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Underwater source localisation system

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The paper presents source localisation system and the method of the underwater moving source tracking in the shallow water. The effect of radiation of acoustic waves by moving source has been used. Additionally the time filtering and time delay estimation method has been shown for estimation of the navigation parameters and visualisation.

Introduction

Underwater source localisation system consists of following functional blocks: antenna team, broadcasting track, time delay estimation block, filtering block and visualisation block (fig. 1.).

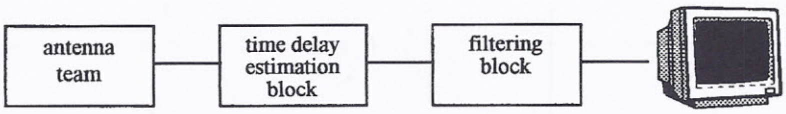

Fig. 1. Schema of functional system

The basic assignment of the antenna arrangement is a reception of signals originated from the sources of underwater movement acoustic waves. These signals are brought to time delay estimation arrangement to delimitate the delay among them, and then delimitations of navigational parameters, such as: bearings, distance, speed. These parameters are surrendered to filtering process in time filtering block. When the position of the antenna arrangement is known, delimitation of position of detected object is possible, and next picturing him on the electronic map.

Antenna arrangement

The antenna arrangement consists of four nondirectional hydrophones seated along straight line. The distance between them is 5m. The distance between hydrophones is a result of length of wave taken of signals. Delays between signals contained to two another hydrophones will be between 0, 3,33 ms in dependences from observation angle of the source. The use of two groups hydrophones seated in perpendicular surfaces in relation to oneself is necessary, because measurement of a very little delays (when source of acoustic waves is found perpendicularly to junctive line hydrophones) can cause formation of large errors. Measured delay makes possible delimitation of bearings and distances to detected object.

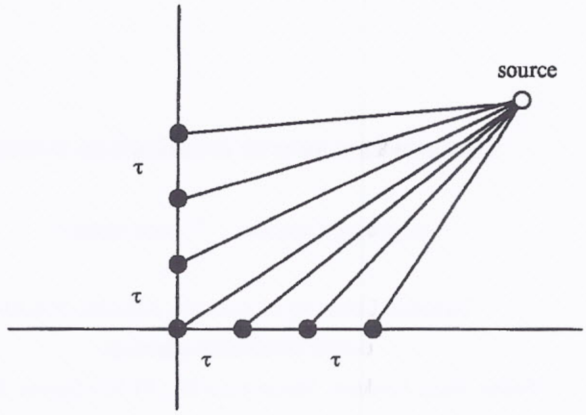

Fig. 2. Localisation of hydrophones.

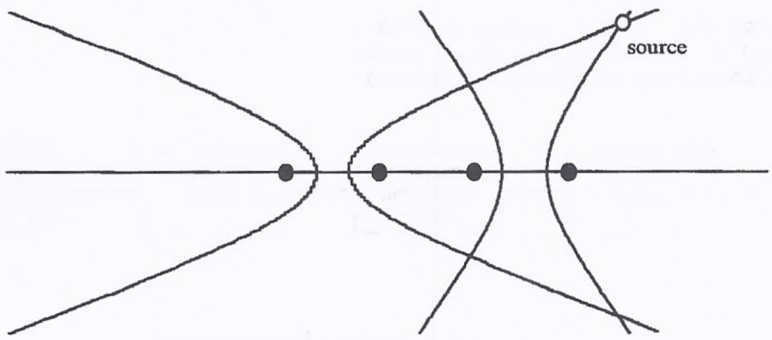

Fig. 3. Localisation of hydrophones in hyperbolic system.

Time delay estimation arrangement

For measurement of time delay used gradient type adaptive algorithm. The adaptive methods are popular because they do not generally require a priori statistics about the signals. The Etter and Stearns gradient adaptive algorithm is attractive because of its simplicity, the lack of matrix operations and the special storage requirements

$$\hat{d}_{k+1} = \hat{d}_k + \mu \cdot e_k \cdot [x_{k-d-1} - x_{k-d+1}] \qquad (1)$$

where k is the time index (sample number) and μ is the step size (convergence parameter). A continuous variable $\hat{d}$ is used in the iteration d, the integer nearest $\hat{d}$ is the estimated time delay between the input signal and its delayed version. The difference between the samples defined by the given time delay δ and its estimation d is the error

$$e_k = x_{k-\delta} - x_{k-d} \tag{2}$$

The bounds for the step size μ are determined

$$0 < \mu < \frac{1}{10R_{xx}} = \frac{1}{10\sigma_x^2} \tag{3}$$

where R_{xx} is the autocorelation function of the input signal and σ_x^2 is its power

