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# VISUAL DIAGNOSTICS OF RAIL FASTENING SYSTEM AS A METHOD TO IMPROVE SAFETY

**P. Bojarczak[*], W. Nowakowski[**], Z. Łukasik[***]**

**Abstract:** *The safety in railway transport is a very important aspect. Safety depends mainly on the state of railway infrastructure. Hence, the methods allowing for the assessment of the infrastructure should be developed. In the paper, authors present visual method allowing for diagnostics of rail fastening system. This method uses wavelet transform to extract feature and neural network to detect (classify) defect occurring in this system.*

**Keywords: Visual diagnostics, Rail fastening system, Neural network, Safety.**

## 1. Introduction

The state of railway track has an immense impact on the safety of railway traffic. The railroad spike is an important element of railway track. Until now in Poland, diagnostics of railroad spikes has been carried out in visual form by inspectors. This method is ineffective and inaccurate. One person is able to check very limited section of railway track. Needless to say that the weariness of inspector has also an influence on the effectiveness. Hence authors proposed the method based on visual algorithms which allows for automation of diagnostics and elimination of people.

## 2. Research problem

All images used in the development of the algorithm presented here come from visual system installed on an ultrasonic flaw detecting carriage. The goal of this system was to enable to the operator to "manually" verify if the defects registered by the ultrasonic equipment were not caused by rail joints or turnouts. This visual system does not perform any image processing and analysis, it just records images of the left and right rails of the track. One video frame of the size 1294 x 964 pixels covers a constant section of the rail, 0.5 meter in length, independently of the speed of the carriage. The visual system records a section of the rail and its vicinity. Therefore, it is necessary to narrow the image under analysis to a fragment containing railroad spikes. It can be realized by the Region of Interest procedure (ROI). Railroad spike lies on the intersection of the rail and railroad tie, therefore ROI should detect both the rail and the spike. Such ROI is presented in (Bojarczak, 2013). Once the fragment of image with spike is extracted, the algorithm for automatic visual diagnostics has to be applied. Fig. 1 presents a block diagram of the proposed algorithm.

It consists of two main components. The first part, called feature extraction, serves to detect the most informative (salient) features describing spikes under analysis. The second, called the detector (classifier), classifies the image under analysis into two classes on the basis of the features extracted. The first and second classes comprise images of spike without and with defects, respectively.

[*] Assoc. Prof. Ing. Piotr Bojarczak, PhD.: Faculty of Transport and Electrical Engineering, Kazimierz Pulaski University of Technology and Humanities in Radom,Malczewskiego 29; 26-600, Radom;PL,p.bojarczak@uthrad.pl

[**] Ing. Waldemar Nowakowski, PhD.:Faculty of Transport and Electrical Engineering, Kazimierz Pulaski University of Technology and Humanities in Radom,Malczewskiego 29; 26-600, Radom; PL, w.nowakowski@uthrad.pl

[***] Prof. Ing. Zbigniew Łukasik, PhD.:Faculty of Transport and Electrical Engineering, Kazimierz Pulaski University of Technology and Humanities in Radom,Malczewskiego 29; 26-600, Radom; PL, z.lukasik@uthrad.pl

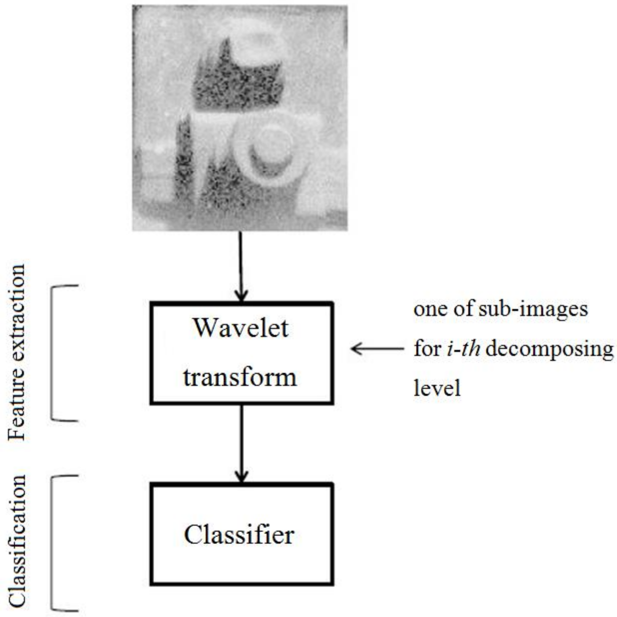



*Fig. 1: Block diagram of the proposed algorithm.*

Two-dimensional Discrete Wavelet Transform (2D DWT) was used to feature extraction. 2D DWT is the extension of one-dimensional Discrete Wavelet Transform (1D DWT). 1D DWT decomposes the analyzed function *f(t)* on finite lasting components called $\Psi(t)$ wavelets (Mallat, 1989 and Daubechies, 1988).

