The Process of Radar Tracking by Means of GRNN Artificial Neural Network with Dynamically Adapted Teaching Sequence Length in Algorithmic Depiction

A. Stateczny & W. Kazimierski
Maritime University of Szczecin, Szczecin, Poland

ABSTRACT: The radar with the function of automatic target tracking is the navigator's basic aid in estimating a collision situation with regard to his own vessel. The quality of radar tracking process affects the reliability of data provided to the navigator for situation assessment, including the vessel's safety. The use of artificial intelligence methods (GRNN network in particular) for this purpose permits a decrease of tracking errors and the shortening of delay of the vector presented in relation to real time. The article presents an algorithmic depiction of radar tracking by means of GRNN-based neural filter. There have been presented a filter diagram, an algorithm of GRNN parameter selection, manoeuvre detection, as well as the process of radar tracking by means of this filter.

1 INTRODUCTION

An effective avoidance of collision at sea is one of the main tasks of the navigation officer keeping watch on the vessel. His basic aid is the radar with automatic target tracking. It is a very good supplement of visual observation, and in conditions of restricted visibility it provides the basis for estimating a collision situation around the vessel. The quality of radar tracking affects the reliability of data supplied to the navigator, and therefore also the vessel's safety.

As shown by research at the Maritime University of Szczecin, the use of artificial intelligence methods for estimating the vector of targets tracked by radar permits a decrease of tracking errors and the shortening of delay of the vector presented in relation to real time. In particular, good results were obtained with the application of General Regression Neural Network (GRNN). (Juszkiewicz & Stateczny 2000, Stateczny 2000, Stateczny & Uruski 2003)

The parameters of the network applied depend on the dynamics of changes in the target's movement. When the tracked target moves at uniform speed, a network with longer teaching sequence should be applied; when the target performs a manoeuvre it is necessary to shorten the teaching sequence. The construction of a filter applicable for both manoeuvring targets and targets moving at uniform motion requires the application of GRNN network with automatically changing teaching sequence. (Stateczny & Kazimierski 2006b,d)

2 THE PROBLEM OF SELECTING GRNN NETWORK PARAMETERS IN THE PROCESS OF RADAR TRACKING

The General Regression Neural Network was designed for solving regression problems. By means of a mathematical algorithm of general regression the output value is estimated as the weighted mean of model values depending on the distance of input argument from the model. Its usefulness for solving particular problems depends on the proper selection of parameters. There are two most essential control elements: the length of the teaching sequence and the network smoothing factor. (Specht 1991)

The length of the teaching sequence is determined by the amount of models the input value will be compared to. As each model is implemented in one teaching neuron, it is this value that determines the network structure. The smoothing factor is mostly determined empirically and depends, *inter alia*, on the distribution of input values and possible normalisation of input signal. (Lula & Tadeusiewicz 2001)

In the process of radar tracking with models, past values of the estimated vector are implemented in the teaching neurons. Their number has effect on the output vector. If in the case of the target's uniform movement, the highest possible number of models is desirable for smoothing the output, then in the case of manoeuvre, models too distant in time introduce larger errors, as vectors from before the manoeuvre are taken into consideration. They cause larger errors and the vector is smoothed on improper values. (Stateczny 2001a, Stateczny & Kazimierski 2006a)

The smoothing factor is selected in an empirical way. Smaller factors cause higher sensibility of the filter. The estimated values have small errors, but are unstable and vulnerable to possible accidental disturbances. A high value of this factor causes a strong smoothing of the signal; at the same time, tracking errors and delays are larger, as the filter reacts less dynamically to new models, significantly different from existing ones.

The selection of proper GRNN parameters is a compromise between smoothing the output signal and decreasing its errors. The fact is also essential that there are no single ideal control parameter values for each situation; they should always be adapted to the nature of the target's movement, so that the filter should find universal application. (Stateczny & Praczyk 2004)

3 NEURAL FILTER WITH DYNAMICALLY ADAPTED LENGTH OF THE TEACHING SEQUENCE

One concept of a GRNN filter permitting the tracking of targets both during manoeuvring and in steady movement, is a GRNN neural filter with dynamically adapted length of the teaching sequence. Its flow chart has been presented in Fig. 1.

