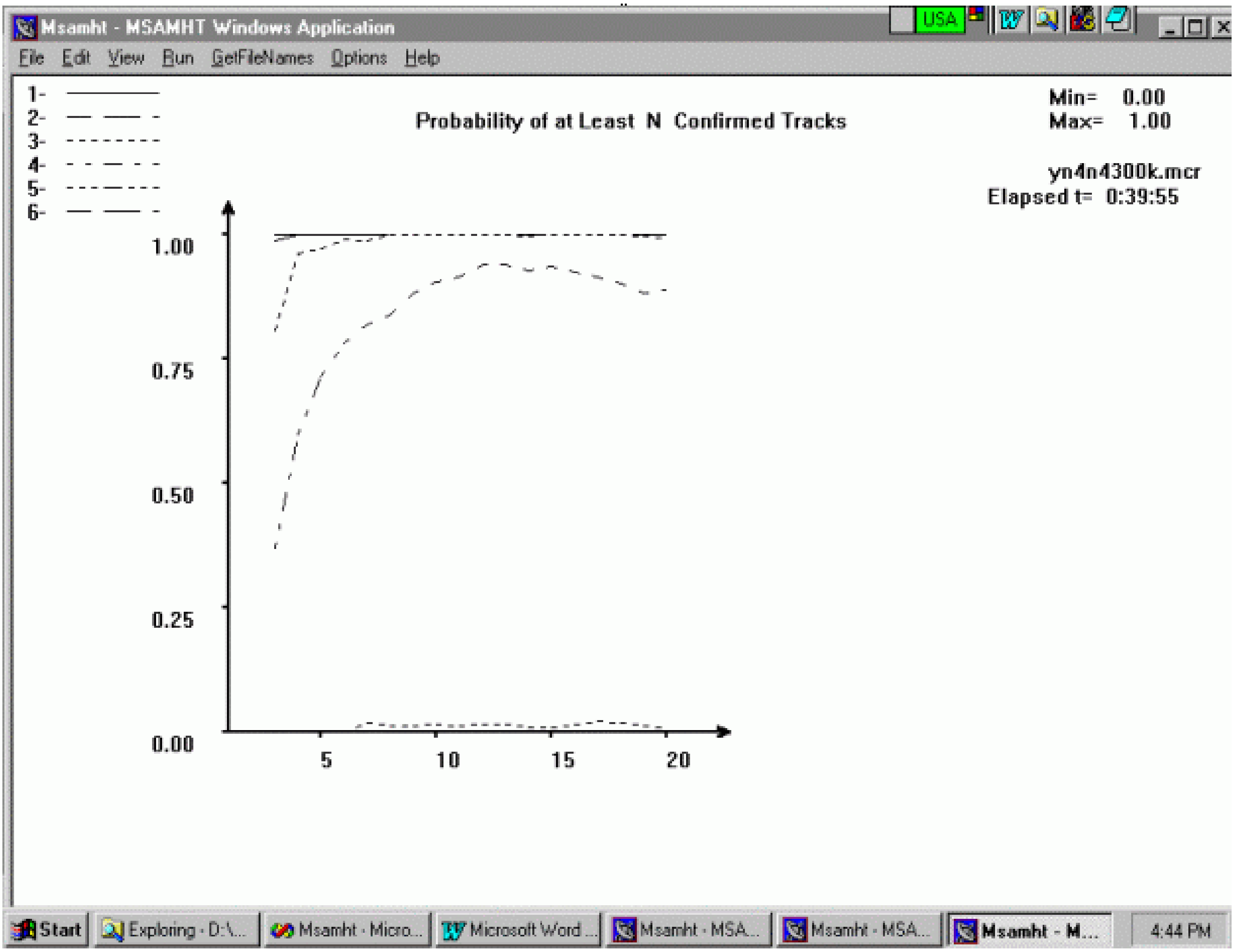

Figure 4: Monte Carlo graphical results visualization

The mentioned algorithms demonstrate high estimation accuracy in the hard case of maneuvering targets; significant clutter resistance; better data association and reduced computational load.[15,18-20] The development of a software package implementing on-line all these MHT algorithms versions will be accomplished in the near future.

The proposed batch-processing data association algorithms from the third group are based on the application of HT as a track initiator and false alarm filter.[17,18,24,25] We have solved problems concerning the identification of the connection between the base parameters of the HT algorithm, the sensor's parameters and the customer requirements related to track initiator performance. Further development of these algorithms is expected in their extension as adaptive track detectors and adaptive trackers.

The recursive data classification & association algorithms using attribute measurement data from the fourth group are based on the combined application of evidence reasoning theory and fuzzy logic. In this way, some hard data association problems have been theoretically overcome: the problem of conflicting evidence, the presence of initial full ignorance in the arriving data, the problem of conflicting assignments etc. The proposed algorithms provide reliable decisions about the targets identity and affiliation.[27-30] The application of the mentioned combined evidence reasoning theory with fuzzy logic approach instead the Bayesian one and is considered another promising area of investigation.

The last group of algorithms concerns the multisource data association problem. It has been considered mostly with the practical aim to find a multisensor track initiation algorithm, resolving the synchronization problem and the combinatorial explosion arising in realistic multitarget cluttered environment. The development of multisensor MHT algorithm is another research direction that we intend to study in a greater detail.[25]

A constant attention in most of the papers is paid to the problem of algorithm performance evaluation. The Monte Carlo simulation approach has been applied as a main tool to compute standard measures of performance in standard test scenarios.[1,4,10,13,15,18-21]

And finally, the problem of practical implementation of MTT algorithms is tightly connected with the required computational load. The inherent parallelism of some of the considered algorithms has been explored and the computational cost has been estimated.[31-33]

5. Conclusion

The brief examination of our strategy and achievements presented in this paper confirms our will to strengthen the relations with the international MSDF science community. Having in mind the emerging process of improving the industrial and financial situation in Bulgaria, we find that currently the R&D joint projects are the most promising opportunity for fruitful cooperation.

Acknowledgement

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Bulgarian MSDF R&D National Program and Activities

Emil Semerdjiev and Tzvetan Semerdjiev

Keywords: MSDF, multiple target tracking

A brief historical view and consideration of Bulgarian strategy and achievements in the field of MSDF is presented in the paper. Current R&D projects are briefly described. We examine the opportunity for joint research and the strengthening of the connections with the international MSDF science community as a promising area of fruitful cooperation.

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AN EFFECTIVE DOPPLER FILTERING USING HIGHER-ORDER STATISTICS

Boryana VASSILEVA

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1.Introduction

The moving target detection (for example of aircraft) in disturbed environment is an important radar processing problem. This task is to be performed by the pulse Doppler signal processor. The latter has two basic functions:

- to maximize the detection probability of a target signal and at the same time maintain a Constant False Alarm Rate (CFAR);
- to estimate the Doppler frequency shift, i.e. to estimate the target radial velocity.

A Doppler processor normally consists of a Reject Filter (RF) followed by a Fast Fourier Transform (FFT) and a CFAR processor. The technique for clutter suppression commonly in use today is RF based on Maximum Entropy Method (MEM) proposed by J. Burg.[1] However, for low Clutter-to-Noise-Ratio (CNR) this technique is not successful. Indeed, as the Power Spectral Density (PSD) of the received signal is already relatively flat due to noise, the MEM filter will not whiten further the PSD significantly.

For the same reason the use of a MEM matched filtering is quite limited and the classical FFT technique is preferable. However FFT does not perform an effective matched filtering when the input Signal-to-Noise-Ratio (SNR) is very poor.[2]

To reduce the degradation of the Doppler filtering in the presence of powerful noise several approaches have been proposed.[3] However, they have only moderate success. Lately, higher-order statistics are finding wider applicability in signal processing.[4] In order to improve radar Doppler filtering under the mentioned condition, MEM algorithm using higher-order statistics is developed and described in this work. The performance of the proposed algorithm is investigated by means of simulation analysis.

2.Background

Let the received signal $z(i)$ be an additive mix of an echosignal $y(i)$ and an independent zero-mean noise $n(i)$ with variance σ_n^2, i.e.

$$z(i) = y(i) + n(i), \quad i = 0,1,\cdots K-1. \qquad (1)$$

The received signal is assumed stationary in a broad sense. Its autocorrelation function (ACF) depends only on the time difference, i.e.

$$R_z(k) = R_y(k) + \sigma_n^2 \delta(k) \quad k = 0,1,\cdots K-1,$$

where $R_y(k)$ is the ACF of the echosignal and $\delta(k)$ is the discrete delta function ($\delta(k) = 1$ when $k = 0$ and $\delta(k) = 0$ when $k \neq 0$). The normalized ACF of the received signal is

$$B_z(k) = R_z(k)/R_z(0) = [rB_y(k) + \delta(k)]/(r+1), \; k = 0,1,\ldots,K-1 \qquad (2)$$

where $B_y(k) = R_y(k)/R_y(0)$ is the normalized ACF of the echosignal, r is the Echosignal-to-Noise-Ratio (ESNR).

The m^{th} order ACF and the normalized ACF are respectively

$$R_{zm}(k) = \begin{cases} z(k) & if \quad m = 0 \\ E\left[z(i) z^{*}(i+k)\right] & if \quad m = 1 \\ E\left[B_{z(m-1)}(i)\, B^{*}_{z(m-1)}\right] & if \quad m > 1 \end{cases} \qquad (3)$$

$$B_{zm}(k) = R_{zm}(k) / R_{zm}(0) \quad k = 0,1,\cdots K-1. \qquad (4)$$

For these functions the biased estimation

$$\hat{R}_{zm}(k) = \sum_{i=0}^{K-k-1} \hat{B}_{z(m-1)}(i) \hat{B}^{*}_{z(m-1)}(i+k) / K \qquad (5)$$

is used. This estimation tends to have less mean-square error for finite data records compared with the unbiased estimation

$$\breve{B}_{zm} = \sum_{i=0}^{K-k-1} \breve{B}_{z(m-1)}(i) \breve{B}^{*}_{z(m-1)}(i+k) / (K-k). \qquad (6)$$

Based on eq. (2), it is proved by means of induction that if the ESNR is not very poor the following relation is true

$$\hat{B}_{zm}(k) - \hat{B}_{ym}(k) \sim C_m(r)\left(1 / K^{m-1}\right) \qquad (7)$$

and therefore

$$\hat{B}_{zm}(k) = \hat{B}_{ym}(k) + O\left(1 / K^{m-1}\right), \quad k = 0,1\cdots K-1. \qquad (8)$$

If $r \to \infty$ then $C_m(r) \to 0$ and $\hat{B}_{zm}(k) = \hat{B}_{ym}(k) + o\left(1 / K^{m-1}\right)$. Consequently, with the increase of the order of the normalized ACFs of the received signal and the echosignal, their estimations approximate each other. The greater the length of the data record is and the greater the ESNR is, the closer they get to each other. The simulation analysis that has been carried out confirms relation (8). When $r = -10\,dB$, $K = 32$ and $m \geq 3$, the estimations $\hat{B}_{zm}(k)$ and $\hat{B}_{ym}(k)$ are sufficiently close to each other for practical purposes. Better results are obtained when $K = 64$.

Further, given the realistic assumption, that the echosignal model is Autoregressive (AR) with coefficients $\beta(l), \quad l = 1,2,\cdots p, \; (p \leq 5)$ 3 the model of the received signal can be expressed in the following way

$$z(i) = \sum_{l=1}^{p} \beta(l) z(i-l) + \sum_{l=1}^{p} \alpha(l)\, \varepsilon(i-l) + \varepsilon(i), \qquad (9)$$

where $\varepsilon(i)$ is the zero-mean white noise with variance σ^2_ε and $\alpha(l)$ are the moving average coefficients. An important relation between the parameters of the process and its normalized ACF $B_{zm}(k)$ exists. It can be achieved as follows. Multiply (9) by $z^{*}(i+k)$, take the expectation and normalize autocorrelation lags thus obtained. If the result is multiplied by $B^{*}_{z1}(i+k)$ and the expectation is taken again, it becomes evident that for the m^{th} order normalized ACF the following relation is true

$$B_{zm}(i) = \begin{cases} \sum_{l=1}^{p} \beta^{*}(l)\, B_{zm}(i-l) \; if\; m\, is\, odd \\ \sum_{l=1}^{p} \beta(l)\; B_{zm}(i-l) \; if\; m\, is\, even \end{cases} \quad , i \geq p+1 \qquad (10)$$

Relation (10) gives the AR model of the normalized autocorrelations, given values of the argument $i \geq p+1$. Hence, in order to estimate the parameters of this model (that in this case are the parameters or the complex conjugated parameters) of the AR model of the echosignal, the MEM can be used.

3.Suboptimal Doppler Filtering Algorithm

In this section suboptimal filtering algorithm for radar Doppler processing, based on the approach described in section 2 is presented. Figure 1 shows a blockdiagram of this algorithm.

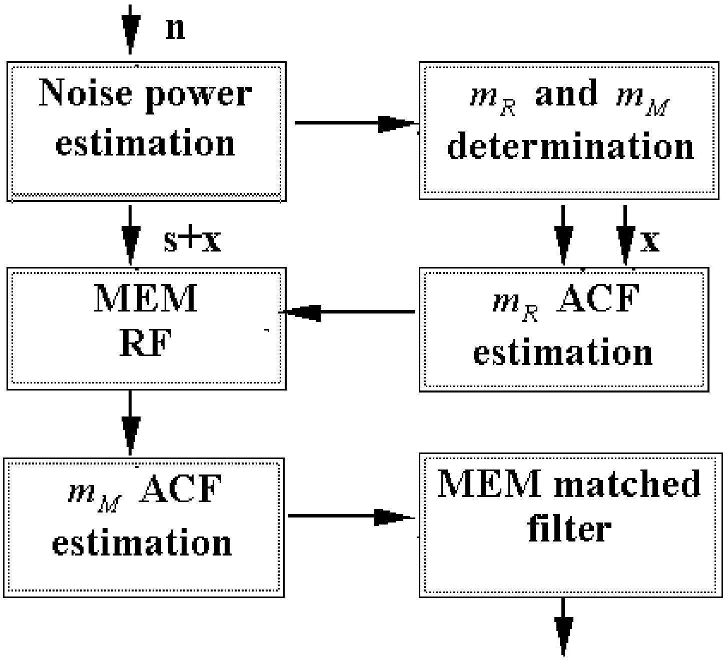

Figure 1

The received noise power is estimated in the passive operating mode of the radar. Depending on the noise power level and the power levels of the expected echosignals the orders of the statistics for the RF input (m_R) and the matched filter input (m_M) are determined for each range cell. The disturbing signals $x_n(k), n = 1,2,\cdots K_r$ received from KK_r range cells around the testing cell are used for estimation of the m_R-order ACF. The so obtained ACF lags $B_n(k), k = p+1,\cdots K$ are used to compute the RF coefficients $a(l), l = 1,2,\cdots p_R$ implementing the multisegment Burg's recursive algorithm.

As the first step forward and backward sequences $f_{l,n}(k)$ and $b_{l,n}(k)$ are initialized as

$$f_{1,n}(k) = B_n(k+1), b_{1,n}(k) = B_n(k), k = p_R + 1,\cdots K-1, n = 1,2,\cdots K_r. \qquad (11)$$

The first reflection coefficient is computed as

$$\rho_l = \frac{\sum_{n=1}^{K_r}\sum_{k=p_R+1}^{K-l} 2 f_{l,n}(k)\, b_{l,n}^{*}(k)}{\sum_{n=1}^{K_r}\sum_{k=p_R+1}^{K-l}\left[\,|f_{l,n}(k)|^2 + |b_{l,n}(k)|^2\right]}, \qquad (12)$$

with l equal to unity.

A recursive relation for the higher-order reflection coefficients is obtained via the update relations:

$$\left.\begin{aligned} f_{l,n}(k) &= f_{l-1,n}(k+1) - \rho_{l-1} b_{l-1,n}(k+1) \\ b_{l,n}(k) &= b_{l-1,n}(k) - \rho_{l-1}^{*} f_{l-1,n}(k) \end{aligned}\right\}, \qquad k = p_R + 1,\cdots K-l. \qquad (13)$$

This is continued until $l = p_R$. The filter coefficients $a(l)$ are then calculated from the recursive relation

$$a_{p_R}(l) = a_{p_R-1}(l) + \rho_l a_{p_R-1}^{*}(p_R - l);\quad a_{p_R}(l) = \begin{cases} 1 & l = 0 \\ \rho_l & l = p_R \\ 0 & l > p_R \end{cases} \qquad (14)$$

For the testing cell the output of the RF is

$$Z(i)=\begin{cases} B_{zm_R}(i)-\sum_{l=1}^{p_R} a^*(l) B_{zm_R}(i-l) & \text{if } m \text{ is odd} \\ B_{zm_R}(i)-\sum_{l=1}^{p_R} a(l)\, B_{zm_R}(i-l) & \text{if } m \text{ is even} \end{cases}, \qquad i \ge p_R+1 \tag{15}$$

$B_{zm_R}(i)$ are the m_R-order normalized ACF lags for $z(i)=s(i)+x(i)$, where $s(i)$ is the useful signal and $x(i)$ is the disturbing signal. The RF output signal is used for m_M-order ACF estimation. The so obtained correlations are input data for the first-order matched filter. The output of this filter is a PSD sequence

$$\hat{\phi}(k)=\frac{\sigma^2}{2\pi\left|\sum_{n=0}^{1}\beta(n)\exp\left(-j\frac{k}{K}n\right)\right|^2}, \qquad k=0,1,\cdots K-1 \tag{16}$$

where $\beta(0)=1$, $\beta(1)$ is calculated from (12) for $n=1$, $l=1$, $k=6,7,\cdots K-1$ and σ^2 is the prediction error power. Formula (16) is the spectral line expression for different frequencies (velocity channels).

4.Simulation example

The following example is used to illustrate the performance of the proposed algorithm. Let the interference be defined by the return echoes from the sea and the Stand-of-Jammer (SOJ) broadcasting wideband noise. Amplitude responses of the first-order RF for $m_R=1$ (RF1) and for $m_R=2$ (RF2) are shown in Figure 2. The numbers of the velocity channels are given along the abscise. The radial velocity of the clutter is determined by the 0^{th} channel. The CNR is $-35\ dB$. The filters coefficients are estimated for $K=64$ and $K_R=2$. The curves show better clutter rejection for RF2. Besides, the significant pass band irregularity of RF1 can distort undesirably the useful signal.

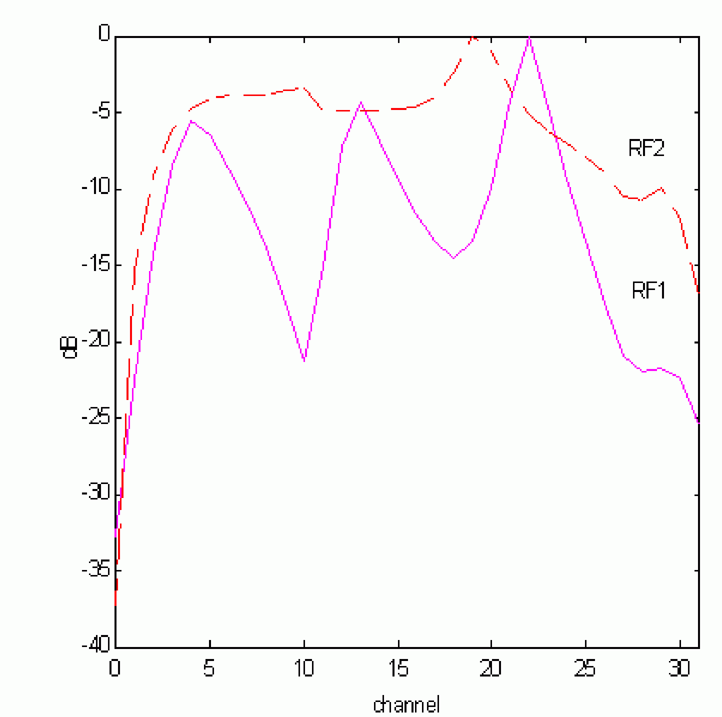

Figure 2

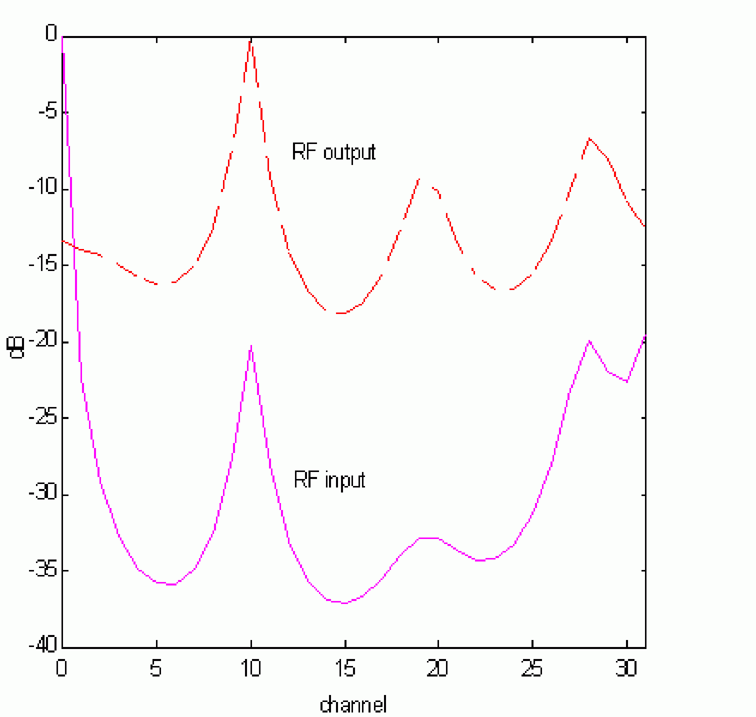

Figure 3

Therefore, RF2 is the preferable filter. Figure 3 presents normalized spectral lines of the interference second-order ACF before and after rejection. We can see the RF2 whitening operation.

To investigate the performance of the complete algorithm the useful signal is added to the considered interference. The SNR is $-10.5\ dB$. The Signal-to-Clutter-Ratio (SCR) is $-5.5\ dB$. The radial velocity of the target (slowly flying airplane) is determined by the second-channel. The line "FFT" on Figure 4 shows the received signal FFT spectrum, which is relatively flat. The "MEM"- line shows the tenth-order MEM spectrum of the second-order signal ACF. Estimation of the echosignals peaks with high resolution is achieved.

The results of the complete algorithm for $m_R=2, m_M=2$ and $p=1$ are shown on Figure 5. The line "Target" shows the selected useful signal spectrum and the line "Noise" shows the residual noise spectrum. The output SNR is more than $20dB$. In spite of nearness of the clutter and target velocity channels, the Improvement Factor (IF) is more than $30dB$. The so obtained IF value ensures high quality of signal detection.

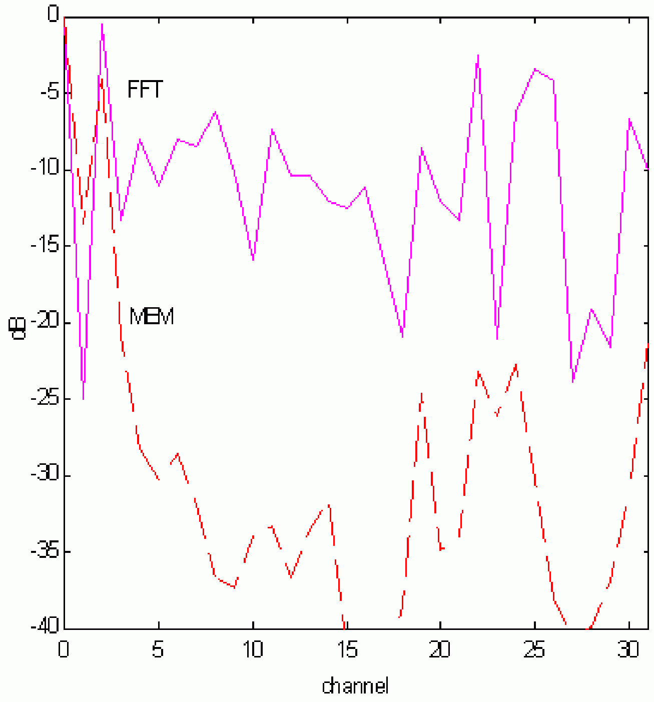

Figure 4

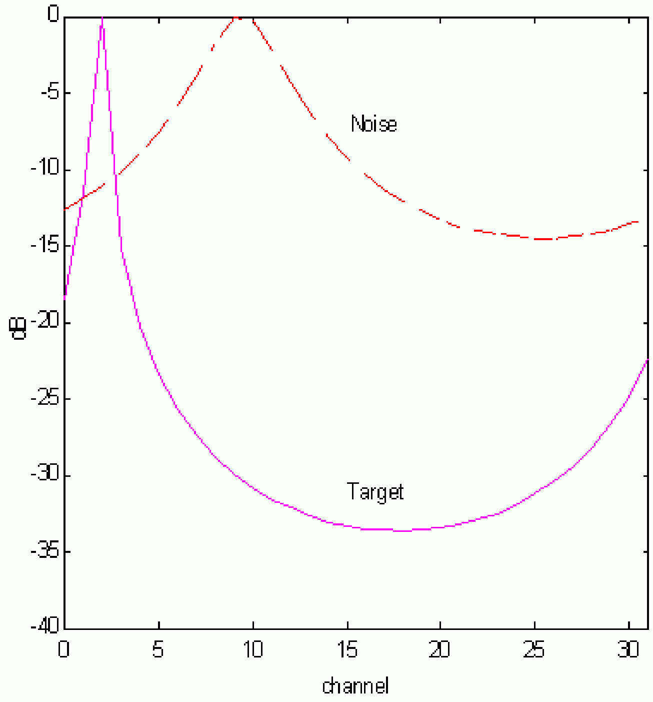

Figure 5

5.Conclusions

In this paper a new algorithm for moving target signal selection in the presence of clutter and wideband jammer is presented. The proposed algorithm includes whitening filter for the interference, followed by a matched filter for the useful signal. This cascade of filters is based on higher-order statistics approach (namely higher-order ACF) and maximum entropy pole estimations. The structure of the described algorithm is relatively simple. It is appropriate for on-line processing. The algorithm performance is investigated by means of the Monte Carlo simulation analysis. The results indicate that the proposed algorithm is very effective particularly for short data records. The obtained frequency resolution and IF values ensure high quality of signal detection.

It should be noticed that for relatively long data records the use of cumulants as a higher-order statistics and maximum entropy pole-zero estimations for radar Doppler filtering is a very promising approach. Future work will focus on developing such a type of adaptive algorithm.

Acknowledgement

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An Effective Doppler Filtering Using Higher-Order Statistics

Boryana Vassileva

Keywords: adaptive Doppler filtering, spectral analysis, linear prediction.

Algorithm for moving target selection in the presence of clutter and wideband jammer is presented. The proposed algorithm includes whitening filter for the interference, followed by a matched filter for the useful signal. This cascade of filters is based on higher-order statistics approach and maximum entropy pole estimations. The algorithm performance is investigated by means of the Monte Carlo simulation analysis. The obtained frequency resolution and improvement factor values ensure high quality of signal detection.

