jet INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2011, VOL. 57, NO. 1, PP. 65–70
Manuscript received January 19, 2011; revised February 2011. DOI: 10.2478/v10177-011-0009-8

Multisensor Tracking of Marine Targets – Decentralized Fusion of Kalman and Neural Filters

Andrzej Stateczny and Witold Kazimierski

***Abstract*—This paper presents an algorithm of multisensor decentralized data fusion for radar tracking of maritime targets. The fusion is performed in the space of Kalman Filter and is done by finding weighted average of single state estimates provided be each of the sensors. The sensors use numerical or neural filters for tracking. The article presents two tracking methods – Kalman Filter and General Regression Neural Network, together with the fusion algorithm. The structural and measurement models of moving target are determined. Two approaches for data fusion are stated – centralized and decentralized – and the latter is thoroughly examined. Further, the discussion on main fusing process problems in complex radar systems is presented. This includes coordinates transformation, track association and measurements synchronization. The results of numerical experiment simulating tracking and fusion process are highlighted. The article is ended with a summary of the issues pointed out during the research.**

***Keywords*—Target tracking, sensor fusion, Kalman filter, neural filters.**

I. Introduction

RADAR Target Tracking is the key source of information about the observed object's movement both on the maritime vessel and in the shore traffic control and management systems. Especially in the second case, where complex systems consist of many radar stations, data fusion allows to improve safety of vessels movement. Each of the tracking radar performs the estimation of the state of observed objects. Its results are predicted movement vectors of targets, which compiled create so called traffic image. It is a basis for VTS (Vessel Traffic Services) operators to undertake decisions about traffic management.

Shore-based traffic control systems are commonly used way of ensuring safety of navigation on waters with heavy traffic. Most of the systems are established on canals, rivers and fairways at the harbor entrance. The VTS systems are widespread on European waters, especially at the North and Baltic Seas. Traditionally used sensor is a radar, which functionality has been increasing over the years with the improvement of radar tracking methods. In the last few years a new system for observing ships – AIS (Automatic Identification System) – has been developed. However it has not replaced, but improved radar systems providing additional information for AIS vessels. Thus radar tracking still remains basic source of information in maritime traffic control systems. This fact is also confirmed by international regulations on Vessel Traffic Systems [1], [2].

A. Stateczny and W. Kazimierski are with Maritime University of Szczecin, Waly Chrobrego 1-2, 70-500 Szczecin, Poland (e-mails: a.stateczny@am.szczecin.pl, w.kazimierski@am.szczecin.pl).

Shore radar system are usually designed in a way to ensure that there are areas of common range coverage for more than one radar. This eliminates blind areas, but also leads to a situation in which one can achieve more than one vector for tracked targets. Here the idea of fusion arise. As shown in [3] the fusion of vectors allows to improve the accuracy and stability of tracking. Overlaying of the coverage means that a few independent state estimates is obtained for them. This leads to unclear situation and can cause a mistake of an operator. The situation in which one receives two or more movement vector for one target is obviously dangerous and should not be allowed. On the other hand a simple choice of only one of the sensors and rejection of the others may lead towards loosing of important information. The solution of this problem is fusion of the estimates originated from a few sources. It is assumed that it will allow improving of tracking accuracy.

The need of fusion can be also seen in the further perspective of joining radar and AIS data. In the algorithm of multisensory data fusion not all sensors have to be radars. In this situation some modifications of the matrixes used has to be made, but the basic concept remains the same.

Most of the commercial approaches to tracking makes use of Kalman Filter and its extensions and mutations. Therefore the first idea of performing tracking data fusion is to create multisensory Kalman Filter. There are however other approaches like applying artificial neural networks for tracking. The studies on these methods have been conducted in the Maritime University of Szczecin for many years. The most important result was developing a multiple-model GRNN filter [1], [4]. Now as the research on the new filter are continued they are focused on fusing neural method with traditional numerical filter. Different algorithms of fusion and different kinds of sensors are included [2], [5], [6].

