

NEURAL NETWORK BASED RECOGNITION OF SIGNAL PATTERNS IN APPLICATION TO AUTOMATIC ULTRASONIC TESTING OF RAILS

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Summary The paper describes the application of neural network for recognition of signal patterns in measuring data gathered by the railroad ultrasound testing car. Digital conversion of the measuring signal allows to store and process large quantities of data. The elaboration of smart, effective and automatic procedures recognizing the obtained patterns on the basis of measured signal amplitude has been presented. The test shows only two classes of pattern recognition. In authors' opinion if we deliver big enough quantity of training data, presented method is applicable to a system that recognizes many classes.

1. INTRODUCTION

The need of automation of ultrasonic testing in transport is obvious, because of the fact that the manually driven measurement do not guarantee enough efficiency and quality and its cost is much higher than the cost of the automatic testing [1]. Railway companies all over the world use railroad ultrasound testing cars to measure railways. The review of used results can be found in [5, 6]. In Poland the testing car was developed by Technical University of Radom in the 1980s. During the period of 1999-2002 the testing car was thoroughly modernized. Computer driven ultrasonic equipment with digital signal processing has been used [3]. The computer system operating the equipment is composed of four units controlling measurements that enable to show and analyze the measuring data.

A railroad ultrasound testing car use a non-destructive measuring method that is ultrasound testing, which is based on a wave reflection on the border between two layers which are different from each other by velocity of the wave. A mechanic wave produced by a probe is reflected by structure discontinuity and creates echo in the measuring equipment. Characteristic parameters for echo are amplitude and registration time, proportional to the depth of the discontinuity. If the echo measurement and the registration are repeated in periods while the probe is moving along the measured object, a series of amplitude measurements and echo location are created, that phenomenon is called a signal envelope. The concept of creating measurement series is illustrated in figure 1.

In the railroad ultrasound testing car, measurements are taken not by single but by multiple probes (from 7 to 9 normal and angle probes 45° and 72°, echo and tandem methods are used). If you registered all echoes at 1 cm measurement resolution and measuring speed ca. 50 km/s, you would get extremely large data stream (10 MB/s). That is why the instrumentation is equipped with hardware amplitude discriminators (monitors) which allow to acquire only those echoes that comply with at least one of the registration criteria

(e.g. are big enough, corresponding to the defects located in the specific part of the rail, etc.).

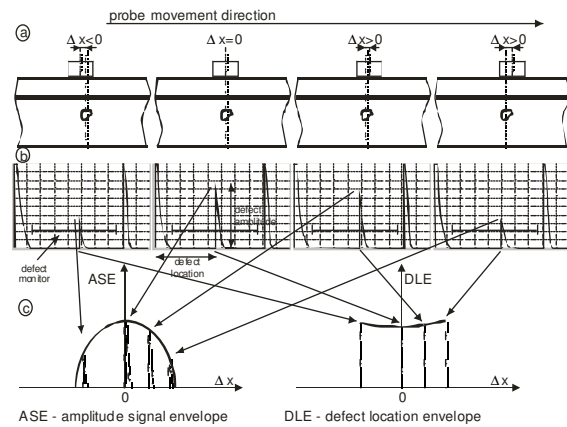


Fig. 1. Signal envelope construction a) probe movement, b) ultrasonic echoes, c) amplitude and location envelope

Thanks to this, the processing data stream decreases to few dozen kB/s. However, during a typical daily testing of a hundred kilometre long section, about 500 MB data is gathered.

During the measurement registration, some simple automatic procedures are realized. These procedures categorize the defects and are based on inductive reasoning. After finishing the measurement, data are thoroughly processed. It is done to join the partial results in a map of defects in a measured rail. The system allows to visualize the registered defects clearly and to correct the automatic classification results. However, in practice the testing car staff usually accepts the classification results without any correction.

A large amount of raw data makes it in practice impossible for anybody to process them. So developing of the automatic defect classification procedures is needed. At the same time it is difficult to construct such procedures because there is no information coming from an expert. It is a paradox that can be solved when you use statistical measurement data processing. Its goal is however to

create some descriptors of gathered data as well as to create statistical evaluation of new measuring data procedure. It is a typical task to learn on the basis of data, so it is natural to use machine learning method, e.g. artificial neural network [2].

