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ANALYSIS OF THE MINING TORQUE SIGNAL WITH CONTINUOUS WAVELET TRANSFORM

SUMMARY

This paper presents an analysis of the excavation torque signal with the use of a Continuous Wavelet Transform. The article also presents results of preliminary research on utilising neural networks to identify excavating cutting tools type used in multi-tool excavating heads of mechanical coal miners.

Selected wavelet coefficients were used as data to teach artificial neural network. The research is necessary to identify rock excavating process with a given head, and design adaptation system for control of mining process with such a head. The results of numerical analyses conducted with the use of Neural Networks are presented.

Keywords*: Continuous Wavelet Transform, multi-tool head, artificial neural network*

ANALIZA SYGNAŁU MOMENTU URABIANIA ZA POMOCĄ CIĄGŁEJ TRANSFORMATY FALKOWEJ

Artykuł przedstawia analizę sygnału momentu urabiania z wykorzystaniem ciągłej transformaty falkowej. Praca przedstawia ponadto rezultaty wstępnych badań nad wykorzystaniem sztucznej sieci neuronowej do oceny rodzaju narzędzi urabiających głowic wielonarzędziowych kombajnu górniczego. Do nauki sieci neuronowej wykorzystano wybrane współczynniki falkowe. Badania te niezbędne są do identyfikacji procesu urabiania w celu opracowania adaptacyjnego systemu sterowania pracą głowicy kombajnu. W artykule przedstawiono wyniki analiz numerycznych, wykorzystując sztuczne sieci neuronowe.

Słowa kluczowe*: ciągła transformata falkowa, głowica wielonożowa, sztuczna sieć neuronowa*

1. INTRODUCTION

The article presents an attempt to use CWT to analyze signals of mining torque with multi-tool head. Mining with longwall shearer head is fast-changing and randomized. Signals registered during mining exhibit nonstationary character (Litak *et al*. 2010). The process meets a series of difficulties in mathematical description.

An aim of performed research was type classification of the tools installed on a multi-tool head. Initial classification tests for types of picks installed on a head were performed using artificial neural network [ANN]. The research was realized for single tool only. Input variables for the ANN were characteristic statistics of the mining signals i.e. variation, skewness, kurtosis (Jonak 2006, 2008). Presented tests were realized for a set of tools installed on a head and included analyses using Wavelet Transforms and Neural Networks. Obtained wavelet coefficients were used as input variables. To compare effect of analysis using neural network an effort of classification basing on time runs was also performed.

A goal of the performed research is building a system for monitoring condition of the multi-tool head tools during mining process. Such system should recognise, amongst others, type of tools installed on a mining device, condition of picks and current type of head movement (all of that in changing conditions of operation). Condition of picks installed on a multi-tool head significantly affects mining consumption energy. Evaluation of the state of tools is an important part of the system (Gajewski 2006).

Results of the numerical tests presented in this work allow to optimistically look on the possibility of using artificial intelligence in the classification problems. Moreover, wavelet coefficients used as input variables gave better results than statistical methods.

2. WAVELET TRANSFORM

Wavelet Transform can be divided into continuous one (CWT) and discrete one (DWT). Since the signal computations performed by computer are executed on discrete data, the CWT is executed using discrete data as well. CWT can be executed for any value of scale and is continuous versus position (Białasiewicz 2004). However, it results in obtaining very large amount of data. Using DWT we can obtain less data but we have decided to use CWT since it ensures signi-ficantly higher legibility of signal.

Continuous Wavelet Transform is defined by the following expression (Misiti *et al* 2002):

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

where:

$f(t)$ – analyzed signal,
$\psi(scale, position)$ – base wavelet,
$C(scale, position)$ – wavelet coefficients.

Transformation results are wavelet coefficients C versus scale and position. Value of coefficients can be understood as correlation measure of wavelet and signal. The higher coefficient, the more "similar" wavelet to the signal is.

