

WHEELED VEHICLES CLASSIFICATION USING RADIAL BASE FUNCTION NEURAL NETWORK

Intelligent Control Systems and Optimization

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Abstract: The paper presents the problem of using neural network for military vehicle classification on the basis of ground vibration. One of the main element of the system is a unit called geophone. This unit allows to measure amplitude of ground vibration in each direction for certain period of time. The value of amplitude is used to fix the characteristic frequencies of each vehicle. If we want to fix the main frequency it is necessary to use Fourier transform. In this case the fast Fourier transform FFT was used. Because the neural network (Radial Basis Function network) was used, the learning set has to be prepared. Please find attached the results of using RBF neural network such as: example of learning, validation and test sets, structure of the networks and learning algorithm, learning and testing results.

1 INTRODUCTION

The main area of the authors' interest is the decision system automation. The results maybe used in military systems. High significance is given to the intelligent ammunition in the vehicle fighting on the contemporary battlefield. Most often, it is presented as the mean of high vehicle hitting efficiency in the field. It differs from other ammunition types in a way that specific action algorithms are used that allow for individual selection of target it is activated by. In the vehicle (danger) detection systems, various types of sensors are used: acoustic, seismic, optical (including infrared ones), while the acoustic and seismic sensors are mostly used to activate the devices (mines) and object recognition, and the IR sensors (as well as the acoustic ones) are used to indicate a direction the signal comes from. This work focuses on the vibrations registered by the seismic sensors (Jackowski, 2002).

In general, the task of qualifying an examined signal for appropriate group (vehicle) can be realized in two ways – by means of determination of distance between the signal being identified and the determined benchmark (Jackowski, Jakubowski,

2002), or on the basis of its position against the separating surfaces (mostly generated by proper algorithms of artificial neuron networks (Hertz et al., 1991; Osowski, 1996; Rutkowska, 1997). In both cases the selection of feature spaces makes an important stage. Usually their determination is conditioned by efforts leading to the selection of significant values and omission of those features that obtain close values for all objects (different vehicles).

In this case the neural network was used as an element of the decision subsystem. The inputs of the network are calculated as characteristic values of the object. These values are the base of the classification. The output values are the answer of the network. Because of the local representation (of the output values) each of the output is connected to one type of the object (one vehicle).

The main problem was to choose the correct characteristics values on the base of ground vibration. The values of the ground vibration amplitude were obtained by using geophone. Figure 1 shows the example of the measurements.

2 THE GROUND VIBRATION ANALYSIS CAUSED BY VEHICLES

For each vehicle it is possible to measure the amplitude of ground vibration. In this case 6 vehicles were chosen: Kraz, Jelcz, Skot, Tatra, Volvo, Land Rover. The measurements were performed with different speed of the vehicles, different types of the ground and obstacles.

There were two possible ways of signal analysis. The first case - analysis of signal amplitude (for certain period of time), the second case - analysis of some amplitude signal transformation. In this paper the Fast Fourier Transform was used (using Cooley-Tukey algorithm).

Each vehicle has its characteristic frequencies because of the front and rear axle vibration and car body vibration.

The whole FFT is too big to be "included" into the learning and validation set. As a result of analysis three parameters were fixed. The first parameter was the value of frequency of the biggest FFT amplitude, the second was the value of the biggest FFT amplitude and the last one was the number of the vehicle axle. The number of the vehicle axle is evaluated on the basis of the value of ground vibration amplitude.

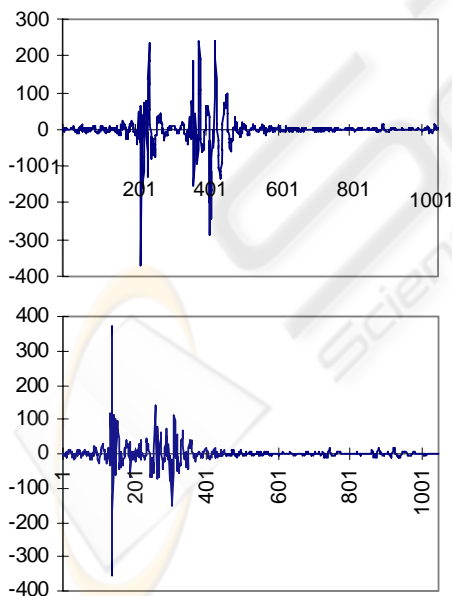


Figure 1: Example of measurements for Kraz (speed 25km/h and 35km/h).