2. PRELIMINARY DATA PROCESSING, EXPERIMENT METHODOLOGY

The railroad ultrasound testing car measurement results were used for the experiments. We chose some of the measurements classified by the operator, which come from an exemplar section where some of the typical rail defects are made. This section is used to calibrate the equipment before the measurements are taken. The detection of artificial defects in the exemplar section guarantees the detection of real defects on the track. The correct detection of patterns in measuring signals from the exemplar section shows that the technology is useful in real testing conditions. Available records contain test measurement in different conditions, especially with different attrition rate of the probes, at different speed and with different resolution that is with different density of the data stream. As mentioned before the data are processed by the operator and equipped with a classification defining if a signal represents a picture of a dangerous defect, a defect that should be observed or a rail joint. Expert's knowledge essential to teach neural networks in supervised manner is available. Different kind of networks were used, e.g. multilayer perceptron (MLP) that realize static patterns classification. In order to teach the MLP on the obtained data, the preprocessing of the data is necessary. The preprocessing stage is realized with the use of specialized software tools. Functional range of these tools covers among others:

- selection of source data that will be put in a data set (measurement time, equipment channel)
- setting of pattern types that will be put in a data set (dangerous defect, defect that should be observed, a rail joint)
- setting of measurement subset put in the data set (e.g. only information about the defect amplitude or in addition the results of the defect location, etc.)
- windowing of measurement signals by setting the length of the window and minimal length of primary pattern included in the window
- adding Gaussian noise to the signal with defined mean value and variance
- generating data sets (including sets containing the expected classifier output values in the format accepted by the software realizing neural network training)
- visual inspection of the generated data sets to control if the process has been conducted correctly.

The need to conduct the processes comes out of the experiment methodology.

The main task is the recognition of the signal pattern made by the rail joint, especially to differ it from the other signal patterns e.g. a defect pattern. It is limited to the signals coming from normal probes (two equipment channels). The rail joint signal is measured in the channels with the angle probes 45° , but the pattern registered by such probes is different from the signal pattern registered by the normal probes, so these experiments are limited only to the normal probes. The success of the recognition of the rail joint in the normal probes means that the neural network is able to carry out the analogous process for another signal pattern, e.g. for the signal coming from the other types of probes. In addition, the task of correcting the classification of the rail joint pattern requires distinction of it from the whole set of patterns obtained from the signal. So the discrimination between the whole pattern groups is needed.

Besides the experiments that include the recognition on the basis of the full information (amplitude and defect location), much more difficult discrimination tests are taken only on the basis of the amplitude signal. Defect location is a very characteristic parameter of the rail joint – all fishplate bolts are at the same depth. If the neural network can create a classifier that uses mainly the information about the location to discriminate, it means that the method is good. It is good when an elastic procedure which is able to create complex models, constructs a simple model when it is possible. However, extending conclusions from the experiments on other, less obvious signal patterns demanded testing the method in more difficult conditions. Distinguishing the rail joint signal from the defect signal without any information about its location can be difficult even for people, so it is a very demanding test for an expert system. Besides there is also a financial aspect. Decreasing the stream of data needed to the process is always economical.

Similarly, it was added another difficulty – the lack of information from a distance counter in the classification. In other words, the information about the exact spatial relations between the particular patterns is omitted. Only the natural placement of the samples that is the information about their vicinity and their sequence. It is worth remembering that in the railroad ultrasound testing car's equipment conditional measurement registration is used, so only the measurements for which the amplitude is bigger than the monitor discrimination threshold are registered. It means that the samples located next to one another can represent any points on the rail. It makes it more difficult to recognize the joint pattern. It is illustrated in figure 2, where the joint patterns are shown in full and conditional recording.