Since the bounds for μ are in terms of the power of the input signal it is reasonable to use the popular idea for making μ data dependent. The step size μ can be normalised on every iteration (for every new input sample) by scaling it by the input signal power

$$\mu_k = \frac{\mu_0}{\sigma_x^2} \tag{4}$$

where μ_0 is a properly chosen constant. The input signal power can be estimated in the popular way

$$\sigma_x^2 = \alpha x_k^2 - (1 - \alpha)\, \sigma_{x\,k-1}^2 \tag{5}$$

where α is a constant and $0 < \alpha < 1$.

Another step size control method utilising the misadjustment error power. The way to update μ on each iteration is

$$c_k = \lambda\, e_k^2 + (1 - \lambda)\, c_{k-1} \tag{6}$$

$$b_k = \beta\, [e_k^2 - c_k] + (1 - \beta)\, b_{k-1} \tag{7}$$

$$\mu_k = \gamma\, b_k \tag{8}$$

where c_k is the estimated average of the misadjustment error power, and b_k represents the estimate of the standard deviation of the misadjustment error power. The constants γ, β and λ control the convergence process.

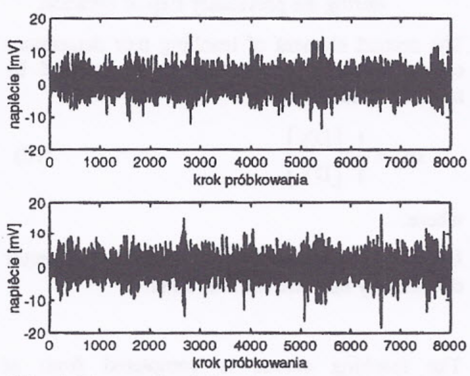

Fig. 4. The received signals

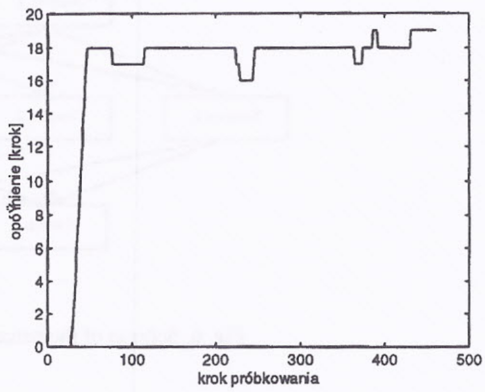

Fig. 5. The delay between signals.

Time filtering arrangement

For construction of the model of neural Kalman filter used the perceptron type neural network. This network is one way flow of signals. The network consists of three layers of neurons. First of layer, called also entrance layer, consists of two neurons and realises part of entry to network. An entrance signal from first layer is given, after multiplication by balances each of enter, to hidden layer. In this model hidden layer consists of twenty neurons. Each of neuron in hidden layer marks own answer on received entrance signals and similarly delivers them to each of two neurons of exit layer. Similarly as previously, appointed signals by hidden layer are multiplied by balance coefficients of exit layer neurons.

To learning previously described network used delta method. In this method each of neural after reception a signals on one's own entry, marks one's own exit signal using earlier settled values of amplification coefficients all of enter and (possibly) threshold. Value of exit signal, appointed by neural on step of process of teaching, is compared with standard answer given by the teacher (classical Kalman filter) in the course teaching. When there are divergences, the neural marks difference between one's own exit signal, and this value of signal, which was correct in the teacher opinion.

When the neural network has one layer, situation is easy and self-evident: each neuron's exit signal is compared to correct value given by the teacher. It gives sufficient base to corrections of balances.