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TRACKING FILTERS FOR RADAR SYSTEMS WITH CORRELATED MEASUREMENT NOISE

Donka ANGELOVA and Boryana VASSILEVA

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1. Introduction

Most tracking filters are based on the Kalman filter equations,[1] where the tracking system model presumes white process and measurement noise. In practice, the measurement noise may not be white. Its bandwidth may be on the order of several hertz. For example, target scintillation (or glint) causes the range and angle measurement errors to have a finite bandwidth. Another example of correlated measurement error is the radial velocity measurement error appearing as a result of radar frequency instability and target velocity fluctuations.

When the measurement frequency is much smaller than the error bandwidth, the errors of successive measurements are approximately uncorrelated and can be treated as white noise. However, the measurement frequency of some modern radars is sufficiently high and the correlation cannot be ignored without tracking accuracy deterioration.

A possible approach to circumvent the effect of colored noise is the target state augmentation technique.[1] However, this yields a singular state covariance matrix, which may be ill-conditioned. A solution to the problem was suggested first by Bryson and Henrikson.[2] They generated a pseudomeasurement, linear combination of two consecutive measurements, which is corrupted by white noise. In this measurement difference approach the application of the Kalman filter equations is straightforward. Rogers modeled colored noise as a first order Autoregressive (AR) process and applied the pseudomeasurement method to the $\alpha - \beta$ filter.[3] But in real-world environment the exact prior information of the AR coefficients is not known. Wu and Chang proposed a method to estimate the AR parameters by removing the state variables from the measurements.[4] Their method and the pseudo-measurement approach are used in the Interacting Multiple Model (IMM) filter for maneuvering target tracking.[4] Thus, significant improvement is obtained.

The application of the pseudomeasurement method is limited to the case where only position is measured. The case where both position and velocity are measured cannot be solved by this approach. Gazit[5] extends the procedure suggested in [2] and formulates an optimal filter for tracking *nonmaneuvering* target without any restriction on the models' dimension. Using this decorrelation approach, a technique for tracking filters design for *maneuvering* targets is presented in this work. *A new algorithm* for AR parameter estimation is proposed. It is appropriate for on-line processing and is incorporated into the IMM filter. Two practical tasks are solved: 1) tracking with position measurements and 2) tracking with position and velocity measurements. The performances of the suggested algorithms are evaluated by Monte Carlo computer simulation.

The paper is organized as follows. Section 2 concisely summarizes the measurement decorrelation approach proposed in [5] and marks the IMM algorithm as an effective estimator of maneuvering targets. Section 3 presents a new algorithm for estimation of AR parameters based on the true state variable removing method.[4] The Monte Carlo simulation results are described in section 4. Conclusions are summarized in the final section.

2. Tracking filter design

Tracking filters have to be correctly designed to obtain best results for a specific practical application. This process is often a trade-off among quality, complexity and possibility for on-line processing. The filter design comprises the choice of a measurement error model, the choice of a noise decorrelation scheme and a filtering algorithm, as well as the selection of their *a priori* parameters.

A. Measurement noise decorrelation. Consider the following model of a linear dynamic system for tracking with colored measurement noise[5]:

$$x(k+1) = \Phi x(k) + G w(k)$$
$$e(k+1) = \Psi e(k) + \eta(k) \qquad (1)$$

where $x(k) \in \Re^{n_x}$ is the target state vector, $e(k) \in \Re^{n_e}$ is the state vector of the measurement error model, $w(k)$ and $\eta(k)$ are random noise sequences, assumed to be white and mutually uncorrelated with covariances $W(k)$ and $V(k)$ respectively. Let target position x_k, velocity v_k, and acceleration a_k be components of the state vector in one-dimensional case: $x(k) = (x_k, v_k, a_k)^T$. The state transition matrix Φ and the noise matrix G are determined by the target dynamics and assumed to be known to the tracking filter. The measurement vector $y(k) \in \Re^{n_y}$ in the measurement model

$$y(k) = Cx(k) + De(k) \qquad (2)$$

is a linear combination of $x(k)$ and $e(k)$. The matrix C selects the measured elements of $x(k)$ (for example, position only, or position and velocity). A state space partition and a reduced order dynamic model are used in [5] to construct a tracking filter *without limitations concerning the order of the error model and measurement vector dimension.* The author rewrites the measurement equation in the form:

$$y(k) = x_a(k) + e_a(k) \qquad (3)$$

where $x_a(k) \in \Re^{n_y}$ and $e_a(k) \in \Re^{n_y}$ are the measured elements of $x(k)$ and $e(k)$. Thus a partition of the state vectors is actually formed. It imposes a similar partition of the transition matrices, noise vectors and their covariance matrices. Analogous to [2] a new measurement vector is defined:

$$y_r(k) = y(k+1) - \Psi_a y(k) \qquad (4)$$

where Ψ_a has dimension $(n_y \times n_y)$ and corresponds to the vector e_a. After appropriate substitutions and transformations the target and measurement equations are reformulated:

$$x_r(k+1) = F x_r(k) + G_r u_r(k) + w_r(k)$$
$$y_r(k) = H x_r(k) + \eta_r(k) \tag{5}$$

where the deterministic input $u_r(k) = y(k)$ and the new state vector $x_r(k)$ of dimension $n_r = n_x + n_e - n_y$ is extended with the unmeasured elements of $e(k)$. The form of the system matrices F, G_r, H can be found in [5]. The new process noise $w_r(k)$ and measurement noise $\eta_r(k)$ are now white sequences, but they are mutually correlated: $E[w_r(j)\eta_r(k)^T] = S\delta_{jk}$. Since the matrix S is small (its elements contain the $6 \div 3$ degree of the sampling interval $T = 0.05\,s$), $w_r(k)$ can be assumed uncorrelated with $\eta_r(k)$ with slight degradation in performance.[7] The system order $n_r = n_x + n_e - n_y$ is smaller than the order of the augmented system $n_x + n_e$.[1] Now the application of the Kalman filter becomes possible and, consequently, the IMM algorithm can be applied to the case of maneuvering target tracking with correlated measurement noise.

B. Measurement error model. The measurement error $e(k)$ is modeled as a first-order AR process. In that case Ψ is the matrix of the AR parameters and $\eta(k)$ is a zero mean white Gaussian noise with variance $E[\eta(j)\eta(k)^T] = V\delta_{jk}$. When only the position of the target is measured, then the system parameters are determined as:

$$n_y = 1;\; n_e = 1;\; x_a(k) = x_k;\, \eta(k) = \eta_k^x;\quad \Psi = \alpha^x;\, \alpha^x = \exp(-\lambda T),$$

where λ is *the bandwidth of the measurement noise.* α_x and the noise variance $(\sigma_k^{\eta^x})^2$ are *two AR parameters which have to be estimated.* When both position and velocity are measured, then:

$$n_y = 2;\quad n_e = 2;\quad x_a(k) = (x_k, v_k)^T;\; \eta(k) = (\eta_k^x, \eta_k^v)^T;\; \Psi = diag(\alpha^x, \alpha^v)$$

and $\alpha^x, \alpha^v, (\sigma_k^{\eta^x})^2, (\sigma_k^{\eta^v})^2$ *are subject to adaptive estimation.*

C. IMM state estimation algorithm. [1] The kinematic behavior of a maneuvering target can be suitably described in the terminology of the stochastic hybrid systems. The aim of the hybrid estimation is to assess the system state and behavior mode based on the sequence of the noisy measurements. Filtering algorithms in general consist of operating in parallel Kalman filters and Bayesian mechanism to organize the cooperation between the individual filters. An underlying Markov chain is assumed to govern the mode switching. The IMM algorithm is one of the most effective recent suboptimal Bayesian filters for hybrid system estimation. It provides the overall system state estimate $\hat{x}(k/k) = \sum_{j=1}^{r} \hat{x}^j(k/k)\mu_j(k)$ and estimates its associated covariance matrix $P(k/k)$ as a weighted sum of the estimates $\hat{x}^j(k/k)$ and its covariances $P^j(k/k)$, formed by r mode-conditional parallel Kalman filters. The posterior mode probabilities $\mu_j(k)$ are calculated on the base of the likelihood of the measurement, received at the current time step.

D. IMM tracking filter design includes: a) selection of target motion models and their parameters; b) assignment of transition probabilities of the underlying Markov chain. The motion modes along one of the Cartesian coordinates are modeled by a *second-order kinematic (nearly constant velocity)* model for uniform motion and two *third-order (nearly constant acceleration)* models for the maneuvers. The process noise standard deviations are chosen after some simulation experiments as follows: $\sigma_{w_r}^1 = 10\,m/s^2$ for nonmaneuvering mode and $\sigma_{w_r}^2 = 90\,m/s^2$, $\sigma_{w_r}^2 = 150\,m/s^2$

respectively for the two maneuvering modes corresponding to different maneuver intensities. The Markovian transition probability matrix is chosen identical to [4] in order to compare the final results.

3. Estimation of AR parameters

A technique that can effectively estimate the AR parameters of the position and velocity measurement noises is proposed in this work. Since the measurement (3) contains state variables x_k and v_k the direct estimation of the e_k^x and e_k^v parameters $(e(k) = (e_k^x, e_k^v)^T)$ is difficult. It will be very helpful to remove state variables:

$$x_k = x_{k-1} + v_{k-1}T + \frac{1}{2}a_{k-1}T^2, \quad v_k = v_{k-1} + a_{k-1}T, \qquad (6)$$

where a_k is the acceleration of the target. Let ξ_k denotes the true target position $(\xi_k = x_k)$ or velocity $(\xi_k = v_k)$. The following filtering operation is used to obtain a new signal $\bar{u}_k$ that does not involve ξ_k:

$$\begin{aligned}\bar{u}_k &= \sum_{i=0}^{l} C_l^i(-1)^i(\xi_{k-i} + e_{k-i}^{\xi}) = \sum_{i=0}^{l} C_l^i(-1)^i \xi_{k-i} + \sum_{i=0}^{l} C_l^i(-1)^i e_{k-i}^{\xi} = \\ &= \sum_{i=0}^{l} C_l^i(-1)^i e_{k-i}^{\xi} + \frac{1}{l-1}(a_{k-1} - a_{k-l})T^{l-1}\end{aligned} \qquad (7)$$

where if $\xi_k = x_k$, then $l = 3$ and if $\xi_k = v_k$, then $l = 2$. Thus the z-transform of (7) is:

$$\bar{u}(z) = (1 - z^{-1})^l e^{\xi}(z) + m(z), \quad m(z) = \frac{1}{l-1}(z^{-1} - z^{-l}a(z))T^{l-1}. \qquad (8)$$

Note that e_k^{ξ} is an AR process. According to (1) its transfer function is:

$$e^{\xi}(z) = \frac{1}{1 - \alpha^{\xi} z^{-1}} \eta^{\xi}(z) \qquad (9)$$

and $\bar{u}(z)$ is:

$$\bar{u}(z) = \frac{(1 - z^{-1})^l}{1 - \alpha^{\xi} z^{-1}} \eta^{\xi}(z) + m(z) \qquad (10)$$

Passing $\bar{u}(z)$ through filter with transfer function

$$F(z) = \frac{1}{(1 - \rho z^{-1})^l}, \qquad (11)$$

where $0 \le \rho \le 1$, the output

$$u(z) = \frac{(1 - z^{-1})^l}{1 - \alpha^{\xi} z^{-1}(1 - \rho z^{-1})^l} \eta^{\xi}(z) + \frac{m(z)}{(1 - \rho z^{-1})^l} \qquad (12)$$

can be obtained. For nonmaneuvering $(a_{k-1} = a_{k-l} = 0)$ and maneuvering with constant acceleration $(a_{k-1} - a_{k-l} = 0)$ cases, the second term of the right-hand side of (12) is zero. If the value of ρ is chosen to be one, u_k is just the colored noise e_k^ξ, i.e.

$$u_k = \alpha^\xi u_{k-1} + \eta_k^\xi \qquad (13)$$

Here an algorithm based on the Burg's method[6] is proposed to estimate the AR parameters. Since e_k^ξ is modeled as a real 1st-order AR process, this algorithm has a simple recursive structure:

$$a_k = \beta a_{k-1} + 2u_k u_{k-1}, \quad b_k = \beta b_{k-1} + u_k^2 + u_{k-1}^2, \quad \alpha_k^\xi = \frac{a_k}{b_k};$$
$$(\sigma_k^{e^\xi})^2 = \frac{1}{2(N-1)} b_k; \quad (\sigma_k^{\eta^\xi})^2 = (1 - (\alpha_k^\xi)^2)(\sigma_k^{e^\xi})^2 \qquad (14)$$

where $0 < \beta < 1$ is the forgetting factor and $N = 1/(1-\beta)$ is the effective memory. If β is large, the algorithm convergence is slow and it cannot respond to the change of α^ξ quickly. Advantage of using large β is the small estimation variance. On the contrary, small β will let fast algorithm convergence. In this case, however, the estimation variance is large. A good compromise between convergence rate and estimation error is achieved for $\beta = 0.99$.

When the target acceleration is not constant $(a_{k-1} - a_{k-l} \neq 0)$ and $\rho = 1$ the low frequency components of $m(z)$ in (12) will be greatly amplified and u_k will be no longer equal to e_k^ξ. This problem can be overcome choosing $\rho < 1$ and using the range of the real e_k^ξ values. Thus, if $u_k^2 \geq 9(\sigma_{k-1}^{e^\xi})^2$ the previous scan estimates remain the same. In this way the parameter estimations are updated when

$$u(z) \approx \frac{(1-z^{-1})^l}{(1-\alpha^\xi z^{-1})(1-\rho z^{-1})^l} \eta^\xi(z). \qquad (15)$$

It is clear from (15) that larger ρ will give better results. However, too large values of ρ will amplify the m_k^ξ. From (8), we find that m_k^ξ is determined by the target acceleration difference $a_{k-1} - a_{k-l}$ and sampling period T. From experience it is found that the estimates are almost not affected for $\rho = 0.97$ if $e_k^\xi = e_k^x$ and $\rho = 0.90$ if $e_k^\xi = e_k^v$. But the estimates are then biased. The biases of the e_k^v parameters estimates are significant and cannot be ignored. The unbiased estimates can be found using the following expressions[4]:

$$\alpha^v = \frac{-(\zeta_3 + \zeta_2)}{2\zeta_3} - \frac{\sqrt{(\zeta_3 + \zeta_2)^2 - 4\zeta_3(\zeta_3 + \zeta_2 + \zeta_1)}}{2\zeta_3} \qquad (16)$$

$$(\sigma^{\eta^v})^2 = \frac{-A + (\rho^2 + \rho^4)(\overline{\alpha}^v)^3}{(1+\rho^2)\overline{\alpha}^v + (2\rho - 4)}(\overline{\sigma}^{e^v})^2 + \frac{2\rho(\rho^2 - 1)(\overline{\alpha}^v)^2 - (\rho^2 + 1)\overline{\alpha}^v}{(1+\rho^2)\overline{\alpha}^v + (2\rho - 4)}(\overline{\sigma}^{e^v})^2, \qquad (17)$$

where

$$\begin{aligned}
&\zeta_3 = (\rho+1)^3, \zeta_2 = (-2\rho^2 - 10\rho - 4) + (-6\rho - 2)\overline{\alpha}^v, \\
&\zeta_1 = (-\rho^3 - 3\rho^2 + 5\rho + 7) + (8\rho + 8)\overline{\alpha}^v, \\
&A = -2\rho^3(\overline{\alpha}^v)^2 + (1-\rho^4)\overline{\alpha}^v + 2\rho
\end{aligned} \tag{18}$$

$\overline{\alpha}^v$ and $(\overline{\sigma}^{e^v})^2$ are biased estimates denotations. The described AR parameter estimation algorithm has simple structure. Its complexity estimation includes 44 multiplications and divisions and one square root operation for one cycle if both position and velocity are measured. The computational complexity of this algorithm is approximately one-tenth of the IMM algorithm of target tracking.

4. Computer simulation results

The performance of the proposed algorithm is investigated by means of simulation analysis. The realized Monte Carlo simulation model implements the following tasks: simulates the real target dynamics; generates measurements according to the accepted noise model; implements the algorithm of interest; performs a posterior statistical processing of the experimental data.

The target motion scenario is chosen as follows. The maneuver lasts from 10 to 30 s with constant acceleration equal to $40\,m/s^2$ (about $4\,g$). The sampling period T is $0.05\,s$. The total tracking interval is $50\,s$ (1000 samples). It is assumed that the standard deviations of measurement noises are $\sigma^{\eta^x} = 100\,m$ and $\sigma^{\eta^v} = 15\,m/s$. During the nonmaneuvering period $(1 \div 10\,s; 31 \div 50\,s)$ the coefficients are: $\alpha^x = \exp(-4T) = .8187$; $\alpha^v = \exp(-1T) = .9512$. During the maneuvering period $(11 \div 30\,s)$ the coefficients are: $\alpha^x = \exp(-10T) = .6067$; $\alpha^v = \exp(-5T) = .7788$. The tracker is initiated $20\,s$ before the formal tracking period. The purpose is to investigate the steady state behavior of the algorithm. One hundred Monte Carlo runs are carried out and the average results are shown under the *Root Mean Square Error* (RMSE) criterion.

The estimation errors of the correlation coefficients (α^x, α^v) and the noise standard deviations $(\sigma^{\eta^x}, \sigma^{\eta^v})$ are indicated by the curves on figures 1 and 2 respectively. They show that in steady state the estimate errors of the parameters are quite small (less than 10 %). The results of the parameters estimation when only position is measured closely correspond to the ones of Wu and Chang[4], but the *computational complexity of their algorithm is approximately two times bigger*. From the above results we know that the proposed algorithm can estimate the AR parameters effectively.

To achieve better tracking performance, we incorporate it into the IMM filter for maneuvering target tracking. The filters performance is examined over the described motion scenario in two cases: *case 1* - position only measurements and *case 2* - both position and velocity measurements.

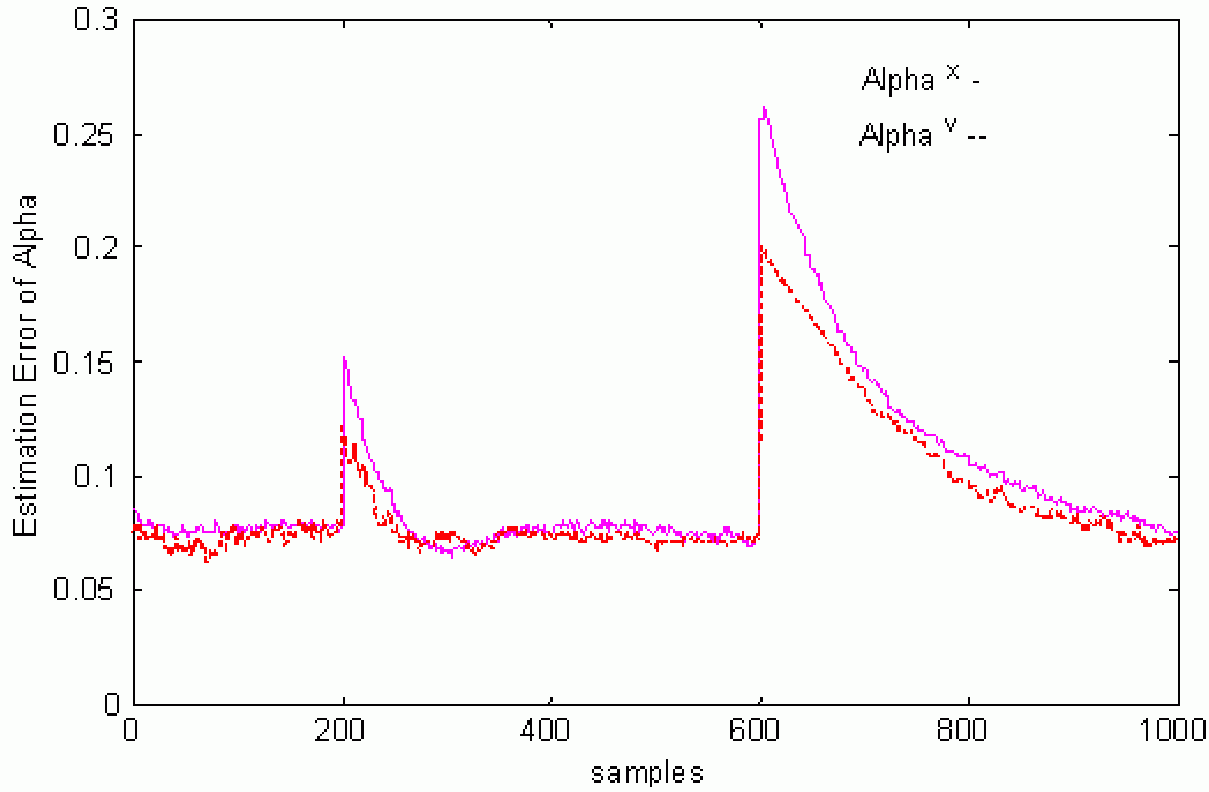

Figure 1

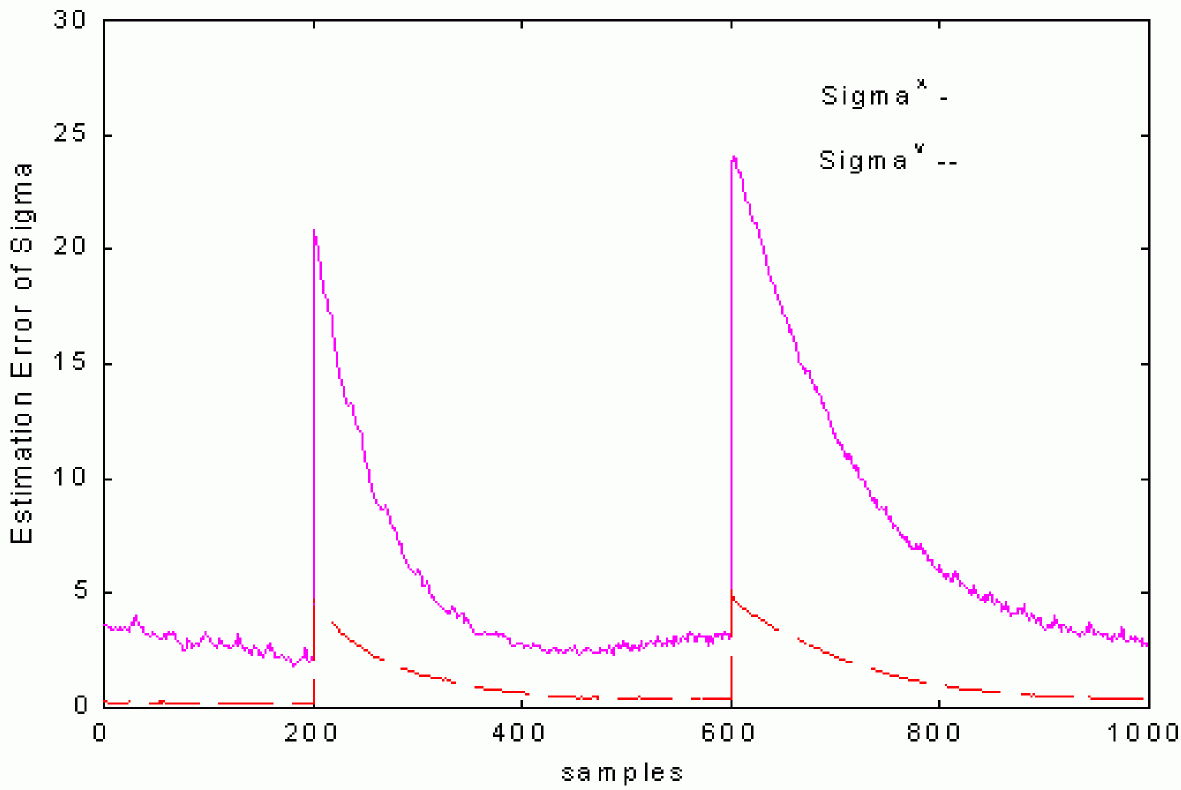

Figure 2

The filters efficiency is evaluated according to: *RMS errors, Peak Dynamic Errors (PDE), Correct Mode Identification (CMI).* In figures 3 and 4 comparative velocity and acceleration RMS errors for tracking without decorrelation and with suggested adaptive decorrelation scheme are shown. From these figures we see that the noise decorrelation improves estimation accuracy, especially in the velocity and acceleration. In *case 1* the improvement in velocity estimation is about 50 % during uniform motion and 30 % during maneuvering phase. For the acceleration these values are 60 % and 30 % respectively. The velocity measurement incorporation in *case 2* additionally improves the estimation accuracy. In both cases, due to the measurement noises decorrelation, PDEs during maneuver on/off switching are considerably reduced. That can be seen from Table 1 as well. The evolution of the posterior probabilities corresponding to the three models of motion is presented on figure 5. It is seen that the IMM filter correctly identifies the true system mode (the delay in maneuver detection is about 20 sampling intervals).

