

RECOGNITION OF PALM FINGER MOVEMENTS ON THE BASIS OF EMG SIGNALS WITH THE APPLICATION OF WAVELETS

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Abstract: The paper describes an EMG signal analysis based on the wavelet transform, applied for the hand prosthesis control. Signal features are represented by wavelet coefficients. A cross-validation method is applied for the feature selection process. The classification algorithm uses multistage recognition. The information about finger posture provided by a data glove is recorded concurrently with forearm EMG signals. The acquired data are used to train the classification algorithm.

Keywords: multistage pattern recognition, EMG signal processing, wavelet transform, dexterous prosthesis control

1. Introduction

The discussed problem concerns the recognition of palm fingers movements on the basis of electromyography (EMG) signals. The elaborated method of recognition is applied to artificial hand control. The analyzed EMG signals create a set of information about the executed movement of fingers. These signals are superpositions of potentials accompanying the activity of the muscle motor units activated by the nervous system for a given type of movement. The different movements are related to stimulation of different motor units, and different spatial location of these units within the analyzed muscles causes the formation of EMG signals with differing features, *e.g.* with different frequency spectra.

Consequently, the authors' earlier investigations concerned the extraction of features on the basis of the Fourier transform [1-3].

The initial experiments were conducted with root-mean-squared (rms) values of EMG signals. For this purpose a two-channel measuring circuit was developed. Each channel contained a differential amplifier with an amplifying coefficient of about 2000 V/V and a filtering-rectifying-integrating (f-r-i) module which formed the output signal proportionally to the rms value of the measured myopotentials. The rms value was then proportional to the level of excitation of the examined muscle. Two muscles, the elbow wrist flexor and the finger extensor, responsible respectively for wrist flexion and extension, were selected for the experiments. The construction of the measuring circuit was preceded by an analysis of the EMG signals' power spectrum to determine the circuit parameters (see Figure 1).

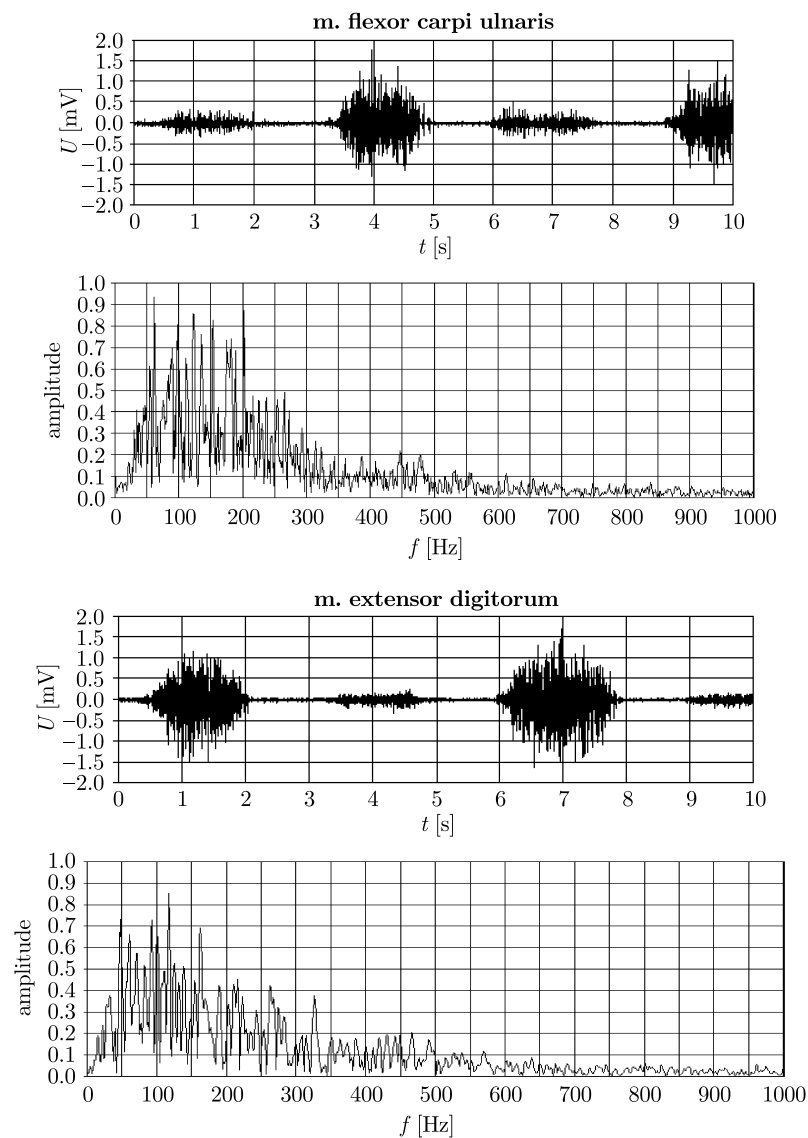


Figure 1. Exemplary plots of EMG signals and their frequency spectrum for the two tested muscles

