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Statistical Analysis of Simulated Radar Target's Movement for the Needs of Multiple Model Tracking Filter

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ABSTRACT: The quality of radar target tracking has a great impact on navigational safety at sea. There are many tracking filters used in maritime radars. Large group of them are multiple model filters in which different filter parameters are used for different states (models) of vessel movement. One of possible filter is multiple model neural filter based on General Regression Neural Network. Tuning of such filter means to adjust its parameters for a suitable target movement model. This paper shows the results of an experiment aiming at determining such models based on statistical analysis of target's movement parameters. The research has been carried out with PC-based simulator in which typical radar measuring errors were implemented. Different manoeuvres of targets have been examined. Based on this, the possibility of movement models description has been stated as conclusion.

1 INTRODUCTION

Radar target tracking is one of the key issue influencing navigational safety of vessels at sea. For several dozen of years radar has been present on board of the ships establishing its position as a very important device on the bridge. It has been commonly used for observation of navigational and collision situation in the vicinity of own vessel. In the restricted visibility it is even the basic source of information, while remaining additional and complementary (to visual observation) source in good visibility.

1.1 *Tracking of maneuvering targets in radars*

Radar's functionality increased rapidly after implementing of target tracking facilities in ARPA systems. Since then it has become possible to support navigator's work by replacing manual plotting with automatic target tracking. The quality of tracking depends however on the implemented tracking algorithm. At the beginning relatively simple numerical algorithms, like α-β were used. In time those were replaced by more complex numerical algorithms based on statistical estimation, like Kalman Filter (Bole et al. 2005). It's main deficiency is the assumption of linear movement of the target, which leads to large errors and delays of tracking during target's and own ship's manoeuvres. These limitations are commonly known to the navigators. Various modifications of Kalman Filter (e.g. Extended Kalman Filter, Unscented Kalman Filter) improved the quality of tracking significantly. The main goal was to include non-linear movement of maneuvering vessels into the algorithm. Thus better quality of tracking was achieved.

One of the possible solution of non-linearity problem is to create a few different filters for different motion stages (linear/ non-linear). This approach is called multiple-model filtering and is thoroughly examined for example in (Bar-Shalom & Li 1998).

Another possibility is to use typically non-linear methods for tracking, for example artificial intelligence. An interesting example might be Intelligent Kalman Filter presented in (Lee et al. 2006).

For several years the research focused on use of artificial neural networks in radar target tracking has been carried out in Maritime University of Szczecin. Particularly interesting results were obtained while using General Regression Neural Network (GRNN), which was presented for example during TransNav 2007 (Stateczny & Kazimierski 2007).

1.2 *Research project and paper scope*

The experience on target tracking with neural networks gained so far, resulted in preparing new research project in Maritime University of Szczecin, called *Elaborating of methods for radar tracking of maritime targets with the use of multiple model neural filtration*. The main goal of the project is to combine neural tracking filters with multiple model philosophy, traditionally used for numerical filters. Different neural filters will be adjusted to track targets with different dynamics of movement. This means that, as the first stage of the project, several models of target's movement has to be declared. The aim of research presented in this paper was to perform statistical analysis of different target's movement to conclude on how to find these unique movement models.

2 GRNN FILTER FOR TRACKING IN MARINE RADARS

The filter proposed for radar target tracking and examined in presented research was based on General Regression Neural Network invented by D. F. Specht (Specht 1991), which is basically neural implementation of kernel regression algorithms presented in (Nadaraya 1964) or (Watson 1964). The structure of the network is strictly defined, but it needs some kind of adjusting to solve particular problem. This means mainly determining of input and output vectors, teaching sequence, radial neurons activation function and smoothing factor of it.

2.1 *Tracking with GRNN*

The concept of using GRNN to track radar targets in maritime navigational radars was shown in (Juszkiewicz & Stateczny 2000), (Stateczny & Kazimierski 2005) and (Kazimierski 2008). The filter proposed in these papers consists of two parallel GRNNs. One of them is to etimate Vx and the other Vy. For additional smoothing of signal, which means more stable vector of target on the radar screen, the second filtration stage, with another pair of the same networks is used. To ensure proper functioning of the filter, since the beginning of observation, the dynamic increase of number of radial neuron in hidden layer and elements of teaching sequence is introduced. Observed (measured) values of movement vectors are used as input and teaching values while estimated movement vector is the output. Movement vector is defined as (1).

$$V = \begin{bmatrix} V_x & V_y \end{bmatrix}^T \tag{1}$$

where V_x = speed vector over x axis, V_y = speed vector over y axis.