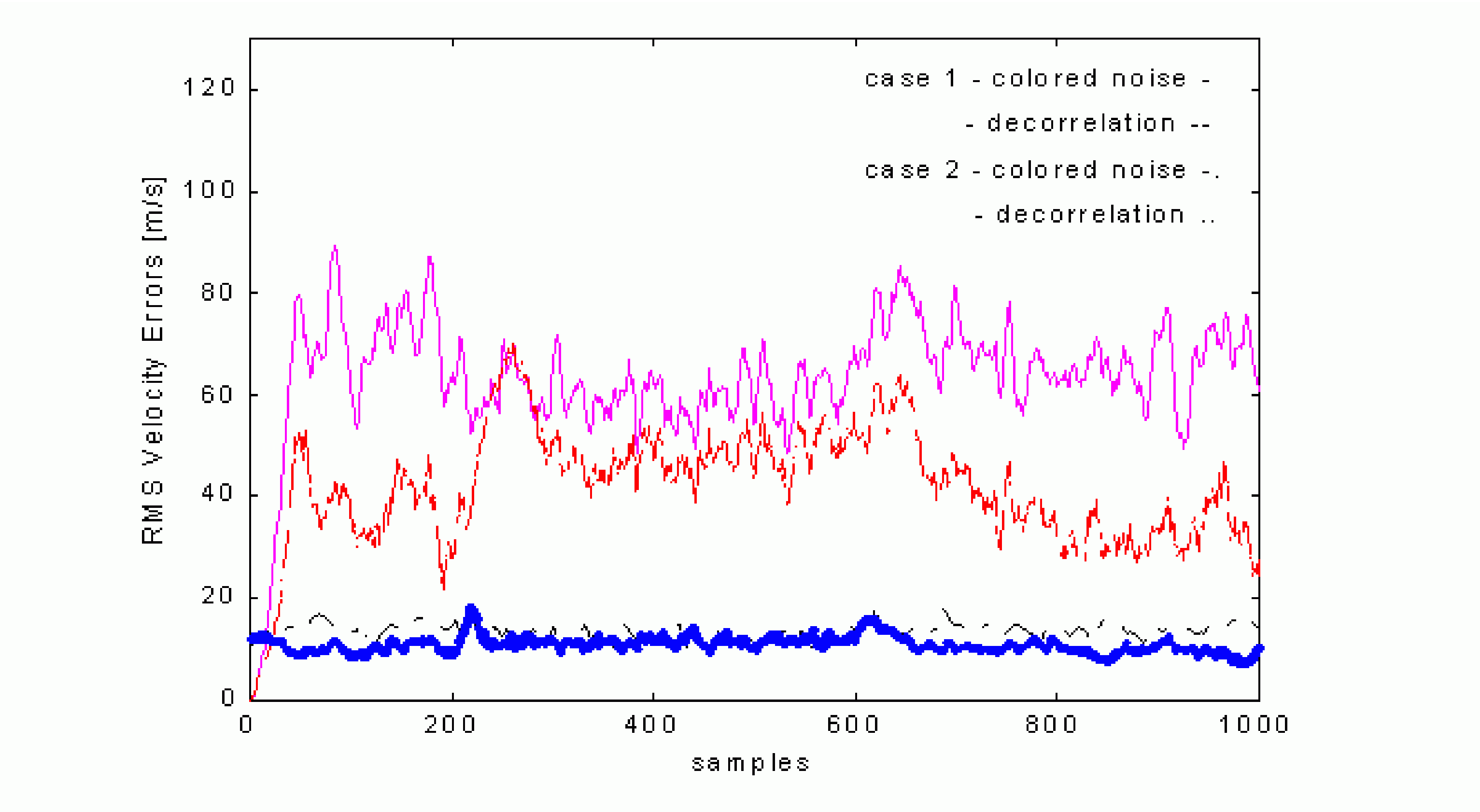

Figure 3

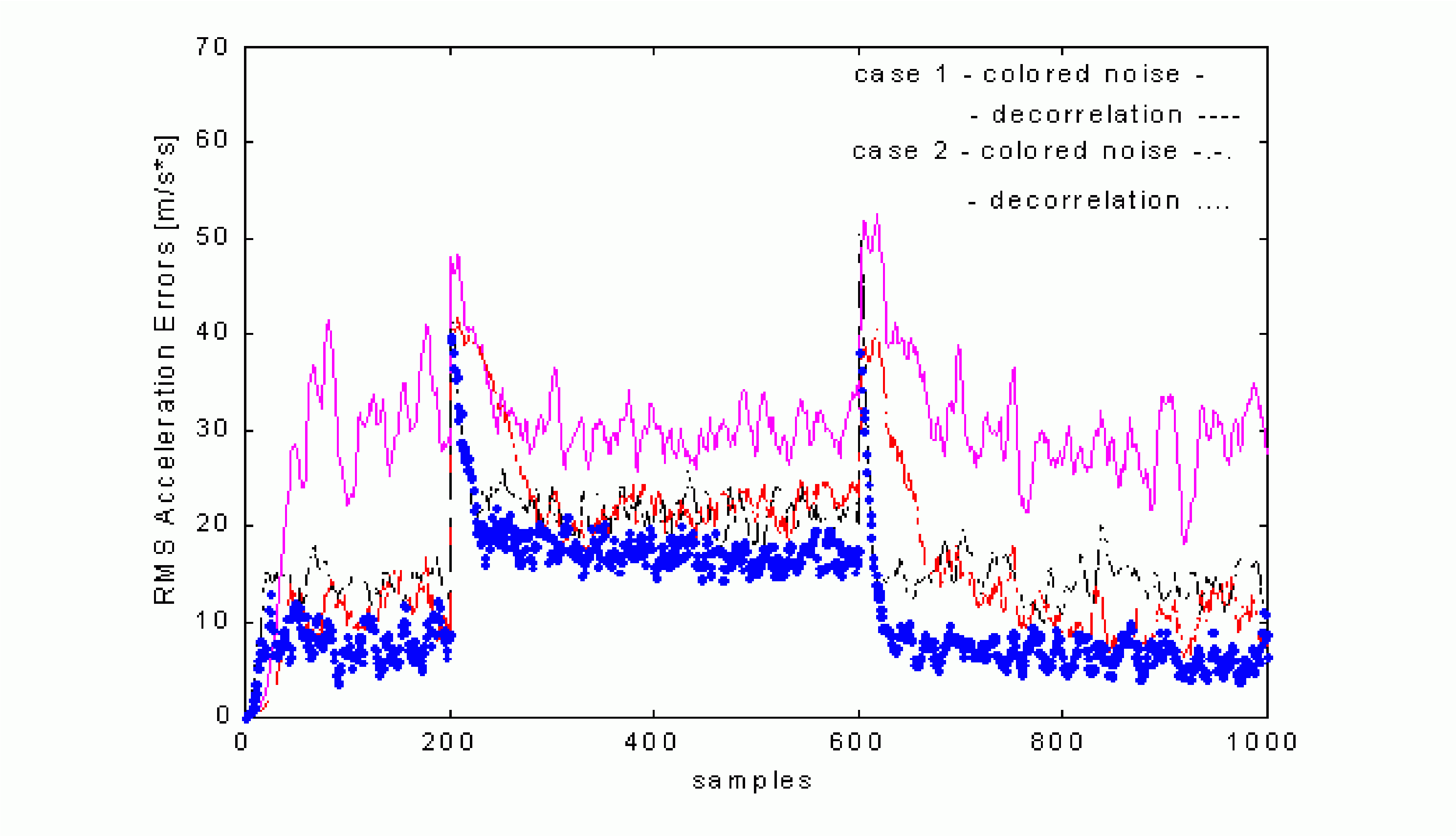

Figure 4

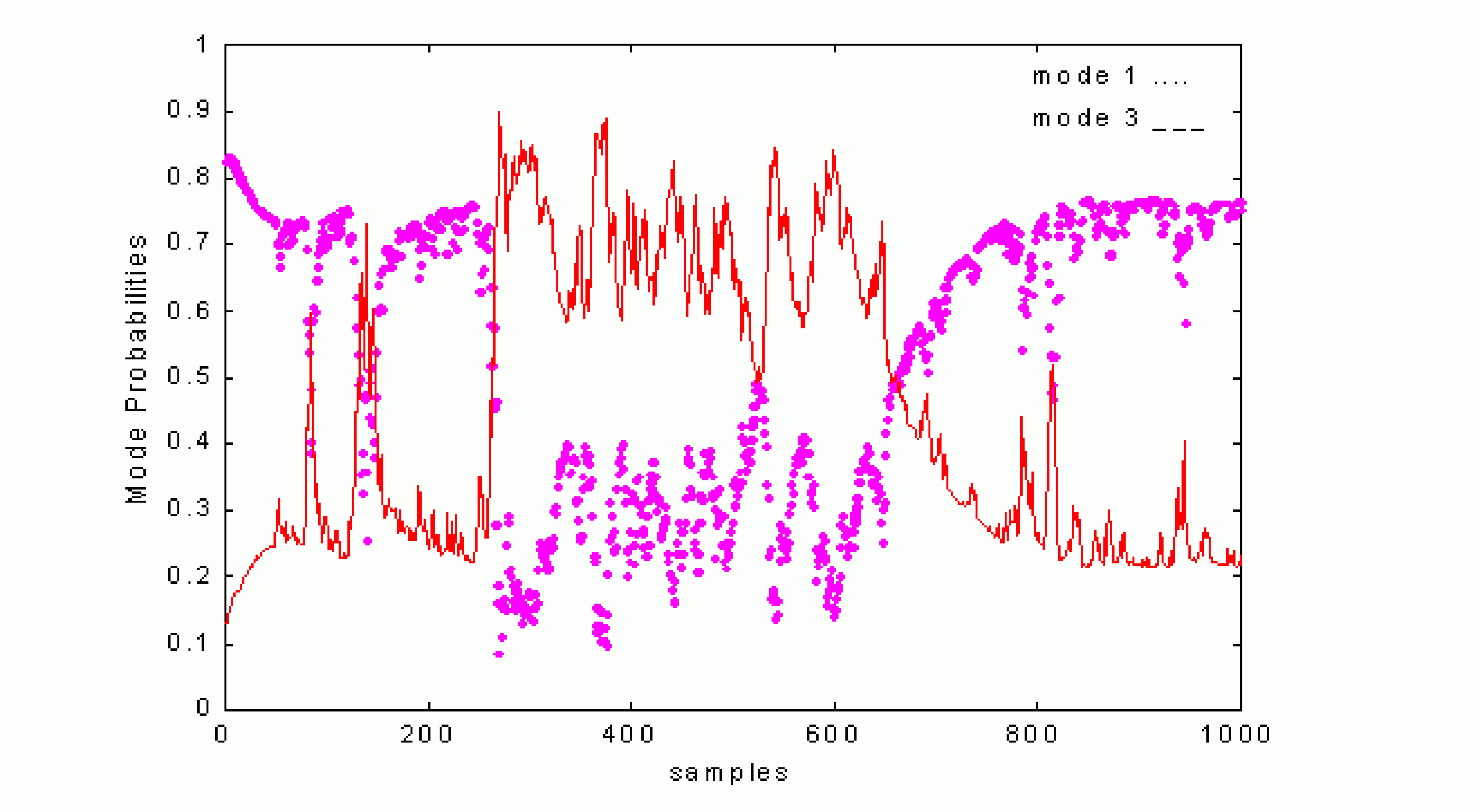

Figure 5

Table 1

Filter	Noise	Position [m]	Velocity [m/s]	Acceleration [m/ s^2]
case 1	undecorrelated	89.23	85.33	51.85
	decorrelated	76.92	64.00	40.74
case 2	undecorrelated	46.15	18.66	50.62
	decorrelated	40.00	18.60	38.21

5. Conclusions

Tracking filters for radar systems with correlated measurement noise are developed in this work. Two practical tasks are solved: 1) tracking with only position measurements and 2) tracking with position and velocity measurements. The noise decorrelation approach and state space partition are applied for tracking maneuvering objects with two-dimensional measurement vector. A new algorithm based on removing the state variables from measurements is proposed to identify the parameters of the colored noise. This decorrelation scheme is included into the cost-effective IMM filter. Simulation results demonstrate fairly better tracking accuracy compared to the undecorrelated measurement errors and almost the same estimation capabilities as in the case of exactly decorrelated measurement errors. The filter structure is simple, practically feasible and suitable for on-line processing. In the measurement equation, only colored noise which is modeled as a first-order AR process is assumed. In real applications white noise also exists in the measurement errors and produces an *Autoregressive Moving Average* (ARMA*)* noise process. In this case, the described decorrelation algorithm becomes suboptimal.

Acknowledgement

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Tracking Filters for Radar Systems with Correlated Measurement Noise

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Keywords: data processing; target tracking; adaptive estimation; linear prediction

An algorithm and computer simulation results for radar data processing are presented in this work. Tracking filter for systems with colored measurement noise is developed. A measurement difference approach and state space partition is used as a decorrelation scheme. The measurement noise is modeled as a first order Autoregressive (AR) process. A new technique for adaptive evaluation of the AR parameters is proposed since in practice they are usually unknown. The realized algorithm, which is appropriate for on-line processing, is incorporated into the Interacting Multiple Model (IMM) estimation algorithm for tracking maneuvering objects. The results from Monte Carlo simulation show that the suggested algorithm provides almost the same tracking accuracy as in the case of exactly known AR parameters and better estimation capabilities compared to the undecorrelated measurement error. The substantial improvement in velocity and acceleration estimation is particularly useful in missile guidance and situation of abrupt changes in acceleration, induced by the pilot.

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AN INTERACTING MULTIPLE MODEL ALGORITHM FOR STOCHASTIC SYSTEMS CONTROL

Ludmila MIHAYLOVA and Emil SEMERDJIEV

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1. Introduction

During the last years the multiple-model (MM) approach has become very popular and widely applied for estimation[2,5,7,9] and control[1,3, 4, 6-8, 10-12] of stochastic systems under different kinds of uncertainty - unknown model structure or parameters. In the engineering applications different multiple model algorithms for system control have been proposed.[3, 10, 11] The greatest number of them are of Bayesian nature.[1,3,4,7,8,10,12] Their common feature is the presence of a bank of estimators providing separate state estimates required for the overall control synthesis. But, the Interacting Multiple Model estimator - the most cost-effective scheme for solving various problems for state and parameter estimation,[2,5,13] has not yet been used to solve problems for systems control.

In the present paper an IMM algorithm is designed for control of stochastic systems in the presence of parametric model uncertainty. The overall system control is formed as a probabilistically weighted sum of the control processes provided by separate regulators. Regulators are synthesized for a set of respective models covering the uncertainty domain. These regulators optimize a quadratic cost function.

The separate state estimates, generated by a modified IMM estimation algorithm and based on the same models, represent the respective regulators' inputs. The model probabilities are the weighting coefficients for the separate control processes, each computed as a full-state feedback. The algorithm performance is evaluated through Monte Carlo simulation experiments and compared to other MM algorithms for control.

2. IMM algorithm for systems control

The system is described by the model:

$$x(k+1) = F(k,m(k+1))x(k) + G_u(k,m(k+1))u(k) + G_v(k,m(k+1))v(k,m(k+1)), \qquad (1)$$

$$z(k) = H(k)x(k) + w(k), \qquad (2)$$

where $x \in \Re^{n_x}$ is the system state vector, $z \in \Re^{n_z}$ is the measurement vector; $u \in \Re^{n_u}$ - the control input vector; $v \in \Re^{n_v}$ and $w \in \Re^{n_w}$ are mutually uncorrelated, white, zero mean Gaussian noises with covariances D_v and D_w, respectively. The parameter m_k presents the current system mode. The structure of the model (1) is supposed known, but its parameters belong to an uncertainty domain and are assumed to depend on different system modes.

The problem consists in synthesizing a control sequence $\{u_k\}$, so that the quadratic cost function

$$J = M\left\{\sum_{k=0}^{\infty}\left[x^T(k)Qx(k) + u^T(k)Ru(k)\right]\right\}, \qquad (3)$$

is minimized, where Q and R are appropriately chosen weighting matrices (Q - positive semi-definite, R - positive definite) and $M\{.\}$ is the mathematical expectation operator.

Because the accurate system model is unknown, the system is described by a number of models from the preliminary determined uncertainty domain. The event that the *i*-th model m_i is actual at time k is denoted as

$$m_i(k) = \{m(k) = m_i\}.$$

It is assumed that the system model sequence is a Markov chain with transition probabilities

$$P\{m_j(k+1) / m_i(k)\} = Pr_{ij}(k) \text{ and } \sum_{j=1}^{q} Pr_{ij}(k) = 1, \qquad i = 1,2,\ldots,q.$$

The main functional components of the IMM algorithm for control are:

- separate estimators- Kalman filters (KF), running in parallel and providing the input signals (the partial state estimates) for the regulators;
- separate regulators, generating the single-model-based control processes.

The control process of the system is computed as a state feedback:

$$u(k) = -\sum_{i=1}^{q} \mu_i(k) K_{r,i}(k;m_i)\hat{x}_i(k), \qquad (4)$$

where μ_i are the IMM mode probabilities, $K_{r,i}$ - the matrices of the regulators working in parallel, $\hat{x}_i$ are partial state estimates generated by q Kalman filters. The partial regulators are linear quadratic Gaussian (LQG). The matrices $K_{r,i}$ are computed through minimization of the cost function J for each system model $m_i\left\{F_i, G_{u,i}, G_{v,i}, H_i, D_{v,i}, D_{w,i}\right\}$, $i = 1,2,\cdots,q$ with matrices chosen from the uncertainty domain. The regulators' gains are generated by solving the Riccati difference equations.

The overall state estimate $\hat{x}_k$, generated by the IMM estimator, has the form:

$$\hat{x}(k) = \sum_{i=1}^{q} \mu_i(k)\hat{x}_i(k). \qquad (5)$$

This standard IMM algorithm step for separate estimates combination is excluded here.

Each IMM partial state estimate $\hat{x}_{i,k}$ ($i = 1,2,\cdots,q$) is computed by a respective Kalman filter:

$$\hat{x}_i(k+1/k) = F_i(k)\hat{x}_i(k/k) + G_{u,i}(k)u(k), \qquad (6)$$

$$\hat{x}_i(k+1/k+1) = \hat{x}_i(k+1/k) + K_{f,i}(k+1)\nu_i(k+1), \qquad (7)$$

$$\nu_i(k+1) = z(k+1) - H_i(k+1)\hat{x}_i(k+1/k), \qquad (8)$$

$$P_i(k+1/k) = F_i(k)P_i(k/k)F_i^T(k) + G_{v,i}(k)D_{v,i}(k)G_{v,i}^T(k), \qquad (9)$$

$$S_i(k+1) = H_i(k+1)P_i(k+1/k)_i H_i^T(k+1) + D_{w,i}(k+1), \qquad (10)$$

$$K_i(k+1) = P_i(k+1/k)H_i^T(k+1)S_i^{-1}(k+1), \qquad (11)$$

$$P_i(k+1/k+1) = P_i(k+1/k) - K_i(k+1)S_i(k+1)K_i^T(k+1), \qquad (12)$$

where $\hat{x}_i(k/k)$ and $\hat{x}_i(k/k-1)$ are the filtered and predicted estimates of $x(k)$; ν_i, S_i are the innovation process and its covariance matrix; $K_{f,i}$ - the filter gain; P_i - the error covariance matrix.

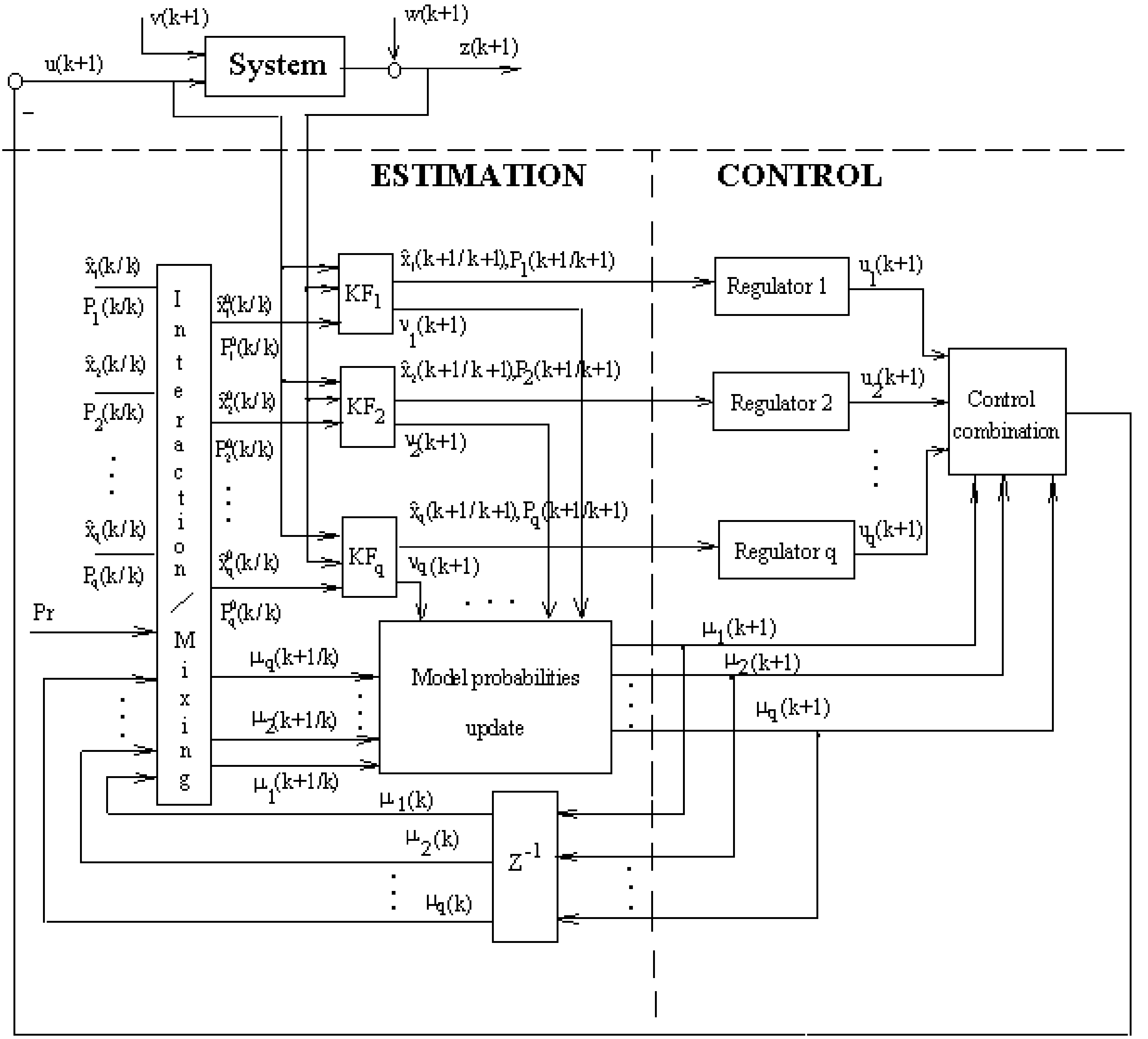

Figure 1: Scheme of the IMM algorithm for control

Figure 1 shows the scheme of the proposed IMM algorithm for control. Similarly to the IMM estimator,[2,5,13] the IMM algorithm for control comprises the four major steps:

- interacting or mixing of the state estimates and their covariances, respectively;
- model-conditional filtering, performed in parallel for each mode through a respective Kalman filter - eqs. (6)-(12);
- model probability update, based on the model conditional likelihood functions;
- control combination, according to (4), which yields the overall control process as the probabilistically weighted sum of the control processes, provided by the regulators.

3. Comparison with other MM control algorithms

The main difference between the proposed IMM algorithm for control with respect to other MM control algorithms[1,3,4,6,7,8,11,12] relies on the nature of the Interacting Multiple Model approach.[2,5,13] The main feature is the dynamic interaction between the single-model filters, obtained by mixing the estimates of all filters at the previous step and using the mixed estimate as initial estimate for the filters in the next step. A very important is the assumption that the transition between the different controlled regimes can be described as a Markov process and it is reflected in the transition probability matrix. The presented control algorithm is compared in the next section with the Multiple Model Adaptive Controller (MMAC), proposed in [8,12]. The two algorithms are characterized by the same multiple model structure, they are of Bayesian type, but the mechanism for model probabilities computation is different. A comparison of the IMM *estimator* for detection and diagnosis of sensor and actuator failures with the MM adaptive estimator (MMAE)[8] is performed in [14].

The multiple model estimator/controller (MMAE/ MMAC)[3,4,7,8,12] uses various heuristic techniques, such as Kalman filtering retuning and bounded conditional mode probabilities. The effect termed "lockout" of these probabilities can be observed in the MMAC algorithm. It expresses itself in probabilities going to zero, that is why an additional lower bound of these probabilities is predetermined.

The decision thresholds for moving of the bank of filters/ controllers are also determined empirically. These techniques enhance the performance of the MMAE/MMAC in an empirical fashion. In contrast to them the IMM algorithm for control is working without additional tuning procedures.

4. Performance evaluation

Results illustrating the efficiency of the proposed IMM algorithm for stochastic systems control are given. Its performance is evaluated by Monte Carlo simulation experiments for 100 runs and compared to the MMAC algorithm performance, presented in [8,12]. The MMAC algorithm is implemented in the simulation experiments with an artificial lower bound for the mode probabilities $\mu_{min} = 0.001$, as imposed in [8]. In the example the overall control for both algorithms is synthesized based on the same steady-state constant gain regulators.

Example. The proposed IMM algorithm for control is applied to a paper machine[14] producing a super-thin condenser paper. The state space model of its headbox section[14] has the form:

$$x(k+1) = Fx(k) + G_u u(k) + G_v v(k),$$

where

$$F = \begin{pmatrix} 0.8667 & 0 & 0 \\ 0 & 0.8667 & 0 \\ 0.1069 & -0.0503 & 0.9099 \end{pmatrix}, G_u = \begin{pmatrix} -0.0344 & 0 \\ 0 & -0.6877 \\ 0 & 0 \end{pmatrix},$$

$G_v = I_3$ and I is the identity matrix. The measurement matrix and the noise covariances are:

$$H = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \; D_v = diag(0.16,\ 0.16,\ 1), \; D_w = diag(0.09,\ 0.16).$$

It is supposed that the system matrix F is inaccurately known. The model uncertainty domain here is approximated by four models:

$$F_1 = \begin{pmatrix} 0.1000 & 0 & 0 \\ 0 & 0.1000 & 0 \\ 0.1069 & -0.0503 & 0.9099 \end{pmatrix}, \quad F_2 = \begin{pmatrix} 0.3000 & 0 & 0 \\ 0 & 0.3000 & 0 \\ 0.1069 & -0.0503 & 0.9099 \end{pmatrix};$$

$$F_3 = \begin{pmatrix} 0.5000 & 0 & 0 \\ 0 & 0.5000 & 0 \\ 0.1069 & -0.0503 & 0.9099 \end{pmatrix}, \quad F_4 = \begin{pmatrix} 0.8000 & 0 & 0 \\ 0 & 0.8000 & 0 \\ 0.1069 & -0.0503 & 0.9099 \end{pmatrix}.$$

The other model matrices coincide with the true model matrices. The fourth model is the closest to the true one. The matrices of the quadratic cost function are chosen to provide rapid transient processes of the closed-loop system: $Q = 100 I_3$, $R = 0.01 I_2$.

The IMM transition probability matrix and the initial mode probability vector are chosen :

$$Pr = \begin{pmatrix} 0.997 & 0.001 & 0.001 & 0.001 \\ 0.001 & 0.997 & 0.001 & 0.001 \\ 0.001 & 0.001 & 0.997 & 0.001 \\ 0.001 & 0.001 & 0.001 & 0.997 \end{pmatrix}, \quad \mu(0) = \begin{pmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{pmatrix}.$$

The following measures of performance are used:

- the recursively computed cost function J (Fig. 2), as instead of the true state x in (3) its overall estimate $\hat{x}$ is replaced;
- the averaged algorithm mode probabilities (shown in Figs. 3 and 4).

