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Application of the wavelet and neural technologies for processing of signals obtained during railway tracks diagnostics by the magnetic flux leakage method

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Abstract. In this article, the approach for detecting a transverse crack in the rail head via ANN with CWT and application created on its basis are presented. The ways of further development of the ANN for improving its work accuracy and the possibility of identification of other types of defects are also presented.
Keywords: defect, transverse crack, CWT, ANN
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1. Introduction

The timely detection of dangerous rail defects is extremely important since they can lead to accidents with significant material costs and human victims. Therefore, rails are systematically inspected for internal and surface defects using various non-destructive testing (NDT) techniques. The most common of them are ultrasonic and magnetic flux leakage (MFL) methods [1]. Nowadays, testing carriages based on MFL are widely used for speed inspection of the railway tracks. They allow controlling state of the rail head on a depth until 7-8 mm at the velocities from 20 to 80 km/h in different weather conditions.

That is why our attention is focused on processing the signals obtained by MFL.

2. Problem and methods of its solving

The most important issue in all methods of NDT is selection of information about defects from defectoscopic signals. Unfortunately, at this time, experience of a wagon-defectoscope operator is the main guideline in choosing the right testing evaluation. That is why automation of the defects detection process is the basic direction for improving existing NDT facilities, implementation of which is impossible without involvement of the modern digital signal processing tools (DSP). As will be shown further, these tools are continuous wavelet transform (CWT) and artificial neural network (ANN).

Since the most dangerous defect of railway tracks is a transverse crack in the rail head, the signals caused by this type of defect are the most interesting during railway inspection. For simplicity, the study will be focused precisely on a transverse crack, but approaches applied to this type of defect can be used for other defect types as well.

The signals from transverse cracks in the rail head, which were recorded by the magnetic wagon-defectoscope, mostly have the waveforms presented in Fig. 1.

One of the most characteristic features of such signal waveforms is sharply expressed asymmetry: negative pulse amplitude is typically in 3-4 times bigger than the maximum positive amplitude. Another very important feature is the ratio of positive pulse amplitudes: the amplitude of the right side pulse is always higher or at least equal to the amplitude of the left side pulse.

Exceptions are the signals from highly developed defects which come to the surface (e and f signals in Fig. 1) [2].

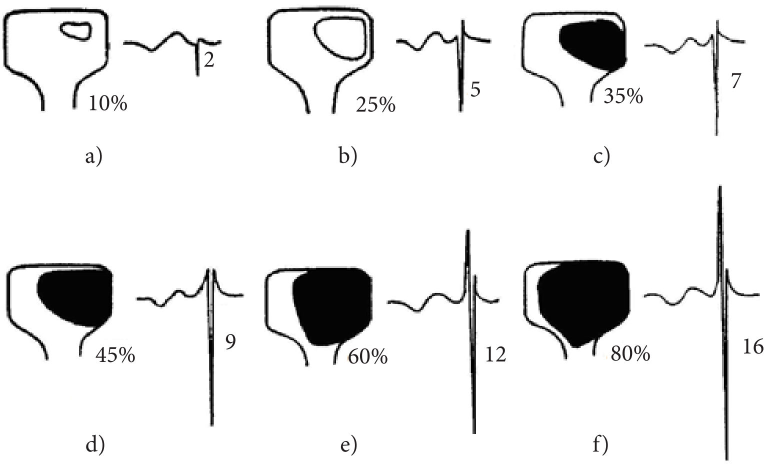

Fig. 1. Typical waveforms from the transverse crack: defects coming to the surface are marked by the black colour; digits — the percentage of the defect area to the cross-sectional area of the rail head and the ratio of the waveform's negative pulse amplitude to the amplitude of substrate signals.

Basing on the characteristics of the defect signal shapes and investigations described in [3, 4] it was decided to pre-process the signals by CWT.

Wavelet, adapted to detection of signals from transverse cracks (Fig. 2), was selected as a mother wavelet for CWT. The process of its creation is described in [5].

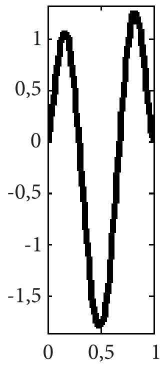

Fig. 2. Wavelet adapted to detection signals from transverse cracks in the rail head.