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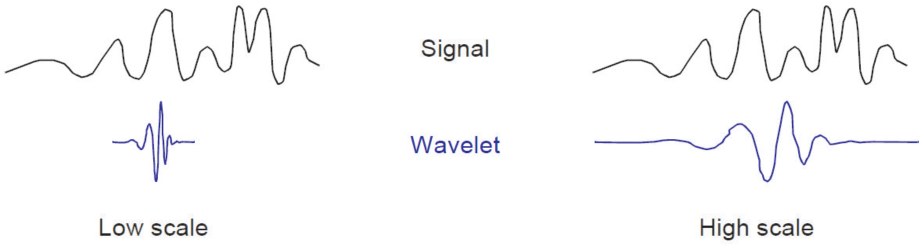

Fig. 1. Base wavelet – different scales (Misiti *et al.* 2002)

Obtained results are presented on the time-scale graph and not as in case of Fourier Transform on the time-frequency graph. Then, how to interpret the scale? There is a similarity between scale and frequency. The larger scale the more "extended" base wavelet is – in other words it is compared to larger part of a signal. It means that it reflects lower frequencies (Fig. 1).

Selection of the base wavelet is also an important problem (Zimroz 2009, Loutridis 2008, Czech, Łazarz 2007). It is caused by a fact that wavelet coefficients are a measure of wavelet and signal similarity hence one should tend to obtain the most similar shapes of wavelet and a signal which is generated by examined phenomenon. Unfortunately, in such case the shape is unknown and that is why wavelet selection is executed empirically.

3. TEST BED

Stand tests were performed using test bed in AGH University of Science and Technology in Cracow. The stand consists of mining head driving assembly, model rock feeding assembly with control equipment and measurement systems (Fig. 2).

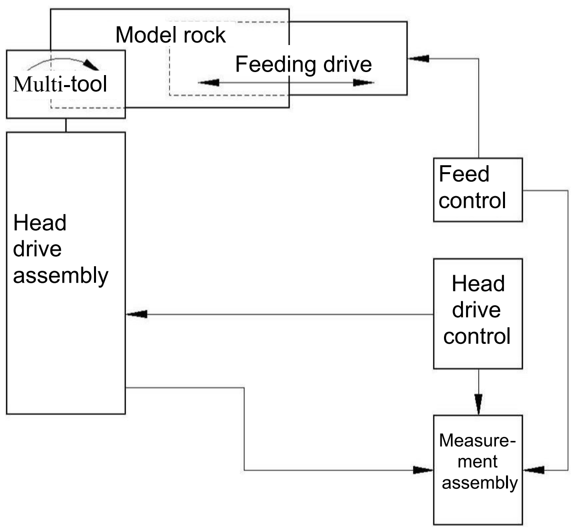

Fig. 2. Test bed scheme

The feed was realized using hydraulic servo-motors that were moving model rock perpendicularly to head rotation axis. Feed speed was adjusted using regulation of flow in the hydraulic assembly.

The tests were performed for two types of picks mounted on the multi-tool head. Used tools were new and technically sharp. They are commonly used in mining industry (Fig. 3 and 4). Performed tests provided time runs of the mining torque of multi-tool head that could be used in numerical research.

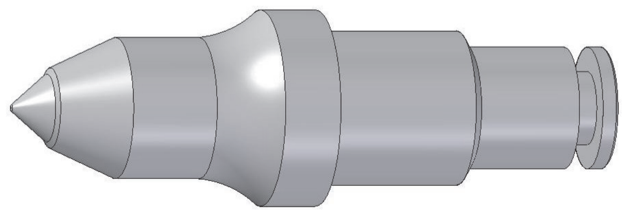

Fig. 3. Tangent-rotational pick

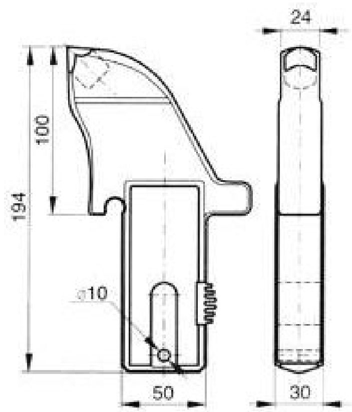

Fig. 4. Wedge pick

The test was performed on model rock. It allowed certain simplification of the number of variables affecting recorded mining signals (using isotropic model rock eliminates influence of factors connected with inhomogeneity of mined material).

4. METHODS OF SIGNAL ANALYSIS

Multi Layer Perceptron ANN was used to classify the type of mining picks installed on the multi-tool head. One hidden layer was considered – it is sufficient in most cases. To teach the network the signals of torque (Fig. 5) for rotational and wedge picks were used. Unfortunately, obtained results were not satisfactory, the best network exhibited validation quality equal to 60.33% (Tab. 1). Table 2 presents sensitivity analysis of the variables used in network learning (the higher value the better variable).