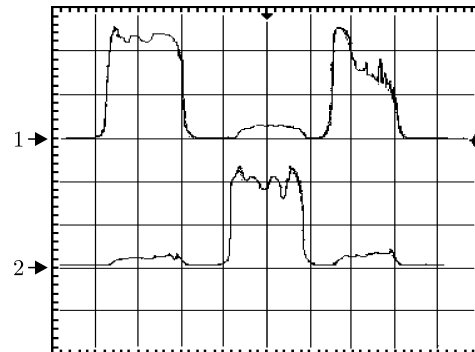


Figure 2. EMG signals after filtering, rectification and integration

The analysis showed that different muscle myopotentials could be measured by channels of the same parameters. After amplification and transformation the analogue signals (Figure 2) were sampled by a prosthesis microcontroller. The analysis of signal amplitude turned out to be reliable enough to control a gripper mechanism with one degree of freedom, if the gripper's opening and closing with controlled velocity was considered.

However, to control prosthesis with a greater number of degrees of freedom the above method was avoided. This resulted from the lack of selective access to EMG potentials from the muscles responsible for separate finger movements.

A consideration of the nature of electrical signals' spatial propagation through the human body led to the conclusion that to control more sophisticated prosthesis movements the Fourier analysis of EMG signals had to be applied.

Therefore, our next experiments were conducted using the Fourier transform and a neural network and statistical model as classifiers. The features were selected by the extrapolation method. The experiments were performed on a group of four healthy persons aged 23–25 (Q1, Q2, Q3, Q4), using the same selected muscle groups. The persons performed eight different movements (plus one neutral movement): (1) flexing and (2) extending the wrist, (3) flexing and (4) extending the fingers, (5) supination and (6) pronation of the wrist, (7) radial deviation and (8) ulnar deviation, plus (9) a neutral state. The sample frequency for two electrode pairs was $f = 1.6\text{KHz}$. The Hamming window function was used to decrease the effects of the not integer number of signal sampling cycles. The number of averaging points was $IP = 10$.

Based on the series of measurements, a 90-element teaching set was obtained (10 patterns for each class) and, after half an hour's break, a 180-element testing set (20 patterns for each class) was created. A multilayer perceptron (MLP) with the back propagation error teaching method and the Kohonen Learning Vector Quantization (LVQ) neural networks, as well as the statistical approach of the k -nearest neighbour (k -NN) were applied as classifiers. The obtained results of the testing set recognition are shown in Table 1.

The LVQ network gives the best results, with an average recognition error of 6.17%. This is a significant improvement from those described by Hudgins [4–6], although 16 persons were tested there, four classes recognised and other muscle groups used.

Table 1. The obtained average errors of recognition

Classifier	Q1	Q2	Q3	Q4	Average
<i>k</i> -NN	12.22%	4.44%	7.78%	8.33%	8.19%
MLP	17.28%	5.83%	5.89%	7.61%	9.15%
LVQ	9.50%	2.94%	5.83%	8.56%	6.17%

So far, our investigations have also shown that the unsteady character of the signals renders the patterns obtained in this way insufficient for a reliable classification of movements of separate fingers. The analysis of signals in the joint domains of frequency and time gives qualitatively new possibilities in this case. This group of time frequency methods comprises the wavelet transform method.

The wavelet analysis is one of the latest and most intensely studied methods. Most often a discrete form of the wavelet transform is used, closely related to multidistributive analysis. Various methods of EMG signal analysis, as well as preliminary results of their applications to finger movement recognition, are discussed in papers [4–11].

Hudgins used signal features in the time domain [4]. He proposed the following features: zero crossing, mean absolute value, mean absolute value slope and trace length, and used these features as the input vector of an artificial network organized as a multilayer perceptron (MLP). The network recognized four classes of arm muscle actions, with a 10% error.

More advanced methods were used by Englehart [5, 6]. He applied joint time and frequency domain methods: the Short-Time Fourier Transform, the Wavelet Transform and the Wavelet Packet Transform. He also used two methods of feature selection: Class Separability (CS) and Principal Components Analysis (PCA), as well as two classification methods: MLP and Linear Discrimination Analysis (LDA). He compared the obtained data with Hudgins' results, using the same recognized classes, and showed that for the time domain approach the best combination is CS and MLP (9.25% error), whereas for the joint time and frequency domain approach the best combination is PCA and LDA (6.25%).