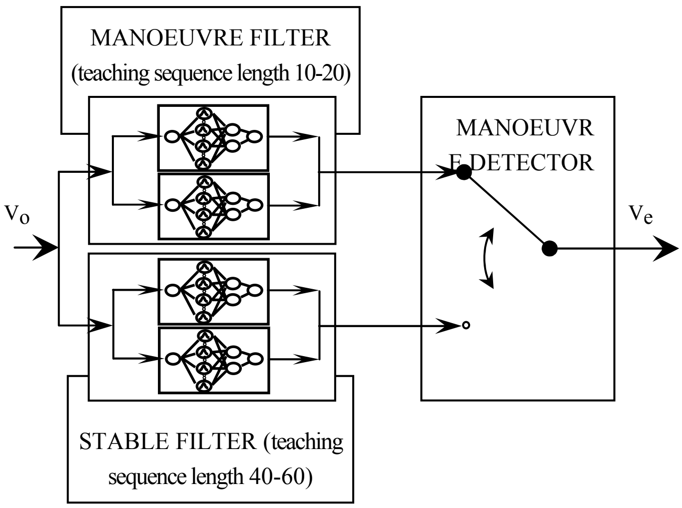

Fig. 1. Flow chart of GRNN filter with dynamically adapted length of teaching sequence. (Stateczny & Kazimierski 2006c)

The filter presented consists of two independently functioning filters and a manoeuvre detector. Each filter consists of two GRNN networks, which estimate the speeds on axes X and Y respectively. One of them (the manoeuvre filter) – with a length of the teaching sequence in the range from 10 to 20 measurements – is responsible for estimating the vector during the target's manoeuvring; the other – with a teaching sequence above 40 measurements (stable filter) estimates the state vector during steady motion. The lengths of the teaching sequences were determined empirically. It was established that the shortening of the teaching sequence to fewer than 10 measurements causes the estimated vector to be not stable enough to be used in navigation. Lengthening of the teaching sequence to more than one minute, on the other hand, causes too large estimation errors.

The task of the manoeuvre detector is, besides detecting the manoeuvre, to switch over the system to obtaining results from a respective filter.

Because of the relatively small calculation load caused by the GRNN network, the most practical solution seems to be the one that assumes both filters to be working without interruption and the manoeuvre detector to switch over the system output to a respective filter. (Stateczny 2001b, Stateczny 2004)

Figure 2 presents the functioning algorithm of a filter with dynamically adapted length of the teaching sequence.

The filter estimates the target movement vector in particular stages, each signifying a successive position measurement. The watched movement vector is then calculated as the difference between successive position coordinates. Such a vector is burdened with radar errors. It is the input signal for the filter.

In each stage, the operation of the filter on obtaining input signal is to single out speed on axis x and speed on axis y by means of Pythagorean theorem.

$$Vx = Vo * \cos KRo \tag{1.1}$$
$$Vy = Vo * \sin KRo \tag{1.2}$$

Next, values Vx and Vy are subjected to the decision block to determine the filter's estimation moment: if it is only the first step (the target has been introduced for tracking), the second, or a further successive step of calculation.

If it is the first step, i.e. the moment of the target's acquisition, the filter must start working. The first stage is to create suitable GRNN structures. The module responsible for construction takes from memory the elements indispensable for the network's creation, introduced by the user in the stage of conceptual filter construction; these are, smoothing factor σ, lengths of teaching sequences of networks applied in the manoeuvre and stable filter, as well as the radial transition function of neurons from the second hidden layer. Gaussian function is the most frequently applied (2)

$$f(x) = \exp\left[-\left(\frac{d(x, x_i)}{\sigma}\right)^2\right] \tag{2}$$

In the first stage the estimated values are the same as the observed ones; they are copied to the model neurons and become the first model. The result is passed to the manoeuvre detector, the activities of which do not as yet affect the result, as both filters (stable and manoeuvre) have the same values implemented in them.

