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ULTRASONIC METHOD FOR METAL RECOGNITION BY MEANS OF FAST WAVELET TRANSFORMATION

ABSTRACT:
A method for classification of metals is proposed in this paper. An ultrasound non-contact echo-location method is used for gathering information from tested metal samples, made of Aluminum, Chrome-Nickel, Brass, Copper, Cast-iron and Steel. The reflected signal is received and processed using methods for recognition of images. For forming of attributes for classification an apparatus of the discrete wavelet transformations with orthogonal wavelet basis functions is applied. The classification is realized by the method of "k-nearest neighbors" (kNN). The received data are shown and an evaluation of errors in the classification is done.

KEYWORDS:
metal recognition, wavelet, ultrasonic non-contact method, ultrasonic sensors

INTRODUCTION

Nowadays because of their advantages the ultrasound acoustic methods find applications in different areas of the contemporary science and engineering: metallographic, flaw detection, medical diagnostics, assessment of geometrical sizes of objects, investigation of physical properties of materials, etc. After the interaction with the tested objects the acoustic vibrations carry information, which can be easily processed in the computer system. For example, in the area of machine-building not always good qualification and practical experience of the staff are enough for identification of metals in different cases of the production process. The identification is necessary also when we need to choose a metal for using in the production or in the determination of its welding. Identification of steel, cast-iron and other metal scraps is especially important in the choice of the regime of their heat treatment in the blast-furnace.

These and many other cases in the practice impose a necessity for identification of metals. A method for non-contact ultrasound identification of metals is proposed in this paper.

Working out a system for identification of materials and particular of metals is a difficult task, requiring a complex theory, fast algorithms for data conversion and good technical facilities. The synthesis of a system for automatic non-destructive recognition is a multi-aspect task. It involves planning and conducting of experiments for collecting information, formation of samples for training and control, selection of classifier, reduction of recognition features, etc. Extracting useful information from the initial amount of data is an important step during every investigation. Analysis and generalization of data with big divergence is a difficult task. Usually the data consist of quantities, corresponding to some set of measured, statistically determined indexes or heuristically sanitized signs. Such set of indexes (signs) can be marked with a vector from numerical values. Every vector is presented with a point in the n-dimensional space. In the cases of two or three dimensions one can build up two or three-dimensional graphics, but when the dimension of data is bigger (n>3), presenting the vectors and their reciprocal connections is practically impossible. Because of that other methods for presenting the data are necessary. One of the main methods of approach is by reducing the dimension of the data. In this aspect a great variety of methods exist, which carry out the initial system of data to a space with a smaller dimension. These methods can be divided into two groups: methods of clusterization and projection methods. From geometrical point of view the main difference between them consists of the possibility the presentation of the input data to develop in a direction, which best recognizes their most essential particularities.

DESCRIPTION

Sequence of the recognition process

The steps that make up this approach are presented in Fig. 1.

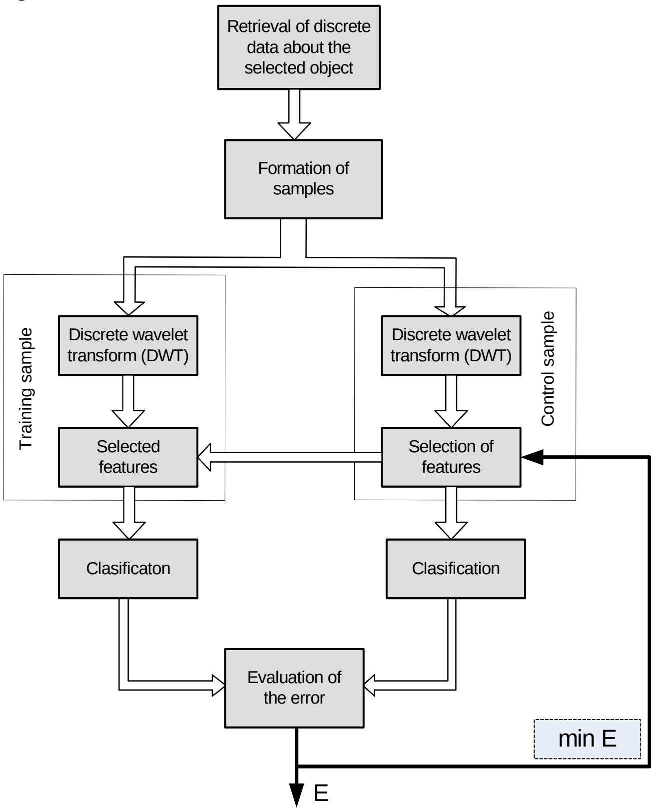

Figure 1 - General structure of the process "synthesis of a classificatory for recognition of metals" with an application of wavelets methods