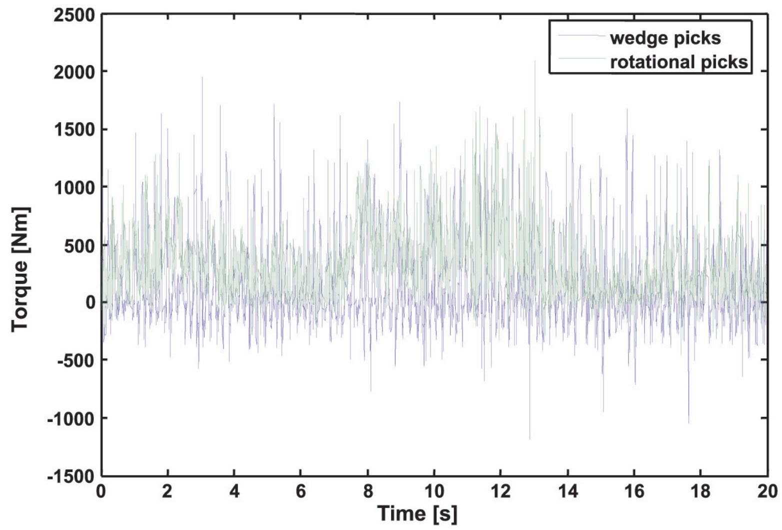

Fig. 5. Torque graph for wedge and rotational picks

Table 1

Results and network learning parameters

Network summary							
Name	Quality (learning)	Quality (testing)	Quality (validation)	Learning alghoritm	Error function	Activation (hidden)	Activation (output)
MLP 2-4-2	56.96	60.33	60.33	BFGS 39	Entropy	Tanh	Softmax

Table 2

Sensitivity analysis of variables

Trials: Learning, Test, Validation		
MLP 2-4-2	**Rotational picks**	**Wedge picks**
	1.0295	1.0007

In order to improve classification of picks an information included in the signal was accentuated executing CWT. After empirical attempts a wavelet from Symlets sym2 family has been chosen (Fig. 6). Transformation resulted in a matrix of wavelet coefficients 64×4000 for every signal.

Graphs of wavelet coefficients for wedge picks are presented in Figure 7 and for rotational ones in Figure 8.