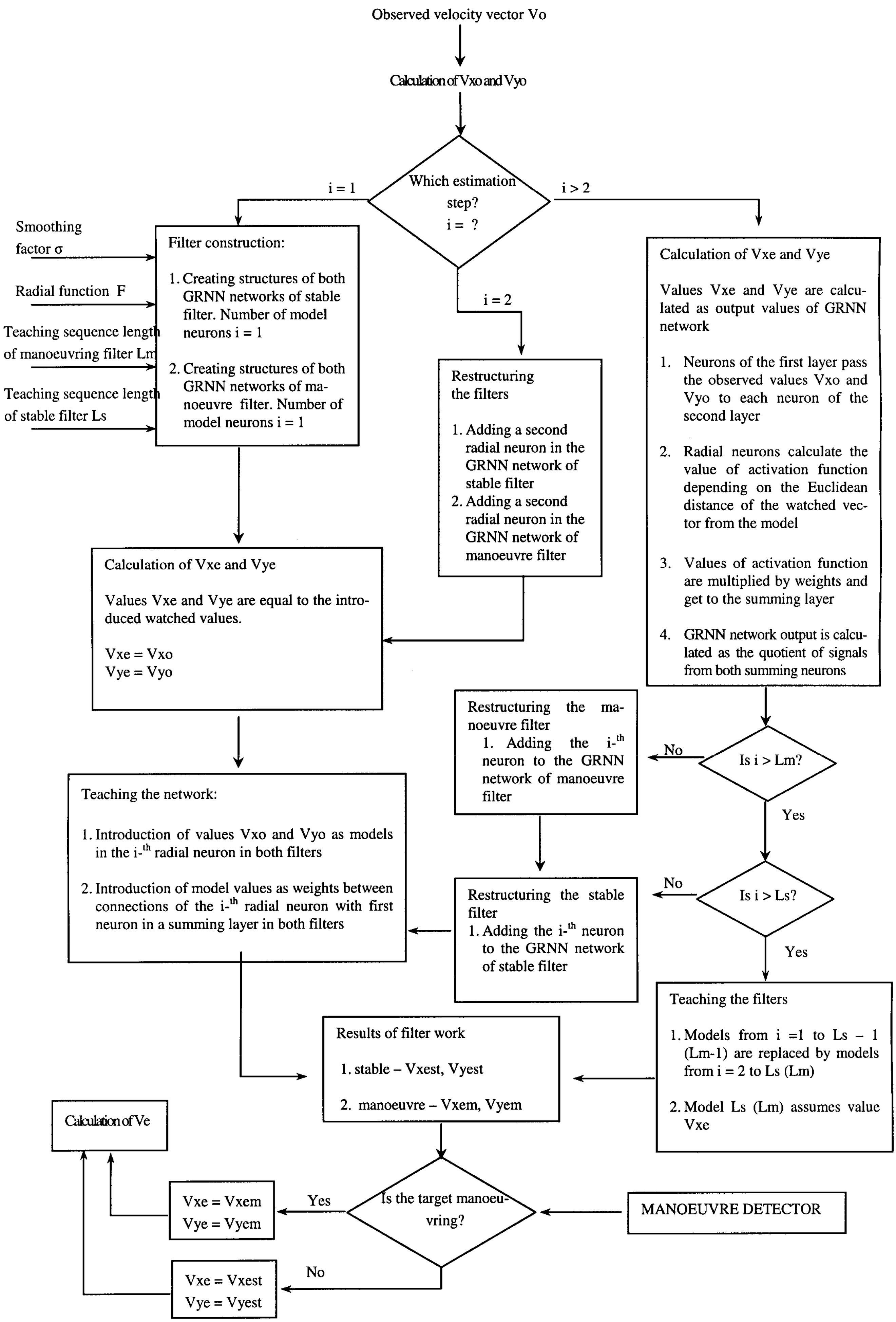

Fig. 2. Functioning algorithm of tracking filter with dynamically adapted length of teaching sequence

The second step of estimation starts like the first and each successive one from calculating Vx and Vy. Next, the structure of each network is developed by one neuron in the radial layer. The observed vectors become now the output values of the filter, which are then copied to the second teaching neuron as models; only from now on is it possible to average the past vectors. As in the first step, in the second step, too, the output signal of the filter is independent from the indications of the manoeuvre detector.