Retrieval of discrete data about the selected object

The most commonly used method for retrieval of discrete data about the specific object is the pulse-code modulation [MM&WEB]. It expands the information about the object (the received analogue signal) by means of a discretization grid with coordinates along X - discretization frequency and along Y - the binary values of the numbers determined by the conversion digit capacity. The general solution is a binary sequence, which defines the discrete values of the signal. The number of solutions is determined by the discretization frequency and the duration of the analogue signal.

Formation of samples

The discrete data about a certain object are used for the formation of the so-called training sample and control sample. One of the ways for practical realization is by using a random-number generator for choosing samples out of the overall data set about the objects. After that the data are subject to further processing. The training sample is used to synthesize the classifiers, and their efficiency is tested by means of the control sample.

Wavelets methods for forming of features for recognition

Using of the method of wavelet transformation gives the possibility to form a complex of features for recognition (classification) of objects by strictly mathematical way. Its advantage in relation to spectral methods (Fourier transformation, discrete cosine transformation, transformation of Wolsh-Hadamard, etc.) for forming features for classification consists of the possibility for localization of different particularities of the analyzed signal, not only in the frequency range, but also in the time scale. The wavelet transformation is intermediate between the completely spectral (frequency) and completely time representation. By its localization in the time scale and in the frequency range the wavelets take a place between well localized in the frequency range sinusoidal functions and the function of Dirac - well localized in the time range. The wavelet transformation discretizes the signal into different frequency components, which gives a possibility for studying every component with good dividing ability, corresponding to its scale, and in such way good frequency-time localization can be achieved. Because of this characteristic the wavelets permit revealing of sharp "break-downs" and "peaks".

The continuous wavelet transform (CWT) is based on the use of two continuous functions that are integrable along the independent variable axis (figure 1):

- $\psi(x)$ - wavelet function showing the signal details and forming the detailizing coefficients;

- $\varphi(x)$ - scaling function determining the signal approximation and forming the approximation coefficients. The scaling functions are only inherent to orthogonal wavelets - Haar wavelets, Daubechies wavelets, Coiflets, etc.

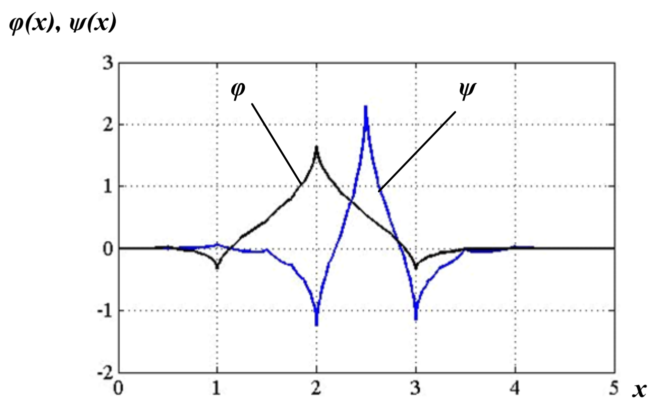

Figure 2 - The basic functions of wavelet Coiflet 1 'coif1'

The choice of the concrete wavelet is determined from the practical application and the type of the signal (smoothness, necessary level of discretization, ever growing time for transformation with growing dimension of the wavelet, etc.).

Despite of comparatively short time of development of the wavelet analysis the variety of wavelet functions is enormous. For example, only the family of orthogonal functions of Daubechies has more than ten representatives with different forms and range of existence. Up to the present moment great number of wavelet functions are well known – functions of Haar, Daubechies, Morlet, etc. [1,2,3,4].