The paper presents basic concepts of fusing different filters for radar tracking. Moreover the results of preliminary research are shown. They consider use of decentralized fusion of Kalman and neural filter for tracking target by three shore radar station.

Next paragraphs describe a comparative overview of Kalman and neural filters, possible approaches to data fusion and the most important problems connected with this process. Then the algorithm of decentralized fusion is proposed and the results of numerical experiment are presented.

II. An Overview of Tracking Algorithms in Maritime Radars

Marine radar trackers have to deal with relatively slow movement ahead comparing to large transversal errors. Various numerical filters were proposed for this task all over the years. The most popular of them is Kalman filter with its numerous modifications [5]. It is however possible to use other approaches like artificial neural networks.

A. Numerical Filters

The family of Kalman filters used for radar tracking is quite numerous, since different structural models of state and measurement vectors can be used. One of possible solution assumes that the target on the radar screen representing a moving object can be described with linear state and measurement equations. The discrete state equation has a form of:

$$x_{k+1} = F_{k+1}x_k + w_k \tag{1}$$

where:
x – state vector;
F – transition matrix;
w – state noise vector – it is usually assumed that it is a white Gaussian noise with known covariance matrix Q.

State vector is proposed in the form of:

$$x = \begin{bmatrix} x \\ y \\ V_x \\ V_y \end{bmatrix} \tag{2}$$

where:
x, y – position of the target;
V_x, V_y – Speed of the target.

The measurement can be described with the following equation:

$$z_{k+1} = G_{k+1}x_k + v_{k+1} \tag{3}$$

where:
v – measurements vector;
G – measurements matrix – of so called gradient matrix;
v – measurement noise vector – it is usually assumed that it is a white Gaussian noise with known covariance matrix R, v is not correlated with w.

The Kalman filter itself is described with the following equations [4]:

$$\begin{aligned} \hat{x}_{k+1} &= x_{k+1/k} + K_{k+1}(z_{k+1} - G_{k+1}x_{k+1/k}) \\ K_{k+1} &= P_{k+1/k}G^T_{k+1}(G_{k+1}P_{k+1/k}G^T_{k+1} + R_{k+1})^{-1} \\ P_{k+1/k} &= F_{k+1}P_kF^T_{k+1} + Q_k \\ P_{k+1} &= P_{k+1/k} - K_{k+1}G_{k+1}P_{k+1/k} \\ x_{k+1} &= F_{k+1}\hat{x}_k \end{aligned} \tag{4}$$

The above presented linear Kalman filter can also be exchanged with Extended Kalman Filter in which transition and measurement matrixes are represented with linearized, nonlinear transition and measurement functions.

As the above mentioned methods suffer from sudden decrease of accuracy during manoeuvres of an object, other numerical approaches have been proposed. They can be generally described as multiple model filters, but can also be divided into more specific groups. The main idea is to choose the best for present situation of the elementary Kalman filters. This can be done via adaptive estimation, decision-based methods or other multiple model approaches like IMM.

B. Neural Filters

Artificial neural networks are the algorithms, that have nonlinearity implemented in its nature. Therefore they should perform quite well in case of nonlinear movement. The research on this has been carried out in Maritime University of Szczecin for the last 15 years. Many network structures had been examined and especially good results have been obtained with the use of General Regression Neural Network.

