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NON-CONTACT METHOD FOR METAL RECOGNITION

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The present article proposes a non-contact method for metal recognition - aluminium, chrome-nickel steel, brass and copper. A piezo-electric emitter sends an acoustic wave to the object to be identified. The reflected signal is received and processed using orthogonal wavelet basis functions. Clusters are formed based on feature spaces of classifiers realized following the k-nearest neighbour (kNN) method. During each subsequent measurement the results are related to a specific cluster. This approach has yielded a 100% recognition of the above materials, as well as three types of explosives

Introduction

It is often necessary in practice to perform identification of brittle materials, and sometimes – of explosives. That is why it is desirable to use a non-contact method, which guarantees a non-destructive effect. This is a difficult process that requires 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.

Description

Sequence of the recognition process

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

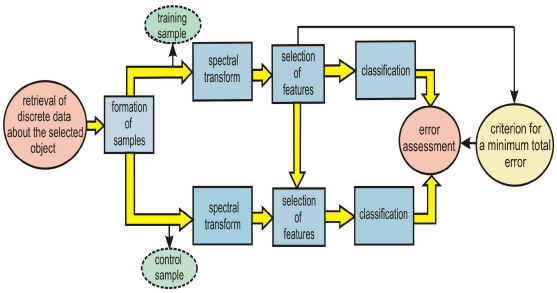

Fig. 1. Sequence of the recognition process

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.

Spectral transforms

The formation of recognition features can be objectified by applying the general spectral theory of signals, using the coefficients of the received expansion of the image signal in a predefined basis in the capacity of features.

The spectral analysis theory enables the synthesis of recognition features, the output description is transformed into a new

space, and the coefficients $C(k)$ from the expansion of $U(x)$ in a suitable basis act as features:

$$C(k)=F.U(x), \quad (1)$$

where F is the transformation operator (transformant).

Thus, instead of the image values in the reference points $U(x)$, the classifier will use their transformation operators $C(k)$ in the capacity of features forming the feature space. This notion of image transformation in feature space mainly results in project objectification, but along with this provides a number of other advantages. For instance, if suitable orthogonal functions are selected as basis functions, this de-correlates the features – spectral components, and eliminates the necessity for studying them according to the strength of statistical connection. Moreover, the spectral components having higher numbers carry a small part of the signal energy and are low image-informative, accordingly. This circumstance supports the study according to feature informativeness, as far as the spectral analysis itself is a solution to the problem [4].

The fast Fourier transform (FFT) enables the transformation of the large amount of time series data into several coefficients that can be used as features, but information about the time component is lost during the transform – the dependence of amplitude on time is transferred into a dependence of amplitude on frequency. The most commonly applied transform has the following disadvantages:

– the Fourier transform gives the global data about the frequency spectrum of the signal studied and does not present the local properties in case of fast time changes of its spectral content;

– the presence of "discontinuities" or "peaks" in the output signal causes insignificant changes in their frequency spectrum, and a large number of low amplitude harmonics is required for presenting them, etc.

Some of the above disadvantages are avoided when applying the windowed Fourier transform, the output signal being expanded within a certain time interval – window function. It is also possible to use other transforms, such as the discrete cosine transform (DCT), fast Walsh-Hadamard transform (FWHT) etc., which often have advantages over the Fourier transform, but in general the transform is always in a space eliminating the time coordinate.

In view of the above circumstances, it is suitable to use a wavelet transform, which yields the dependence of amplitude on frequency and time.

Wavelets are functions localized along the independent variable axis (t or x), capable of shifting along it and scaling (shrinking / stretching), and having the form of short wave packets with zero average value of the wavelet function $\psi(x)$, i.e.:

$$\int_{-\infty}^{\infty}\psi(x)dx=0, \quad (2)$$

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

– $\psi(x)$ – wavelet function showing the signal details and forming the detail 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 [5, 6].

The basis wavelet function $\psi_0(x)$ has to satisfy (2) and the performance of the operations:

– shift along the independent variable axis –

$$\psi_0(x-b), \quad (3)$$

where $b\in R$ (real number) and determines the location of the wavelet packet;

scaling

$$a^{-1/2}\psi_0\left(\frac{x}{a}\right), \quad (4)$$

where $a>0$, is also a real number $à\in R$ and determines the width of the wavelet packet.