Successive steps of the filter's work now carry out complete estimation of the target's movement vector. The calculation pattern is similar in each step. First, values Vxo and Vyo calculated from the watched velocity vector are given as input signal to respective networks. Next, estimation of the output vector takes place, on the basis of existing models. In the following part of the step the estimated vectors join the models and are copied into the last radial neuron. Thus, in each step the network's work cycle is carried out, and then teaching it a new model, possibly coupled with developing the structure. Each network functions independently from others, estimating the vector respective to itself.

Neurons of the first layer have only the task of passing the input value to all neurons of the radial layer; they are linear neurons, their output signal being a linear function of the input signal.

In the radial layer there follows the calculation of Euclidean distance between input and model vector, and then the value of activation function for this distance, according to formula (2).

This value is passed to the third layer, that is, to two summing neurons. The first sums the values passed from all neurons in the hidden layer. The values passed to the second of summing layers are multiplied "on the way" by the values corresponding to the arguments from the models. Neurons of the third layer sum the numbers obtained and pass them to the fourth layer.

The neuron in the fourth layer divides the sums obtained from summing units by itself, obtaining as regression result the estimated velocity vector on axis x or axis y (depending on which network).

Mathematical calculations performed by GRNN network may be presented by means of formula (3),

$$Ve = \frac{\int_{-\infty}^{\infty} Vof\left(Vo, Ve\right)dy}{\int_{-\infty}^{\infty} f\left(Vo, Ve\right)dy} \tag{3}$$

where f is Gaussian function presented by formula (2).

So long as the planned length of the teaching sequence is not reached, it is also necessary to develop each network by one model neuron; this development is performed before the teaching process. After calculating the estimated vector the filter checks if the number of current estimation step (equal to the number of model neurons) has already reached the required length of the teaching sequence for the manoeuvre filter. If not, a successive neuron is added both to the manoeuvre and to the stable filter along with a set of connections. If the rated length of the manoeuvre filter has been reached, the sequence length of the stable filter is checked. If there are still fewer teaching neurons than previously assumed, one neuron is added along with connections. If the teaching sequence lengths of both filters have already reached the required value, the teaching process begins. It consists in copying the vector of this step to the last (empty) model neuron. In the case when the teaching sequence already has the rated length, the values of all models are copied earlier to the previous one, whereby the value most distant historically disappears from the teaching sequence and the last neuron is set at nought, in order for the new model to be copied in.

After calculating the estimated values by the manoeuvre filter and stable filter, one of these values is selected by the manoeuvre detector. The current target movement dynamics is checked. If the target is manoeuvring, then the value obtained from manoeuvre filter is the output value. If the target is moving with uniform motion, the value from stable filter is assumed as final.

The estimated values Vxe and Vye thus obtained permit an easy calculation of the Ve target's speed vector, as well as the estimated target's course.

There follows the next measurement of the target's position and the next step of estimation.

4 MANOEUVRE DETECTION FOR THE NEEDS OF RADAR TRACKING

The algorithm presented in Figure 2 presents the manoeuvre detector merely as a block part of the whole filter. A precise detection algorithm has not been worked out yet; research on it is in progress, as it significantly affects the quality of suggested solution.

The problem of manoeuvre detection is very essential for the filter's functionality. Incorrect functioning of this element will produce an improper signal given on the output; as a result, the obtained vector will be burdened with a larger error than the one worked out within the filter. There are two concepts of manoeuvre detection. The first consists in comparing the increments of the estimated vector obtained by means of one of the filters. The second compares the values of estimated parameters originating from the manoeuvre and the stable filter. The first method is more manoeuvre sensitive, but it depends on prevailing external conditions. In various conditions there are different increment values in the same time unit, which makes the method not universal enough, requiring constant tuning according to prevailing conditions. A merit of the other method is independence from external conditions. In both methods manoeuvre detection according to a definite value in one step only seems pointless due to disturbances. It results from the research conducted that the moment when in three successive steps the assumed value determined in further empirical research is exceeded, it can be considered as the moment of starting the manoeuvre.