GRNN performs kernel regression, resulting in computing weighted average of teaching vectors. The weights are the values of Gaussian kernel function for the distances of input vector to teaching vector. The teaching sequence consists of previously measured vectors. Thus GRNN performs the estimation of movement vector according to following equation [1]:

$$\begin{bmatrix} Vxe_i \\ Vye_i \end{bmatrix} = \begin{bmatrix} \dfrac{\sum\limits_{i=1}^{n} Vxo_i * e^{-(\frac{||t-t_i||}{2\sigma})^2}}{\sum\limits_{i=e}^{n} e^{-(\frac{||t-t_i||}{2\sigma})^2}} \\ \\ \dfrac{\sum\limits_{i=1}^{n} Vxo_i * e^{-(\frac{||t-t_i||}{2\sigma})^2}}{\sum\limits_{i=e}^{n} e^{-(\frac{||t-t_i||}{2\sigma})^2}} \end{bmatrix} \tag{5}$$

where:
Vxe, Vye – estimated speed vector on axis x and y;
Vxo, Vyo – observed speed vector on axis x and y;
σ – smoothing factor of Gaussian kernel function;
t – actual time step;
t_i – former time steps.

The research showed that due to considerable differences in dynamics, uniform rectilinear motion and non-linear motion require the application of different GRNN parameters. Linear motion requires a longer teaching sequence and a higher value of network smoothing coefficient; during the target's maneuver, on the other hand, the network with a shorter teaching sequence and a smaller smoothing coefficient does better. A universal GRNN should thus make it possible to effectively detect a maneuver and also automatically change the GRNN parameters used for estimation. The conception prepared assumes the simultaneous functioning of two networks-maneuver and stable network- switching module with the task of detecting the start and the end of the maneuver and switching of the output signal to the respective network output. A construction diagram of such a filter has been presented in Fig. 1.

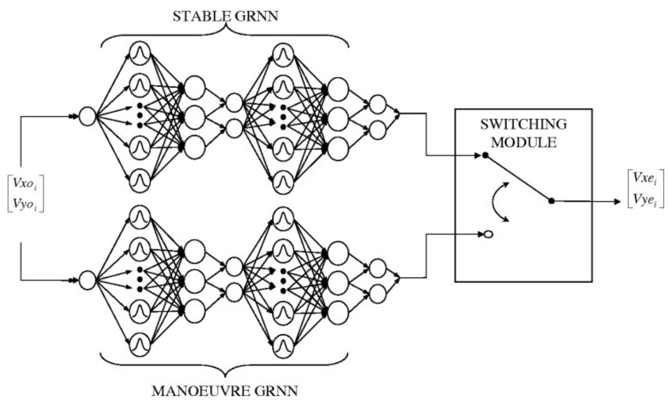

Fig. 1. GRNN filter for target tracking [4].

The switching module is a logical algorithm with the task of selecting the network to take the output signal from one of the networks and transmitting it to the filter output. For this purpose it is necessary to determine whether the tracked target is in the phase of maneuver or of uniform motion by detecting the maneuver start or completion. Another essential task of the module is switching from one network to the other in a way that the vector stability should be maintained. The differences between the outputs of both networks may be large enough to cause a sudden vector jump on the radar screen by direct switching over. This function may be joined with the detection depending on the detection method applied [7].

The patent application for the above method has been made in 2008. The main problem of using GRNN in respect of data fusion is that the mentioned algorithm estimates only the movement vector, not the state vector in the form of (2). Thus different concepts of fusion are further proposed.

III. Fusion in Maritime Radars

As it has already been pointed out, there are areas of common coverage of radars in radar shore systems. Each radar performs its own tracking calculation, which results in having a few different movement vectors for a single target. To avoid this behavior a data fusion has to be performed. It can also be used for improving the tracking process with additional radar sensor in system.

A. Concepts of Neuro-Numerical Tracking Data Fusion

The basic way of tracking data fusion is to use separate numerical filters to built one multisensory Kalman Filter. It is possible to fuse numerical and neural filters. There is however one important problem with this – GRNN filter can estimate only movement vector (without position), not state vector like it is in Kalman Filter. Thus three concepts of such a fusion are:

- Hybrid Kalman/GRNN filter – only movement vector is estimated. The main idea is similar to Decision-based filters. The system use either Kalman or GRNN filter, depending on a situation. At the beginning of tracking and during maneuvers – GRNN is used. The maneuver is detected based on GRNN,
- GRNN as maneuver detection – when maneuver is stated, Kalman filter is reinitialized. Until it becomes stable, GRNN is used for the output (no position).
- Movement vector fusion – the movement vector, which is in both filters, is fused as weighted average of two vectors and the position is always derived from Kalman Filter state vector without any fusion. This approach to fusion was examined in a numerical experiment.
- The above can be recalled as the philosophies of fusion. From the mathematical point of view the fusion can be divided to central and decentralized fusion [8]. Despite the fusion method chosen, there are always a few problems to be considered.