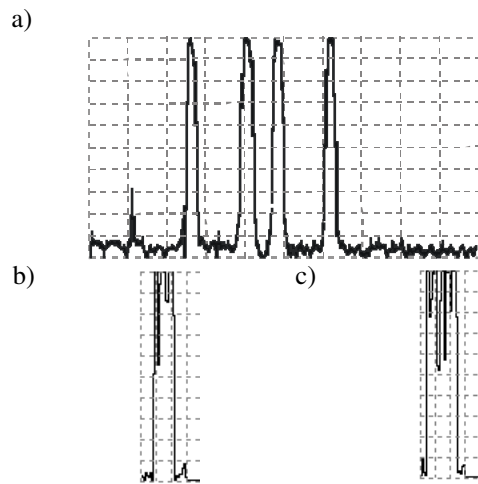


Fig. 2. Signal patterns a) rail joint (full recording), b) rail joint (conditional recording), c) dangerous crack (conditional recording)

There is also shown a defect pattern in conditional recording. It shows that the neural network able to discriminate patterns must recognize subtle relations between the samples coming from their vicinity and their sequence.

The estimation of generalization was assumed to evaluate the quality of the created classifier. Good generalization is the true goal of the neural network training process. A good classifier should not be equal to the training data, because that can be achieved by making the model more complex. The true test is the precision of data classification that did not take part in the learning process. In the machine learning theory the generalization error is defined as an expected error value on all possible data sets that have defined size and the same probability density distribution as the whole input data group. In practice this estimation is realized by checking the classifier on the testing set which is big enough. The rule that is used most often is that 70% of all data are selected for learning and 30% are left for testing. The quality of the constructed classifier is estimated as an error in the testing set.

NeuroSolutions 5.0 software has been used for the simulation. The software uses object technique to neural network modelling. This application is a very complex system where one can simulate most of the neural network architectures.

3. USING STATIC PATTERN RECOGNITION TO DETECT RAIL JOINTS

In the experiment we tried to learn the multilayer neural network to recognize the joint signal on the basis of 30-sample signal fragments containing the pictures of joints and defects. The length of the window has been chosen on the basis of the histogram of the length of the examples from the raw data generated by one of the tool programs

on the basis of measurements taken at the testing rail with artificial defects. These histograms are presented in figure 3.

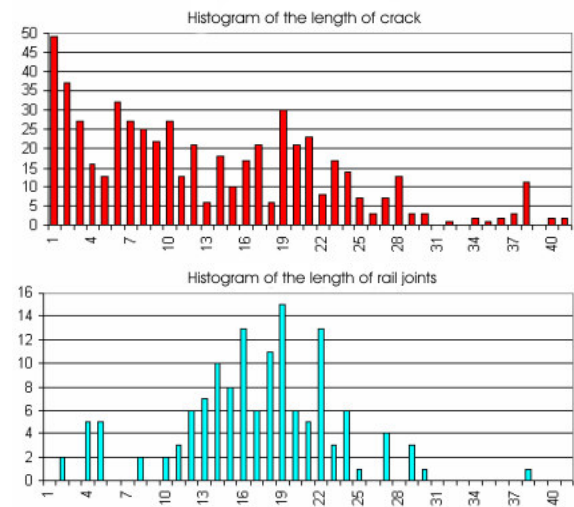


Fig. 3. Histograms of the length of crack and rail joint patterns

Most rail joint patterns are included in the length of 8 to 29 samples. However, this variety means that the joints are registered by the ultrasonic equipment in many different ways (because of changing the quality of linking probes with the rail). All joints from the range are used to windowing. The minimal pattern length in the window is 8. So from 129 rail joint examples in primary data there are 5128 windows for which the classifier should answer "rail joint" (coded in a file that contains information about the expected values as 1). If we consider defect patterns, most of the histogram is included in a window of 30 samples, but in that case minimal expected defect length equals 1. As a result of windowing one gets 21749 examples for which the classifier should answer "not rail joint" (coded as 0). Every sample in the window is a two dimensional vector which components describe an amplitude expressed in one byte and a defect location on one byte.

The data sets has been divided into two groups, one of 70% and the other of 30%, that gives 18814 examples in the training set and 8063 examples in the testing set. The MLP architecture was accepted and one hidden layer with five neurons was used. A learning algorithm called Delta-Bar-Delta was used. It is a type of algorithm with backpropagation with adaptive training speed coefficient.

In figure 4 a fragment of the Neurosolutions window is presented and it shows network project visualization and a window showing the status of learning process after having conducted 791 iterations. The highest classification error (both rail joints and defects) is about 10% both in the training and the testing set.