Both of the networks can be joined into one - more complex structure presented in the figure 1. Such a network has two basic parameters – the smoothing factor and the length of teaching sequence, usually both adjusted empirically.

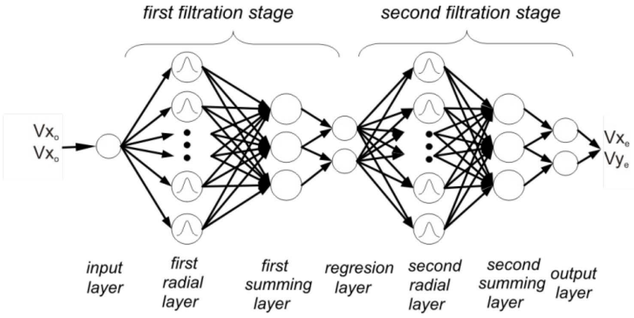

Figure 1. Two-stage GRNN for target tracking.

The smoothing factor determines the range of gaussian function in radial neurons and the teaching sequence determines how many observed vectors are included in estimating the state vector.

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. Thus the estimation of movement vector is calculated according to following equation (Kazimierski 2008):

$$\begin{bmatrix} Vxe_i \\ Vye_i \end{bmatrix} = \begin{bmatrix} \dfrac{\sum_{i=1}^{n} Vxo_i \cdot e^{-\left(\frac{\|t-t_i\|}{2\sigma}\right)^2}}{\sum_{i=1}^{n} e^{-\left(\frac{\|t-t_i\|}{2\sigma}\right)^2}} \\ \dfrac{\sum_{i=1}^{n} Vyo_i \cdot e^{-\left(\frac{\|t-t_i\|}{2\sigma}\right)^2}}{\sum_{i=1}^{n} e^{-\left(\frac{\|t-t_i\|}{2\sigma}\right)^2}} \end{bmatrix} \tag{5}$$

where Vxe and Vye = estimated speed vector on axis x and y, Vxo and 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.

2.2 *Multiple model filtering*

Multiple model approach is the development of so called decision based filters. The main idea is similar. The filter consists of a few elementary filters, each of them tuned to track target in unique movement stage, called model. They are running simultaneously. The final estimation can be a chosen output of one of elementary filters (in the decision based methods) or a combination of elementary estimates (in multiple model approach).

There are several particular algorithms of multiple model tracking, in which different interaction methods between elementary filters is used. Usually the probability of target being in each particular mode state is the criterion. Thus the estimated state vector is weighted average of elementary estimates. Fine description of most popular multiple model methods is given in (Bar-Shalom & Li 2001) and (Li & Jilkov 2005).

2.3 *GRNN multiple model filter*

The empirical research (Stateczny & Kazimierski 2006) or (Kazimierski 2007) has shown that different values of smoothing factor and of teaching length are needed in GRNN filter for different movement characteristics. For uniform motion – longer teaching sequences and bigger smoothing factors and for maneuvers shorter teaching sequences and smaller values of smoothing factor are expected. This gave the idea of creating multiple model neural filter, which can be implemented as decision based filter as well. A suitable patent application was issued. An example of such a filter is given in figure 2.

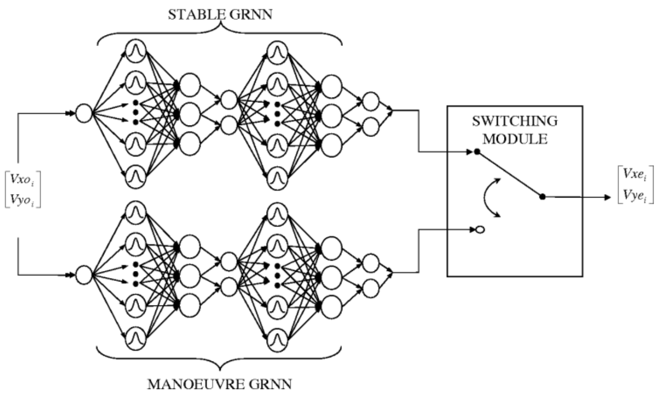

Figure 2. GRNN filter for target tracking.

Main problem in such an approach is to tune elementary filters for suitable movement model. This of course shows the need of defining such models.

3 NUMERICAL EXPERIMENT

The research based on simulation presented in this paper is just an initial phase and preparation for further parts in which real data will be involved. This time PC- based tracking radar simulator was used.

3.1 *Experiment overview*

The main goal of the experiment was to find any statistical dependency, that can be useful for defining tracked targets movement models. To ensure usefulness of experiment results for any tracking method, the unfiltered data were analyzed. These were obtained in the simulator by implementing suitable noise of measurements prior to any filtration.