It is denoted below: "1" - the IMM algorithm for control and "2" - the MMAC algorithm.[8]

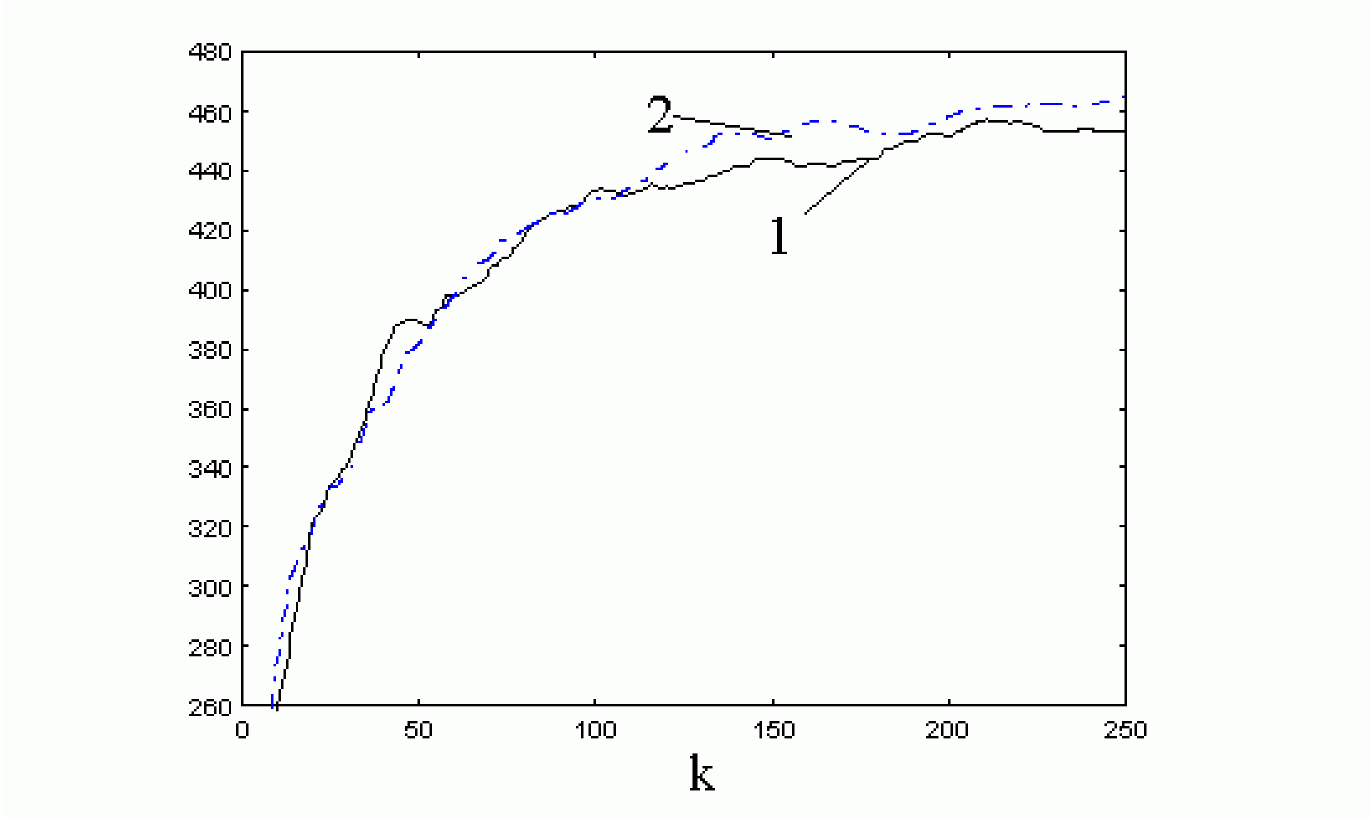

Figure 2: Cost function J

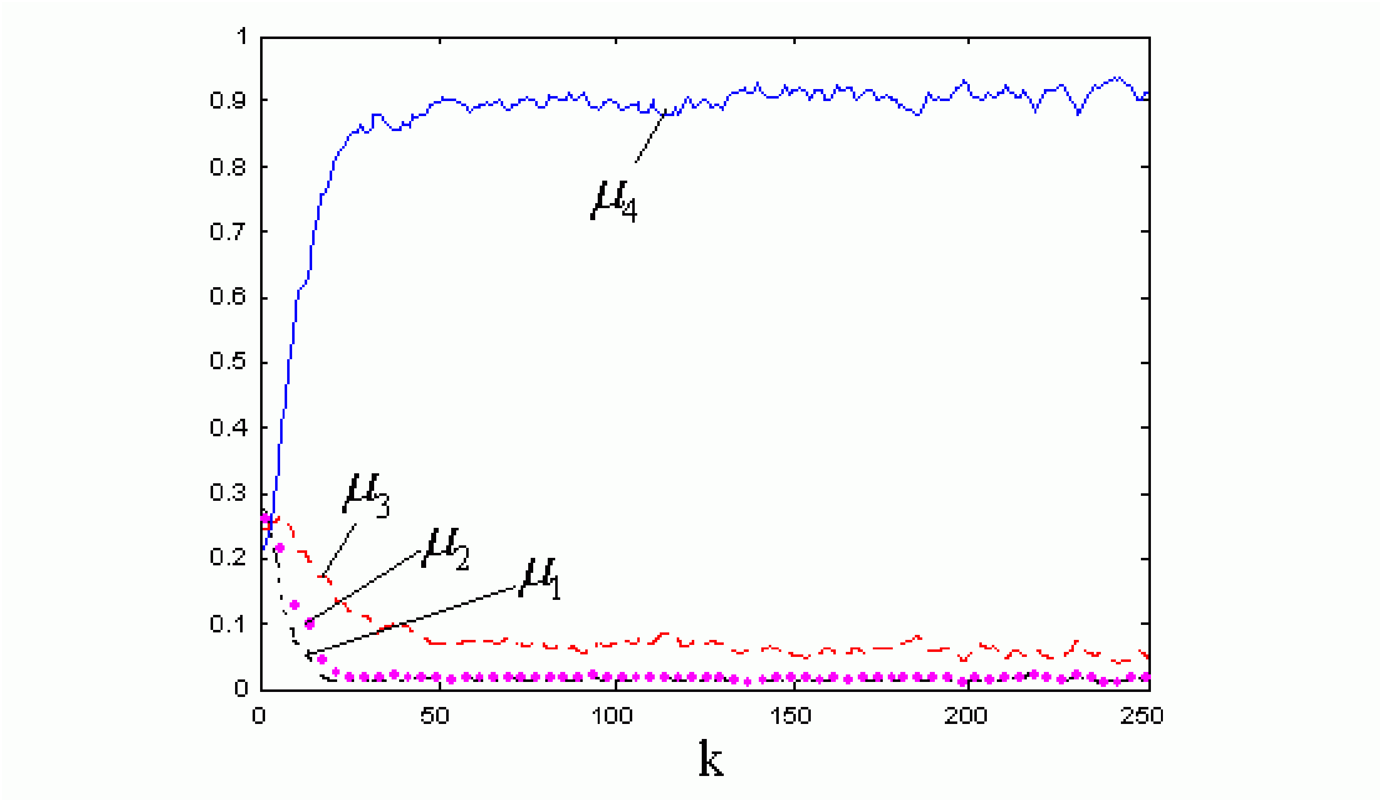

Figure 3: Average IMM mode probabilities

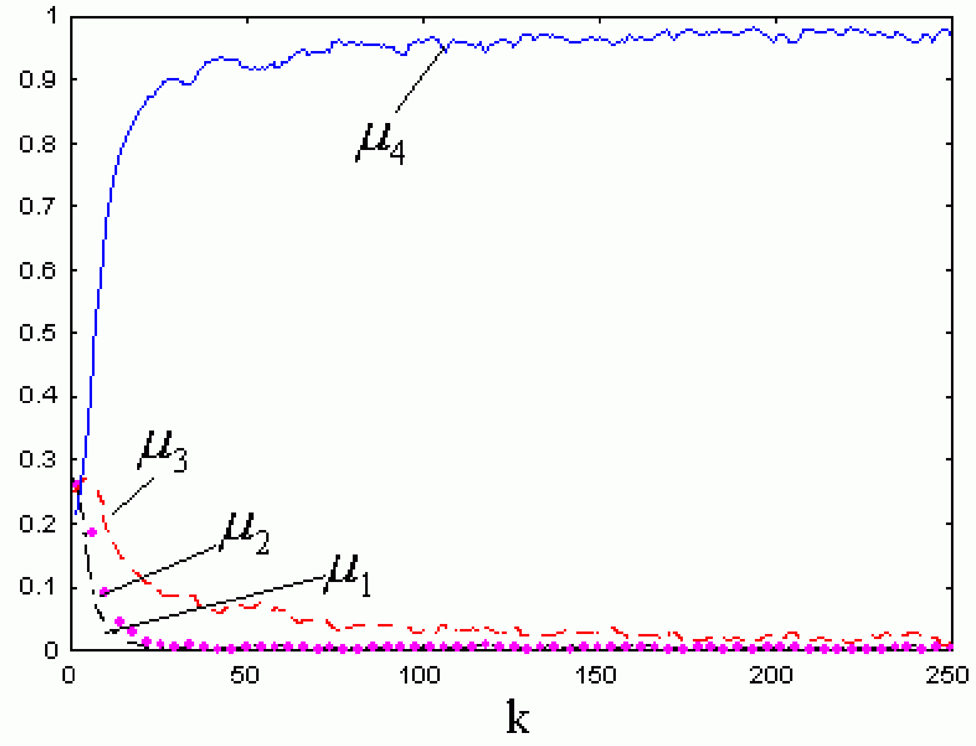

Figure 4: Average MMAC mode probabilities

In the considered here stationary example both algorithms show nearly equal performance: they quickly recognize the fourth model as the closest to the true one (its probability is the greatest).

The test scenario has been artificially complicated to evaluate the algorithm performance in the nonstationary case. In the next scenario abrupt changes arise in elements of the matrix F:

$$F = \begin{cases} \text{true matrix } F, \text{ for } k < 50 \\ F_4, \text{ for } 50 \le k < 70 \\ F_3, \text{ for } 70 \le k < 150 \\ F_1, \quad \text{for } k \ge 150 \end{cases}.$$

The computed cost function J and the mode probabilities are presented in Figs. 5-7.

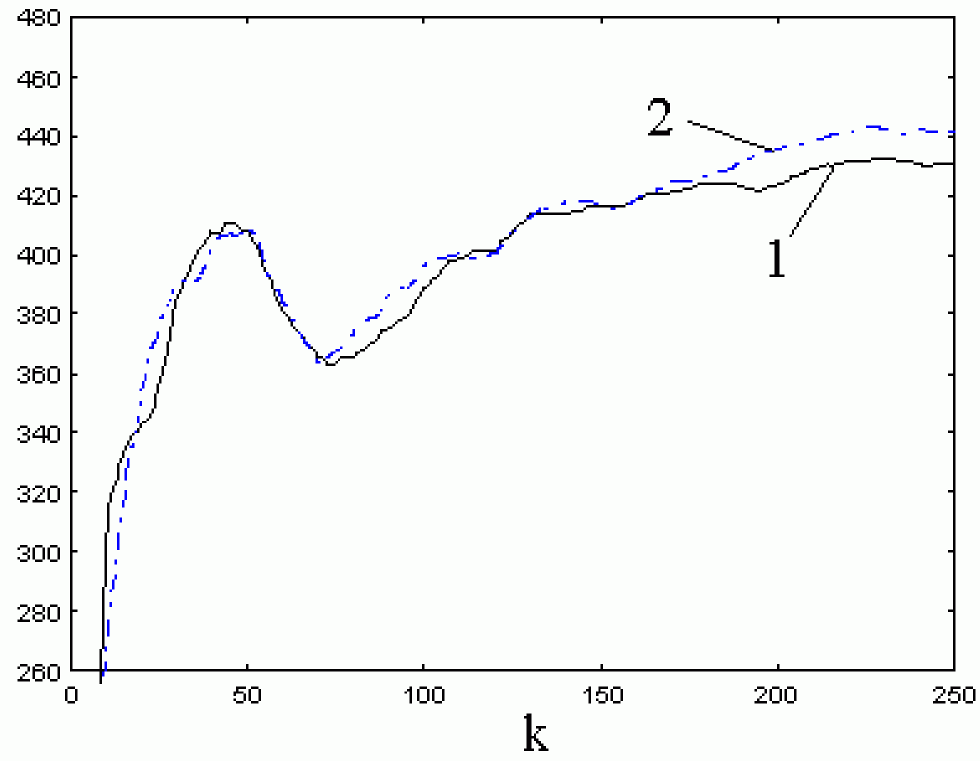

Figure 5: Cost function J

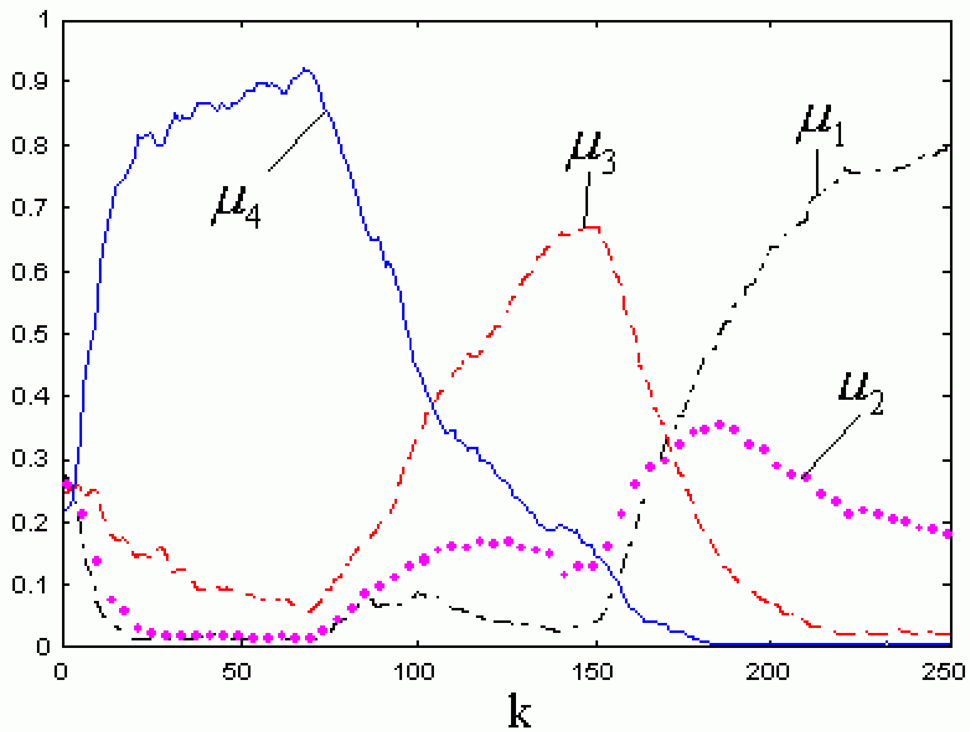

Figure 6: Average IMM mode probabilities

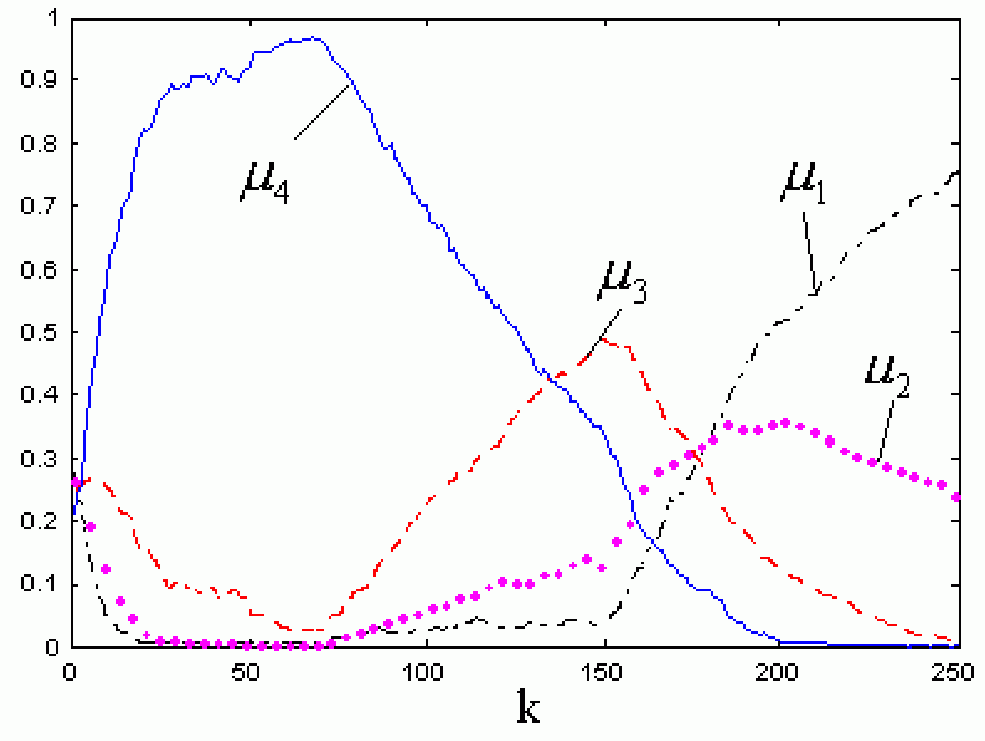

Figure 7: Average MMAC mode probabilities

In both simulation experiments the cost function of the IMM algorithm for control is smaller than the respective MMAC values. The obvious priority of the IMM algorithm for control is due to the faster response to abrupt changes in the parameters (see Fig.6 and Fig.7). On the basis of the simulation experiments it can be concluded that in stationary conditions the results of both algorithms are comparable, but in the nonstationary case, the IMM algorithm for control yields better overall performance than the MMAC algorithm with respect to fast response and reliability.

5. Conclusions

An Interacting Multiple Model (IMM) algorithm for stochastic systems control in the presence of parametric model uncertainty is designed, for stationary and nonstationary systems. It is based on the cost-effective IMM estimator. The overall system control is synthesized as a probabilistically weighted sum of the control processes received from separate regulators. These regulators are synthesised for each model from the uncertainty domain. The overall control process is computed as a state feedback. The well known and cost effective IMM filter is used for partial state estimates generation. The IMM partial state estimates are used by regulators working in parallel to compute the partial control processes and the common state feedback. Each regulator is synthesised based on a quadratic cost function minimization. Results from simulation experiments are given. The algorithm presented is compared to other MM algorithm for control of Bayesian type. The simulation results demonstrate that the IMM algorithm for control provides better results in the presence of abrupt changes in the parameters than the MMAC algorithm. The performance of both algorithms is comparable in a stationary mode.

Acknowledgement

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An Interacting Multiple Model Algorithm for Stochastic Systems Control

Ludmila Mihaylova and Emil Semerdjiev

Keywords: multiple model estimation and control, adaptive control, parameter uncertainty, Bayesian algorithms

During the last years the multiple-model approach has become very popular and widely applied for estimation and control of stochastic systems under different uncertainties - unknown model structure or parameters. In the engineering applications different multiple model algorithms for system control have been proposed. The greatest number of them are of Bayesian nature. Their common feature is the bank of estimators providing separate state estimates required for the overall control synthesis.

In the paper an Interacting Multiple Model (IMM) algorithm for stochastic systems control in the presence of parametric model uncertainty is designed. It is based on the cost-effective IMM estimator. The overall system control is synthesized as a probabilistically weighted sum of the control processes from separate regulators working in parallel. These regulators are synthesised for each model from the uncertainty domain. The regulators are based on linear system, quadratic cost function and Gaussian noise assumptions. The overall control process is computed as a state feedback. The cost effective IMM filter is used for partial state estimates generation. The algorithm presented is compared to other MM Bayesian algorithm for control through Monte Carlo simulation experiments. The simulation results demonstrate that the IMM control algorithm provides better results in the presence of abrupt changes in the parameters than the MMAC algorithm. The performance of both algorithms is comparable in a stationary mode.

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MULTIPLE HYPOTHESIS TRACKING USING HOUGH TRANSFORM TRACK DETECTOR

Emil SEMERDJIEV, Kiril ALEXIEV, Emanuil DJERASSI and Pavlina KONSTANTINOVA

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1. Introduction

The Multiple Hypothesis Tracking algorithm (MHT) is an effective algorithm for moving objects detection and tracking.[1,2] Few versions of this complex algorithm are described and evaluated in [1,2,4]. Its *measurement oriented* version is considered as the most effective from theoretical point of view, but its practical implementation is limited because of the required significant computational load in cluttered environment. Several techniques minimizing this load were proposed,[1,2,4] but they do not provide general solution to these problems. A new problem solution is proposed in this paper. A Hough Transform (HT) track detector is used for preliminary filtering of arriving false alarms (FA). The tracks detected in this way are processed asynchronously with another standard MHT algorithm to include them in the overall MHT scheme. The standard and the proposed MHT-HT algorithm (MHT^2-HT) are evaluated and compared in the paper. The proposed algorithm shows remarkably good performance in cluttered environment at the cost of delayed track detection process.

2. HT track detector

The Hough transform algorithm (HTA) maps each point from feature space (FS, or the space of measurements) to a curve in parameter space (PS).[3,5] If a set of points in FS lies along a straight line, the corresponding curves intersect in a single point in PS. An appropriate mapping equation is proposed[5]:

$$\rho = r\sin(\theta - \alpha)\,, \quad (1)$$

where (r,α) is 2-D measurement vector in FS; ρ and θ are trajectory shift and heading. The range $r \in [0, r_{max}]$ and the azimuth $\alpha \in [0, 360^\circ]$) arrive in radar polar coordinate system $rO\alpha$ oriented to the "North" direction.

In the HTA the trajectory is searched among a fixed finite set of $N_\theta N_\rho$ trajectories, with the following standard headings and shifts: $\theta_l = l\,\delta\theta \in \left[0, 360^o\right]$, $l = \overline{0, N_\theta}$ and $\rho_m = m\,\delta\rho \in \left[0, \rho_{max}\right]$, $m = \overline{0, N_\rho}$; $\delta\theta$ and $\delta\rho$ are the primary discretization steps of the PS. For each measurement (r, α) HTA consecutively substitutes increasing values of θ_1 to compute the shifts $\rho_1 = \rho(r, \alpha, \theta_1)$, $l = \overline{0, N_\theta}$ - the addresses of measurement votes.

If the discrete heading coincides with the real one ($\theta_1 = \theta$), the peak of votes will locate the parameters of the real trajectory (Fig. 1).

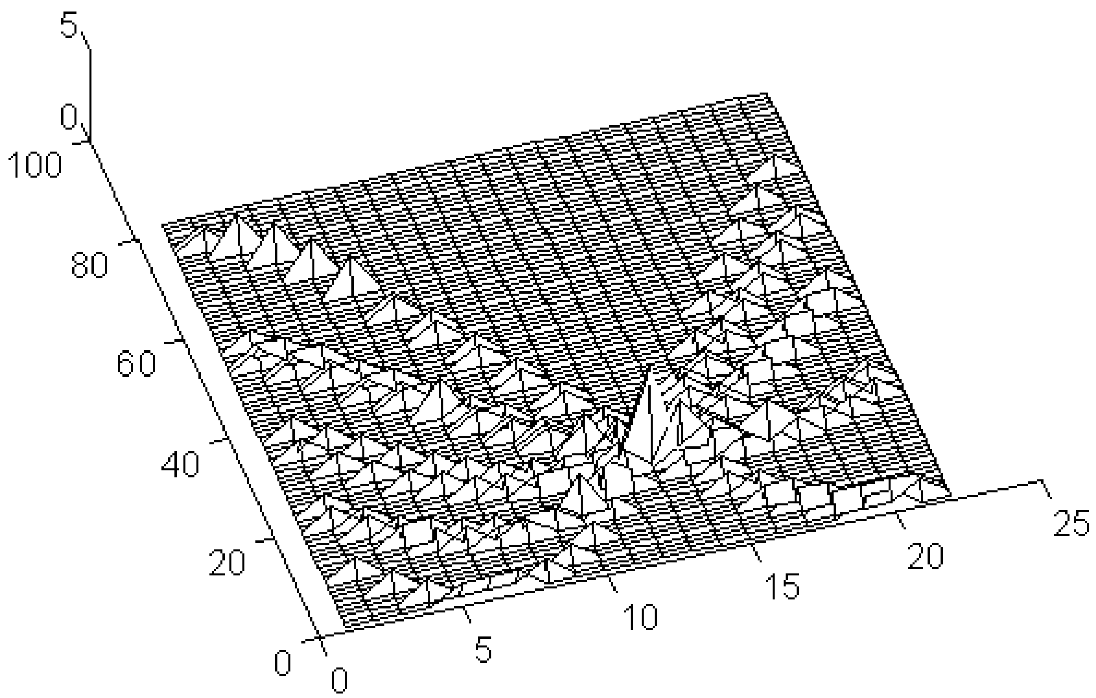

Figure 1: Peak location

If the real trajectory does not coincide with any standard one or, if there are measurement errors, the HTA detects (with some probability) the standard trajectory with the closest shift and heading instead the real one.

Appropriate equations determine the HTA accumulator size ($\Delta\rho$, $\Delta\theta$) and PS discretization steps as functions of sensor's measurement errors $\delta r \sim N\left(0, \sigma_r\right)$ and $\delta\alpha \sim N\left(0, \sigma_\alpha\right)$ at given probability of successful measurement vote P_G.[5] They define strips in FS, which shape cover the area of spatial measurement oscillations around known trajectory (ρ, θ) with a desired probability P_G. The false alarms accumulation and the reduction of HTA's resolving abilities are avoided in this way.

The PS discretization steps $(\delta\rho, \delta\theta)$ determine the worst case of non-coincidence between standard HT trajectories and an arbitrary chosen one (ρ, θ). The closest accumulator has coordinates:

$$\theta_{cl} = \delta\theta \,\mathrm{round}\left(\frac{\theta}{\delta\theta}\right), \rho_{cl} = \delta\rho \,\mathrm{round}\left(\frac{\rho}{\delta\rho}\right).$$

The strip shape is formed as a sum of n rectangular sub-strips (corresponding to sub-accumulators $(\rho_j, \theta_i), i = \overline{i_1, i_n}$) with size $(\Delta\rho, \delta\theta)$, where $\Delta\theta = n\,\delta\theta$.

The probability $P_{G'}$ of the event *'measurement hits a strip'* is a product of probabilities corresponding to the independent events: '$|\delta r| \leq k\sigma_r$' and '$|\delta\alpha| \leq k\sigma_\alpha$':

$$P_{G'} = Pr\{|\delta r| \leq k\sigma_r\}\ Pr\{|\delta\alpha| \leq k\sigma_\alpha\} = 4\Phi_0^2(k).$$

The lowest guaranteed $P_{G'}$ is:

$$P_G \geq P_G^\rho\left(\frac{\delta\rho}{2\sigma_r}\right)P_G^\theta\left(\frac{\delta\theta}{2\sigma_\alpha}\right),$$

$$P_G^\rho\left(\frac{\delta\rho}{2\sigma_r}\right) \geq \Phi_0\left(k - \frac{\delta\rho}{2\sigma_r}\right) + \Phi_0\left(k + \frac{\delta\rho}{2\sigma_r}\right),$$

$$P_G^\theta\left(\frac{\delta\theta}{2\sigma_\alpha}\right) = \Phi_0\left(k - \frac{\delta\theta}{2\sigma_\alpha}\right) + \Phi_0\left(k + \frac{\delta\theta}{2\sigma_\alpha}\right).$$

To choose detection threshold M, the probabilities P_{RTD} and P_{FTD} are introduced. The first one is determined as a *probability to obtain exactly M measurements from N consecutive scans*:

$$P_{RTD}(M,N) = \binom{N}{M}\left(P_G P_D^{HT}\right)^M\left(1 - P_G P_D^{HT}\right)^{N-M}.$$

The second probability is determined as a *probability to obtain at least one FA per scan in the considered strip in exactly M scans from N consecutive scans*:

$$P_{FTD}(M,N) = \binom{N}{M}\left[1-\left(1-P_{fa}^{HT}\right)^{\mu}\right]^M\left(1-P_{fa}^{HT}\right)^{\mu(N-M)},$$

where P_D and P_{fa} are considered constant and $\mu = \mu(\rho, \theta, \Delta\rho)$ is the number of elementary volumes in the strip. A suitable detection threshold is chosen to maximize P_{RTD} at fixed P_{FTD}.