B. Valid Problems of Fusion

There are three main fusion problems with targets from different radar sensors:

- track association,
- coordinates transformation,
- measurements synchronization.

Each of these will surely arise when implementing the fusion algorithm in practice and each of them could be a subject of a separate paper. They will be, however, briefly presented in this paragraph.

Track association is the key issue in the process of fusing any kind of targets. When performing fusion one has to be sure (on the desired level of confidence) that the tracks he is about to fuse describe the same target. If not the result of fusion can be contrary to expected – the information about other target fused with the information about tracked target will cause less accuracy of the estimation. The problem of track association can be described as the process of finding such a similarity between tracks, that it can be said on the given level of confidence, that analyzed tracks belong to the same target.

The easiest technique for associating tracks is to compare the position of the target achieved from the sensors. Additionally the movement vector can be analyzed. Some authors include track association process in fusion algorithm. Then it involves complete estimated state vectors and its errors as it can be find in [3].

The transformation of coordinates is also necessary for proper data fusion. It affects the preparing phase for tracking. Radar sensors in a system are somehow distributed in the area of tracking system. Each of them measures bearing and distance in its own polar coordinate system centered at the position of the sensor. One cannot fuse the estimates found in many different coordinate systems. The most practical approach will be to assign one of the sensor and its coordinate system as the fusion origin. Then all the coordinates should be converted to this system. Moreover for the reasons of further application it is much better to use Cartesian coordinates than polar coordinates. Thus the fusion coordinate system should be Cartesian and probably (but not necessary) centered at the position of selected sensor. As the position of radars in the system is usually geographically expressed, the conversion of coordinates will also include transformation from geographical

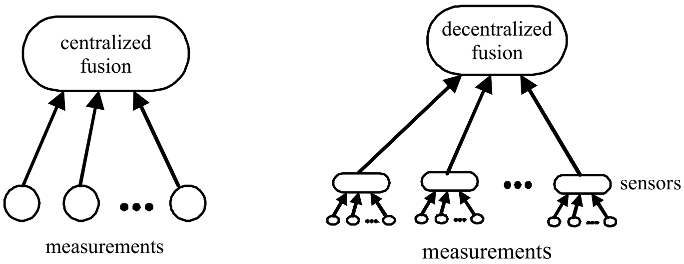

Fig. 2. Models of multisensor data fusion.

system to local x, y, z system. This problem is also a key issue, as the fusion cannot be performed if targets are described in different coordination systems.

Third problem is also very important in the data fusion. It would be very naive to assume that the data of all sensors will be gathered at the same time of an observation. Moreover they will be transferred for fusion with different delays. There are several techniques, which allow taking into account lack of measurements synchronization. In practical implementations, the main problem here is to include process noise. It can be however omitted in some situations. A fine discussion on this issue is given in [3].

All the main problems shown in this paragraph give the picture, that fusion of radar targets data is a quite complicated issue and not limited only to matrix algebra and filtering.

C. Centralized and Decentralized Fusion

There are two basic approaches to multisensor fusion, which has to be considered. First is called decentralized fusion and can be explained as weighted average of target state estimates calculated in each sensor. The second one is called centralized fusion. In this approach the combination of sensors takes place in the measurement level and then one common measurement vector is further processed in one filter [5]. The state is updated with all the measurements from all the sensors and fused estimate is calculated. There are two ways of state updating. It can be done sequentially after every arriving measurement or parallel. In this situation one common measurements vector is built and its size is enlarging after each new measurement. This forces the rebuilding of measurements matrix and measurement noise covariance matrix [3]. The models of fusion are showed in the fig. 2.