Taking into consideration requirements (3) and (4):

$$\psi(x) = a^{-1/2}\psi_0\left(\frac{x-b}{a}\right), \qquad (5)$$

At present a number of basis wavelet functions are known – Haar, Daubechies, Morlet etc.

The fundamental principle of orthogonal expansion by means of wavelets consists in the possibility of independent analysis of a given signal (function) in different scales. The wavelet transform is intermediate between the purely spectral (frequency) transform and the pure time presentation [1, 3, 5]. As regards their localization in both the time and the frequency domains, wavelets are intermediary between the sinusoid functions that are well localized in the frequency domain and the Dirak function – well localized in the time domain.

When using wavelets, the product of the time and the frequency ranges remains constant during function re-scaling, i.e. the area remains constant (Fig. 2). This allows the low-frequency components of the signal to be well localized in the frequency domain, and the high-frequency components – in the time domain (leaps, peaks, etc.)

The wavelet transform has a great "redundancy" and to represent a specific occurrence, it is sufficient to determine the coefficients in certain points in the plane (*x, f*), for instance, in the centers of each cell (Fig. 2).

a3 < a2 < a1

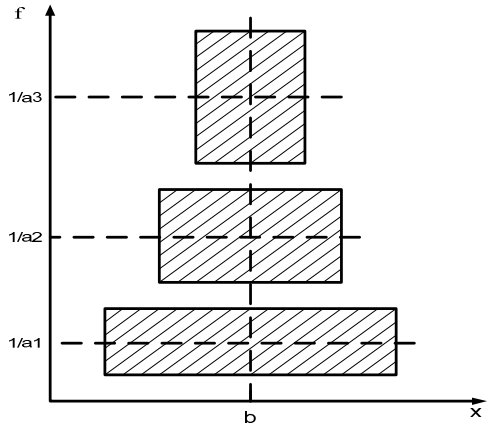

Fig. 2. Wavelet transform in the plane (*x, f*)

For a material recognition transform to be applicable, it must be based on an orthogonal system of basis functions and there must be fast conversion algorithms. A suitable transform is the discrete wavelet transform (DWT) with orthogonal wavelets with the elaborated fast wavelet conversion (Mallat algorithm).

For discrete values –

$$a = 2^m \text{ and } b = k\,2^m, \qquad (6)$$

where k and m – integers, dependence takes the form:

$$\psi_{m,k}(x) = 2^{-m/2}\psi_0\left(2^{-m}x - k\right), \quad (7)$$

The approximation coefficients of the forward discrete wavelet transform on level m are calculated according to the dependence [1, 2]:

$$A(m,k) = \int_{-\infty}^{\infty} 2^{-m/2}\varphi_0\left(2^{-m}x - k\right)U(x)dx, \quad (8)$$

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

$$D(m,k) = \int_{-\infty}^{\infty} 2^{-m/2}\psi_0\left(2^{-m}x - k\right)U(x)dx \quad (9)$$

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

$$U(x) = \sum_{k=-\infty}^{\infty} A_{m,k}\varphi_{m,k}(x) + \sum_{j=1}^{m}\sum_{k=-\infty}^{\infty} D_{j,k}\psi_k(x) \quad (10)$$

Wavelets are capable of localizing well low-frequency details along the frequency axis and high-frequency details along the time axis. This ability of wavelets to find a compromise between time localization and frequency localization of the studied signal is one of the most important characteristics in analyzing signals of complex shape. The wavelet transform splits the signal into frequency components, which allows each of these components to be studied with a resolution corresponding to its scale, and thus to achieve a good frequency-time localization. Thanks to this property, wavelets allow the manifestation of sharp "discontinuities" and "peaks" in the signals.

Compared to the analysis using harmonic expansion, the analysis by means of wave packets (wavelets) has the following advantages [1, 4]:

– the wavelet transform provides information about the studied signal in the time-frequency domain, while the spectral analysis yields a spectrum in the frequency domain.

– the wavelet transform provides information about the occurrence of a given spectral component and the time of its existence. This approach is suitable for analysis of signals with high-frequency components of short duration and low-frequency components of long duration.

The wavelet transform enables signal analysis in different time scales and the manifestation of various properties of the signal related to changes in its structure in case of transition from one scale into another, with energy distribution between scales, etc. [4, 5].

What has been stated so far makes it possible to conclude that the wavelet analysis allows the structure of the studied signal to be assessed and the behaviour of the components to be observed.