In our investigation we used orthogonal wavelets, because for them a fast wavelet transformation exists, known yet as a pyramidal Mallat algorithm [5,6]. It is realized on the basis of an iteration algorithm following the diagram shown in Fig. 3. Signal U is passed to a low-frequency filter H and a high-frequency filter G with transfer functions, respectively [2,3]:

$$H(\omega) = \sum_{n \in Z} h_n e^{-in\omega} \qquad (1)$$

$$G(\omega) = \sum_{n \in Z} g_n e^{-in\omega}\ , \qquad (2)$$

corresponding to wavelet functions $\psi(x)$ and $\varphi(x)$. The filter coefficients h_n and g_n are calculated depending on the applied wavelet, and n is an integer. After reducing the number of the frequency components in half (binary decimation operation ($\downarrow 2$)), the approximation coefficients are obtained on level m = 1 - $a_{1,k}$ from filter H, while detailizing coefficients $d_{1,k}$ are obtained from filter G. In case of a higher level expansion, the approximation coefficients on level m = 1 ($a_{1,k}$) undergo analogous operations according to the diagram in Fig. 3.

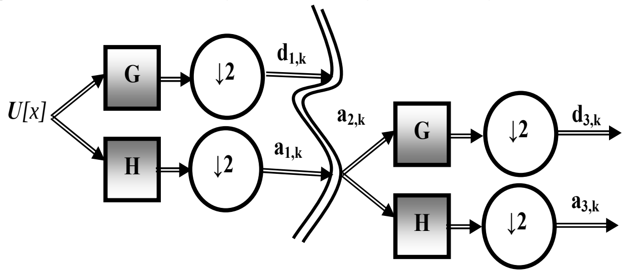

Figure 3 - Diagram of fast wavelet transformation m=3 levels

The approximation coefficients of the forward discrete wavelet transform on level m are calculated according to the dependence [7,8]:

$$A(m,k) = \int_{-\infty}^{\infty} 2^{-m/2} \varphi_0\left(2^{-m} x - k\right) U(x)\,dx\ , \qquad (3)$$

but the detailizing coefficients are calculated after substitution of $\psi_0(x)$ by $\varphi_0(x)$:

$$D(m,k) = \int_{-\infty}^{\infty} 2^{-m/2} \psi_0\left(2^{-m} x - k\right) U(x)\,dx \qquad (4)$$

In the general form the output signal on level m is represented by the expression:

$$U(x) = \sum_{k=-\infty}^{\infty} A_{m,k} \varphi_{m,k}(x) + \sum_{j=1}^{m} \sum_{k=-\infty}^{\infty} D_{j,k} \psi_k(x) \qquad (5)$$

The proposed algorithm can be quickly executed in Matlab software environment.

EXPERIMENTAL SETUP SCHEME FOR RECOGNITION OF ALUMINUM, CHROME-NICKEL, BRASS, COPPER, CAST-IRON AND STEEL

The experiments conducted for collecting information have been realized using ultrasonic sensors of the type UST40T/UST40R [9].

The analysis of the ultrasonic signal returned upon reflection makes it possible to recognize various physical media. The block diagram of the experimental setup is shown in Fig. 4.

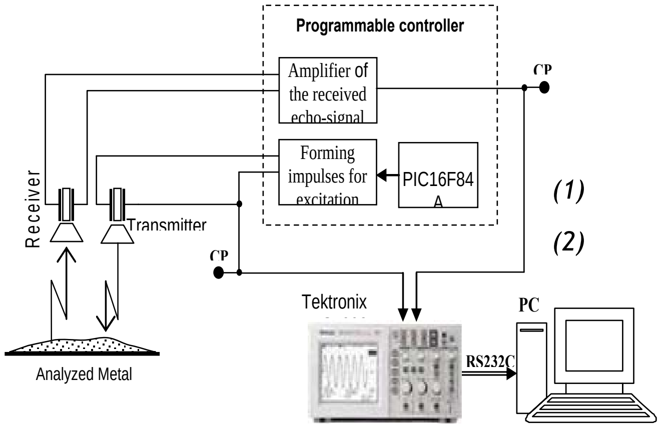

Figure 4 - Experimental setup scheme

The single-chip microcontroller excites the pulse former and a series of six pulses, each having a duration of 12,5 μs (40 kHz), is passed to the ultrasonic transducer, followed by a pause of interval 12 ms (Fig. 5). As a result, a short sequence of ultrasonic waves generated by a piezoelectric transducer is propagated in the working medium near to the analyzed object.