Both approaches of fusion are possible to implement in the process of multiradar target tracking. Choosing one of them should be based on empirical initial research. The first approach however seems to be easier for implementation.

In this article the first approach is proposed and discussed in further paragraph.

IV. NUMERICAL EXPERIMENT – DECENTRALIZED APPROACH

The experiment presented in this paper included neuro-numerical fusion of vectors estimated in three shore radar stations. Other experiments, including other scenarios and centralized fusion are planned to be undertaken in future.

A. Fusion Algorithm Overview

The decentralized data fusion is based on the assumption, that each radar sensor provides the state estimate and its covariance. If the estimates describe the same target, fused state vector can be obtained as a weighted average of the particular estimates according to the following equations [2], [9]:

$$\hat{x}(k) = \sum_{i=1}^{l} A_i(k)\hat{x}_i(k) \tag{6}$$

where:
$A_i(k)$ – weights matrixes;
$\hat{x}(k)$ – fusion of state vector estimates;
$\hat{x}_i(k)$ – state vector estimate of i-th sensor.

Weight matrixes are calculated as:

$$A_i(k) = \left[\sum_{j=1}^{l} P_{jj}^{-1}(k) \right]^{-1} P_{ii}^{-1}(k) \tag{7}$$

where:
$P^{ij}(k)$ – cross-covariance matrix of filtration errors between i-th and j-th sensor, which can be obtained from [9]:

$$\begin{gathered} P^{ij}(k) = [I - K^i(k)G^i(k)]\cdot \\ [F(k-1)P^{ij}(k-1)F(k-1)' + Q(k-1)]\cdot \\ [I - K^j(k)G^j(k)] \end{gathered} \tag{8}$$

where:
I – identity matrix;
$K^i(k)$ – gain matrix of the Kalman filter for the i-th sensor in step k.

It can be assumed that this fusion will allow achieving of more accurate state vector than a single sensor if fusing considerably accurate sensors [3].

Neuro-numerical fusion means that GRNN filter is also included in multisensory Kalman filter structure. In this purpose Kalman matrixes F, G, Q and K has to be calculated.

B. Research Scenario

The research has been conducted on the PC based radar tracking simulator, written in VB.NET. The simulator allows to implement different filters and to simulate various maneuvers. In the programme it is possible to watch the movement of targets that do not change their movement parameters, but also to simulate manoeuvres by course and manoeuvres by speed. Errors of radar devices are simulated by means of suitable correlation of values obtained from a generator of pseudo-random numbers.

In the research scenarios, tracking of vessel by three shore stations was prepared. The stations were distributed in the triangle nodes in the distances of 10 Nm. Different sensor errors were implemented in each station. Kalman filter was implemented in each radar. Station no. 1 had GRNN tracking implemented additionally.

Two scenarios were examined. In the first one tracked target was moving with constant course and speed. In the second

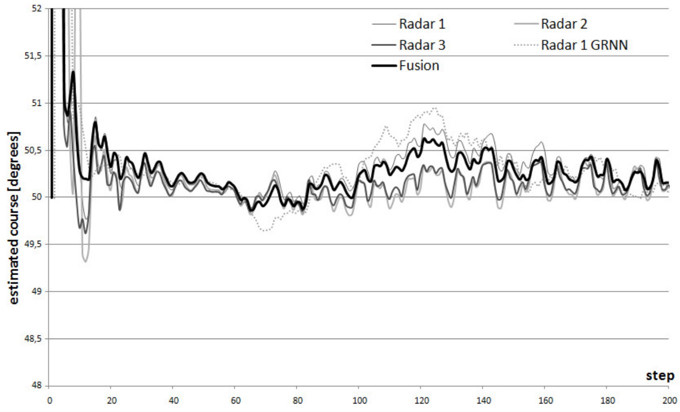

Fig. 3. Estimated course of target tracked by 3 radars and their fusion.