An additional *velocity selection* of measurements in each detected track (ρ_m, θ_l) is performed to filter the remaining FA. Let $N_{m,l}$ measurements are associated with this track. The velocities corresponding to each possible measurement pair are computed:

$$v_{i,j} = \left\{\frac{r_i\cos(\theta_l - \alpha_i) - r_j\cos(\theta_l - \alpha_j)}{\delta V(T_i - T_j)}\right\}_{Int},$$

where $i, j = \overline{1, N_{m,l}}$, $T_i \neq T_j$ - moments of measurements arrival, δV - velocity discretization step. If $|v_{i,j}| \in [v_{\min}, v_{\max}]$, it votes in a set of $n_v = 2\frac{v_{\max} - v_{\min}}{\delta V}$ accumulators. The HT track detection is confirmed when the number of measurements in any of velocity accumulators exceeds threshold M.

3. HT track detector implemented in MHT

The standard MHT measurement oriented version is described in [2]. The track initiation procedure takes place in following cases:

- *Case 1 (C1)*: at the first scan;
- *Case 2 (C2)*: when a measurement does not fall in any gate of existing tracks;
- *Case 3 (C3)*: when MHT considers every measurement in a gate of each track as a *potential* track.

A HT track detector (initiating rectilinear trajectories) is proposed to filter the FA in cases C1 and C2 before the application of the standard MHT tracks initiation procedure. The application of this procedure in case C3 is a source of redundant tracks, but here it is left unchanged as an effective tool for recognition and resolution of closely spaced tracks.

A description of the proposed algorithm is given in Fig. 2 (the standard MHT steps are written in italic, the new steps are written in bold). The algorithm starts with a HTA measurement accumulation. If a track is detected all measurements accumulated in the corresponding accumulator during the last N scans are processed scan-by-scan, by second standard MHT algorithm. Its purpose is to initiate and evaluate a new standard MHT cluster containing MHT tracks and hypotheses in it. This procedure is performed in the remaining time of the current scan frame. Because of this second MHT algorithm (used in parallel), the resulting MHT algorithm version is denoted here *MHT* ^{2}*-HT*. Finally, the new cluster is added to the others and starting at the next scan it is processed in standard way.

First scan:

Read basic input data & first scan data;

-HT initiation & observation accumulation;

Next N-1 scans:

Read the next scan data

-HT observation accumulation;

Next scans after the first N ones:

-Read the next scan data,

-Delete old observations associated to tracks form HT accumulators;

-HT observations accumulation;

-HT track detection & velocity selection;

---If an observation falls in the track gate of this cluster & in a track gate from another one:

----Make super cluster from these clusters.

---If an observation is out of all gates, then make a new cluster;

-For each old cluster:

--For each observation in the cluster:

---For each hypothesis in the cluster:

----For each track from the hypothesis:

-----If the observation falls in the track gate:

------If this track-observation pair is not encountered yet:

-------*Create a new track from this pair;*
------*Add a new hypothesis with a new track in the cluster;*
----*Make a new track from the current observation;*
----*Add the new track to the above hypothesis;*
---*Leave first M1 hypotheses & prune others;*
--*Combine tracks (closely spaced or made up of one and the same observations);*
--*Combine hypotheses made up of one and the same tracks;*
--*Leave best M2 hypotheses & prune others;*
--*Filter all tracks in the cluster;*
--If a HT track is detected:
—use standard MHT to create a new cluster of tracks & hypotheses;
—add this cluster to already existing ones;
--*Split clusters if possible;*
-*Delete clusters with no tracks in them.*

Figure 2: The MHT[2]-HT algorithm version

3.1. Measures of performance

A variety of measures of performance are formulated for MHT algorithm performance evaluation.[2] To estimate the noise resistance of the compared algorithms, just measures of performance depending on the clutter density P_{fa} are considered below. They are computed on the basis of the Monte Carlo simulation at scenario consisting of L independent runs. Within an experiment, for a given performance parameter C, the sample mean $\bar{\mu}_C^1$ over L runs is recursively computed.[2]

The following measures of performance[2,6] are computed, at each scan k, for the experimental data gathered for each MHT cluster, from its best hypothesis:

- *Expected number of tracks* N_{tr} - sample mean over L runs of the number of tracks $N_{tr\,k}$ ($N_{tr\,k}$ - the number of *Tentative* and *Confirmed* tracks at scan k).
- *Expected number of deleted tracks* N_{dt}: sample mean over L runs of the difference $N_{tr_{k-1}} - N_{tr_k}$. If $N_{tr_{k-1}} < N_{tr_k}$, it is set 0.
- *Expected number of false tracks* N_{ft} - sample mean over L runs of the subtraction $N_{tr\,k} - N_{tk}$ (N_{tk} - the number of targets in track at scan k).
- *Probability of at least* N *confirmed tracks without later deletion* P_{ndt}^N: a sample mean of the number of the occurrences of the event $\{N_{ndt} \geq N\}$ in L runs (N_{ndt} is the number of *confirmed* tracks existing till the run end).

4. Performance evaluation

4.1. Algorithms parameters

A standard Extended Kalman Filter is used in both MHT versions. It is based on the nonlinear model:

$$X_{k+1/k} = X_k + Tv_k \sin \varphi_k;$$

$$Y_{k+1/k} = Y_k + Tv_k \cos \psi_k;$$

$$\psi_{k+1/k} = \psi_k;$$

$$v_{k+1/k} = v_k,$$

where the state vector $x' = (X, Y, \psi, v)$ consists of target coordinates, heading and velocity. The initial values X_0, Y_0, ψ_0 and v_0 are known. The radar sampling interval is T. No process noise is considered.

The measurement equation is: $z_k = h(x_k) + v_k$,

where: $z' = (r, \alpha)$ is the measurement vector, $h(x_k) = \begin{pmatrix} \sqrt{X_k^2 + Y_k^2} \\ \arctan\frac{y}{x} + \kappa\frac{\pi}{2} \end{pmatrix}$ is the measurement matrix, and $v_k \sim (0, R)$ is a white Gaussian measurement noise with covariance matrix $R = \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\alpha^2 \end{pmatrix}$.

The probability of a new target appearance in an elementary volume, the detection probability of appearance of FA in an elementary volume are chosen equal for both algorithms:

$$P^{MHT}_{New\ target} = P^{MHT^2-HT}_{New\ target} = 4 \cdot 10^{-5},\ P^{MHT}_D = P^{MHT^2-HT}_D = P^{HT}_D = 0.9,\ P^{MHT}_{fa} = P^{HT}_{fa} = 10^{-5}.$$

It is also set for both algorithms: gate size - 16; number of hypotheses retained after each observation *M1* = 8; number of hypotheses retained after each scan *M2* = 4; expected track length - 60 scans. In MHT^2-HT it is also chosen $N = 6$ and $M = 4$. The number of HTA accumulators is chosen $N_\rho \times N_\theta = 27 \times 140 = 3780$. The velocity selection is performed in 8 accumulators at velocity bounds: $v_{min} = 0\ m/s$ and $v_{max} = 20\ m/s$.

4.2. Simulation

Results from $L = 100$ Monte Carlo independent runs are obtained from common simulation model and scenarios. Each run lasts 35 scans. The scenario includes two closely spaced ships rectilinearly moving on crossing trajectories:

Ship	X_0 [*km*]	Y_0 [*km*]	ψ [^{0}]	v_0 [*m/s*]
1	3	4	35	16
2	2	4	45	16

The measurement errors are modeled as Gaussian distributed zero-mean random variables with covariance $\sigma_r = 100m$ and $\sigma_\alpha = 0.3^o$.The measurement misses are modeled with: $P_D = 0.8$. The number of FA is modeled as random variable with binomial distribution along the r axis, depending on P_{fa} and on the sizes of the elementary volume ($\Delta r = 100\ m$, $\Delta\alpha = 1^o$). Two scenarios with different flows of FA (moderate - $P^{low}_{fa} = 5 \cdot 10^{-5}$ and dense - $P^{high}_{fa} = 1 \cdot 10^{-3}$) with uniformly distributed coordinates are considered. The surveillance region which size is $r \in [0, 16\ km]$, $\alpha \in [0, 90\ ^o]$ contains 160x90=14400 elementary volumes. The sampling interval is chosen $T = 10s$.

4.3. Simulation Results

The measures of performance obtained for the standard MHT at P_{fa}^{low} (denoted by "1") and P_{fa}^{high} (denoted by "2") and their values for the newly proposed MHT^2-HT algorithm at P_{fa}^{high} (denoted by "3") are presented by Fig. 3 ÷ 6. They illustrate the superiority of the proposed new algorithm:

- N_{tr}, N_{ft}, N_{dt}: While P_{fa}^{high} generally deteriorates the performance of the standard MHT algorithm, the MHT^2-HT algorithm shows a remarkable noise resistance - its plots obtained for P_{fa}^{high} coincide with these obtained by the standard MHT algorithm for P_{fa}^{low}.
- P_{ndt}^{N}: The standard MHT algorithm shows increased "noise" probability P_{ndt}^{3} at $P_{fa} = P_{fa}^{high}$ due to the increased number of false tracks, while the competing MHT^2-HT algorithm considerably reduces this probability: $P_{ndt}^{3}\left(MHT^2 - HT, P_{fa}^{high}\right) \approx P_{ndt}^{3}\left(MHT, P_{fa}^{low}\right)$.

Both algorithms provide $P_{ndt}^{i} \approx 1,\ i = 1,2$ and $P_{ndt}^{4} = 0$, for all considered P_{fa}.

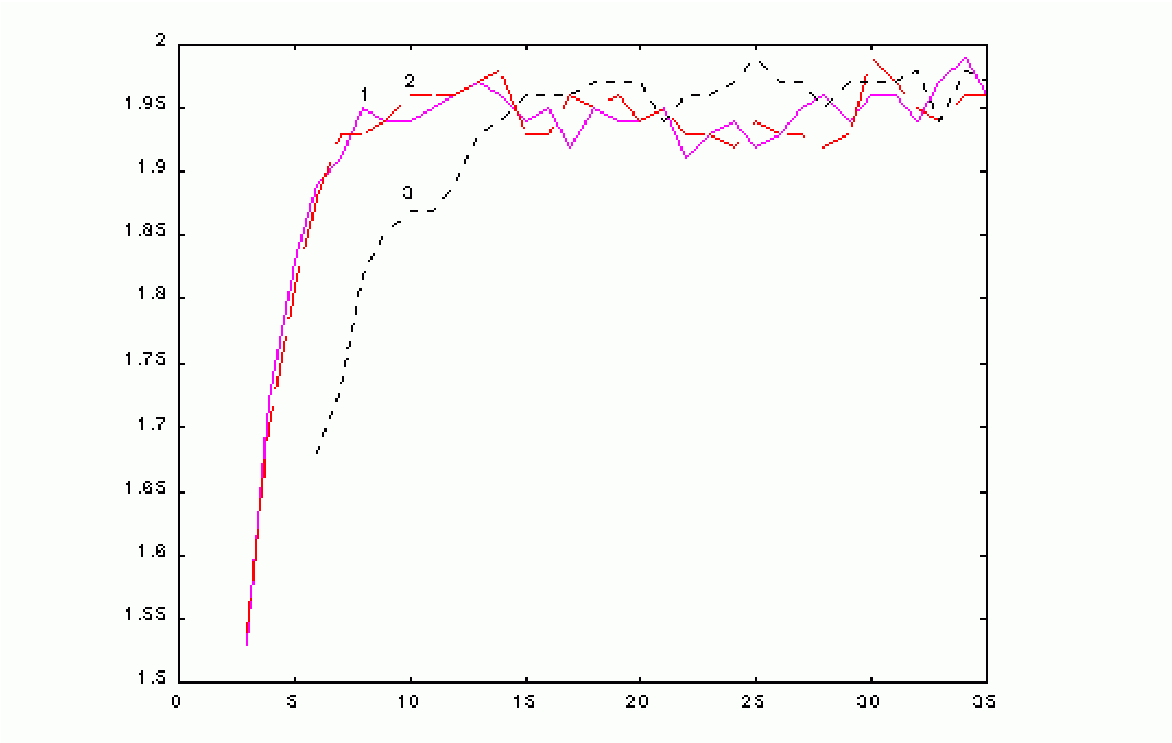

Figure 3: Average Target Number $N_t = N_t\left(P_{fa}\right)$

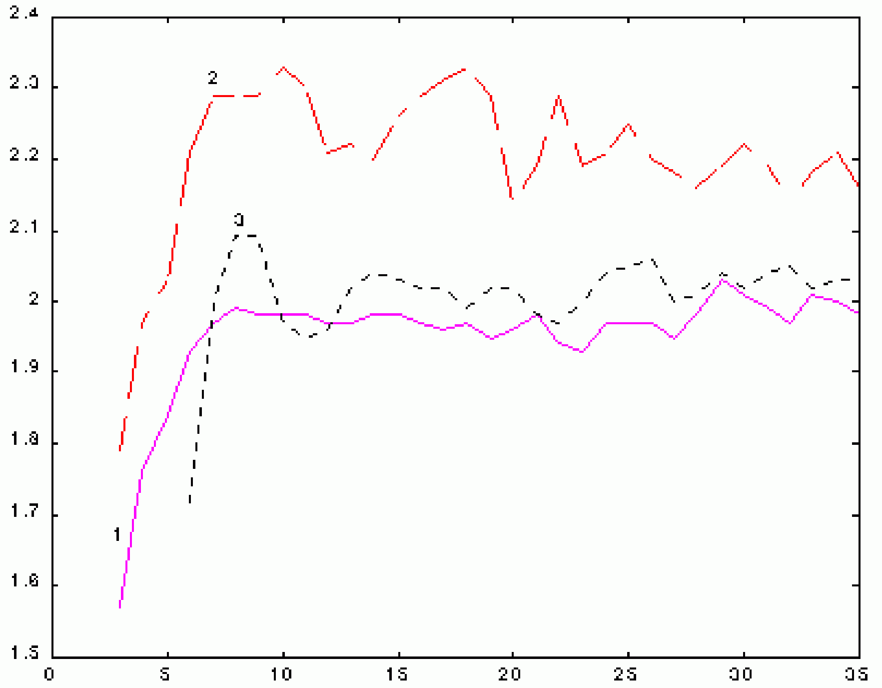

Figure 4: Average Track Number $N_{tr} = N_{tr}\left(P_{fa}\right)$

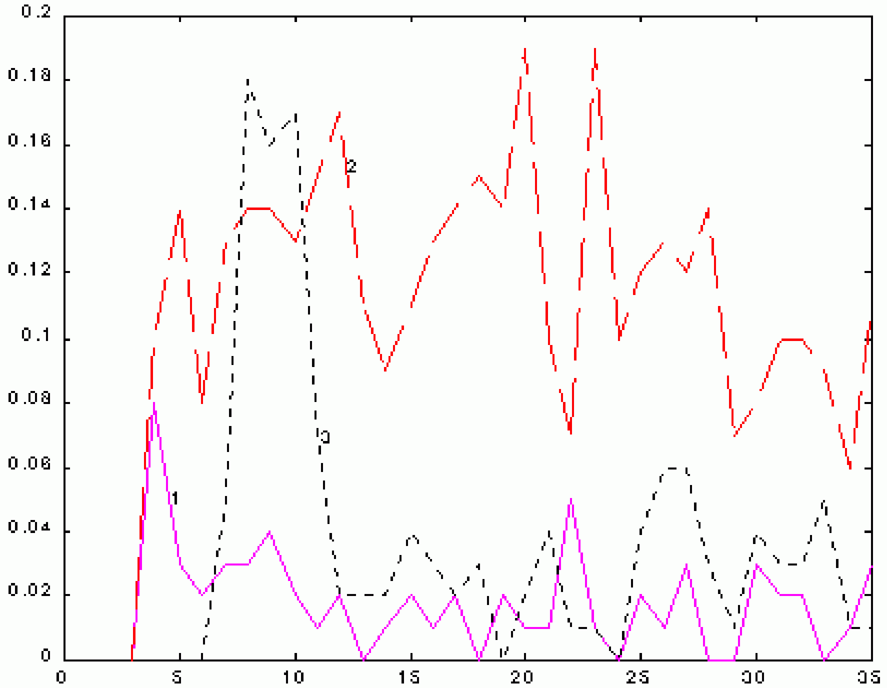

Figure 5: Average Deleted Track Number $N_{dt} = N_{dt}\left(P_{fa}\right)$

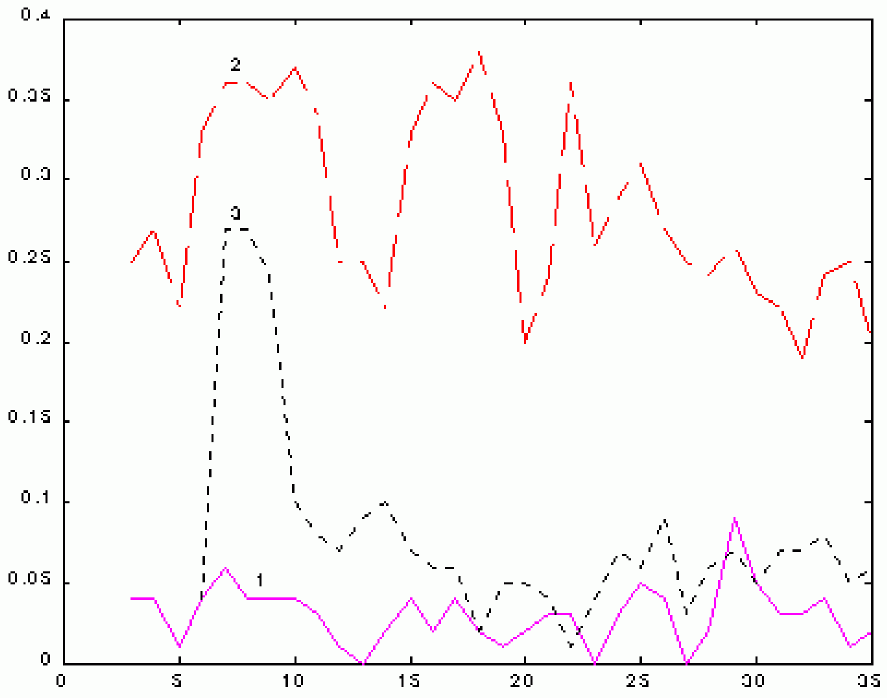

Figure 6: Average False Track Number $N_{ft} = N_{ft}\left(P_{fa}\right)$

5. Conclusion

A new version of the standard MHT measurement oriented algorithm is proposed and evaluated in the paper. A Hough Transform track detector is implemented in MHT to filter arriving false alarms. The measurements included in such tracks are arranged in MHT tracks by second, standard MHT algorithm used in parallel. The new MHT^2-HT algorithm shows a remarkable performance and noise resistance at the cost of delayed track detection procedure.

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Multiple Hypothesis Tracking Using Hough Transform Track Detector

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Keywords: Multiple Hypothesis Tracking, Hough Transform

A modification of the standard Multiple Hypothesis Tracking (MHT) measurement oriented algorithm version is proposed and evaluated in the paper. A Hough Transform track detector is implemented in MHT to filter false alarms. The measurements belonging to already detected tracks are arranged in MHT tracks by another standard MHT algorithm used asynchronously. At the cost of delayed track detection this MHT^2-HT algorithm shows remarkable good performance and noise resistance.

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INTERACTING MULTIPLE MODEL ALGORITHM FOR MANOEUVRING SHIP TRACKING BASED ON NEW SHIP MODELS

Emil SEMERDJIEV, Ludmila MIHAYLOVA, Tzvetan SEMERDJIEV and Violeta BOGDANOVA

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1. Introduction

Tracking of manoeuvring targets is a problem of a great practical and theoretical interest. The real-world tracking applications meet a number of difficulties caused by the presence of different kinds of uncertainty due to the unknown or not precisely known system model and random processes' statistics or because of their abrupt changes. [2-5, 9] These problems are especially complicated in the marine navigation practice, [7, 14, 15, 19] where the commonly used simple models of rectilinear or curvilinear target motions do not match the highly non-linear dynamics of the manoeuvring ship. A solution of these problems is to derive more adequate descriptions of the real ship dynamics and to design adaptive estimation algorithms.

Such a solution is proposed in the paper. A new ship model is derived in Section 2 after an analysis of the basic hydrodynamic models. The derived model is implemented in a new version of the Interacting Multiple Model (IMM) tracking algorithm - the most cost-effective multiple model algorithm for hybrid estimation. [3, 6, 10, 11] The proposed model and tracking algorithm are presented in Section 3 and evaluated in Section 4.

2. Model identification

Results of a study, described in [16, 17, 18] are summarised in this section. It should be noted that the high complexity of the hydrodynamic processes caused by the ship motion in deep and confined water and the wide variety of ship forms and sizes lead to various non-stochastic ship models. These models can be divided in two groups: precise models, topical for particular ship forms and sizes (the Sobolev, [19] Cubic, [1] Quadratic [13] and MMG [14] models) and models with greater generality but lower accuracy (the Pershitz [15] and Nomoto [12] models). Here, the widely used continuous-time (CT) Pershitz model [15] is chosen as a basic model to assure a good trade-off between complexity and accuracy:

$$\frac{dX}{dt} = K_V V_0 \sin(\psi - \beta), \qquad (1)$$

$$\frac{dY}{dt} = K_V V_0 \cos(\psi - \beta), \qquad (2)$$

$$\frac{d\psi}{dt} = K_V \omega, \qquad (3)$$

$$\frac{d\omega}{dt} = -\left(\frac{V_0}{L}\right)^2 (q_{31}\beta + s_{31}\delta) - \frac{V_0}{L} r_{31}\omega, \qquad (4)$$

$$\frac{d\beta}{dt} = -\frac{V_0}{L}(q_{21}\beta + h_1\beta|\beta| + s_{21}\delta) - r_{21}\omega, \qquad (5)$$

$$V = V_0 K_V; \qquad (6)$$

$$K_V = \frac{V(\omega)}{V(0)} = \frac{V}{V_0} = \left(1 + 1.9\,\omega^2 L^2 V_0^{-2}\right)^{-1} \leq 1.$$

The state vector of the considered CT model is $x = [X, Y, \psi, \omega, \beta, V]'$. It includes the ship coordinates and heading, rate of turn, drift angle and velocity; δ is the control rudder angle deviation. The constants q_{21}, r_{21}, s_{21}, h_1, q_{31}, r_{31} and s_{31} are hydrodynamic coefficients depending on the ship geometry, most of all, and on the ship length L. [20] Equations (3) and (6) illustrate the main feature of the considered dynamics - *the non-linear dependence between the rate of turn and the velocity of the ship*. This is the main difference between the presented model in this paper and other well-known simple models. [2, 5, 9]

Very often in the available literature sources [15, 20] this model is simplified by substituting the factor $|\beta|$ with an off-line computed factor:

$$\beta_0 = \frac{-q + \sqrt{q^2 + 4h_1 r_{31} s|\delta|}}{2h_1 r_{31}},$$

where: $q = q_{21}r_{31} - q_{31}r_{21}$, $s = r_{21}s_{31} - r_{31}s_{21}$. Then, the system of two first-order differential equations consisting of equation (4) and the modified equation (5) is transformed in two independent second-order differential equations, omitting the negligible second-order derivatives:

$$2p\frac{d\omega}{dt}\frac{L^2}{V_0^2} + q\,\omega\frac{L}{V_0} + s_{31}\delta = 0; \qquad (4')$$

$$2p\frac{d\beta}{dt}\frac{L}{V_0}+q\beta+s_{21}\delta=0, \qquad (5')$$

where $p=0.5\left(q_{21}^{*}+r_{31}\right)$, $q^{*}=q_{21}^{*}r_{31}-q_{31}r_{21}$, $q_{21}^{*}=q_{21}+h_1\beta_0$. The final CT model (1)-(3), (4') and (6) is obtained by setting $\beta\equiv 0$.

The respective discrete-time (DT) model is:

$$X_{k+1}=X_k+TV_k\sin\psi_k, \qquad (7)$$

$$Y_{k+1}=Y_k+TV_k\cos\psi_k, \qquad (8)$$

$$\psi_{k+1}=\psi_k+TV_k\left[\Omega_k+0.5T\tau V_k\left(\Omega_k-\Omega_0\right)e^{TV_1\tau}\right], \qquad (9)$$

$$\Omega_{k+1}=\Omega_k e^{TV_1\tau}+\Omega_0\left(1-e^{TV_1\tau}\right), \qquad (10)$$

$$V_k=V_0K_V=V_0\left(1+1.9\Omega_k^2L^2\right)^{-1}, \qquad (11)$$

where

$$\tau=\frac{-0.5p+\sqrt{0.25p^2-q^{*}}}{L},\ [m^{-1}],\quad \Omega_0=\frac{\omega}{V_0}=-\frac{\left[s_{31}\delta+sign(\delta)q_{31}\beta_0\right]}{r_{31}L},\left[\frac{rad}{m}\right].$$

and $k=1,2,\cdots$; T is the sampling interval.

The full coincidence between the results obtained by the CT model (1)-(6), and these obtained by the derived DT model (7)-(11) is demonstrated in [17]. Model (7)-(11) is used for true data generation in further simulations.