5 RÉSUMÉ AND CONCLUSIONS

The correct construction of a neural filter based on GRNN network requires a detailed functioning algorithm of such a device. The GRNN network itself, like most tools of artificial elements, is a rather complicated element and a fluent management of its parameters requires good knowledge of its structure.

It turns out that the selection of proper values of the network's control elements essentially affects the accuracy of results obtained.

A filter based on network with dynamically adapted length of teaching sequence is a proposal possible to be applied for various dynamics of target movement, permitting the estimation of target movement vector in the process of radar tracking with higher accuracy and smaller delays than in the solutions applied so far. The concept presented still requires the improvement of certain elements, with the manoeuvre detector seeming to be of most essential significance; an improvement factor could also be the automation of selecting the smoothing coefficient.

The chief merit of the algorithm presented is its universality; the filter itself is able to adapt to changing circumstances and apply networks with various parameters. Introducing more than two networks working in parallel seems pointless, as it would cause an unnecessary complication of the filter structure, whereas the existing structure permits sufficient adaptation to the situation.

Interference in the network structures – increasing and decreasing the length of the teaching sequence – is uncomplicated enough to consider constructing a filter composed of only two networks (one for estimating Vx, the other for Vy), with the possibility of altering the length of the teaching sequence depending on the situation.

REFERENCES

Bar Shalom Y. & Li X.R 1998, Estimation and tracking: principles, techniques, and software, *YBS*, Norwood.

Duch W. & Korbicz J. & Rutkowski L. & Tadeusiewicz R. 2000, *Sieci neuronowe (Neural Networks)*, Akademicka Oficyna Wydawnicza Exit, Warszawa.

Juszkiewicz W. & Stateczny A. 2000, GRNN Cascade Neural Filter For Tracked Target Manoeuvre Estimation, *Proceedings of the Fifth Conference 'Neural Networks and Soft Computing'*, Zakopane.

Lula P. & Tadeusiewicz R. 2001, *Wprowadzenie do sieci neuronowych (Introduction to Neural Networks),* Kraków.

Specht, D.F. 1991, A Generalized Regression Neural Network, *IEEE Transactions on Neural Networks.*

Stateczny A. 2000, Neural State Estimation in Sea Navigation, *Geodezja i Kartografia* nr 4.

Stateczny A. 2001a, *Nawigacja porównawcza (Comparative Navigation).* Gdańskie Towarzystwo Naukowe, Gdańsk.

Stateczny A. 2001b, Neural manoeuvre detection of the tracked target in ARPA systems, *Proceedings CAMS 2001 Glasgow*.

Stateczny A. (red) 2004, *Metody nawigacji porównawczej (Methods of Comparative Navigation),* Gdańskie Towarzystwo Naukowe, Gdańsk.

Stateczny A. & Kazimierski W. 2006a, Automatic Target Tracking in Radar Systems Using GRNN, Konferencja Morska Gdynia 2005- *Polish Journal of Environmental Studies, Vol., supp. 1*

Stateczny A. & Kazimierski W. 2006b, Aspects of Tuning GRNN Networks for the Needs of Estimating Target Movement Vectors in Marine Radars, *Polish Journal of Environmental Studies, Vol.15, No.4B.*

Stateczny A. & Kazimierski W. 2006c, Detection of Manoeuvre for the Needs of Estimating the Target's State Vector in the Process of Radar Tracking, *International Radar Symposium,* Kraków.

Stateczny A. & Kazimierski W. 2006c, The Length of GRNN Network Teaching Sequence in the Process of Estimating a Target's State Vector in an ARPA Device, *Proceedings of the ICAISC*, Zakopane.

Stateczny A. & Praczyk T., 2002, *Sztuczne sieci neuronowe w rozpoznawaniu obiektów morskich (Artificial Neural Networks in recognizing Marine Targets),* Gdańskie Towarzystwo Naukowe, Gdańsk.

Stateczny A. & Uruski P., 2003, Comparison of neural-network and Kalman-filter approaches to a maritime target tracking, *Proceedings of the International Radar Symposium*, Dresden.