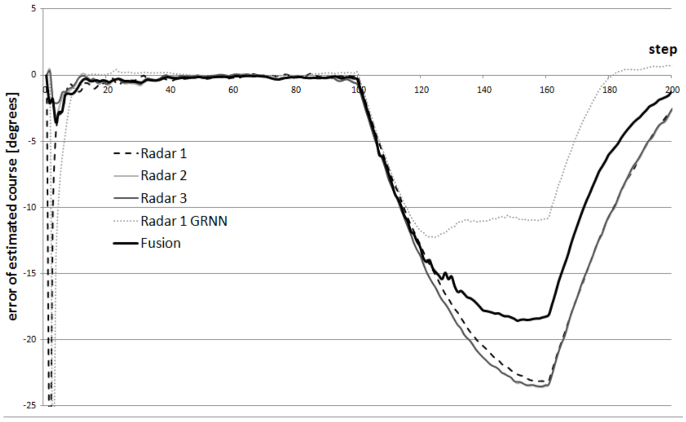

Fig. 4. Estimated course error for target tracked by 3 radars and their fusion.

scenario target was changing course (45° to starboard with rate of turn 15°/minute) after a period of steady tracking. The simulated target had a speed of 10 knots.

A 100 Monte Carlo runs have been simulated. The fusion of three traditional linear Kalman Filters and one GRNN filter has been examined. The simulation lasted 200 steps of estimation, which represents about 10 minutes of real movement.

C. *Results of Experiment*

Figure 3 presents a Monte Carlo course as an average of 100 runs. It can be noticed, that average estimation errors are rather small. As it could be foreseen all of the filters offers similar quality of tracking (errors and stability of vector) during stable movement in the steady phase of tracking. The fusion vector is close to vectors estimated in radar 1 (both filters). This means that worse estimation in radars 2 and 3 were somehow included in fusion. Estimated course errors achieve 2-3° and errors of speed are smaller than 0,5 knots. The quality of tracking in all radars complies with the requirements of IMO Resolution MSC.192(79). According to them, the estimated course accuracy shall not be worse than 5°, and estimated speed accuracy shall not be worse than 0,5 knots or 1%, whichever is greater (95% probability figures).

In the Figure 4 course error during course manoeuvre (2nd scenario) is presented. The error is calculated as an average of 100 Monte Carlo runs.

From Fig. 4 one can notice that tracking error during manoeuvre rises rapidly. The first one to follow the manoeuvre is GRNN filter, which then stabilizes on a New course the soonest. Errors of numerical filters keep on growing up to the end of the manoeuvre. Then the filters are slowly stabilizing on the new course.

The fusion algorithm seems to give satisfactory results. Neuro-numerical fusion follows the manoeuvre faster than numerical filters, but not as fast as GRNN itself. During the manoeuvre the best results were obtained with GRNN filter. It estimates with the smallest tracking errors and stabilization time is the smallest as well.

While using 4-dimensional state vector, the problem of stabilization on the wrong course after the manoeuvre was observed. The problem was solved by omitting estimated speed increments. However more attention should be paid to this problem in future to find more sophisticated solution.

D. *Conclusions*

The experimental research shows that there is a possibility of using multisensory Kalman filter for tracking targets in complex radar shore systems. Fusing of filters allows to decrease tracking errors by using information from both sensors. Monte Carlo runs confirmed statistical significance of this solution.

Using of such a fusion can be however tricky. Let's consider two sensors with significantly different accuracy.

Using of fusion will be profitable only for the worse filter. The better one will be only "slowed down" by less accurate filters in fusion. Thus it can be stated that the best sensors for fusion are these with the similar measurement errors. Of course in case of tracking, there is a lot of other than, *apriori* accuracy of radar, things, which affects tracking, like for example ship-radar geometry.

It is important, that GRNN filter can be included in multisensory Kalman filter as one of the sensor.