To obtain statistical information, 100 Monte Carlo runs were performed for each research scenario. For each run, an average value and a standard deviation of ship's course, speed, Vx, Vy and increments of Vx and Vy as well as covariance between Vx and Vy were calculated. After the simulations, obtained values were examined and analyzed with the use MS Excel

The research scenarios were planned in such a way to examine both uniform motion state and maneuver state.

3.1.1 *Simulator description*

The simulator used in research showed in this paper is a PC-based application, prepared by the author in MS Visual Studio.

The idea of radar target simulation used in the simulator derives from (Kantak et al. 1988) and is based on adding to non-cluttered measurement, process noise. Thus the position of simulated target is obtained. The noise is calculated as a product of maximum sensor noise and pseudo-random value. Start point of random numbers is changing, which allows carrying out Monte Carlo simulation.

Own ship movement is also simulated and typical errors of gyrocompass (0,5°) and log (0,05 kn) are included. The auto-correlation function factors were established based on (Stateczny et al. 1987).

The simulator has also other possibilities and functionalities, which were not used for the research for this paper, however they can be used for many other purposes.

3.1.2 *Research scenarios*

The idea of the research is to find different movement models based on statistical analysis of non-filtered target data. The research scenarios therefore include both - uniform target movement and maneuvers.

The first part of research focused on finding statistics for linear movement as the basis for comparison with maneuvering stages. Five different scenarios were examined for uniform movement. Initial situation was the same for each of them, except of course and speed values which differ for particular scenarios. The scenarios are described in Table 1.

Table 1. Scenarios for uniform movement

Scenario no	1	2	3	4	5
Initial situation					
Bearing			030°		
Range			8 Nm		
Own ship course			000°		
Own ship speed			10 kn		
Target movement parameters					
Target course [°]	135	180	270	135	135
Target speed [kn]	10	10	10	20	30

These research scenarios allowed to check the influence of various speed and courses on statistical dependences of target movement during steady movement.

The second part of research aimed at finding results during maneuver of target. The maneuver of course changing was examined as the most and advised in COLREG popular way of collision avoidance. The maneuver was applied with different rate of turn in different scenarios. As the same change of course was assumed, the maneuvers were lasting for different time in each scenario. The statistics were calculated only for the time during maneuver. Detail description of scenarios can be found in Table 2.

Table 2. Scenarios for maneuvering target

Scenario no	1	2	3	4	5
Initial situation					
Bearing			030°		
Range			8 Nm		
Own ship course			000°		
Own ship speed			10 kn		
Target course			135°		
Target speed			10 kn		
Course maneuver					
Course change			90° to starboard		
New course			225°		
Rate of turn [°/min]	10	20	30	40	50

Examining of the maneuvers with different dynamics allowed to answer the question if there is any statistic dependent of turn rate, which can become a basis for establishing movement models in multi model filter.

Each scenario covers 200 measurement steps, which means about 10 minutes of simulation time.

3.2 *Results of experiment*

The simulator used for experiment prepares the output statistics for each of 100 Monte Carlo runs in ASCII file. In the next step it was imported to MS Excel to prepare graphs and to perform further analysis. The results are divided into two parts – uniform motion and maneuver. The conclusions are stated for each part separately and then jointly for all simulations.

3.2.1 *Uniform motion*

The scenarios in which the course was different were analyzed together and the scenarios in which the speed was different were also analyzed jointly.

Figure 3 shows the standard deviation of *Vx* during simulation for each of 100 runs. Scenarios 1, 2 and 3 were included. It can be noticed, that the value of standard deviation does not vary significantly for the scenarios, although in case of scenario 3 the values of standard deviation is slightly bigger than in other scenarios.

Similar results were obtained for other measured values – standard deviation of *Vy*, course and speed. this can lead to the conclusion that standard deviation of movement vector parameters does not change significantly in case of uniform movement with different courses.

In figure 4 the same standard deviation of *Vx* is presented but for the scenarios in which the target was moving uniformly but with different initial speed. Once again the value of standard deviation seems not to vary much in different scenarios.