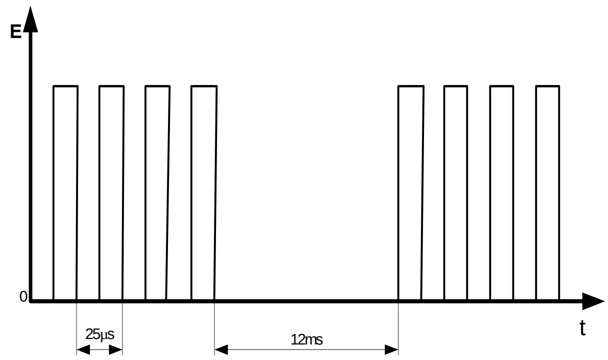

Figure 5 - Packets of square pulses for excitation of the transducer

The returned signal is amplified by the receiver and is then sent to the oscilloscope input. The discretization of the reflected signal is performed using the analogue-to-digital converter built in the oscilloscope with discretization frequency 500 kHz. Each measurement yields 2500 discrete values (records). The data are converted in an ASCII text file.

For the investigation of the above-mentioned materials (aluminum, chrome-nickel, brass, copper, cast-iron and steel) 60 measurements for each of them are performed with an equal distance (which is 50 cm) between the transducer and the analyzed medium.

The choice of these metals is based on their close similarity as a structure, the fact that they are different as substances and their wide use in industry.
By means of simulation using the Matlab software product [3], the approximation and detailizing coefficients of the occurrences in the training sample have been obtained (100 occurrences) on levels $m = 1$ through $m = 9$, applying DWT with orthogonal Haar, Daubechies, Coiflets and Symlet wavelets. During this processing, after reaching level m=8, the feature parts are reduced to 10 coefficients as a result (obtained upon dividing 2500 discretes by 2^8). Fig. 6, 7, 8, 9, 10 and Fig. 11 present the results after the continuous wavelet transformation (continuous wavelet spectrum), compared to the reflected signal for the respective material.