V. Summary

The paper showed the concept of neuro-numerical fusion of radar target's vectors. The results of initial research regarding vector fusion were presented. Continuation of research towards neuro-numerical fusion is planned in the nearest future.

The article presented one of the possible approaches to radar data fusion in multisensory radar systems. Such a fusion can be used and needed in maritime complex radar tracking systems like VTS. Morover looking at the growing potential of inland shipping in Europe and the intense developing of River Information Systems, they can be also treated as the potential area of implementation for multiradar data fusion.

Radar data fusion in the paper is understood as finding one estimated state vector for each target seen by many sensors in system. Two possible approaches were presented and the thorough algorithm of one of them – decentralized data fusion was shown.

As a conclusion of the article it can be said, that the algorithm of decentralized fusion of tracked estimates seems to be not so complicated, however bearing in mind the problems stated in paper it is not easy, it requires a suitable knowledge of mathematics (mostly matrixes algebra), estimation techniques, geodesy and the radar processing itself as well.

REFERENCES

[1] W. Kazimierski, "Two-stage General Regression Neural Network for Radar Target Tracking," *Polish Journal of Environmental Studies*, vol. 17, no. 3B, 2008.
[2] P. Borkowski and A. Stateczny, "An Algorithm of Navigational Data Integration," *Problemy Eksploatacji*, no. 1, pp. 181–188, 2008.
[3] Y. Bar-Shalom and X. Li, *Multitarget-multisensor Tracking: Principles and Techniques*. CT, USA: Yaakov Bar-Shalom, 1995.
[4] T. Kantak, A. Stateczny, and J. Urbaski, *Basis of Automation of Navigation*. Gdynia: AMW, 1988, (in polish).
[5] A. G. Bole, W. O. Dineley, and A. Wall, *Radar and ARPA Manual*. Elsevier Science & Technology Book, 2005.
[6] A. Stateczny, "Integration of RADAR, EGNOS/GALILEO, AIS and 3D ECDIS," in *Proceedings of International Radar Symposium*, Warszawa, 2004.
[7] A. Stateczny and W. Kazimierski, "Determining Manoeuvre Detection Threshold of GRNN Filter in the Process of Tracking in Marine Navigational Radars," in *Proceedings of International Radar Symposium*, Wrocaw, 2008.
[8] D. P. Mandic, D. Obradovic, A. Kuh, T. Adali, U. Trutschell, M. Golz, P. De Wilde, J. Barria, A. Constantinides, and J. Chambers, "Data Fusion for Modern Engineering Applications: An Overview," in *Proceedings of Interanational Conference on Artificial Neural Networks*. Berlin: Springer Verlag, 2005.
[9] A. Stateczny, A. Lisaj, and M. Chavan, "Navigational Data Fusion on the Base on Kalman Filter," in *Proceedings of Explo-Ship*, Szczecin, 2006, (in polish).
[10] *IALA Recommendation V-128 – On Operational and Technical Performance Requirements for VTS Equipment*, 3rd ed., IALA, 2007.
[11] A. Stateczny, "AIS and Radar Data Fusion for Maritime Navigation," *Zeszyty Naukowe AM*, 2004.
[12] A. Stateczny and W. Kazimierski, "General Regression Neural Network (GRNN) in the Process of Tracking a Manoeuvring Target in ARPA Device," in *Proceedings of International Radar Symposium*, Berlin, 2005.
[13] ——, "A Comparison of the Target Tracking in Marine Navigational Radars by Means of GRNN Filter and Numerical Filter," in *Proceedings of IEEE Radar Conference*, Rome, 2008.
[14] ——, *Marine Navigation and Safety of Sea Transportation*. London, UK: Taylor & Francis Group, 2009, ch. Target Tracking in RIS.
[15] ——, "Integration of Navigational Data in Vessel Traffic Control Systems," *Polish Journal of Environmental Studies*, vol. 18, no. 5A, 2009.