The final DT model, suitable for implementation in Kalman filter, is composed on the basis of the assumptions [17, 18]:

- It is assumed that the observed ship maneuvers with a constant rate of turn:

$$\Omega_{k+1}=\Omega_k \qquad \text{(i.e. } \tau\equiv 0\text{).}$$

- The whole domain of unknown control parameters Ω_k is replaced by a set of three control parameters corresponding to the three basic kinds of ship motions: rectilinear motion (Ω_1), left and right turns (Ω_2 and Ω_3):

$$\Omega=\left[\Omega_1,\Omega_2,\Omega_3\right]'=\left[0,U,-U\right]',$$

where U denotes the preset constant rate of turn. The vector Ω covers all possible ship manoeuvres and system noises in the band $[U,-U]$. The particular choice of U is made by taking into account general considerations from the marine practice and some important international navigation restrictions.[20]

- The attempt to introduce respective vector of possible ship lengths has been recognised in [17] as unsuccessful because of bad distinction of the resulting models. The uncertainty, concerning the ship geometry has been overcome by introducing a constant average ship length $l = const$.[17]

So, the final version of the requested ship model takes the following general form:

$$x_{i,k+1} = f(x_k, \Omega_i, l),\ i = 1, 2, 3,$$

where $x_k = [X_k, Y_k, \psi_k, V_{0,k}]'$ and where:

$$X_{i,k+1} = X_{i,k} + TV_{i,k+1} \sin \psi_{i,k}, \qquad (12)$$

$$Y_{i,k+1} = Y_{i,k} + TV_{i,k+1} \cos \psi_{i,k}, \qquad (13)$$

$$\psi_{i,k+1} = \psi_{i,k} + TV_{i,k+1}\Omega_i, \qquad (14)$$

$$V_{i,k+1} = K_{V,i} V_{0,k}, \qquad (15)$$

where

$$K_{V,i} = \left(1 + 1.9\Omega_i^2 l^2\right)^{-1}, \qquad \Omega = [\Omega_1, \Omega_2, \Omega_3]' = [0, U, -U]'.$$

Another model, based on the extended state vector $x_{i,k}^e = [X_{i,k}, Y_{i,k}, \psi_{i,k}, V_{i,k}, \Delta\Omega_{i,k}]'$ is suggested in [18]. The corresponding extended ship models ($i = 1, 2, 3$) have the form:

$$X_{i,k+1} = X_{i,k} + TV_{i,k+1} \sin \psi_{i,k}, \qquad (16)$$

$$Y_{i,k+1} = Y_{i,k} + TV_{i,k+1} \cos \psi_{i,k}, \qquad (17)$$

$$\psi_{i,k+1} = \psi_{i,k} + TV_{i,k+1}(\Omega_i + \Delta\Omega_{i,k}), \qquad (18)$$

$$V_{i,k+1} = K_{V,i} V_{0,k}, \qquad (19)$$

$$\Delta\Omega_{i,k+1} = \Delta\Omega_{i,k}, \qquad (20)$$

where $K_{V,i} = \left(1 + 1.9\Omega_i^2 l^2\right)^{-1}$. It takes into account possible differences $\Delta\Omega_{i,k}$ between the unknown true value of the ship rate of turn Ω_k and its values Ω_i fixed in the IMM algorithm. The influence of $\Delta\Omega_{i,k}$ on the velocity is not taken into account because of its insignificance.

3. IMM algorithm for tracking of manoeuvring ship

Models (12)-(15) and (16)-(20) are expanded in [17] in Taylor time-series up to first-order terms around the estimated state vector. They are used in an Extended Kalman Filters (EKF) and respective IMM algorithms. The IMM algorithm based on model (12)-(15) is denoted as IMM-A and the proposed IMM algorithm based on model (16)-(20) is denoted as IMM-B.

The measurement equation has the form:

$$y_k = Hx_k + w_k,$$

where H is the measurement matrix,

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix},$$

w_k is a white Gaussian measurement noise with covariance matrix R_k.

For convenience, the polar measurements "range-bearing" $y_k = \left[r_k, \beta_k\right]'$, are transformed here in Cartesian ones:

$$X_k = r_k \sin\beta_k, \; Y_k = r_k \cos\beta_k.$$

So, the measurement vector acquires the new form $y_k = \left[X_k, Y_k\right]'$. Respectively, the covariance matrix of the measurement errors is [8]:

$$R_{i,k} = \begin{bmatrix} \sigma_r^2 \sin^2\beta_k + r_k^2\sigma_\beta^2 \cos^2\beta_k & \left(\sigma_r^2 - r_k^2\sigma_\beta^2\right)\sin\beta_k\cos\beta_k \\ \left(\sigma_r^2 - r_k^2\sigma_\beta^2\right)\sin\beta_k\cos\beta_k & \sigma_r^2\cos^2\beta_k + r_k^2\sigma_\beta^2\sin^2\beta_k \end{bmatrix},$$

where σ_r and σ_β are the standard deviations of the range and bearing angle.

The equations of the i^{th} ($i = 1, 2, 3$) EKF are:

$$\hat{x}_{i,k/k} = \hat{x}_{i,k/k-1} + K_{i,k}\gamma_{i,k}$$

$$\hat{x}_{i,k+1/k} = f\left(\hat{x}_{i,k/k}, \Omega_i, l\right),$$

$$\gamma_{i,k} = y_k - H_i\hat{x}_{i,k/k-1},$$

$$P_{i,k/k-1} = \phi\, f_i^x P_{i,k-1/k-1} \left(f_i^x\right)',$$

$$S_{i,k} = H_i P_{i,k/k-1} H_i' + R_{i,k},$$

$$K_{i,k} = P_{i,k/k-1} H_i' S_{i,k}^{-1},$$

$$P_{i,k/k} = P_{i,k/k-1} - K_{i,k} S_{i,k} K'_{i,k}.$$

Here, $\hat{x}_{i,k/k}$ and $\hat{x}_{i,k+1/k}$ are the filtered estimate of the state x_k and its one-step prediction; $\gamma_{i,k}$ and $S_{i,k}$ are the filter residual process and its covariance matrix, $P_{i,k/k}$ is the error covariance matrix, $K_{i,k}$ is the filter gain matrix, $\phi \geq 1$ is the fudge factor.

The Jacobi matrix $f_i^x = \left.\frac{\partial f_i}{\partial x_i}\right|_{x_i = \hat{x}_i}$ computed based upon the model (12)-(15) has the form:

$$f_i^x = \begin{bmatrix} 1 & 0 & T\hat{V}_{i,k+1} \cos\hat{\psi}_{i,k} & TK_{V,i} \sin\hat{\psi}_{i,k} \\ 0 & 1 & -T\hat{V}_{i,k+1} \sin\hat{\psi}_{i,k} & TK_{V,i} \cos\hat{\psi}_{i,k} \\ 0 & 0 & 1 & TK_{V,i}\Omega_i \\ 0 & 0 & 0 & K_{V,i} \end{bmatrix};$$

the one based on model (16)-(20) is:

$$f_i^x = \begin{bmatrix} 1 & 0 & T\hat{V}_{i,k+1} \cos\hat{\psi}_{i,k} & TK_{V,i} \sin\hat{\psi}_{i,k} & 0 \\ 0 & 1 & -T\hat{V}_{i,k+1} \sin\hat{\psi}_{i,k} & TK_{V,i} \cos\hat{\psi}_{i,k} & 0 \\ 0 & 0 & 1 & TK_{V,i}\left(\Omega_i + \Delta\hat{\Omega}_{i,k}\right) & T\hat{V}_{i,k+1} \\ 0 & 0 & 0 & K_{V,i} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

A hard logic is introduced in both IMM algorithms to avoid undesired combination of the estimates $\hat{V}_{1,k}$, $\hat{V}_{2,k}$ and $\hat{V}_{3,k}$ [17]:

$$\hat{V}_{i,k} = \hat{V}_{1,k}, \qquad (i = 2,3);$$

$$\hat{V}_k = \hat{V}_{1,k}, \quad if\ \mu_{1,k} > 0.5,$$

where $\mu_{i,k}$ is the probability of the event: "the i^{th} model is topical at time k ", $\hat{V}_k$ is the overall estimate of the ship velocity.

4. Performance evaluation

The performance of both IMM algorithms is compared by Monte Carlo simulations.[2] Results for 100 independent runs, each one lasting 200 scans (600*s*, T =3*s*) are given.

The simulation parameters of the true model (7)-(11) are standard [20,17]: q_{21} = 0.331, r_{21} = -0.629, s_{21} = -0.104, h_1 = 3.5, q_{31} = -4.64, r_{31} = 3.88, s_{31} = -1.019, *L*=99*m*, $\delta_{min} = 3^o$, $\delta_{max} = 30^\circ$. The chosen initial conditions are: $X_0 = Y_0$ = 10000*m*, $\psi_0 = 45^\circ$, V_0 = 30 *m/s*. Initially the ship moves rectilinearly. The applied pulse-wise rudder angle control law is:

$$\delta = \begin{cases} \delta_{max}, & k \in [51, 67] \\ 0, & k \notin [51, 67] \end{cases}.$$

The true ship trajectory is presented in Fig.1.

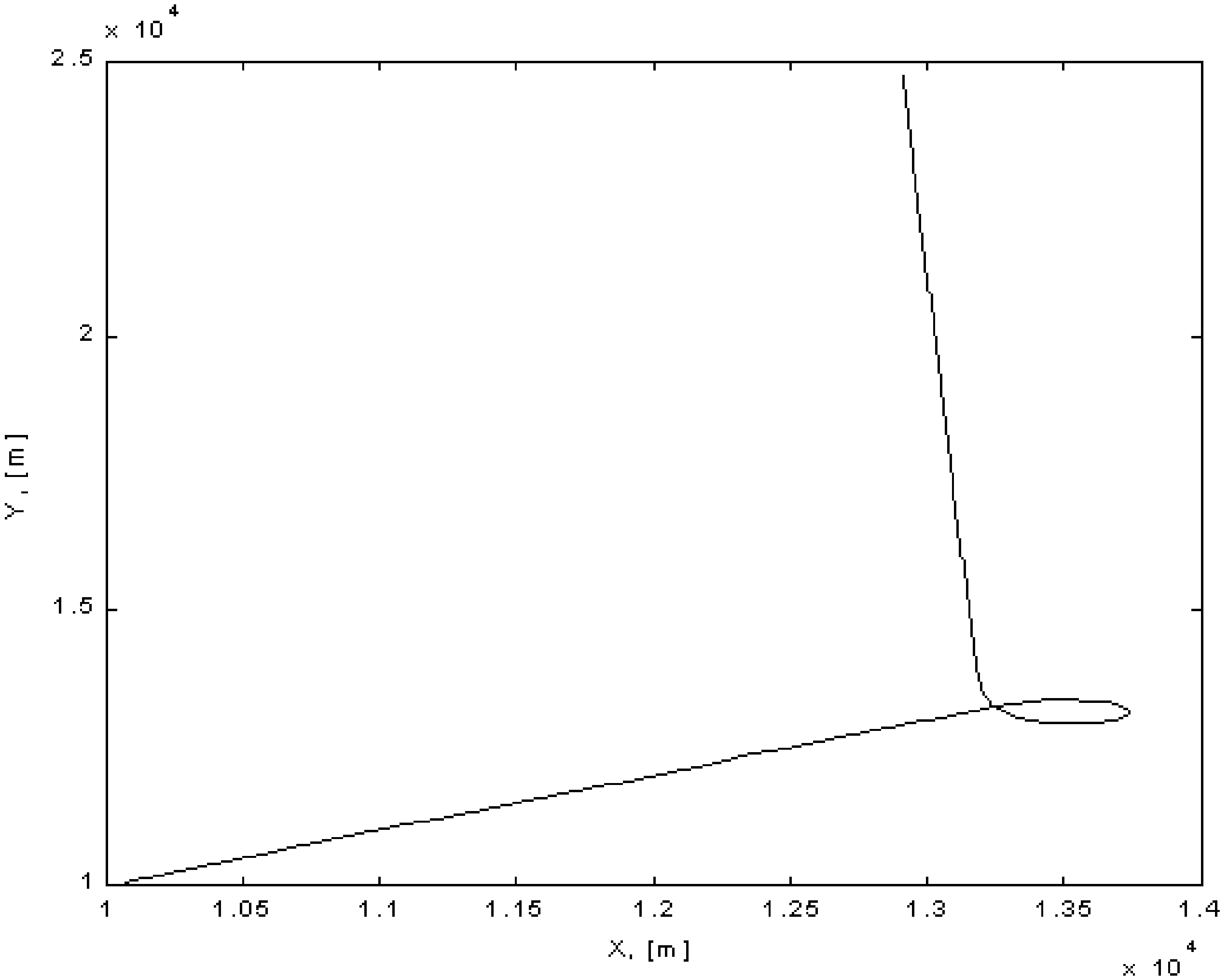

Figure 1: The true ship trajectory

Both considered IMM algorithms a use constant ship length *l*=69 *m* for each of the three models, control parameter U = 0.0066 m^{-1} (360 $^o/min$) and fudge factors $\phi^A = \phi^B$ = 1.03. To compute the measurement error covariance matrix, it is preset: σ_r = 100*m*, σ_β = 0.3°. The initial error covariance matrices $P_{i,0}$, the initial mode probability vectors μ and the transition probability matrices Pr are chosen as follows:

$$P_{i,0}^{A} = diag\{\sigma_X^2 \quad \sigma_Y^2 \quad \sigma_\psi^2 \quad \sigma_V^2\},\ P_{i,0}^{B} = diag\{\sigma_X^2 \quad \sigma_Y^2 \quad \sigma_\psi^2 \quad \sigma_V^2 \quad \sigma_{\Delta\Omega}^2\},$$

$$\mu^A = \mu^B = \begin{bmatrix} 0.95 \\ 0.025 \\ 0.025 \end{bmatrix},\ Pr^A = Pr^B = \begin{bmatrix} 0.6 & 0.2 & 0.2 \\ 0.5 & 0.5 & 0 \\ 0.5 & 0 & 0.5 \end{bmatrix}.$$

$$\sigma_X = \sigma_Y = \sigma_r,\ \sigma_\psi = 0.1^\circ,\ \sigma_V = 10\,m,\ \sigma_{\Delta\Omega} = 0.01\,rad/m\,.$$

The Monte Carlo simulation results are shown in Figs. 2-13. General estimation of the algorithms' performance is given in Fig.2. The IMM-B algorithm possesses better consistency during the manoeuvring stage.

These inferences are confirmed by results received for the *mean error (ME)* and the *root mean square errors (RMSE)* of the state vector [2] (Figs.3-6 and Figs.7-10). The average mode probabilities are presented in Figs.11-12. The computed ME of the estimated IMM-B control parameter change is given in Fig.13.