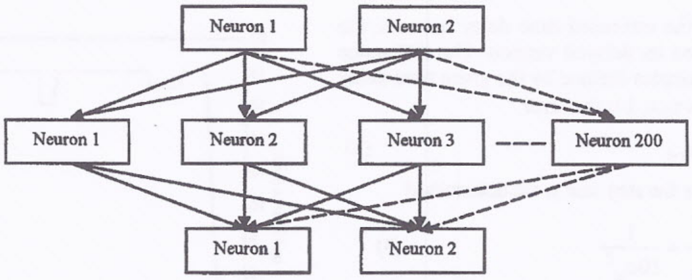

Fig. 6. Schema of the perceptron used in neural Kalman filter

In many-layered network (this same network was used in talked model of neural Kalman filter) situation is more complicated. Neurons of final layer (exit layer) can have estimated errors in easy and certain manner - as previously, by comparison of the signal produced by each of neural with standard signal given by the teacher. It is necessary to mathematical estimate errors of earlier layers' neurons.

The method, which is universally practical to valuing of hidden layers' neurons errors, is back propagation method. This method relies on reproduction of presumable deeper layers' network errors on the ground of backward projecting errors detected in exit layer (considering neural of hidden layer is taken into consideration errors all of neurons), to which of them it sent one's own exit signal. Next errors are added, taking into account sizes of connections' balances between considered neuron and neurons, which errors are added. Progressing in this manner and advancing from exit to network's entry marks oneself presumable errors all of neurons. This oneself obtains bases to qualifications of corrections' balance coefficients these of neurons. How results from previously considerations, in neural Kalman filter model used variant of teaching network by the teacher (in this chance numeric Kalman filter is the teacher) based on previously described rules. Teaching process nets relies on network introduction of example series of signals (entrance images) and answering to them exit signals (exit images).

The collecting of this examples (another called teaching course) is presented to network, till network wont work out of correct exit signal. The exactitude, which has to assure the neural network in the teaching process, is assumed by qualification of error size. This error is defined as difference of exit signal, appointed by network on another step of teaching process and standard answers given by teacher in the teaching course.

The teaching course is completed during the work of classical Kalman filter. This course contains twenty teaching pairs, which determines: counted vector of relative object speed and responding him estimated vector of relative speed of this object, appointed by classical Kalman filter.

The counted vector of relative speed is marked by based dependence:

$$xu_{zi} = \begin{bmatrix} \dfrac{R_{i+1} \cdot \cos(\beta_{i+1}) - R_i \cdot \cos(\beta_i)}{T} \\ \\ \dfrac{R_{i+1} \cdot \sin(\beta_{i+1}) - R_i \cdot \sin(\beta_i)}{T} \end{bmatrix} \tag{9}$$

where:

R_{i+1}, β_{i+1} – the distance and the bearing, which is observed to estimated object, obtained during the actual step of iteration.

Ri, β_i - the distance and the bearing, which is observed to estimated object, obtained during the previously step of iteration.

The second element of teaching pair determines estimated vector of relative speed counted by numeric Kalman filter:

$$xu_i = \frac{1}{T} \cdot \begin{bmatrix} DX \\ DY \end{bmatrix} \tag{10}$$

where:

DX, DY - the composition of relative way vector obtained by numeric Kalman filter.

The teaching course is completed from of twentieth estimation step. When iteration step is 1 milisecond, then numerical Kalman filter works after 20 miliseconds. The reason of this procedure is the fact, that in the first twenty steps of iteration of work filter gives results burdened by too large errors, which would be used in teaching process of network.

It is required to graduate the entrance sizes given to network. In this model, forecasted entrance sizes graduating, both in teaching process, and composition of neural network, from 0 to 1. In this chance exit signals (answer of network) contains oneself in section from 0 to 1 and is required another graduation of these signals.

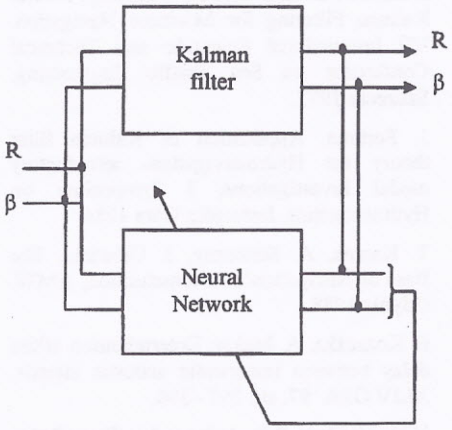

Fig. 7. Schema of neural- numerical arrangement estimating navigation parameters.