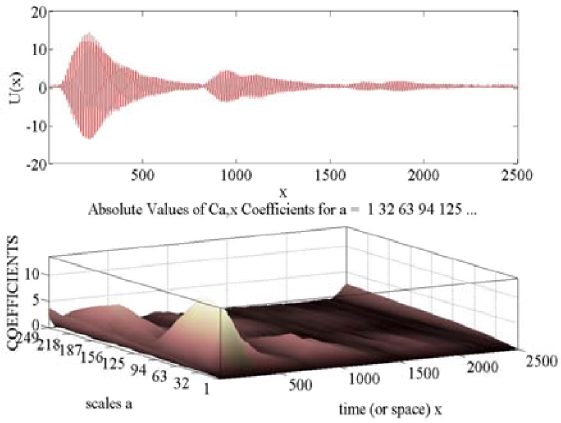

Figure 6 – Aluminum

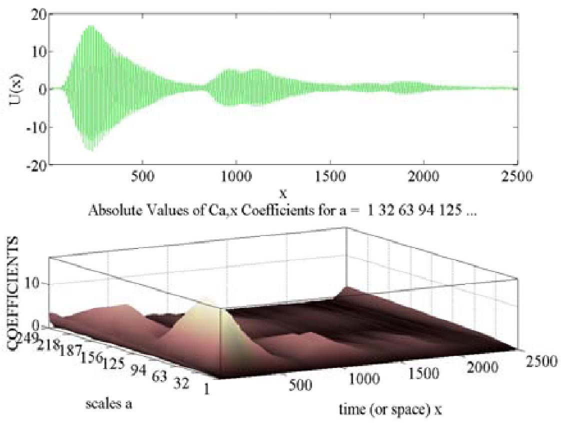

Figure 7 – Chrome-nickel

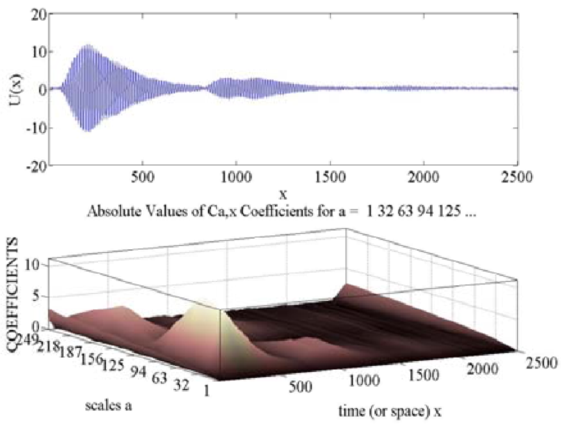

Figure 8 - Brass

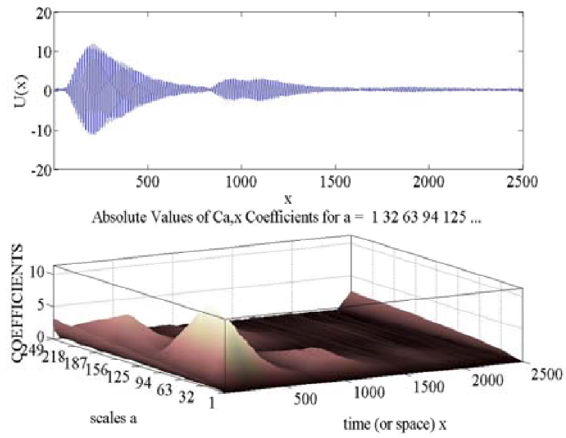

Figure 9 – Copper

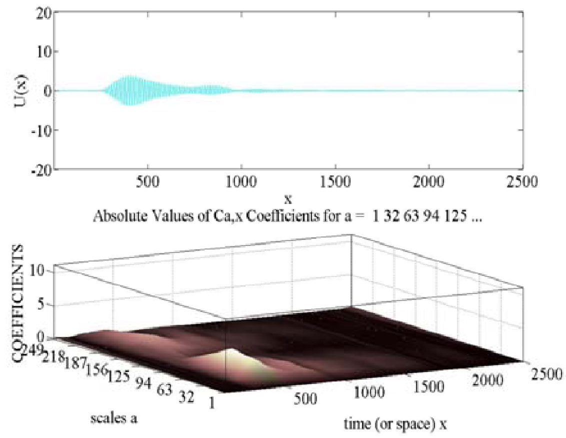

Figure 10 – Steel

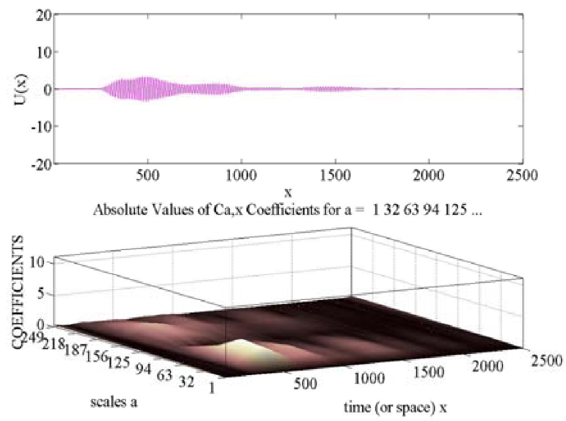

Figure 11 - Cast-iron

The obtained coefficients have been studied in the capacity of recognition (classification) features. Fig. 12 and Fig. 13 present the approximation and detailizing coefficients after discrete wavelet transform (DWT) on level m=8, which yields the best results. As can be seen from the obtained 10 features (coefficients), the greatest distinction is achieved for number one and number four.
On the basis of the obtained features, six clusters have been defined, corresponding to the materials to be identified. These are presented in Fig. 14 and Fig. 15.