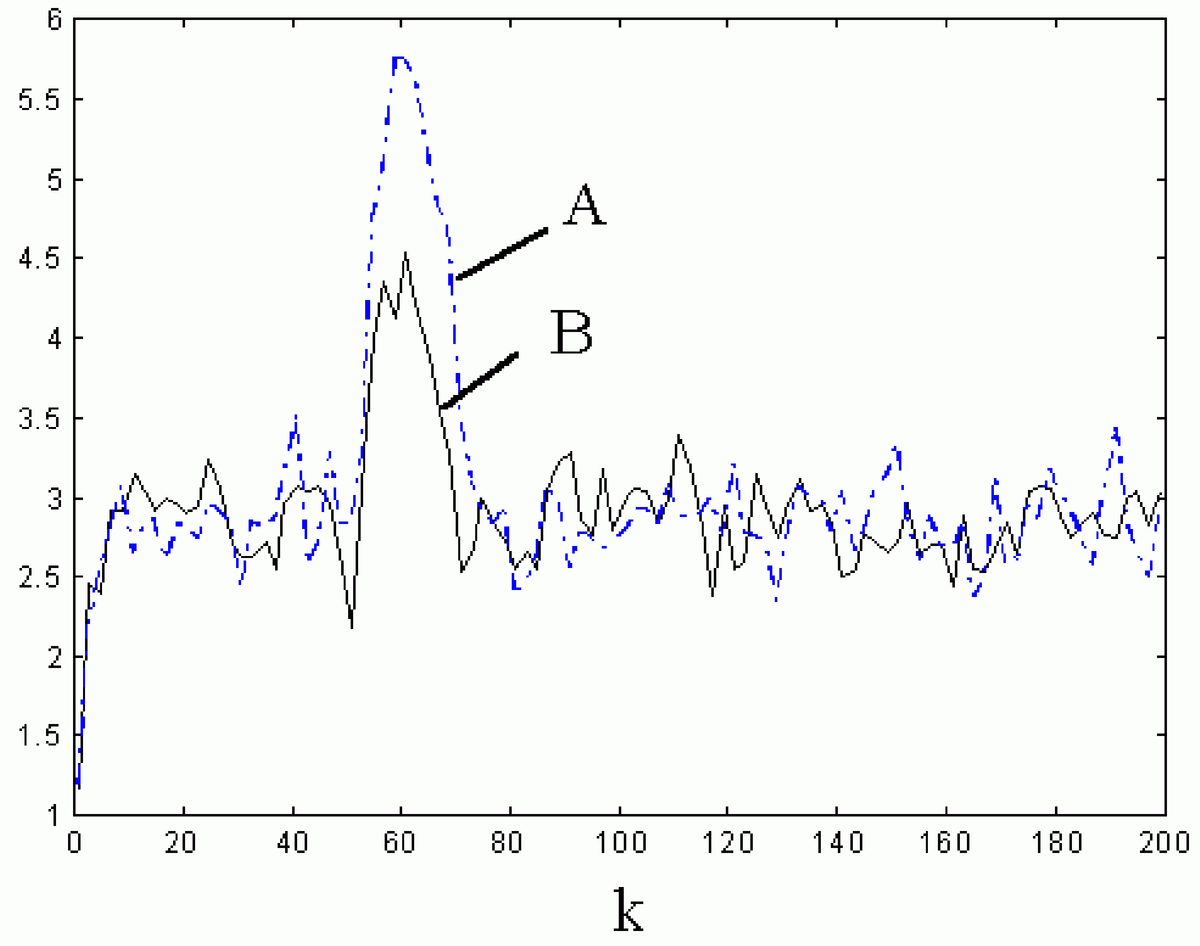

Figure 2: Normalized Estimation Error Squared

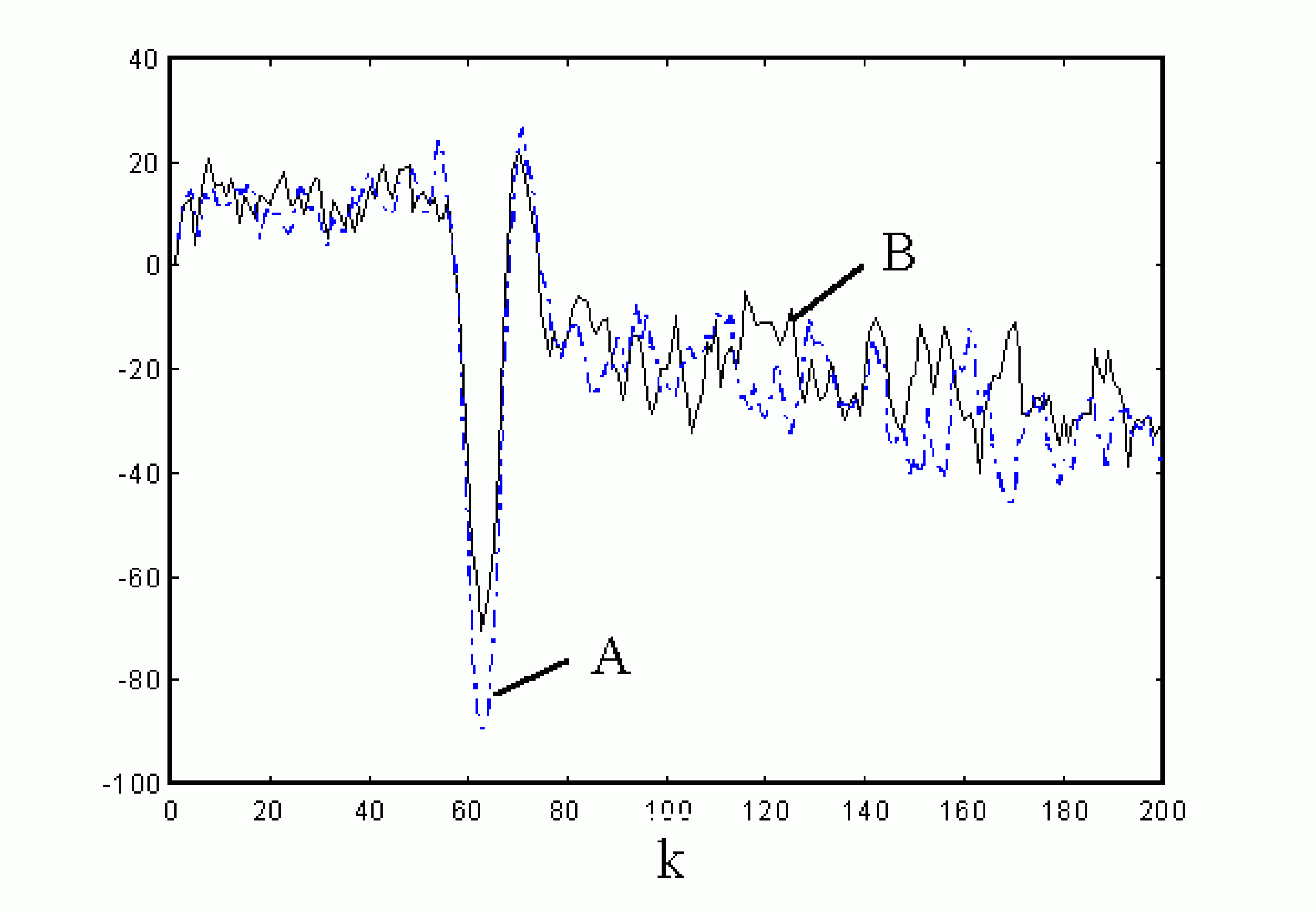

Figure 3: X Position ME

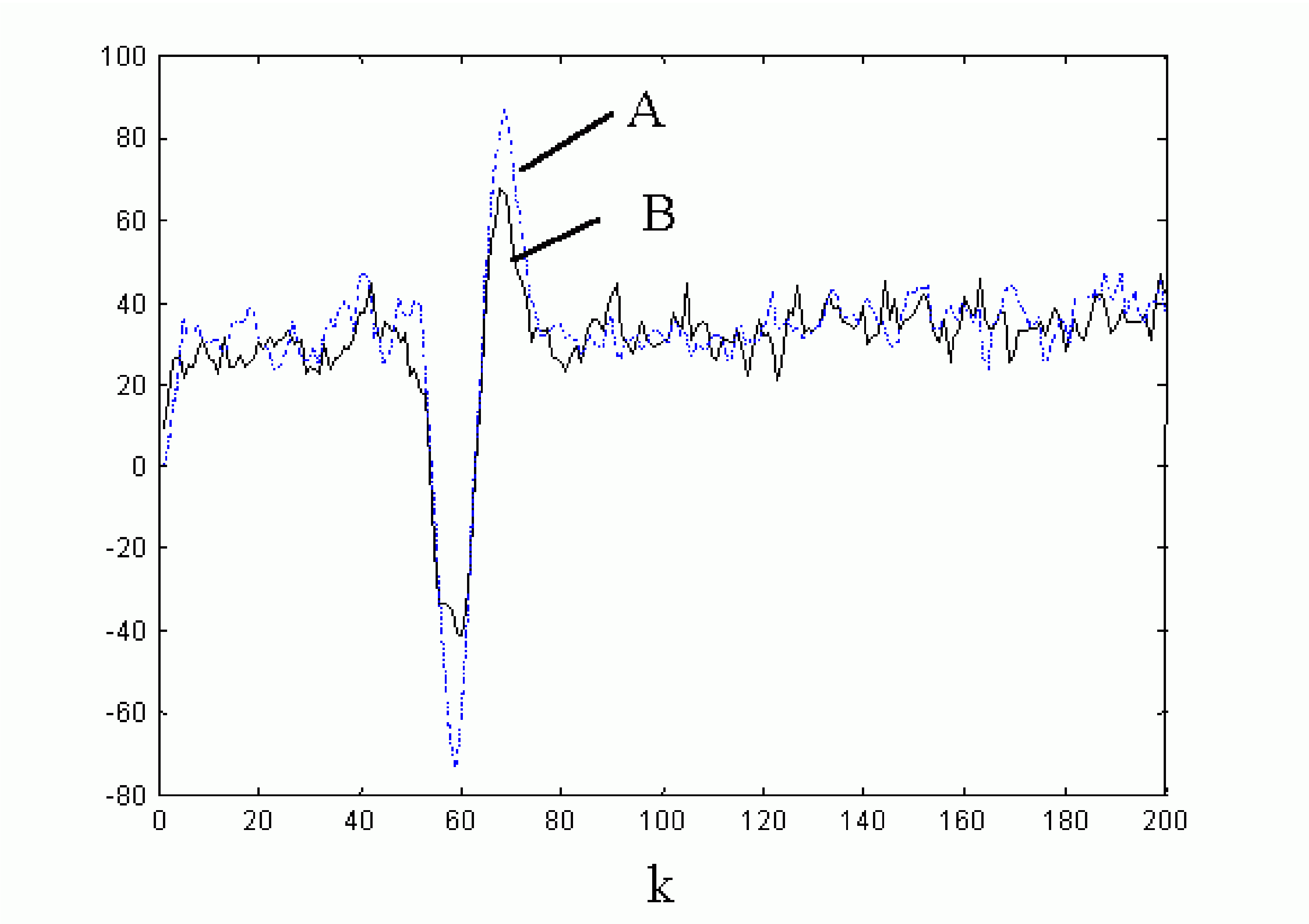

Figure 4: Y Position ME

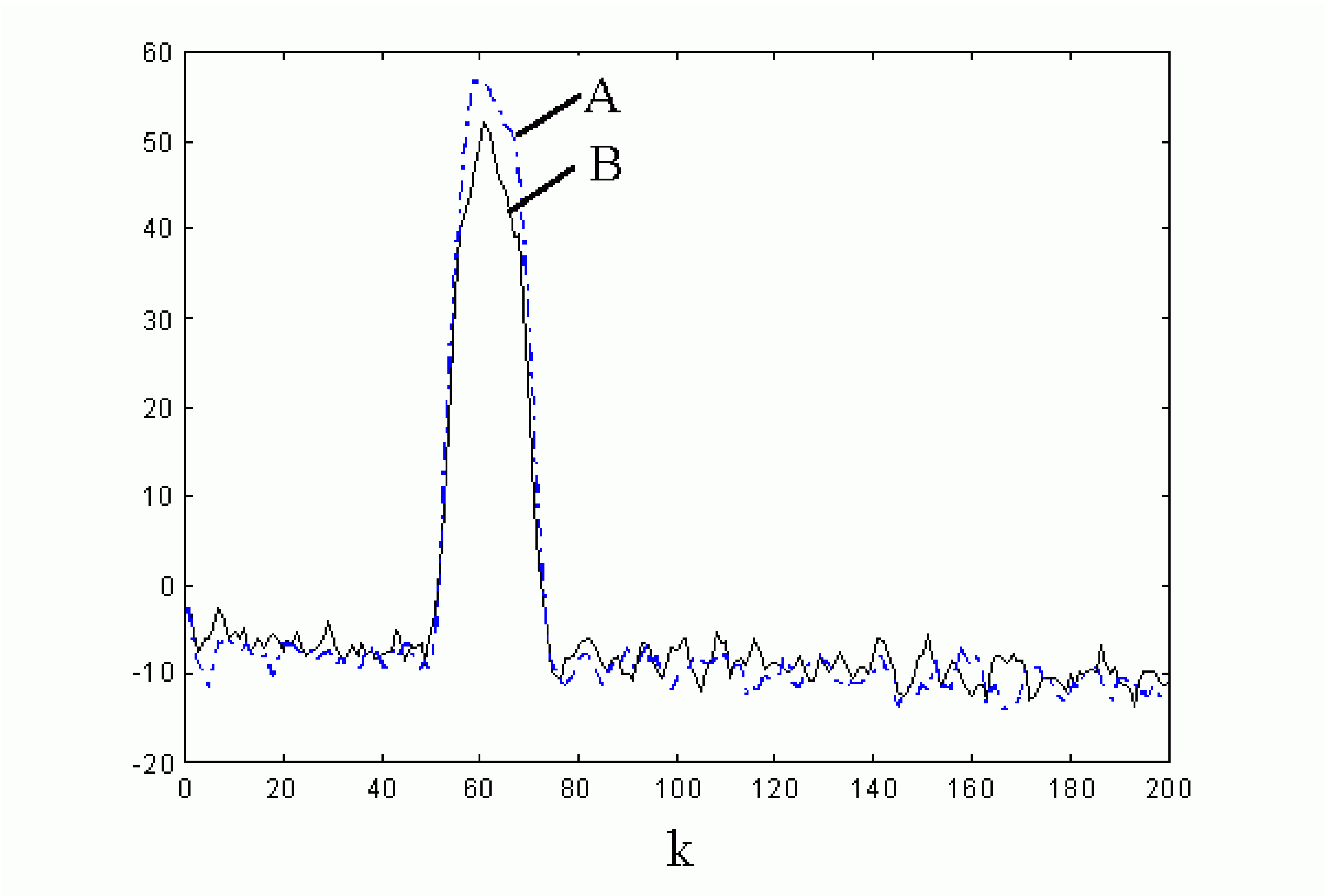

Figure 5: Heading ME

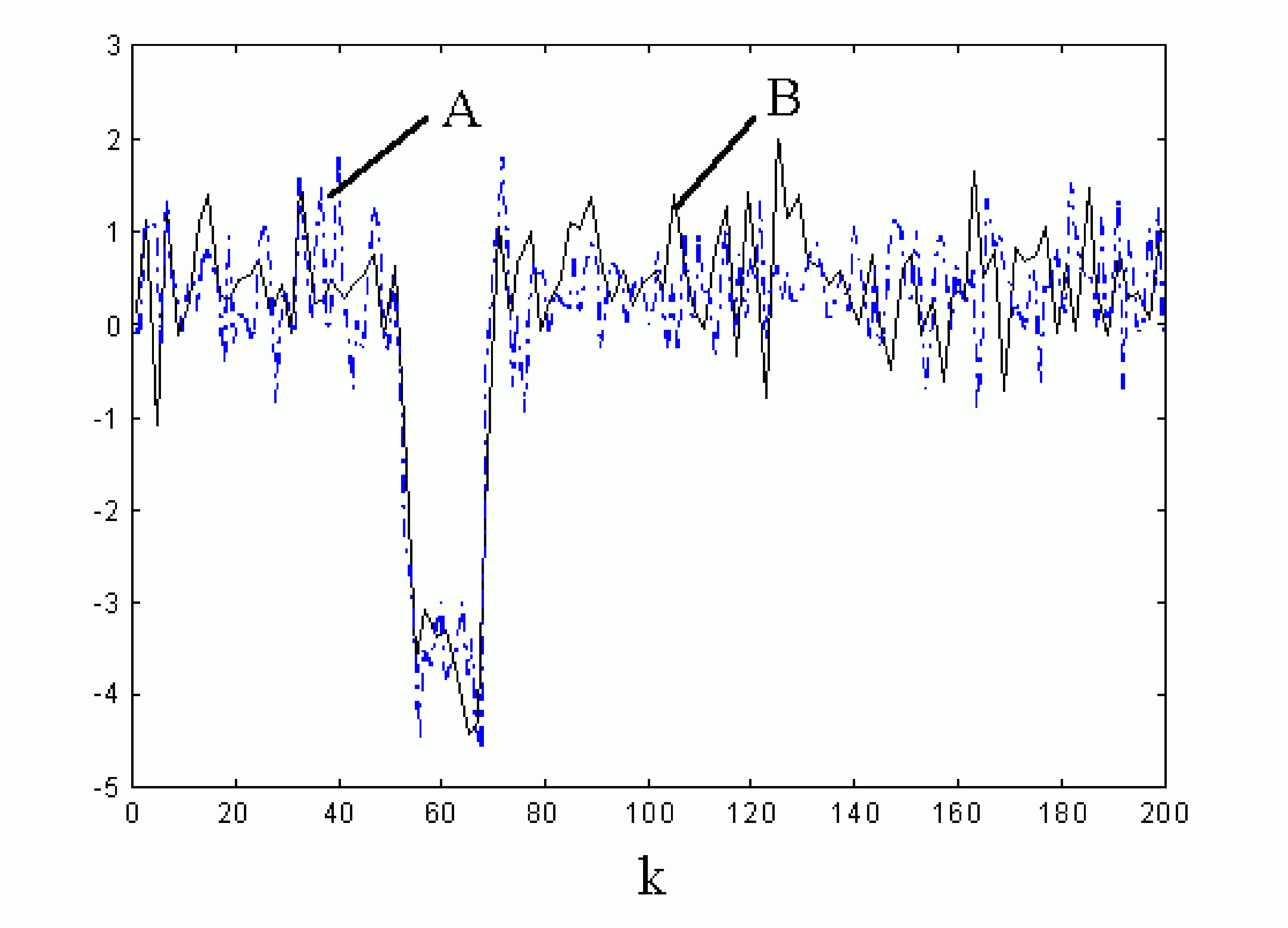

Figure 6: Velocity ME

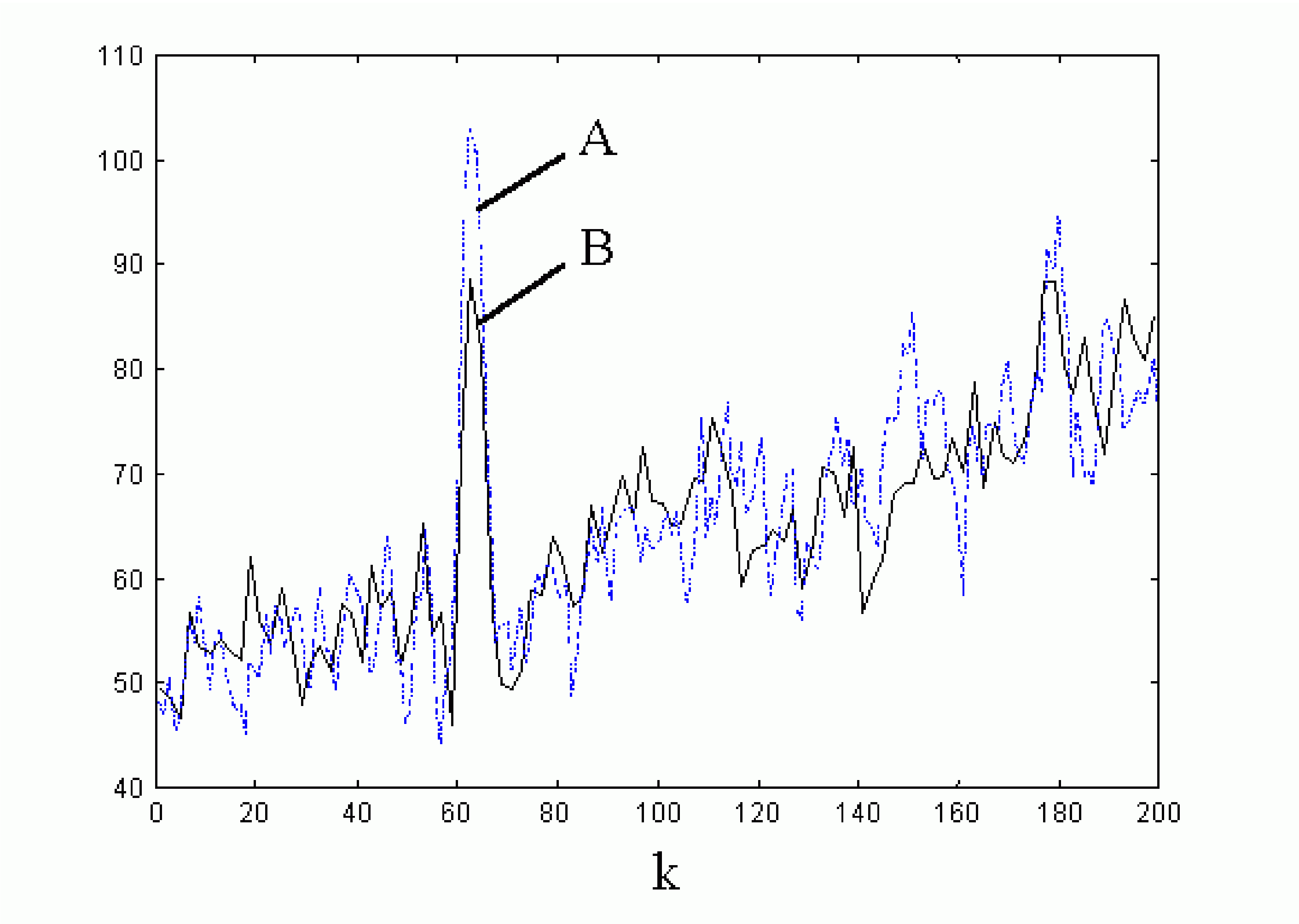

Figure 7: X Position RMSE

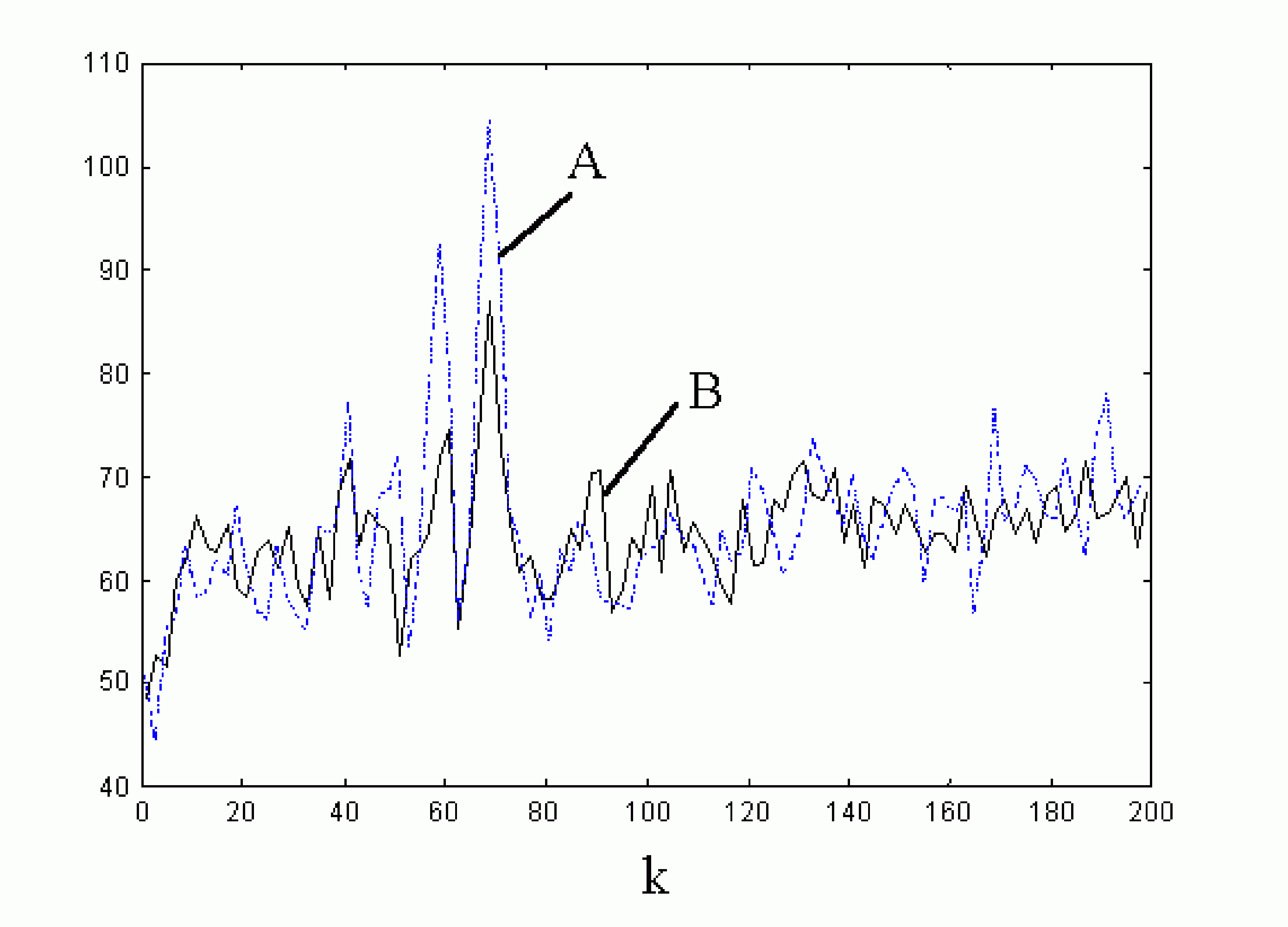

Figure 8: Y Position RMSE

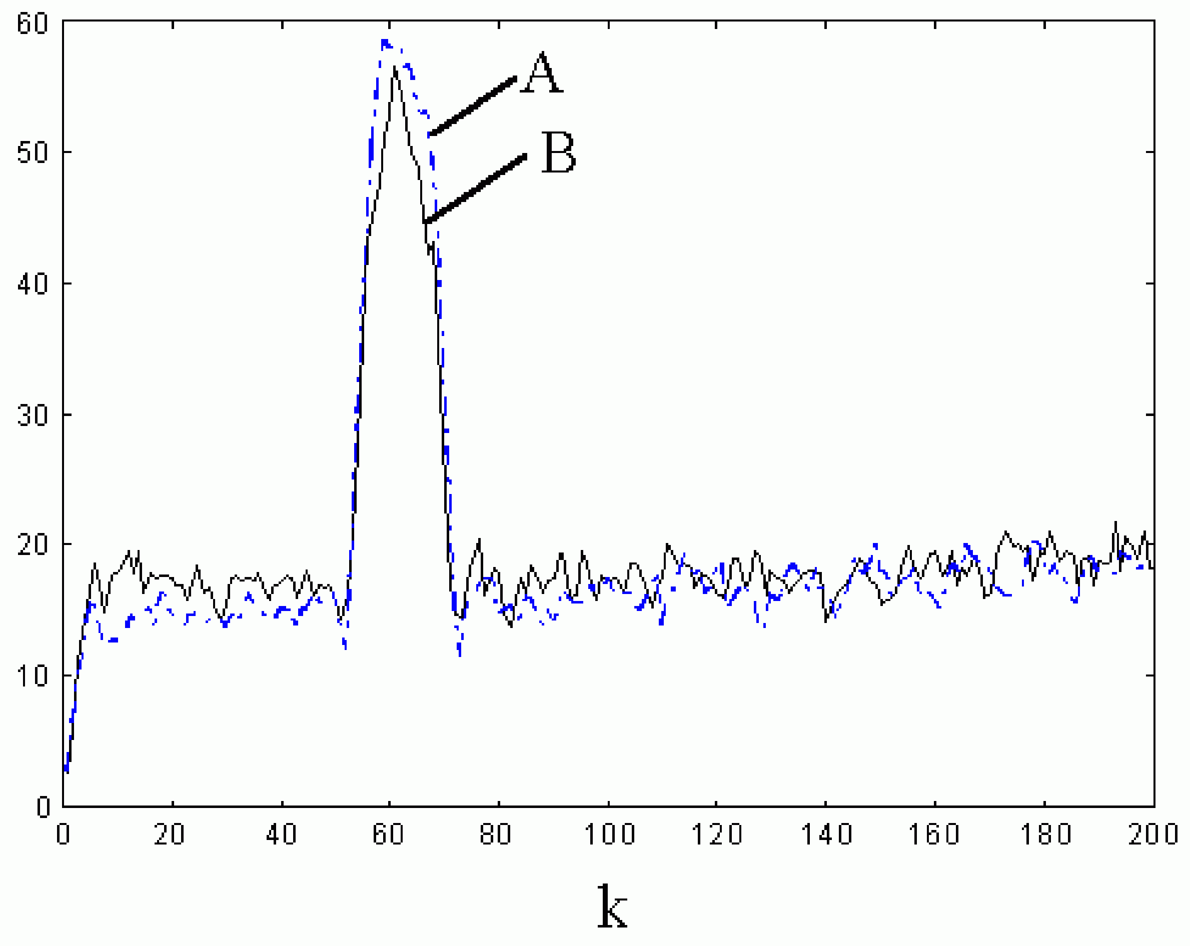

Figure 9: Heading RMSE

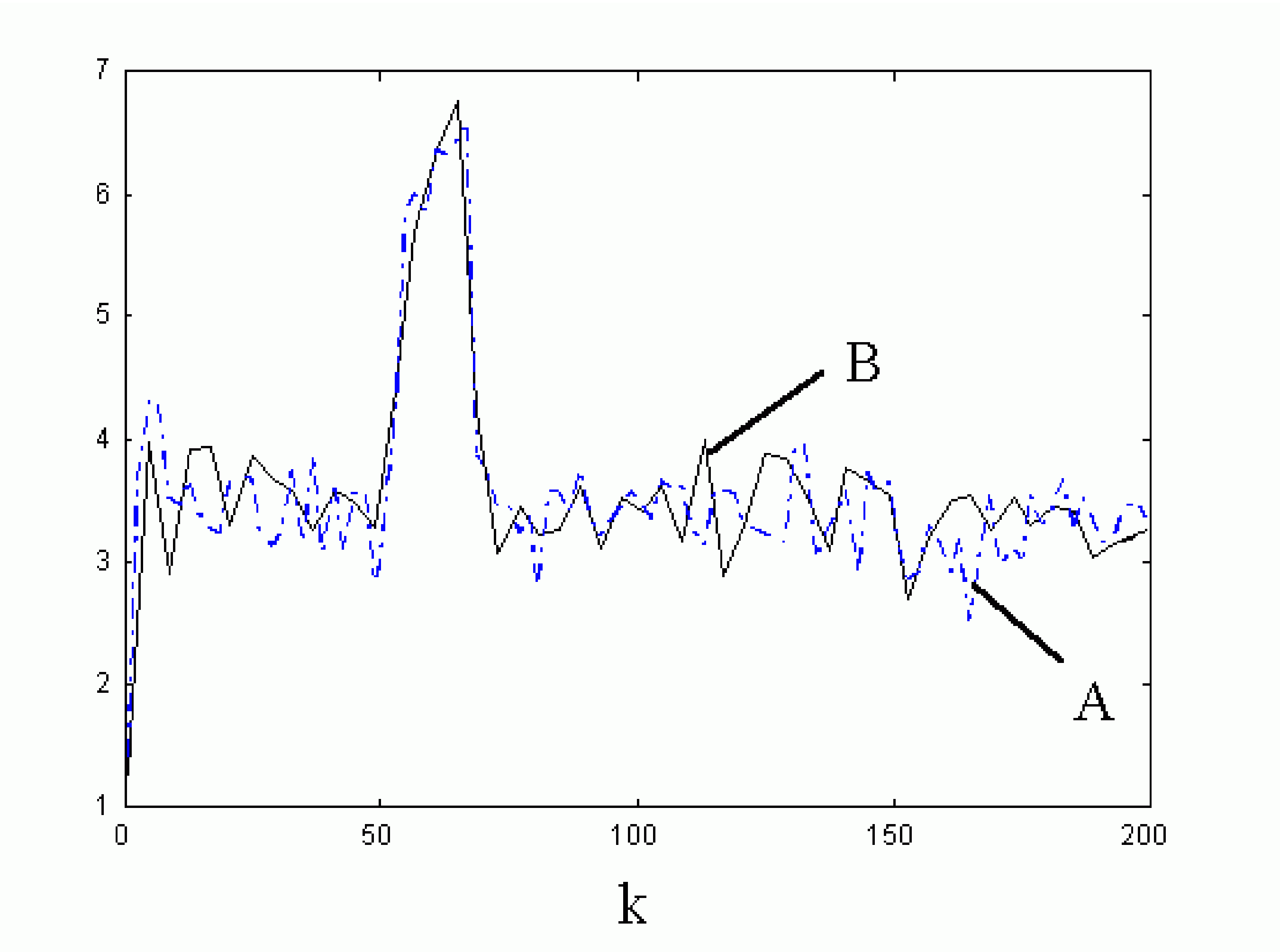

Figure 10: Velocity RMSE

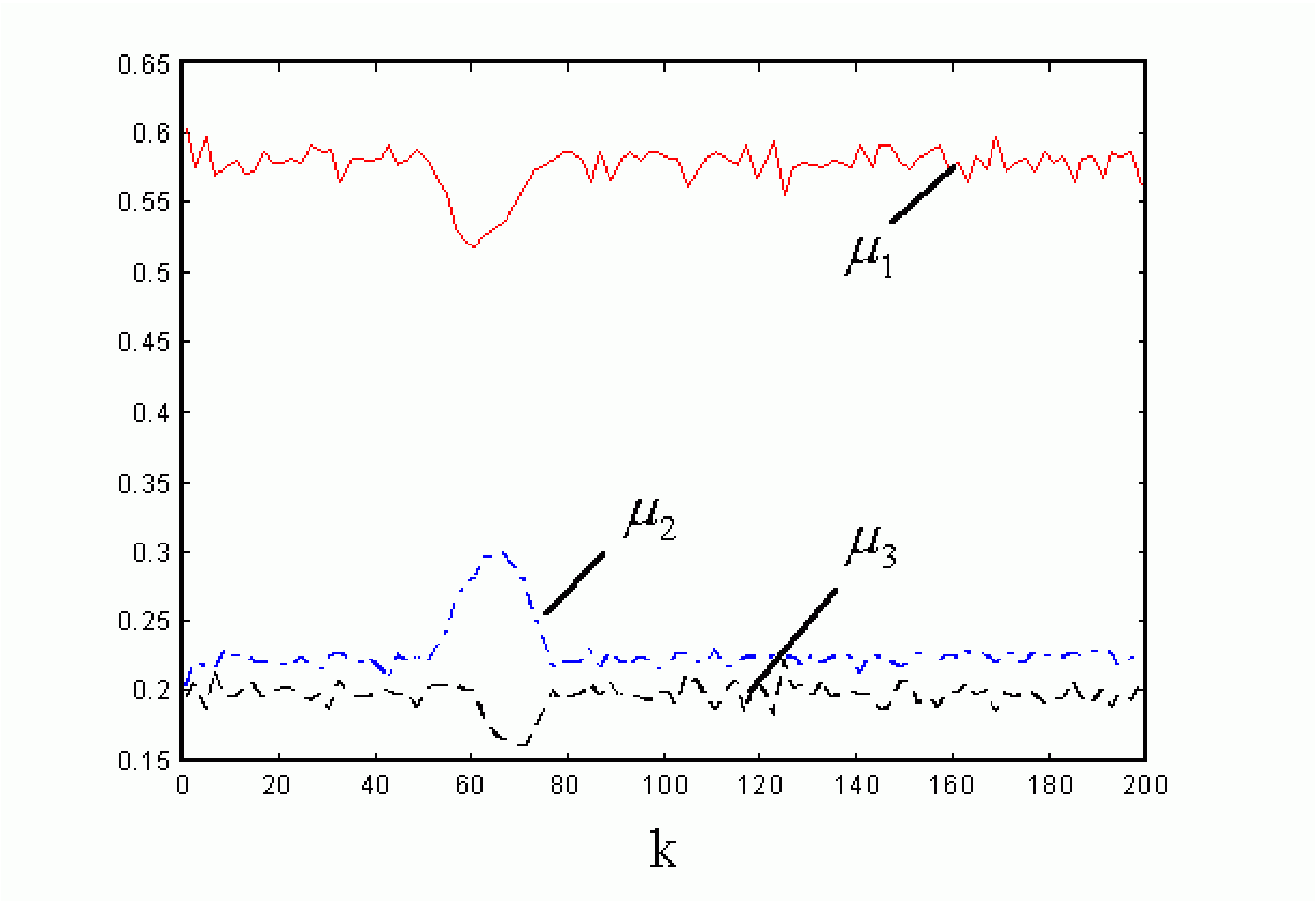

Figure 11: Average Mode Probabilities for IMM-A

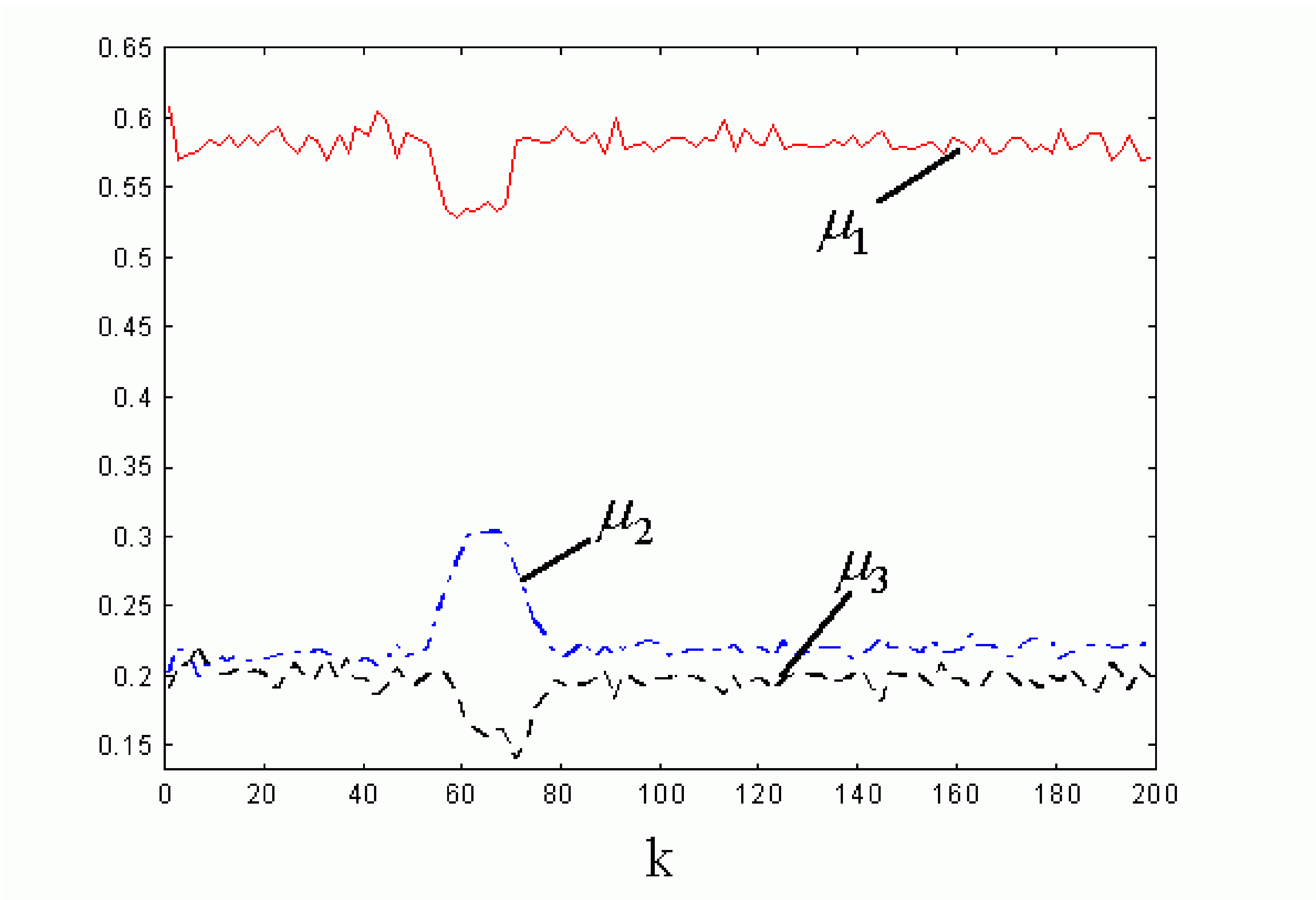

Figure 12: Average Mode Probabilities for IMM-B

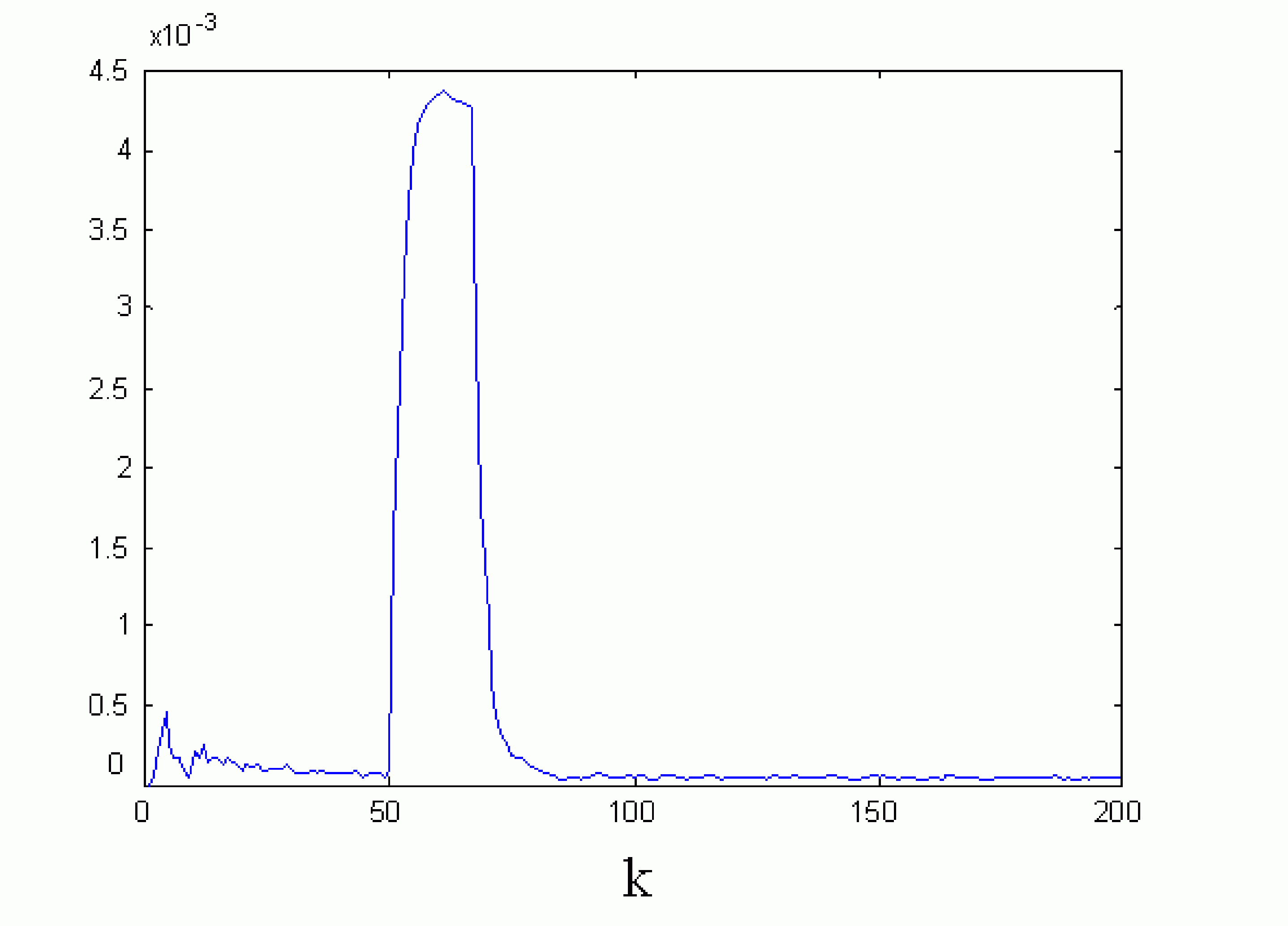

Figure 13: IMM-B control parameter change ME

5. Conclusions

New models adequately describing the non-linear dynamics of maneuvering ship motion are proposed in the paper for manoeuvring ship tracking. They are implemented in a standard and in newly designed IMM versions. The proposed new IMM uses extended state vector and model to compensate the difference between the fixed control parameter of the currently used IMM model and its real value. The performed Monte Carlo simulations show excellent model fit and estimation performance.

Acknowledgement

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Interacting Multiple Model Algorithm for Manoeuvring Ship Tracking Based on New Ship Models

Emil Semerdjiev, Ludmila Mihaylova, Tzvetan Semerdjiev and Violeta Bogdanova

Keywords: marine targets tracking, model identification, adaptive hybrid estimation

Tracking of manoeuvring targets is a problem of a great practical and theoretical interest. The real-world tracking applications meet a number of difficulties caused by the presence of different kinds of uncertainty due to the unknown or not precisely known system model and random processes' statistics or because of their abrupt changes. These problems are especially complicated in the marine navigation practice, where the commonly used simple models of rectilinear or curvilinear target motions do not match to the highly non-linear dynamics of the manoeuvring ship motion. A solution of these problems is to derive more adequate descriptions of the real ship dynamics and to design adaptive estimation algorithms. In the paper a new ship model is derived after an analysis of the basic hydrodynamic models. This model is implemented in a new version of the Interacting Multiple Model (IMM) tracking algorithm - the most cost-effective multiple model algorithm for hybrid estimation. The proposed new IMM uses extended state vector and model to compensate the difference between the fixed control parameter of the currently used IMM model and its real value. The performed Monte Carlo simulations, show excellent model fit and estimation performance.

MULTI SENSOR DATA FUSION

by Edward Waltz and James Llinas,

Artech House Radar Library, ISBN: 0-89006-277-3, 464 pages, 1990

This book is devoted to a rapidly developing area of research and development, which involves significant integration of a number of research disciplines. The initial acquaintance with multisensor data fusion technology surprisingly involves more interdisciplinary relations than expected. Communications and decision theories are related to epistemology and uncertainty management. Estimation theory, digital signal processing and computer science are applied in parallel with artificial intelligence.

The book gives a thorough introduction into the taxonomy of functional architectures of the multisensor data fusion systems and defense applications. Contemporary sensors, sources and communications links are presented and sensor management is depicted. Data fusion for state estimation is separately discussed in the context of target tracking applications. An important part of the book covers military concepts of situation and threat assessment. The discussion on implementation approaches for situation and threat assessment is very useful for all specialists working in this area. They will find in the book data fusion system architecture design guidelines, how to model such systems and how to evaluate their performance. The emerging role of artificial intelligence techniques is also presented.

This book is an important introduction to multisensor data fusion technology and its application in military command, control, and intelligence operations. The presentation is given at a system-level. It could be useful to all specialists working in the area of data fusion and C^4I systems development.

INFORMATION WARFARE PRINCIPLES AND OPERATIONS

by Edward Waltz

Artech House Radar Library, ISBN: 0-89006-511-X, 380 pages, 1998

The book presents a system engineering-level introduction in the field of Information Warfare. It provides an overview of the emerging threats in the information space to commercial, civil, and military information systems. It describes how these threats can be identified and how contemporary C^4I systems can be protected.

An important part of the book is devoted to a detailed consideration of components, principles, technologies, and tactics of the information warfare. Three areas critical to success are studied: Information Dominance, Information Defense, and Information Offense. Their comprehensive discussion provides engineers, system operators and information technology users with an understandable overview of the quantification of information, and with deductive and inductive processes that create knowledge. An essential technical background in data mining is given here. All information security technologies are thoroughly discussed including encryption, authorization, and attack detection. In addition, possible information attack technologies, including physical, infrastructure, and perceptual methods, are also analyzed. The book could be of interest for all specialists working in the area of C^4I systems development, as well as to students of information warfare and information operations.

BAYESIAN MULTIPLE TARGET TRACKING

by Lawrence D. Stone, Carl A. Barlow, Thomas L. Corwin,

Artech House Radar Library, ISBN: 1580530249, 300 pages, October 1999

The book is devoted to one of the currently most popular areas of theory and practice – *Multiple Target Tracking*. The well known problem in this area is related to the significant uncertainty in regard to the relevance of the used stochastic models, and the correctness of their application for target position and motion prediction over time. Most of the up-to-date target tracking approaches result in algorithms, which are effective in presence of high amount of data and significant rates of their accumulation. Unfortunately, very often in reality this is not the case. Facing real world problems, the authors focus their attention on the case of low data collecting rates and low signal-to-noise ratio, which is the most wide spread situation currently.

Having in mind that in electronic warfare environments most of the sensors provide ambiguous information about the number of targets and their state, the authors propose Bayesian inference approach as basic theoretical framework for design and development of effective tracking algorithms. Following this path, a general solution of the tracking problems in conditions of insufficient sensor resources is developed. Thus, the use of Bayesian inference framework provides a base for successful design and development of mathematically sound algorithms for dealing with up-to-date tracking problems involving multiple closely spaced targets, multiple netted sensors, and multiple moving platforms. Respectively, such powerful tracking method as non-linear Multiple Hypothesis Tracking is thoroughly discussed. Also, the *Theory of Unified Tracking* approaches is presented as a promising instrument for successful development of multiple target tracking algorithms in cases of critical uncertainty.

The book contains many illustrative examples, concept descriptions, and specific algorithms. Cases with nonlinear target behavior models, non-Gaussian measurement error distributions, low scanning rates, low signal to noise ratios and multiple closely spaced targets are under special consideration. The authors treat a number of topics such as the problem of multiple target detection and tracking; the case for the Bayesian inference; single target tracking; Bayesian filtering; Kalman filtering; discrete Bayesian filtering; classical multiple target tracking; general multiple hypothesis tracking; classical multiple hypothesis tracking; multiple target tracking without contacts or association; general multiple target model; relationship to multiple hypothesis tracking; the theoretical foundations for likelihood ratio detection and tracking; as well as implementation issues.

The book might be of significant interest for students, specialists and professionals working in field of reliable situation and threat assessment on the base of effective multisensor data fusion. It will be especially useful for people searching effective procedure for crisis, conflict and collision avoidance, conflicts prevention and crisis management on the base of reliable data processing. The approach offered in the book for dynamic objects state estimation and prediction in case of significant volatility, uncertainty, complexity and ambiguity is an effective instrument for solving real world problems.

MULTITARGET/MULTISENSOR TRACKING:

APPLICATIONS AND ADVANCES - VOLUME III

by Yaakov Bar-Shalom and William Dale Blair

Artech House Radar Library, Approx. 460 pages, Available in July 2000

The book is a significant addition to previous fundamental authors' works in the area of Multisensor Multitarget Tracking. It provides the most up-to-date available information and guidance to development of new practical and effective solutions for sensor data processing systems. For people searching for innovative solutions it discusses the most important contemporary problems of advanced target tracking applications, giving the reader a chance to be in touch with the forefront of this professional area.

In particular, the book presents the modern viewpoint on multisensor tracking problems, on the allocation of insufficient resources, and on advanced hardware and software development. A thorough consideration of assignment techniques for multitarget data association is presented. It includes the incorporation of the Nearest Neighbor Joint Probabilistic Data Association algorithm into the Interacting Multiple Model estimator. It also considers non-linear filtering for fusing target's kinematic state measurements and target's signature measurements. A Variable Structure Interacting Multiple Model (VS-IMM) estimator combined with an Assignment algorithm for tracking multiple ground targets is thoroughly discussed. The effective use of MTI data obtained from an airborne sensor is studied and the obtained results could be of great interest for professionals involved in radar data processing.

The book includes an in-depth discussion of techniques, related to corrupted radar tracking performance. It presents ways of modeling and simulating ECMs, using computers. A detailed signal processing model is proposed to help sonar/radar waveform optimization for reliable tracking. A comprehensive introduction to variable structure estimators is provided and an accession of their practical applications is made.

The book covers practical aspects of multisensor tracking and sensor resource allocation; survey of assignment techniques for MTT; IMM estimator with nearest neighbor; joint probabilistic data association; tracking; closely-spaced, deformable objects; tracking for Ballistic Missile Defence; joint target tracking and identification: an application of nonlinear filtering; ground target tracking with topography-based variable structure IMM Estimator; radar signal processing for tracking; optical sensor signal processing for tracking; modeling of electronic countermeasures for multitarget tracking and data association; sonar/radar waveform design for optimal tracking performance; engineer's guide to variable structure estimators for tracking.

The book will be of great interest for designers and systems engineers, involved in sensor data processing for wide area of application. It could be especially useful for professionals, engaged in R&D of multisensor data fusion algorithm for conflict prevention, collision avoidance and crisis management in air, ground and sea applications. Also, it could be of interest for specialists applying dynamic objects state estimation in variety of public safety ensuring systems.

SENSORS FOR PEACE

APPLICATIONS, SYSTEMS AND LEGAL REQUIREMENTS FOR MONITORING IN PEACE OPERATIONS

Editors: Jurgen Altmann, Horst Fisher and Henny van der Graaf

United Nations Publication, New York, 1998, ISBN 92-9045-130-0

The book is devoted to one of the vital problems of peace operations: monitoring of situations and threats in unstable, uncertain, complicated and deceptive environments. The main goal of the authors is to analyze the use of unattended ground sensor systems in four important areas of application, and to provide recommendations on the employment of sensors in peace operations. The importance of this publication is unquestionable. There is no clearer example of practical effectiveness of the system of multiple sensor utilization and its potential contribution to increasing international security. But in our point of view, the most valuable contribution of this publication are lessons learned in the sensor system utilization during difficult times of particular peace operations.

The presentation begins with thorough consideration of operational aspects of the use of sensors in peace operations. It clearly shows how sensors fit into different tasks carried out by peace forces, and how sensor systems and personnel requirements interact. Special attention is paid to the use of sensors under various circumstances, i.e., in mobile tasks such as patrolling. Very useful is the presentation of operational requirements cost estimation and organizational set-up. Using many tables with technical characteristics and rich illustrations, the authors introduce the reader into the essence of the sensor systems information fusion and the specifics of their application.

An important evaluation of the Questionnaire on Application of Ground Sensors during peacekeeping Operations is presented next. The study covers up-to-date technology capability utilization, systems optimization, and efficiency improvement. It describes capabilities provided by systems already available on the market. The cost of such systems and their development are specified in detail.

The legal aspects of ground sensor utilization in peace operations are discussed at the end of the book. International law aspects are carefully investigated and the need for new rules in regulating the sensor systems implementation is confirmed.