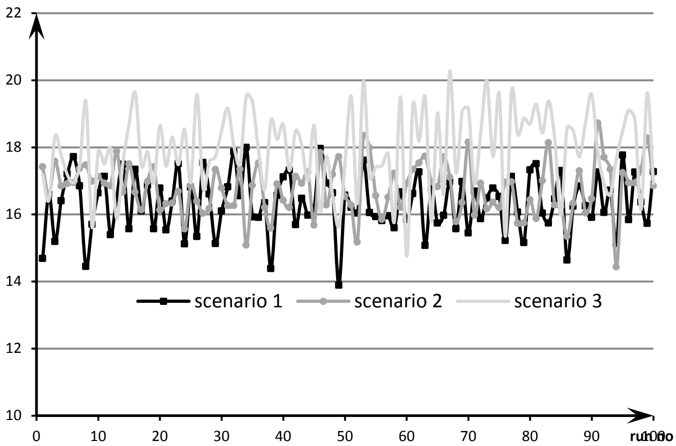

Figure 3. Standard deviation of Vx during 100 Monte Carlo runs for uniform motion of target with different course.

The values for scenario 5 in which the speed was the biggest are usually a bit smaller. As similar results were obtained for other parameters it can be concluded, that standard value of them does not change significantly for the uniform motion, even if the speed is different.

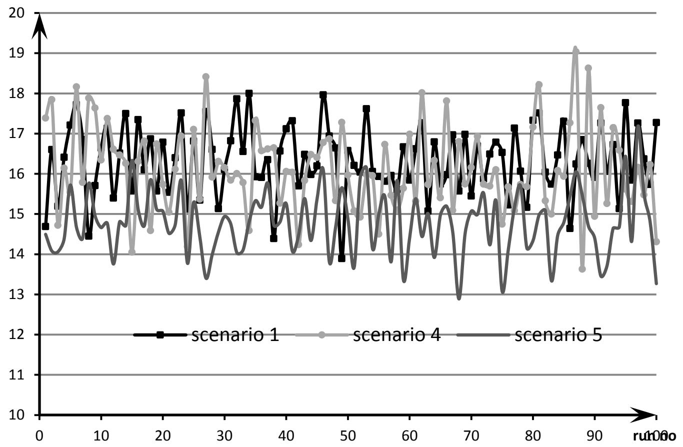

Figure 4. Standard deviation of Vx during 100 Monte Carlo runs for uniform motion of target with different speed

An interesting issue of statistical analysis of movement vector can be covariance of *Vx* and *Vy* vectors. It was measured as the covariance of random samples *Vx* and *Vy*. Figure 5 shows the average value of average covariance in each of Monte Carlo runs. It can be noticed that, although average value vary for different scenarios, the standard deviation remains on the same level. This means that covariance value vary in different scenarios, but it remains in the same "statistical frame" for all of them and it could not be easily stated which scenario is it, based only on the results.

The most important conclusion of the first part of experiment is that one movement model for non-maneuvering target is sufficient. Changes of course and speed do not influence significantly on statistical factors for movement vector parameters. The next question is if this is also true for maneuvering target.

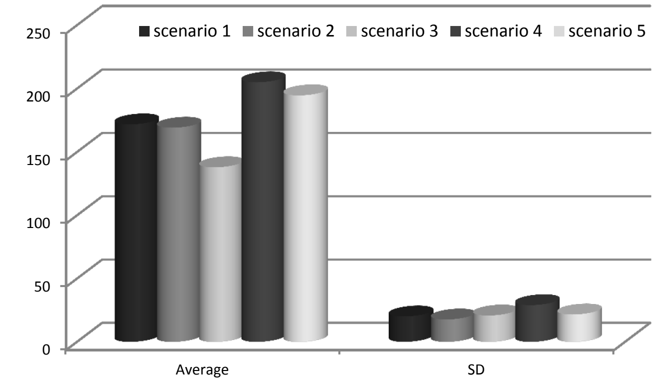

Figure 5. Average value and standard deviation for average covariance in 100 Monte Carlo runs for non-maneuvering target.

3.2.2 *Maneuver*

In the second part of research, maneuvering target was observed. Only course maneuver was implemented. Based on earlier works it was assumed, that conclusions for speed maneuver would be similar.

One maneuver was examined but with five different dynamics, represented by rate of turn.

Figure 6 contains four graphs in fact. Two of them present average values of Vx and Vy during maneuver and two other presents standard deviations of these. The values are presented for 100 Monte Carlo runs. Only two selected scenarios are presented on this figure, namely scenario 1 (rate of turn = 10°/min) and scenario 5 (rate of turn = 50°/min). Graph for these extreme values presents the nature of statistics sufficiently and adding other (middle valued) scenarios to the graph would only decreased its readability.