According to the study [6], for successful using of CWT for analysis and detection of specific defectoscopic signals, the following conditions should be provided:

- Mother wavelet function of CWT should be maximally similar to the signal pattern, which is expected to detect.
- The most significant, for particular type of defect, CWT scales should be selected. For transverse crack, scales in the range from 8 to 21 are proposed.
- Priority should be given to smaller scales (high frequencies) because it affects the accuracy of defect detection on time (spatial) axis.
- It is necessary to choose optimal thresholds on the value of wavelet coefficients for each of the selected scales. According to these thresholds can be taken a decision on presence or absence of the signal from defect.

To fulfil the last condition, ANN looks very promising [7, 8].

As a result of the network type and parameters selection (described in [9]), three layers ANN (Fig. 3) was obtained. It consists of one input, one output and hidden layer.

Input layer of the network has eight inputs on which CWT coefficients (scales from 8 to 15) are passed. Input signals are duplicated and fed to each of the three hidden layer nodes. They are multiplied with the weights W (which were adjusted during the network training), added and taken into account the bias node b passed to the transfer (activation) function. A bias value allows shifting the transfer function along the horizontal axis which can be crucial for successful training.

Then, the signals from three hidden nodes come to the output layer neuron. Depending on the similarity to the signal from a transverse crack, the network generates a signal that corresponds to defect presence or absence.

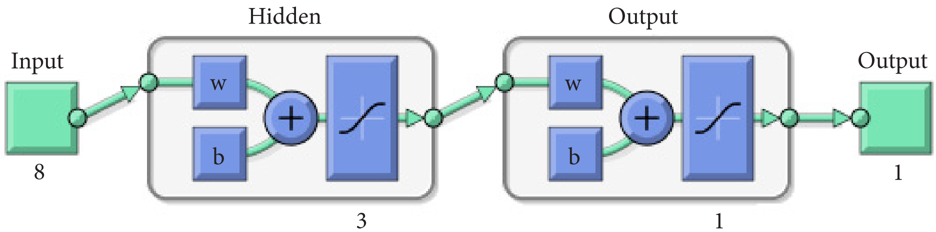

Fig. 3. ANN for automatic detection of signals from the transverse rail cracks: numbers are the amount of knots in the input, hidden and output layers, respectively.

3. Results

For the possibility of visual analysis of ANN performance, utility application shown in Fig. 4 was developed.

The top graph shows a fragment of defectoscopic signal corresponding to 25 meters of rail length (2500 samples), and the bottom-ANN reaction on this fragment. The horizontal axis of both graphs presented in samples.