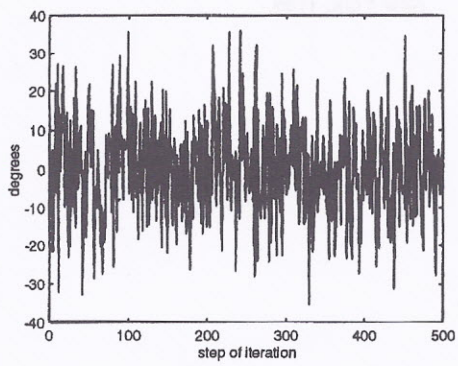

Fig. 8. The mean error value of the bearing obtained no filter

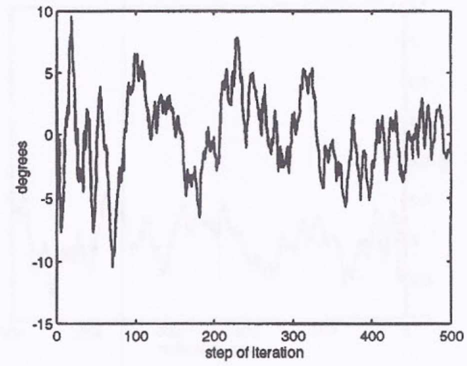

Fig. 9. The mean error value of the bearing obtained by means of numeric filter

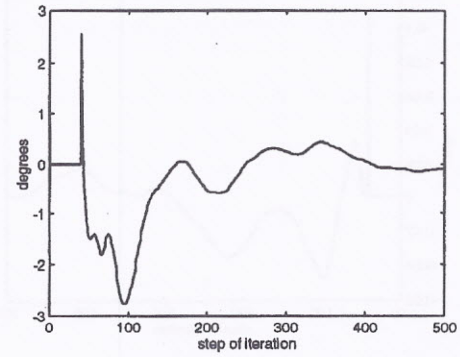

Fig. 10. The mean error value of the bearing obtained by means of neural filter

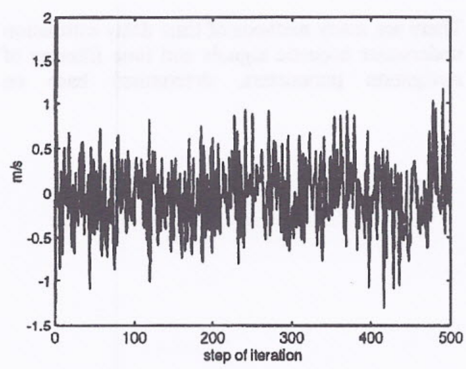

Fig. 11. The mean error value of the speed obtained no filter

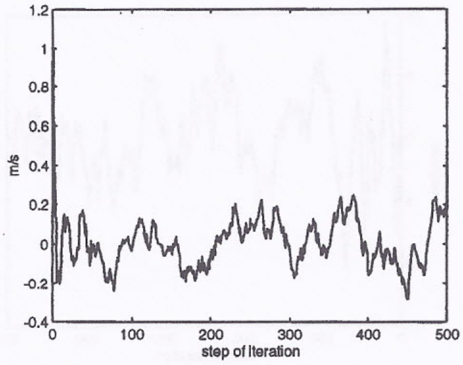

Fig. 12. The mean error value of the speed obtained by means of numeric filter

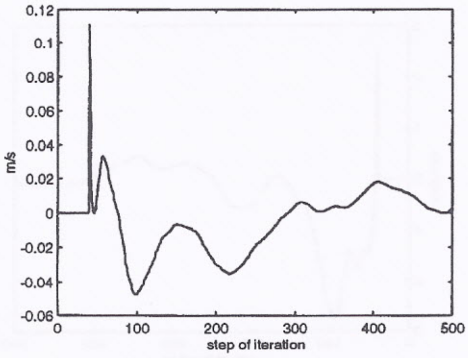

Fig. 13. The mean error value of the speed obtained by means of neural filter

Conclusion

There are many methods of time delay estimation underwater acoustic signals and time filtering of navigation parameters, determined base on measurement of time delays. Methods used to construction the model of detection underwater objects arrangement gives us satisfactory results. Development of artificial neural networks can use them in underwater navigation to movement parameters qualifying of the acoustic wave source. As the teacher of this network can be numeric filter. Using of artificial neural networks joins time delay of navigation parameter qualifying, because of stabilisation of numeric filter and network's teaching process. When the step of iteration is about 1 milisecond, it works very well.

References

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