Fast wavelet conversion

Fast wavelet conversion has been developed for orthogonal wavelets – this is Mallat pyramidal algorithm [3]. 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

$$\mathrm{H}(\omega) = \sum_{n \in Z} h_n e^{-in\omega} \quad \text{and} \quad (11)$$

$$\mathrm{G}(\omega) = \sum_{n \in Z} g_n e^{-in\omega}, \quad (12)$$

corresponding to wavelet functions $\psi(t)$ and $\varphi(t)$. The filter coefficients h_n and g_n are calculated depending on the wavelet applied, 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–A1 from filter H, while detail coefficients D1 are obtained from filter G. In case of a higher level expansion, the approximation coefficients on level m=1(A1) undergo analogous operations according to the diagram in Fig. 3.

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

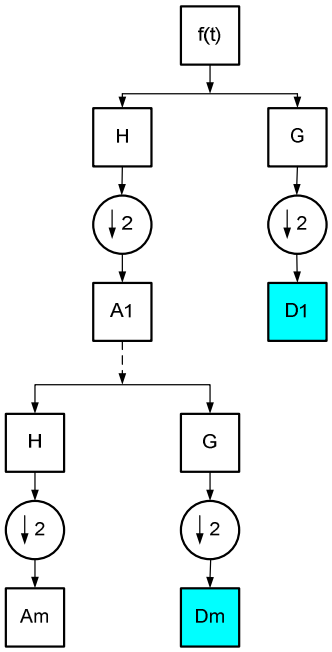

Fig. 3. Diagram of fast wavelet conversion on m levels

Experimental model for recognition of aluminium, chrome-nickel steel, brass, copper

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

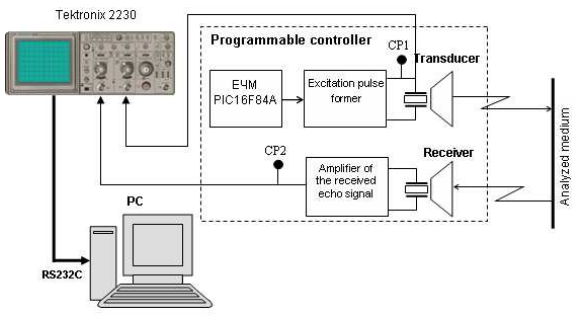

Fig. 4. Block diagram of the experimental setup

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 the object

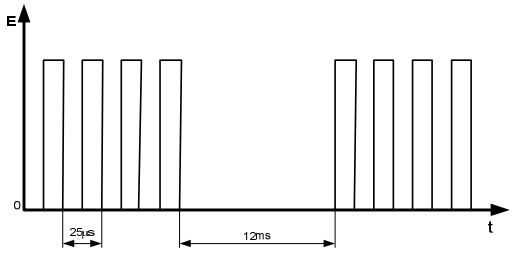

Fig. 5. Packets of square pulses for excitation of the transducer

to be analyzed. 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.

The investigation of the above-mentioned materials – aluminium, chrome-nickel steel, brass and copper – required taking 60 measurements for each of them, the distance between the transducer and the analyzed medium being 50 cm. 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 [5], the approximation and detail 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, Fig. 7, Fig. 8 and Fig.9 present the results after the wavelet transform (wavelet spectra), compared to the reflected signal for the respective material.

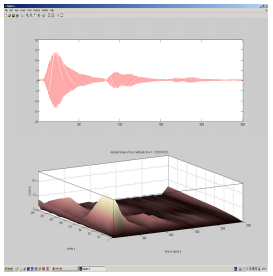

Fig. 6. Aluminium

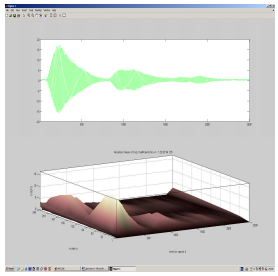

Fig.7. Chrome-nickel steel

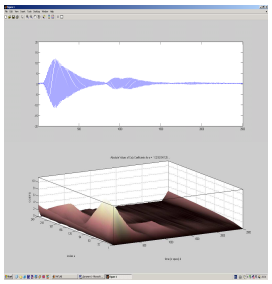

Fig.8. Brass

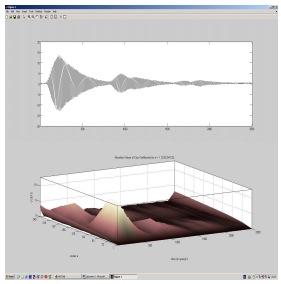

Fig. 9. Copper

The obtained coefficients have been studied in the capacity of recognition (classification) features. Fig. 10 and Fig. 11 present the approximation and detail 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, four clusters have been defined, corresponding to the materials to be identified. These are presented in Fig. 12 and Fig. 13.