3 THE RADIAL BASE FUNCTION NEURAL NETWORK FOR OBJECTS CLASSIFICATION

The neuron with radial base transfer function is the main element of the RBF (Radial Base Function) neural network.

Figure 2 shows the model of the radial neuron where (t_i) is the center of radial function. Value (e) (activation value) is calculated as follows:

$$e = \sum_{i=1}^n (x_i - t_i)^2$$

The next equation shows the example of radial function:

$$\varphi(x) = e^{-\frac{\|x-t\|^2}{2\sigma^2}}$$

As we can see, the value on the output of the radial neuron depends directly on its value on the inputs as well as the value of the centers (t_i). For each input of the neuron the differences between input values and centers are calculated. This differences are the argument of the transfer function (radial function). According to the above equation the radial neuron "is activated" only for limited range of value ($x-t$). The specific functioning of the whole Radial Base Function network is the result of that features.

The radial neurons are located in the hidden layer of the network. The output values of the hidden layer are put (in the simplest case) into the inputs of the single output.

The radial function depends on the value $r = \|x - t_i\|$. The value of (r) is usually calculated using Euclidean norm. In more complex models of RBF neural networks the weighted norm is applied. It means that the value (r) is multiplied (for each direction) by the value (Q_i):

$$r_i^{Q_i} = Q_i(x - t_i)$$

Because the function argument is (r^2), so we can write:

$$r_i^{Q_i^2} = \|x - t_i\|_{Q_i}^2 = [Q_i(x - t_i)]^T [Q_i(x - t_i)]$$

The values of (Q_i) are evaluated during the learning process of neural network.

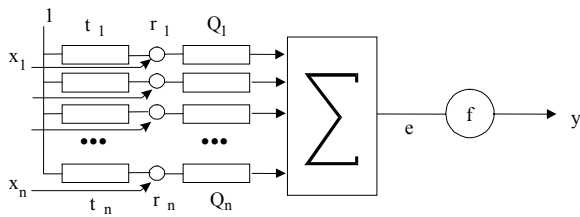


Figure 2: Model of the neuron of HRBF neural network.

The structure of HRBF neural network consists of neuron as above (Wantoch-Rekowski, 1994). The output layer consists of neurons with sigmoid transfer function. It means that the values on the outputs of the network belong to the range (0,1). The number of neural network inputs (n) depends on size of the analyzed space (R^n). The number of radial neurons in the hidden layer is evaluated during the learning of the network. The number of output neurons is connected to the number of different classes (number of object types).

3.1 Learning algorithm

During the experiments the supervised type of learning algorithm was applied (with gradient method). The main element of the algorithm - the criterion function is fixed on the basis of RBF neural network structure. The criterion function is directly connected to the optimization method, as shown (for network with one output neuron):

$$E = \frac{1}{2} \sum_{i=0}^K [W_i \varphi_i(x) - d]^2$$

where:

- W_i - values of output neuron weights,
- d - required value on the output of the neural network,
- K - number of radial neurons in hidden layer,
- x - values of network inputs.

The form of the transfer function in the hidden layer is as follows:

$$\varphi_i(x) = e^{-\frac{1}{2}[Q_i(x-t_i)]^T [Q_i(x-t_i)]}$$

In each step of learning algorithm the new values of the output neuron weights and values of (t) and (Q) are calculated.

4 THE EXPERIMENTS AND RESULTS

4.1 Structure of learning, testing and validation sets

Because of the learning process difficulties the values of characteristics parameters were changed in the learning, testing and validation sets. The values of the biggest amplitude (1st parameter) were divided 100 times and the number of axes were multiplied 10 times.