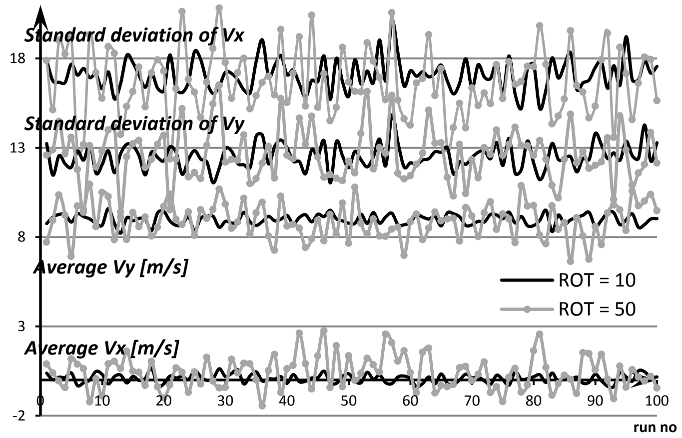

Figure 6. Average values and standard deviations of Vx and Vy in the scenarios with target course maneuver

It can be derived from figure 6, that average values of both Vx and Vy for different scenarios are more or less on the same level, however the variance of them is definitely bigger for more dynamic maneuvers. Similar observation can be made for standard deviation of Vx and Vy. Although in this case it is not so obvious, but larger spread of standard deviation values for maneuvers with bigger rate of turns can be noticed.

The conclusions derived from figure 6 should be confirmed with the analysis presented on figure 7.

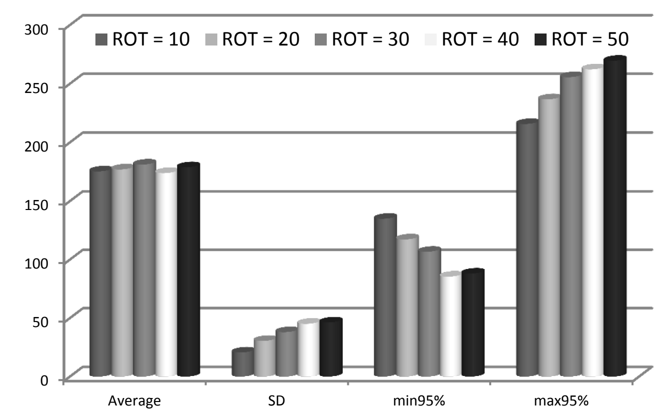

Figure 7. Statistics for covariance of Vx and Vy in 100 Monte Carlo runs.

It can be easily noticed, that average value of covariance remains on the same level for each scenario. What seems to be very interesting, the value of standard deviation is changing at the same time and the tendency is obvious. The faster the turn is (rate of turn is bigger), the bigger standard deviation – the covariance is more spread.

In the figure 7 the boundaries of 95% confidence levels are additionally shown. It was calculated based on average and standard deviation values. These two graphs visualize directly how the region of 95% confidence is enlarging with the increase of rate of turn value.

An important conclusion derives from figures 6 and 7, namely that dynamic of the maneuver can be noticed during statistical analysis. Especially the value of covariance of Vx and Vy can be very useful in determining maneuver rate.

3.3 *Conclusions*

To conclude jointly the research figures 5 and 7 shall be compared. The average value of calculated covariance is basically the same for non-maneuvering and for maneuvering targets. The standard deviation on the other hand is clearly increasing as the rate of turn is getting bigger. So for the steady motion standard deviation is small and for fast maneuvers is bigger.

Statistical analysis of movement vector parameters (course, speed, Vx, Vy) can also be used for differing steady motion from maneuvers, the analysis however is not so obvious.

This leads to a conclusion, that covariance between Vx and Vy is the best value to define movement models and the definition should be based on standard deviation analysis.

4 SUMMARY

The idea of building multiple model neural filter seems to be promising alternative for numerical filters in the light of earlier research.

Definition of movement models is of the key issue for this project. The paper presented the analysis of possibility of determining such models, based on statistic dependences. The results of the research showed that statistical analysis of covariance of movement vector elements (Vx, Vy) can be particularly useful for this purpose. It has been proven that standard deviation of such a covariance is increasing when the target is maneuvering faster.

The determination of particular models, based on standard deviation threshold, shall be the subject of empirical research. This will probably be one of the future steps for continuation of presented research. However prior to these more simulation research shall be conducted. These shall include especially the influence of own ship – target geometry for the statistics observations.

An important conclusion derived from research is also the fact that one movement model is sufficient for describing uniform motion, while for the maneuvers a few models shall be established. The number of them should be the result of empirical research.

Another problem will be to "translate" statistical model to GRNN, thus to adjust network parameters accordingly.

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