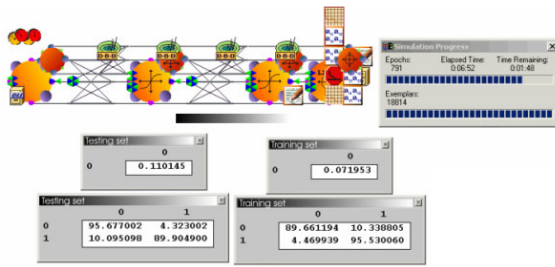


Fig. 4. Fragment of the Neurosolutions window: neural network architecture and additional display panels showing: mean square error calculated on the training and testing set; misclassification matrices for both sets; learning progress monitor

Due to low measurement precisions of ultrasound testing car (its evidence is the spread of the length of the rail joint pattern signal) it is a good result. It took 791 training cycles. The continuation of training from that moment makes the error in the training set lower, but the error in the testing set is increasing, which is a signal of network overtraining.

The experiment was repeated for a reduced architecture containing three processing elements in a hidden layer. The misclassification matrix for the test is presented in a tab. 1.

Tab. 1. Misclassification matrix for a network including 3 neurons in the hidden layer; training contains 672 cycles

	Training set		Testing set	
	0	1	0	1
0	89.381767	10.618233	95.595436	4.404568
1	4.463670	95.536331	10.095098	89.904900

The network has trained to recognize the rail joint patterns correctly as easy as in the first case.

Further, the classification test with one amplitude signal was taken. The preliminary tests have shown that the learning process of the same architectures as in the previous experiments is very slow and it does not give any good results. That is why the authors used the architecture capable of creating a strongly non-linear processing function that is a network with two hidden layers, with 15 neurons in the first hidden layer and 5 in the second. This network requires much more training cycles. Tab. 2 shows a misclassification matrix for all of the cases after 12600 training cycles.

Tab. 2. Misclassification matrixes with two hidden layers (5 and 15 processing elements) trained in 12600 cycles

	Training set		Testing set	
	0	1	0	1
0	35.197552	64.802452	39.415585	60.584415
1	5.243790	94.756210	11.096434	88.903564

In the table we can see that the MLP has the tendency to classify everything as rail joints. It has to be emphasized that the classification effectiveness

at the rate of 40% (the total of 0 column) is worse than simply taking a chance, which gives the expected error value at 50% at dichotomic discrimination. So the multilayer network classifying the statistical pattern recognize the pattern without any difficulty if they have full information about the amplitude and the location, but the tested architectures are not able to recognize having only the information about the amplitude.

4. CONCLUSIONS

As a result of the taken tests it has been shown that the adaptive, non-linear methods of the signal processing, like the neural networks, are capable of processing the measuring data coming from the automatic ultrasound testing. The networks show satisfactory classification certainty. Unfortunately, in our test the possibility of limiting the data necessary for making decision for the measurement process has not been found. It would help to limit the size of the data stream registered by the system. The authors may get better results by using the dynamic neural networks.

The results concern the recognition only of two classes of patterns, but in the authors' opinion it would be possible to use it in a system that recognizes many classes, if the training data set is big enough.

REFERENCES

- [1] Baluch, H.: *Diagnostics of track structure, WKiL Warsaw (1978) (in Polish)*
- [2] Bishop, C. M.: *Neural Networks for Pattern Recognition, Oxford University Press (1997)*.
- [3] Bojarczak, P., Ciszewski, T., Golabek, P., Korneta, A., Lesiak, P., Rojek, B., Wieczorek, D.: *New intelligent equipment for ultrasonic testing of rails, Krynica (2000) pp.187-194 (in Polish)*.
- [4] Ciszewski, T., Golabek, P., Lesiak, P.: *Using neural networks to detect patterns in flaw detector data, Gdansk (2002) pp. 27-32 (in Polish)*.
- [5] Ciszewski, T.: *Data compression and signal processing method in application to automatic ultrasonic testing of rails and train wheels, Radom (2003) (in Polish)*.
- [6] Lesiak, P.: *System for Automatic Ultrasonic Quality Control of Railroad Rails, Russian Journal Of Nondestructive Testing, Vol. 28:7, (1992) pp. 383 388*