$$W(a,b) = \int_{-\infty}^{+\infty} f(t) * \Psi_{a,b}(t)dt \tag{1}$$

where:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \tag{2}$$

is a wavelet function of time scale (dilatation) equal to a and time shift (translation) described by *b*. If wavelets functions are only chosen for *a=2k* and *b=2kn* where *k* and *n* are integer number, then formula describes discrete wavelet transform of original function *f(t)*. DWT can split original function *f(t)* into two parts: $f_o(t)$ corresponding to coarser approximation of *f(t)* and $g_o(t)$ corresponding to high frequency detail function, defined as a difference between *f(t)* and its approximation version. The approximated version $f_o(t)$ can be further split into two parts – coarse approximation $f_1(t)$ and the detail part $g_1(t)$. This process can be continuously performed up to some assumed level. The splitting process is also called decomposition level. In case of 2D DWT the wavelet decomposition is performed twice: first on the rows of the image and then on its columns thus 2D DWT generates 4 sub-images: $f_{LL}((x,y)$, $f_{LH}(x,y)$, $f_{HL}(x,y)$ and $f_{HH}(x,y)$ corresponding to smooth sub-image, horizontal details sub-image, vertical details sub-image and diagonal details sub-image, respectively.

Support Vector Machine (SVM) has been used to classify (detect) railroad spikes with and without defects - Classifier block in Fig. 1. While designing the SVM classifier, the hyper-plane separating the data into two classes (one containing a spike with defect and one containing a spike without defect) is constructed in *M*-dimensional input space (Burges, 1998 and Cristianini, 2000). SVM is a linear system performing linear separation in *R*-dimensional feature space created by nonlinear projection of *M*-dimensional input space (*R*>*M*) with the use of the function $\varphi(x)$. The main advantage of the SVM is the maximal-margin separation between data of the two classes, which in turn ensures maximum classification rate. In practice, if instead of function $\varphi(x)$ the kernel function $K(x, x_i) = \varphi^T(x_i)\varphi(x)$ is applied. There are three types of kernels: linear, polynomial and Gaussian. If the kernel is of the linear form, then the hyper-plane is constructed in the original *M*-dimensional input space. However, if the kernel is of polynomial or Gaussian form the hyper-plane is constructed in a higher dimensional space.

## 3. Results

The crucial issue is the right choice of the wavelet, decomposing level and the type of sub-image. Hence authors examined $f_{LL}(x,y)$, $f_{LH}(x,y)$ and $f_{HL}(x,y,)$ sub-images for up to fourth decomposing level and nine wavelets. Fig. 2 presents example of sub-images of spike for 2-th level of decomposition with bior1.1 wavelet.

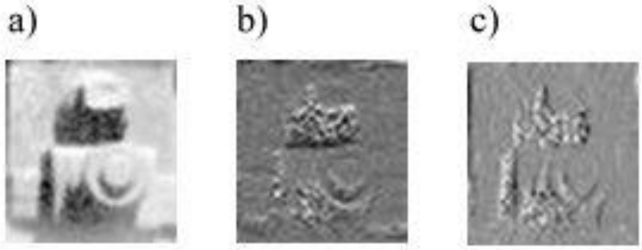
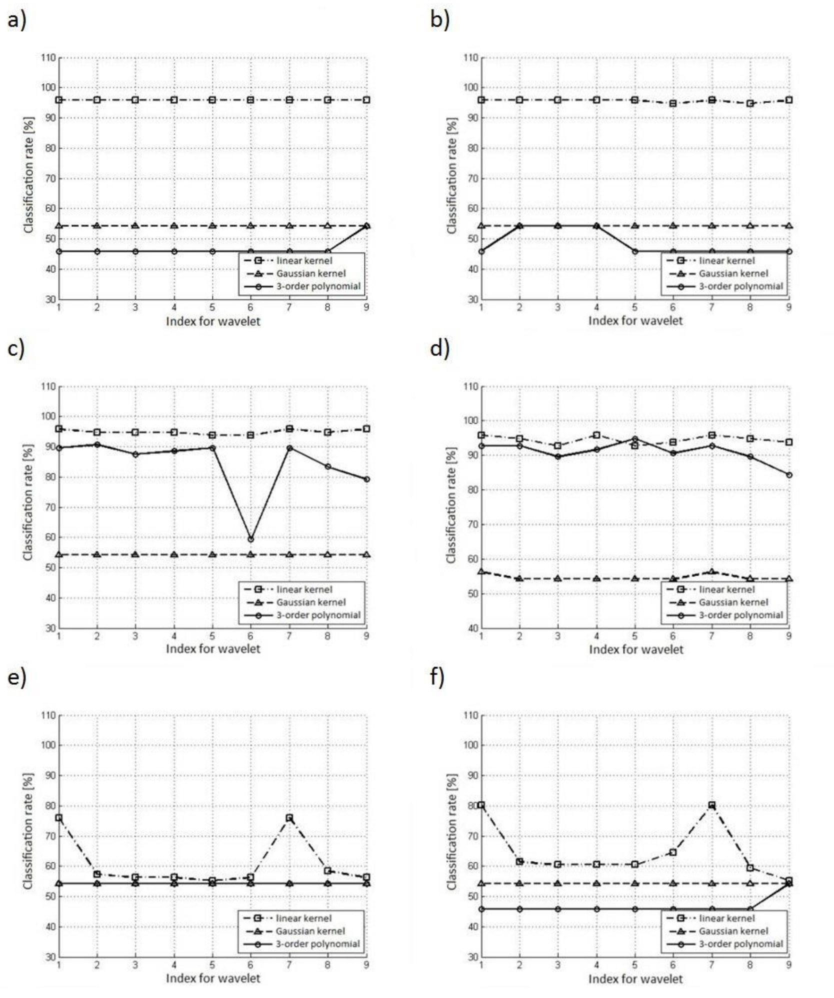