Finally, a set of important conclusions and recommendations are formulated. Options for decision-makers and policy recommendations for United Nations, as well as for contributing states are given. Thus, the book may be regarded as an important study, which establishes close connections between multisensor data fusion and security issue. It will be useful for specialists, working in the area of multisensor data fusion engineering applications.

INFORMATION FUSION TERMINOLOGY

Information Fusion encompasses theory, techniques and tools conceived and employed for exploiting the synergy in information acquired from multiple sources (sensor, databases, information gathered by human, etc.). The objective is that the resulting decision or action is in some sense better (qualitatively or quantitatively, in terms of accuracy, robustness etc.) than it would be possible if any of these sources were used individually, i.e., without exploiting synergy. (B. V. Dasarathy, Dynetics, Inc.)

In the process of fusion events, activities and movements are correlated and analyzed as they occur in time and space. The purpose is to determine location, identity and status of individual objects (equipment and units), to assess the situation, to determine qualitative and quantitative characteristics of threats to coalition operations, and to detect patterns in activities that reveal intent or capability. Specific technologies are required to refine, direct and manage the information fusion capabilities.

In relation to Multisensor Data Fusion, Multi-Sensor Collaboration is performed as an innovative technical approach, which is engaged to eliminate limitations in the current capabilities of sensors. Sensor collaboration technology must address ground, airborne and spaceborne systems and processes in a fully distributed environment. A special goal is the development of a predictive intelligence assessment of the warfighter's battlespace situation.

Data Fusion is a process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, complete and timely assessment of situations and threats, as well as their significance.

Often, data fusion is accompanied by sensor management. A sensor management system is any system which provides automatic control of a suite of sensors or measurement devices. In general, a sensor management system must answer the following four questions: 1) What sensor? 2) Which service? 3) Where to point? 4) When to start? The sensor manager output is a schedule defined over an interval of time where each entry of the schedule is a scheduling vector containing the answers to these questions.

In practice, Data Fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources, and for the exploitation of their synergy in order to obtain information whose quality cannot be achieved otherwise. More philosophically (B. V. Dasarathy, Dynetics, Inc.) - "When you borrow information from one source, it’s plagiarism; When you borrow information from many, it’s information fusion"

Concerning multisensor fusion, the general problem can be restated as: how is it possible to observe a dynamical scene with a set of sensors by controlling their configuration, i.e. their sequencing, as well as the scheduling of the resources, be they directly attached to the sensors or centralized. Evaluating the reliability of different information sources is crucial when the received data reveals some inconsistencies and we have to choose among various options. In fact, the reliability of the source affects the credibility of the information and vice-versa. It is necessary to develop systems that deal with couples (information, source) rather than with information alone.

Decentralized distributed detection and decision fusion systems attract significant interest due to the increasing need to employ multiple sensors for surveillance, intelligence and communications. Some of the motivating factors are the natural advantages of distributed detection over centralized detection: reliability, survivability, increases in required coverage of surveillance, and reduction in communications bandwidth.

One purpose of Sensor Fusion is to realize new sensing architecture by integrating multi-sensor information and to develop hierarchical and decentralized architecture for recognition such as human beings further. As a result, more reliable and multilateral information can be extracted, which can realize high-level recognition mechanism.

INTRODUCTORY LITERATURE:

D.S. Lawrence, D. Stone, et.al., Bayesian Multiple Target Tracking, (Artech House Radar Library, 1999).

A. Zembower, "Emerging Trends in Sensor Data Management," in Proceedings of the 15th Annual AESS/IEEE Dayton Section Symposium Sensing the world: Analog Sensors and Systems Across the Spectrum (May 1998), 71-78.

M.S. Markin, et.al., *Data Fusion and Data Processing* (The Report of the Defence and Aerospace Foresight Working Party, 1997).

K. Varshney, Distributed Detection and Data Fusion (Springer 1996).

J. Manyika and H. Durrant-Whyte, Data Fusion and Sensor Management: A decentralized information theoretic approach (Ellis Horwood, 1994).

D.L. Hall, Mathematical Techniques in Multisensor Data Fusion (Artech House, 1992).

M.A. Abidi and R. C. Gonzalez, Data Fusion in Robotics & Machine Intelligence (Academic Press, 1992).

J.J. Clark and A.L. Yuille, Data Fusion for Sensory Information Processing Systems (Kluwer Academic Publishers, 1990).

E. Waltz and J. Llinas, Multisensor Data Fusion (Artech House, 1990).

INTERNET ADDRESSES FOR REFERENCES:

http://www-datafusion.cma.fr/fund/definitions.html

http://www.inform.unian.it/area/cognitive/Fusion.htm

http://dflwww.ece.drexel.edu/research/dds

http://roadway.ivhs.washington.edu/pubs/fusion_abstract.htm

INTERNATIONAL SOCIETY OF INFORMATION FUSION EVENTS:

SPIE's International Symposium on AeroSense - Signal Processing, Sensor Fusion and Target Recognition IX, Orlando, FL, USA.

World Computer Congress - WCC'2000, Beijing, China, August 21-25, 2000.

Threats, Countermeasures, and Situational Awareness: Teaming for Survivability - Symposium and Exhibition, Virginia Beach, June 20-22, 2000.

Fusion2000 - Third International Conference on Information Fusion, Paris, France, July 10-13, 2000.

Fusion of Soft Computing & Hard Computing in Industrial Applications, Session at SMC2000, Nashville, TN, USA, October 8-11, 2000

Central Laboratory for Parallel Processing

The Central Laboratory for Parallel Processing (CLPP) was established in 1985 as a Coordination Center of Informatics and Computer Technology (CCICT). The main idea was to coordinate research in the field of Computer Science and Computer Technologies conducted by scientists from the Bulgarian Academy of Sciences, Bulgarian universities and R&D institutes closely connected with industry, as well as to promote international cooperation in the area of theoretical and practical problems of the new generation of computers. Special emphasis was placed on the following issues:

- high performance computer systems and algorithms for parallel processing
- distributed computer systems
- computer networks
- intelligent man-machine interface, etc.

Annually, the scientists from the Laboratory publish approximately 140 papers, and about hundred of them are published in refereed international journals and proceedings of high quality international conferences. In 1996, CCICT was renamed as Central Laboratory for Parallel Processing. CLPP is headed by a Director, a Deputy Director and a Scientific Secretary. Currently, Prof. D.Sc. Ivan Dimov is Director of CLPP. General and scientific policy of the Laboratory is formulated by Board of Directors, including all Department heads, and the 24-member Scientific Council. Currently, the CLPP consists of a Computer Center and six departments:

- Distributed computing systems and networks
- Parallel algorithms
- Scientific computing
- High performance computer architectures
- Linguistic modeling
- Mathematical methods for sensor information processing.

The **Department of Distributed Systems and Networking** was founded in 1985. It is chaired by Prof. Dr. K. Boyanov, Corresponding member of the Academy of Sciences. Main areas of research within the department are:

- Network Protocols
- Parallel and Distributed Heterogeneous Computing Environments
- High Speed Local Area Networks
- Data Messaging
- Broadband communications

- Parallel interpretation of object-oriented programs
- Dynamic load balancing in distributed systems

A concept of distributed computer architecture with reconfigurable communications interconnection was developed. Based on this architecture several high performance computers with modular structure and up to 64 processors were constructed. Architecture allowing flexible use of high-speed networks has been suggested. The department is coordinator of the Bulgarian Academic Network. The studies accomplished in the Department are aimed at the creation of a methodology for effective parallel interpretation of wide range of applications which would merge the advantages of parallel processing and the specification of user applications by means of graphical (diagrammatic) high level object-oriented language. Currently, the Department of Distributed Systems and Networking participates in several international joint research programs such as ACTS, NATO Science for Peace, as well as in bilateral reasearch projects on parallel algorithms. Its staff consists of one corresponding member, two full professors, three associate professors, eight research fellows, and four support specialists.

The main research activities of the **Department of Parallel Algorithms** are in the following areas:

- New efficient parallel algorithms;
- Monte Carlo algorithms (differential and integral equations, linear algebra, spectral problems, data processing);
- Fractal methods for image processing;
- Computational geometry and topological graph theory;
- Applications of parallel algorithms and supercomputing (large-scale problems, parallel and/or vector computers, clusters of workstations).

The Department of Parallel Algorithms participates in several international joint research programs financed by the Commission of the European Communities, NATO Science for Peace and other sources.

The Department organizes a number of international scientific meetings - conferences, workshops and seminars. The traditional IMACS Seminar on Monte Carlo methods is jointly organized by IMACS and the Central Laboratory for Parallel Processing.

The Department of Parallel Algorithms employs one academician, one full professor, four associate professors, six scientific researchers, and one supporting specialist.

The **Department of Scientific Computing** was founded in 1997. The major objectives of the research activities of the Department are as follows:

(i) to develop new efficient numerical methods which are robust with respect to the problem and method parameters, and which can also perform efficiently on modern computer systems, including parallel ones;

(ii) to implement the developed algorithms and to create software tools, as well as to test them on benchmark problems close to the advanced requirements of real-life computer simulation practice.

Currently the Department of Scientific Computing participates in several international joint research programs financed by EU, NSF-USA, Volkswagen, etc. The successfully finalized in 1998 Copernicus Project "High Performance Computing in Geosciences. Safety of Constructions with Respect to Rock Deformations and Movements" represents the abilities of the group from the Department of Scientific Computing to perform high level research in an interdisciplinary international research team.

The Department organizes the biannual Workshop on "Large-Scale Scientific Computations".

The Department of Scientific Computing numbers two associated professors, two senior research fellows and one supporting researcher.

The **High Performance Computer Architecture (HPCA) Department** at the Central Laboratory for Parallel Processing was founded in 1998 at the Bulgarian Academy of Sciences and is chaired by Prof. Vladimir Lazarov who led High Performance Systems and Parallel Algorithms Laboratory existing since 1986. The research and development areas cover:

- Computational Models;
- Advanced Computer Architectures;
- Computer Simulation of HPCA.

The department staff consists of eight researchers: three associate professors and five senior researchers.

The **Department of Linguistic Modeling** was set up in 1987 as Linguistic Modeling Laboratory. The formation of the Laboratory was intended to meet the modern trends in the research and application of natural language processing. The Department's main tasks are:

- Computer modeling of basic fragments of the Bulgarian language - lexical and grammatical resources. A computer dictionary of Bulgarian (70 000 units) was prepared in two versions.
- Computer modeling of Slavonic languages. (Computer dictionary of Russian - 100 000 units).
- Computer processing of multilingual resources (Bilingual aligned Corpora base is compiled for French-English, French-Bulgarian and English-Bulgarian parallel texts: 2.5 Million words).
- Methods and tools for knowledge based machine aided translation (System for

machine-aided human translation with generation of explanations in natural language).

The Department of Linguistic Modeling have actively participated in twelve international projects.

The personnel of the Department of Linguistic Modeling enlists nine researchers, two of them being associate professors and five research fellows.

The **Mathematical Methods for Sensor Data Processing Department** (MMSDP) at the Central Laboratory for Parallel Processing (CLPP) is founded in 1988 at the Bulgarian Academy of Sciences.

It specializes in solving complex theoretical and practical problems involving sensor data processing for Bulgarian Ministry of Education and Science, Ministry of Industry, Ministry of Defense, Air Traffic Control Authorities, and Sofia Technical University.

Employing modern mathematical approaches and high performance computers, the researchers in the Department provide R&D products for solving basic problems of sensor data processing systems: automation, performance improvement, initial operator education and training. The efforts of the research team are directed both to new applications and to technological upgrade of existing sensor data processing systems. Significant experience in developing and applying effective sensor data processing approaches and methods for real-time multisource kinematic and attribute data correlation, association, estimation and fusion is accumulated. The main R&D areas cover the following directions of real-time sensor data processing:

- Multiple Sensor Multiple Target Tracking (track initiation, measurements data association, measurements and tracks fusion)
- Stochastic systems identification and hybrid estimation
- Automated collision warning/avoidance in navigation conflicts (object’s optimal control)
- Parallel MTT algorithm design and implementation.

In 1999, the department consists of 13 researchers: two full professors, two associate professors and seven senior researchers. Two of them have D.Sc. degrees and nine have Ph.D. degrees.

More information on Central Laboratory for Parallel Processing is available at its Web site: **http://www.acad.bg/**

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