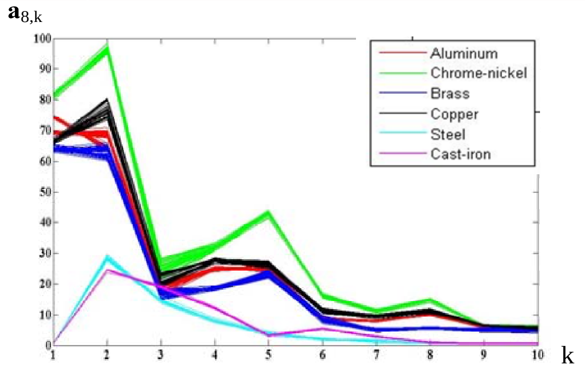

Figure 12 - Approximation coefficients at level m=8

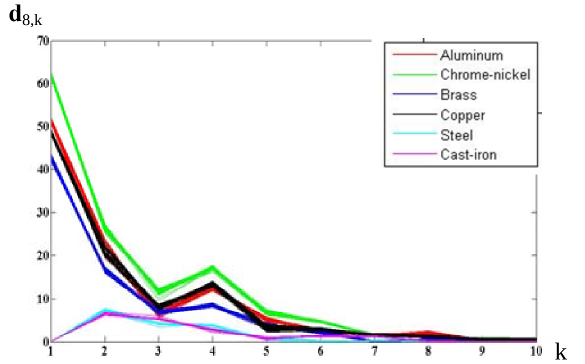

Figure 13 - Detailizing coefficients at level m=8

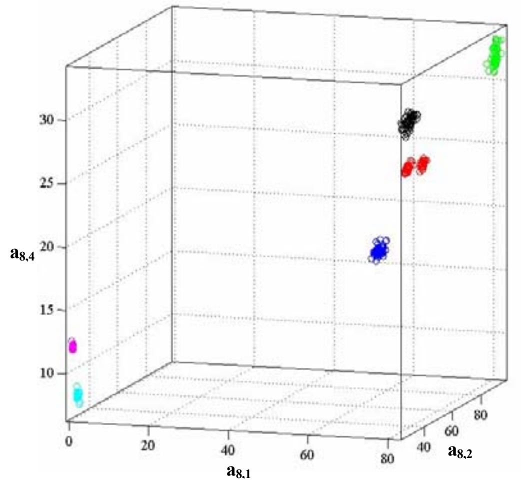

Figure 14 - Clusters with approximation coefficients $a_{8,k}$ k=1,2 and 4

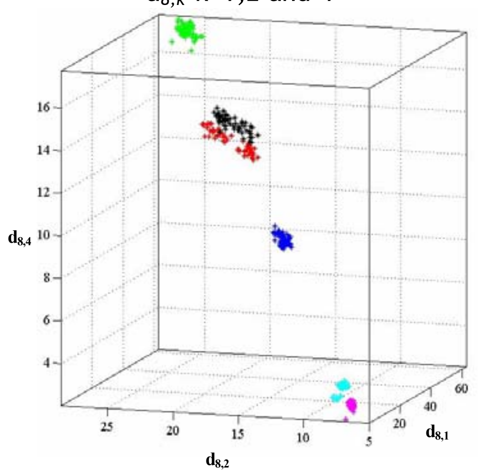

Figure 15 - Clusters with detail coefficients $d_{8,k}$ k=1,2 and 4

It can be seen in Fig. 14 and Fig. 15 that there is no overlapping, instead there is a clear distinction between the cluster zones, which is, in practice, a prerequisite for error-free operation. The selected classifier that operates using the k-nearest neighbor (KNN) method [10] takes into account the Euclidean distance to the three nearest neighbors – figure 16.

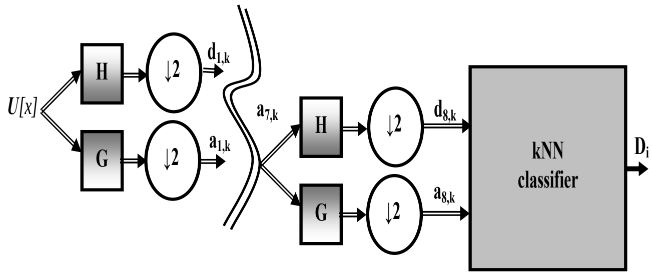

Figure 16 - Block-diagram of kNN classifier with wavelet forming of features

Table 1 - Results obtained for the classification of the validation set (197 measurements) with wavelet "Haar", level m=8 of features $a_{8,k}$ k=4

Metals for identification		Classified by the classifier, number							Errors	
		Al	CrNi	CuZn	Cu	Steel	Cast-iron	Total	Real	Main
Class	m_{ik}	m_{i1}	m_{i2}	m_{i3}	m_{i4}	m_{i5}	m_{i6}	бр.	g_i,%	e_i,%
Al	m_{1k}	27	0	0	0	0	0	27	0	0
CrNi	m_{2k}	0	34	0	0	0	0	34	0	0
CuZn	m_{3k}	0	0	38	0	0	0	38	0	0
Cu	m_{4k}	0	0	0	36	0	0	36	0	0
Steel	m_{5k}	0	0	0	0	28	0	28	0	0
Cast-iron	m_{6k}	0	0	0	0	0	34	34	0	0
Total	бр.	27	34	38	36	28	34	197	General error E=0%	

Table 1 summarizes the results obtained for the classification of the validation set of 197 measurements (other than those included in the training sample). As can be seen in the used classifier working with one feature only, the error is equal to zero and all measurements taken of the materials have been related to 100% of the respective clusters. On this basis one can train a system for recognition of different materials.

CONCLUSION

The main advantage of the applied method is in the possibility for receiving the features for classification by strictly mathematical procedure, so avoiding the subjectivity during heuristically forming of features. That makes a classificatory practically applicable.

ACKNOWLEDGMENT

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