*Fig. 2: 2DWT a) $f_{LL}(x,y)$ sub-image; b) $f_{HL}(x,y)$ sub-image; c) $f_{LH}(x,y)$ sub-image for 2 decomposing level and bior1.1 wavelet.*

First, the SVM classifier was trained on 160 images of spike without defect and 115 images of spike with defect. These images correspond to appropriate sub-images obtained after performing *n-th* decomposition. Next, the operation of proposed algorithm was checked on testing set including 160 images of spike without defect and 115 images of spike with defect. This set did not take part in training process. Fig. 3 presents the relationship between classification rate and the type of wavelet. Numbers on horizontal axis corresponds to type of wavelet: 1- db1; 2 - db3; 3 - db3; 4 - coif1; 5 - coif2; 6 - coif3; 7 - bior.1.1; 8 - bior2.3 and 9 - bior3.1. Classification rate is defined as ratio of the number of correctly classified images to total number of testing images.



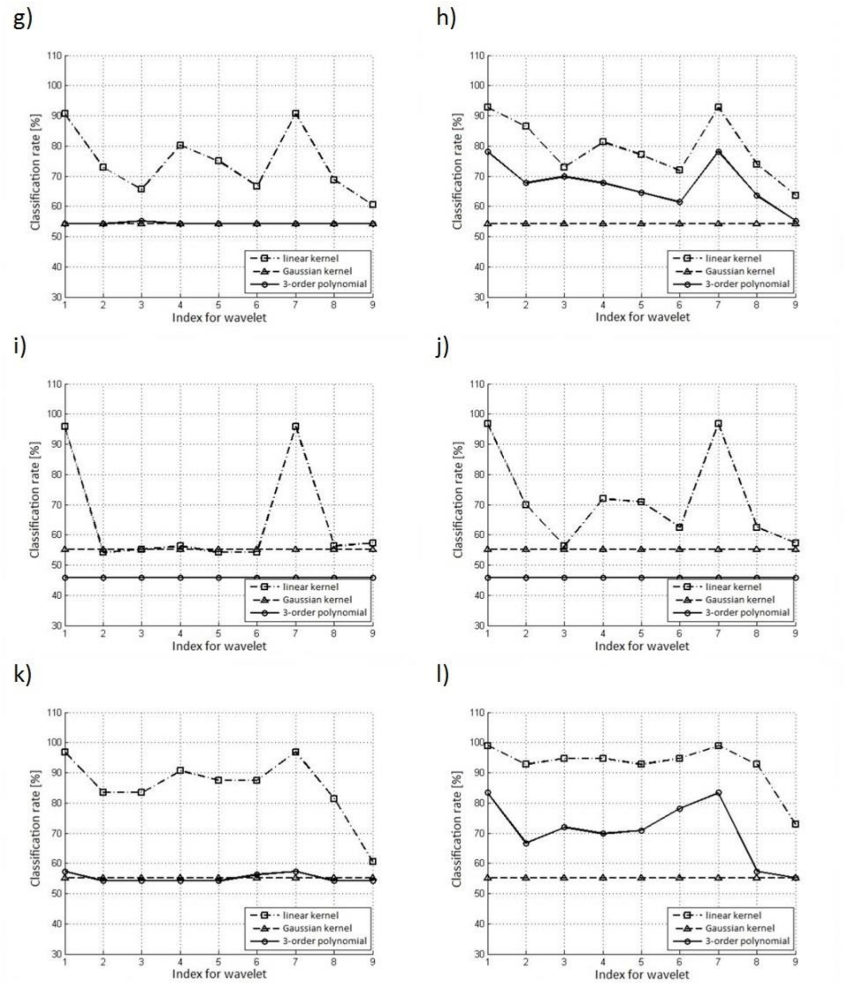



*Fig. 3: Relationship between classification rate and type of wavelet for a), b), c), d) $f_{LL}(x,y)$ sub-image; e), f), g), h) $f_{LH}(x,y)$ sub-image; i), j), k), l) $f_{HL}(x,y)$ sub-image for up to 4 decomposing level.*

## 4. Conclusions

According to Figs. 3a and 3b for $f_{LL}(x,y)$ sub-image and first and second decomposing level, the classification rate is equal to 96 % (for SVM with linear kernel) and does not depend on the type of wavelet used in decomposition. It depends only on the form of kernel used in SVM classifier. Therefore the feature extraction part of the presented algorithm can be omitted and the image of spike can be directly given to SVM with linear kernel. The presented algorithm is able to detect defect occurring in spike based on its image.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