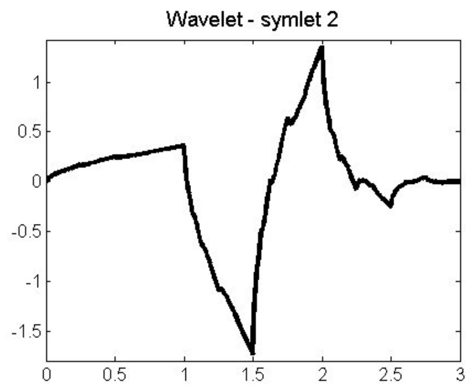

Fig. 6. Wavelet symlet 2

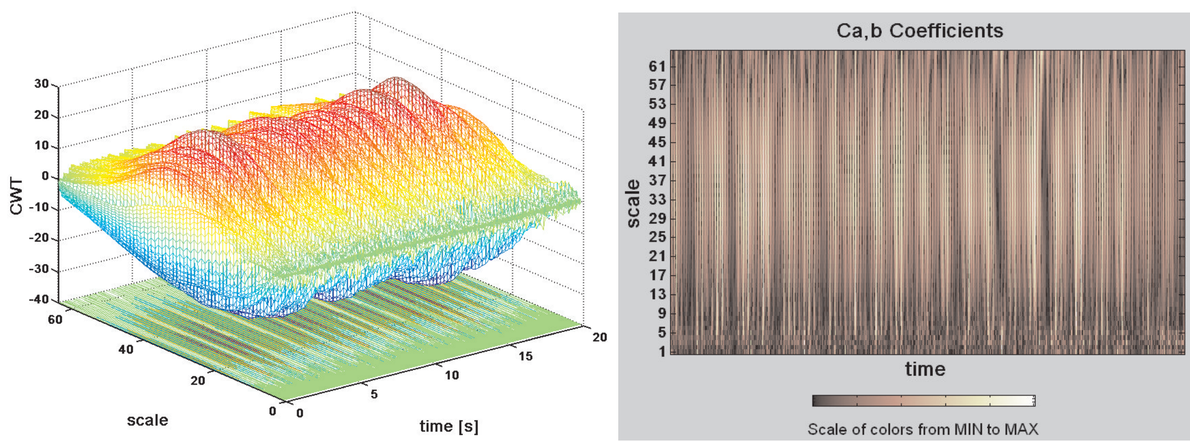

Fig. 7. Graph of wavelet coefficients for wedge picks

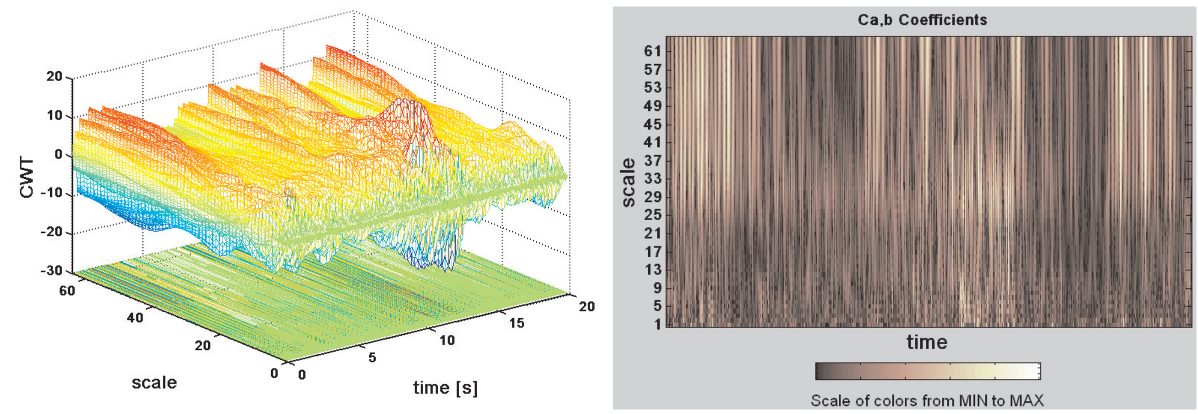

Fig. 8. Graph of wavelet coefficient for rotational picks

Reminding interpretation similarity between scale and frequency one can state that in case of wedge picks regular, periodic changes in wide frequency structure occur. In case of rotational picks the structure is irregular in time and frequency.

Selected wavelet coefficients were used as data to teach artificial neural network. 9 coefficients were used starting from 20 to 60 (step 5 coefficients). Obtained results classifying type of a mining tool are satisfactory – quality of learning, testing and validation reaches approx. 95% (Tab. 3). Table 4 shows sensitivity for the particular variables – wavelet coefficients. Table 5 shows summary of mining tools type classification.

5. SUMMARY AND FINAL CONCLUSION

Performed research confirmed usefulness of the artificial neural networks in classification of type of tools working together on a mining head. Direct use of mining torque time runs as input variables provided unsatisfactory results. Neural network exhibited low effectiveness.

One should special attention to the second method of obtaining input data for ANN. Wavelet coefficients (presented in the spatial graphs) for both types of tool unequivocally indicate differences in the signals of both processes what is not so obvious in case of direct analysis of time runs. Mentioned difference, determined thanks to

Table 3

Results and network learning parameters

Network summary							
Name	**Quality (learning)**	**Quality (testing)**	**Quality (validation)**	**Learning alghoritm**	**Error function**	**Activation (hidden)**	**Activation (output)**
MLP 9-19-2	95.78	95.33	95.83	BFGS 96	Entropy	Tanh	Softmax

Table 4

Sensitivity analysis of variables

Trials: Learning, Test, Validation									
MLP 9-19-2	**Zmn3**	**Zmn2**	**Zmn4**	**Zmn8**	**Zmn1**	**Zmn5**	**Zmn6**	**Zmn9**	**Zmn7**
	53.60	43.61	40.14	24.62	19.37	18.72	18.57	12.02	8.55

Table 5

Summary of mining tools type classification

Trials: Learning, Test, Validation				
MLP 9-19-2		**Rotational picks**	**Wedge picks**	**All**
	Together	4000	4000	8000
	Correct	3885	3773	7658
	Incorrect	115	227	342
	Correct (%)	97.12	94.32	95.72
	Incorrect (%)	2.87	5.67	4.27

executing Continuous Wavelet Transform, originates in different character of both processes. Wedge tools exhibit more dynamic operation if compared to contact-rotational ones.

Wavelet coefficients obtained from investigated signals allow to "teach" the network correct classification at level allowing serious considering application of the system in practice.

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