The part of the learning setⁱ for the example presented in the paper is shown below. The three (left) columns are the values of the characteristic parameter. The next 6 columns describe required values on the RBF network outputs.

```
; DANE PROGRAMU RWR-RBF.EXE
; Learning data (part of the file)
; DATASTRUCTURE=<Column description>
; INPUT - input data, NOTUSED - not
used data, OUTPUT - required data
```

```
PAIRS=(224)
DATACOLUMN[ 1]=INPUT
DATACOLUMN[ 2]=INPUT
DATACOLUMN[ 3]=INPUT
DATACOLUMN[ 4]=OUTPUT
DATACOLUMN[ 5]=OUTPUT
. . .
DATACOLUMN[ 9]=OUTPUT
```

LEARN DATA						
8.05	16.77	30	1	0	0	0
9.22	19.03	30	1	0	0	0
6.83	18.76	30	1	0	0	0
6.83	21.01	30	1	0	0	0
8.54	19.17	30	1	0	0	0

The whole learning set consists of 224 elements with 6 types of wheeled vehicles. The structure of the testing and validation set is similar to the learning set. The testing set consists of all elements from learning set to some other additional elements.

4.2 Structure of the RBF neural network

The structure of the network is the result of the task presented in this paper. The number of hidden neurons was evaluated during the learning of the

network. Description of the RBF is presented belowⁱⁱ:

```
; RBF Network structure RWR-RBF.EXE
; (C) Roman WANTOCH-REKOWSKI,
LAYER INPUT NODES=<3>
LAYER HIDDEN NODES=<16> FUNCTION=GAUSS(1)
LAYER OUTPUT NODES=<6> FUNCTION=SIGMOID(0.9)
```

4.3 RBF neural network learning

The presented learning algorithm (gradient method) was used to learn the neural network. The value of learning coefficient was calculated during the learning process. The initial value of the learning coefficient was the biggest while the final value the lowest. Parameters of the RBF network are included in the *vehicle.net* file.

File presented below (it is the *vehicle.lre* file contents.) shows the example of learning process for RBF neural network using the learning set from the file *vehicle.lrn*.

E	%CU	%CW	Net Err	Lrn cof	Max grad	ukr
1	0.0	0.0	0.14147	0.92700	0.0153	16
2	7.6	16.7	0.05981	0.95481	0.0141	16
3	53.6	50.0	0.03919	0.98345	0.0196	16
4	82.1	66.7	0.02138	1.01296	0.0677	16
5	96.9	100.0	0.00059	1.04335	0.0106	16
6	100.0	100.0	0.00002	1.20952	0.0011	16

where: *EPOKA* - the number of learning epoch, *% CU* - the percent of correct recognized elements of learning set (*.lrn), *% CW* - the percent of correct recognized elements of validation set (*.val), *Net Err.* - the network error value, *Lrn cof.* - the value of learning coefficient, *Max grad.* - the biggest value of network gradient, *ukr* - number of hidden (radial) neurons.

5 CONCLUSIONS

The experiments show that the RBF neural network can be used for vehicles classification on the basis of ground vibration. The main problem was to fix the correct characteristic parameter of FFT.

REFERENCES

Jackowski, J., 2002. Ground vibrations resulted by vehicle motion. *Biuletyn WAT* 11/2002.

Jackowski, J., Jakubowski, J., 2002. Analysis of differentiation possibilities of ground vibrations resulted by the vehicle motion. *Biuletyn WAT* 11/2002

Hertz, J., Krogh, A., Palmer, R., 1991. Introduction to the Theory of Neural Computation. Addison-Wesley Pub. Amsterdam.

Osowski, S., 1996. Neural Networks. WNT. Warsaw.

Rutkowska, D., Piliński, M., Rutkowski, L., 1997. Neural Networks, Genetic Algorithm and Fuzzy Systems, PWN. Warsaw- Lodz.

Świątnicki, Z., Wantoch-Rekowski, R., 1999. Neural Networks; Introduction, Bellona. Warsaw.

Wantoch-Rekowski, R., 1994. Structure of Neural Network Using in Classification Process (in Polish). *Proceedings of Symposium "Neural Network and their Applications"*. Kule.

ⁱ It is the *vehicle.lrn* file contents.

ⁱⁱ It is the *vehicle.str* file contents.