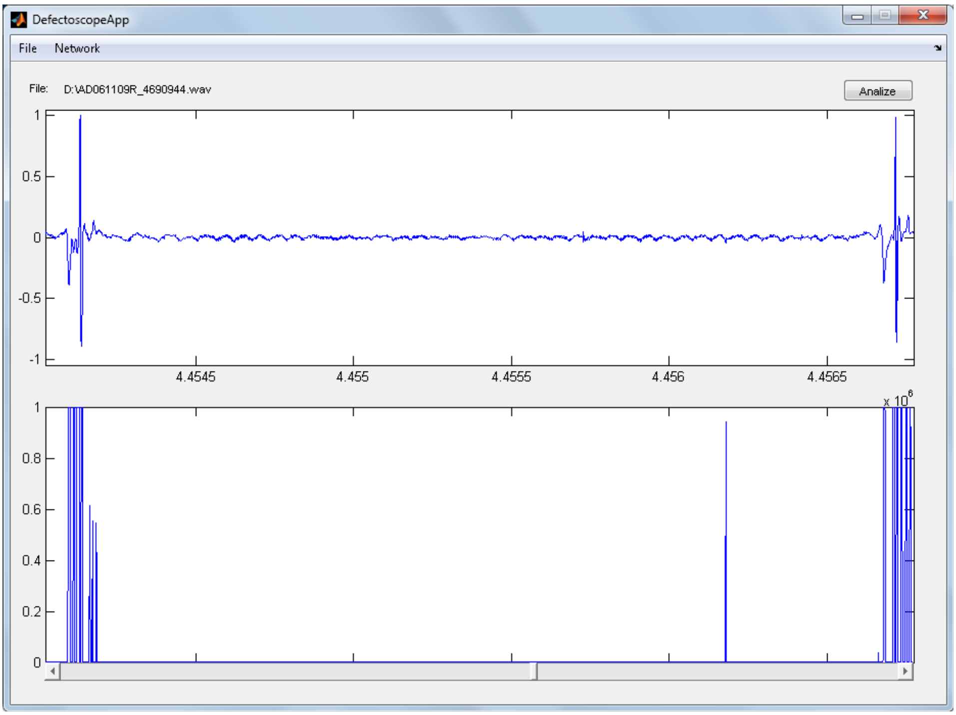

Fig. 4. Result of analysis of the defectoscopic signal (received during the checking of railway region Lviv–Syanky–Chop, 06.11.2009, km: 44 picket: 5) using the ANN.

As an example of the network operation it was loaded a fragment of a defectoscopic signal recorded during the checking of railway region Lviv–Syanky–Chop, 06.11.2009 (top graph in Fig. 4). At the edges of this fragment, the signals from the rails joints are shown, and along the whole of its length — the signals from the rails substrates (similar to background noise) are also shown.

Besides detected by the operator of wagon-defectoscope defects, ANN additionally found dozens of other signals which in their shape resembles a transverse crack.

One of such signals is presented in Fig. 4 (against vertical line of the bottom graph) and Fig. 5 (scaled version).

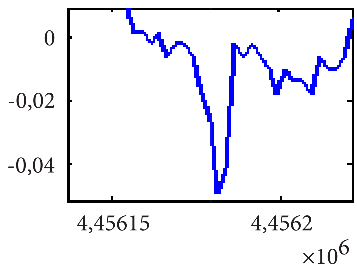

Fig. 5. The signal detected by the ANN (scaled version of the signal presented in Fig. 4).

As shown in Fig. 4, the amplitude of the detected signal is slightly allocated on the background of signals from substrates. It testifies about signals detection from the less developed defects. Such defects do not pose a threat to traffic safety, but in the case of their progressing can lead to emergencies.

Observation of such signals for several wagon-defectoscope races will enable monitoring of the defects development. In case of absence of such signals in the following races — the previous network triggering will be considered as false.

Of course, among the signals detected by the ANN, there are incorrect detections. By involving additional data to the analysis process, probability of their detection can be reduced. This will help to make the right decision about the presence or absence of defects. Such data could be the signals from other NDT systems of rails and, as already mentioned, data from the previous races. It will require the increasing number of neurons in the input and hidden layers of ANN.

4. Conclusions

Combination of ANN and CWT allows reliable detection of signals from transverse cracks in the case of advanced defects.

Also, ANN allows detecting signals from defects on early stages of their development which can provide monitoring of defects progressing.

The accuracy of defects detection can be improved by involving the data from other systems of NDT.

To be able to detect other types of defects, the research should be extended in one of the following directions:

1. Expanding of the existing ANN structure. In that case, the number of neurons in the output layer of the network should be equal to the number of defect types. It will increase the number of input and hidden layer neurons and will require (entire!) ANN retraining each time you add a new type of defect or update training set for any of the existing (those that network can detect) types of defects.
2. Modular. Construction for each new type of defect separate ANN in a similar way as for transverse crack. This approach is more secure as it guarantees that changes for a particular type of defect will not affect other modules.

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Zastosowanie fali elementarnej i neuronowych technologii do przetwarzania sygnałów, otrzymanych w czasie diagnostyki torów kolejowych, za pomocą metody strumienia rozproszenia magnetycznego

Streszczenie. W artykule rozpatrzono sposób ujawnienia poprzecznego pęknięcia w glowicy szyny kolejowej metodą ciąglej transformacji falkowej (CTF) oraz metodą sztucznej sieci neuronowej (SSN). Przedstawiono program stosowany do analizy sygnałów defektoskopijnych. Zaproponowano sposoby dalszego rozwoju SSN w celu poprawy dokładności jego pracy i możliwości zidentyfikowania innych rodzajów wad.

Słowa kluczowe: defekt,wada, poprzeczna szczelina, ciągła transformacia falkowa (CTF), sztuczna sieć neuronowa (SSN)
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