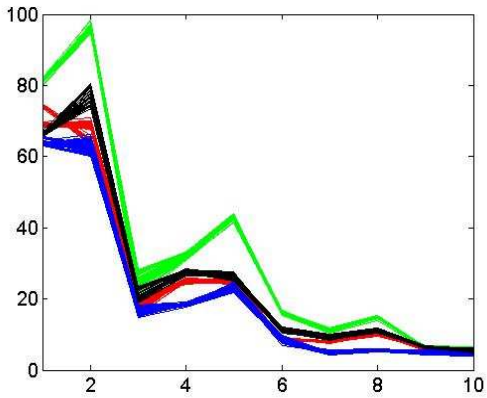

Fig. 10. Approximation coefficients

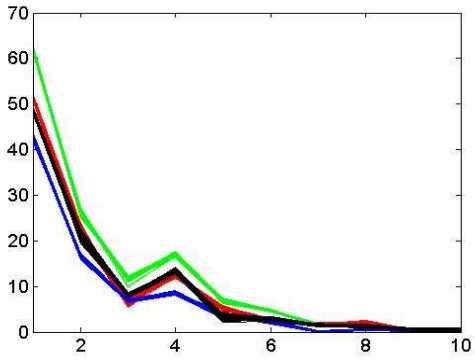

Fig. 11. Detail coefficients

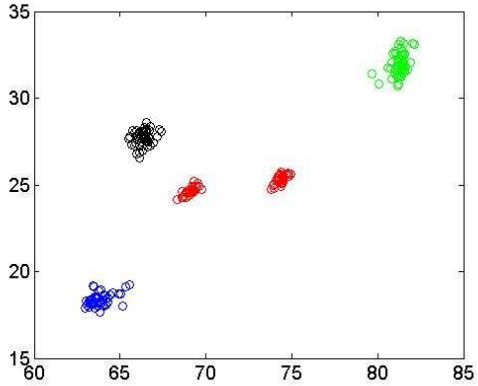

Fig. 12. Clusters of approximation

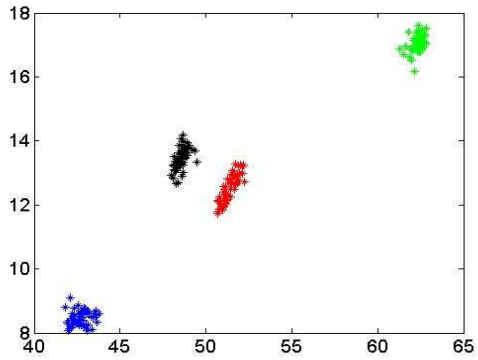

Fig. 13. Clusters of detail coefficients coefficients

The selected classifier that operates using the k-nearest neighbour (KNN) method [8, 12] takes into account the Euclidean distance to the three nearest neighbours. It can be seen in Fig. 12 and Fig. 13 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.

Table 1 summarizes the results obtained for the classification of the validation set (133 occurrences). As can be seen in it, the error is equal to zero with the classifier used, which works with two features only, and 100% of all measurements taken of the materials have been related to the respective clusters.

This can serve as a basis for training of a material recognition system.

Table 1. Results from the classification

Analyzed material		Classified by the classifier, number					Errors	
		Al	CrNi	CuZn	Cu	Total	Actual	Major
	m_{ik}	m_{i1}	m_{i2}	m_{i3}	m_{i4}		g_i,%	e_i,%
Al	m_{1k}	39	0	0	0	39	0	0
CrNi	m_{2k}	0	34	0	0	34	0	0
CuZn	m_{3k}	0	0	29	0	29	0	0
Cu	m_{4k}	0	0	0	31	31	0	0
Total	бр.	39	34	29	31	133	Total error E = 0 %	

Conclusions

The main advantage of the proposed approach lies in the possibility for obtaining the features in a strictly defined mathematical procedure, avoiding the subjective factor in the heuristic formation of features. This makes the classifier practically applicable. On the basis of this approach, three types of explosives have been studied, with a 100% recognition achieved.

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