SIGNAL PATTERNS RECOGNITION IN ULTRASOUND RAILROAD TESTING CAR

Tomasz CISZEWSKI¹, Zbigniew LUKASIK²

Abstract: The article presents how to apply the neural network to recognize signal patterns in measuring data gathered by the railroad ultrasound testing car. It describes the elaboration of smart, effective and automatic procedures that recognize the obtained patterns on the basis of measured signal amplitude and location of echo. The test shows four classes of pattern recognition. These are: “lack of defect”, “rail joint”, “defect that should be observed” and “dangerous defect”. If we deliver a quantity of training data which is large enough, the presented method will be applicable to a system that recognizes more classes.

Key words: rail, ultrasound testing, neural network, pattern recognition, safety

Introduction

The need of automation of ultrasonic testing in transport is obvious, because of the fact that the manually driven measurement does 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 solutions can be found in [5]. In the period 1999–2002 the testing car was thoroughly modernized. Computer driven ultrasonic equipment that processes digital signal has been used [3].

A railroad ultrasound testing car uses a non-destructive measuring method that is ultrasound testing, which is based on a wave reflection on the border between two layers which differ from each other by the velocity of the wave. A mechanic wave produced by a probe is reflected by the 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 [6]. 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 (up 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

¹ ph.D. Tomasz Ciszewski, Technical University of Radom, Malczewskiego 29, 26-600 Radom, Poland e-mail: tciszew@pr.radom.net
² prof. Zbigniew Lukasik, Technical University of Radom, Malczewskiego 29, 26-600 Radom, Poland e-mail: zlukasik@pr.radom.net
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.).

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.

There are some simple automatic procedures that are realized during the measurement registration. These procedures based on inductive reasoning categorize the defects. When the measurement is finished, data is 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 (fig. 2) 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 it is necessary to develop the automatic defect classification procedures. At the same time it is hard to construct such procedures because of the lack of 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. multilayer perceptron (MLP) [2].

**Methodology**

We used the railroad ultrasound testing car measurement results 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 and gathered during regular testing car measurements. 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 “lack of effect”, “a rail joint”, “a defect that should be observed” or “a dangerous defect”. Expert’s knowledge essential to teach MLP in supervised manner is available. Different kind of networks were tested. The preprocessing of the data is necessary to teach the MLP on the obtained data. The preprocessing stage is realized with the use of specialized software tools; that among other possibilities allow: windowing of measurement signals by setting the length of the window and minimal length of primary pattern included in the window and adding Gaussian noise to the signal with defined mean value and variance.
The main task is to discern four classes of the signal pattern “lack of defect”, “rail joint”, “defect that should be observed” or “a dangerous defect”, so the discrimination between the pattern groups is necessary.

We would like to emphasize another difficulty that is 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 sample that contains the information about its vicinity and sequence is preserved. 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.

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.

**Recognition of signal patterns in the flaw detector data**

In the experiment we tried to teach the multilayer neural network to recognize four classes of 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. Histograms are presented in figure 3.

![Histogram of the length of crack and rail joint patterns](image)

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

All patterns from the range are used for windowing. The minimal pattern length in the window is 8 for the joints and 1 for other classes. Table 1 shows the number of examples coded in a file that contains information about the expected values for each class.

<table>
<thead>
<tr>
<th>Class of pattern</th>
<th>lack of defect</th>
<th>rail joint</th>
<th>defect that should be observed</th>
<th>dangerous defect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of examples</td>
<td>19234</td>
<td>7431</td>
<td>118977</td>
<td>78838</td>
</tr>
</tbody>
</table>

The data sets have been divided into two groups, one of 70% and the other of 30%, that gives 157136 examples in the training set and 67344 examples in the testing set. The MLP architecture was accepted and two hidden layers with five and fifteen neurons were 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 7334 epochs. The highest classification error does not exceed 20% (usually it is about 15%) both in the training and the testing set. “Lack of defect” is the only exception where the error level reaches 35%. It is in a way justifiable, because not all the measurements are registered, but only those which were regarded as defects by the hardware amplitude discriminator. So it is not surprising they are often regarded as defects by the network (ca. 95% wrong qualifications).

Due to low measurement precision of ultrasound testing car the result is good, especially because the network has the tendency to find the threads larger than they are in reality. E.g. in case of the misclassification error “defect that should be observed” is usually recognized as “dangerous defect”. So the results are better than the simple misclassification error analysis would show.

Conclusions

The experiments proved that the adaptive, non-linear methods of the signal processing, like the neural networks, are capable of processing the measuring data. If the network architecture is well chosen and the learning process is well conducted, the networks show satisfactory classification certainty. If we acknowledge that the operators verify the results, it means that in most cases the operator’s role is only to accept the results, which decreases testing time. If a defect was omitted by the operator, it would not be a problem because of the tendency to find the threads larger than they are in reality mentioned earlier.

References


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.