Similar research was conducted by Nishikawa [7–9], who used a wavelet Gabor transform and applied an interactive trainer unit in the neural network classifier. It recognised 6 classes on the basis of two EMG signals with average results of 81.5% on-line learning and 70.9% off-line learning.

Moshou [10] used the wavelet transform for feature generation and applied two methods for feature set reduction: soft thresholding and hard thresholding. He also applied the Self-Organized Maps Kohonen Network as a classifier and used it for car driver fatigue recognition.

Jeong-Su Han [11] recognised 8 classes using the fuzzy pattern classifier and the fuzzy min/max neural network. The measurements were performed with a 4-channel circuit. He used four types of time domain features: integral absolute value (IAV), average IAV slope (ASIAV), variance (VAR) and zero cross (ZC), and one in the frequency domain: frequency ratio (FR). His recognition results were in the range a 83-90% of correct results. The system controlled a robot arm mounted on a wheelchair.

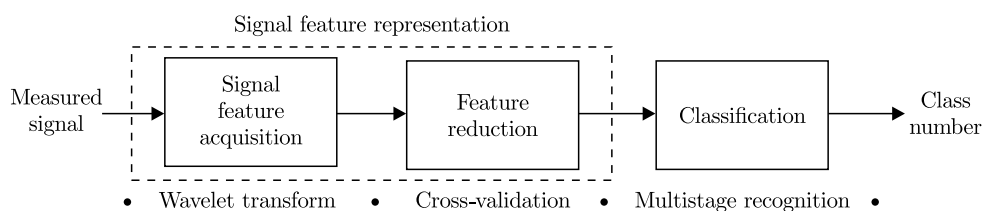


Figure 3. A block diagram of the EMG signal recognition process

A general block diagram of the recognition process is shown in Figure 3. It includes two basic stages:

- (a) determination of features of the measured signal and
- (b) signal classification on the basis of the determined features.

The realization of the first stage consisted in developing an algorithm of feature extraction and selection using a wavelet transform, the second – in developing an algorithm of multistage recognition using a statistical model with a teaching set. These algorithms are discussed in the following paragraphs.

2. EMG signal analysis

The wavelet transform method (WT) transforms a signal in the joint fields of time and frequency, offering a possibility to locate the harmonic components of the signal in time. This method offers much better analytical possibilities for unsteady signals in comparison with the Fourier transform method (FT). It locates quick changes of the signal in time and frequency well, whereas FT averages energy over frequencies in the analysed time window and thus locates frequency of stationary signals well. This is illustrated in Figure 4. In the FT method, the size of the time window is constant and independent of frequency, which implies a constant frequency resolution. However, in the WT method the size of the time window varies with frequency. This gives good time location for high frequencies, as well as good frequency location for large time windows. According to Heisenberg's indeterminacy principle, it is impossible to estimate concurrently the exact time and frequency location. An additional advantage of WT is a higher speed of its operation resulting from its lower computational complexity in comparison with FT. The complexity of FT and WT

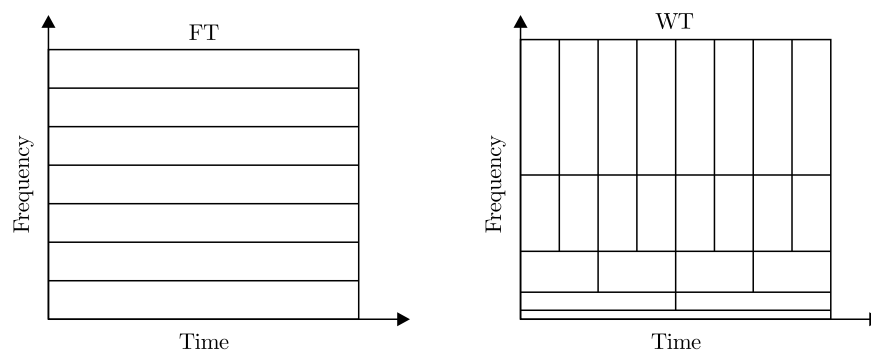


Figure 4. The partition of the time-frequency space into Heisenberg rectangles for the FT and WT methods

amounted to $O(n \log(n))$ and $O(n)$, respectively: that means a smaller number of necessary operations for the wavelet transform method.

The conducted investigations used the fast discrete Wavelet transform algorithm given by Mallat [3, 5]. The algorithm exploits the multidistributive representation of signals. It uses the banks of filters associated with the suitable wavelets. The transform is lossless.

2.1. The algorithm of the discrete wavelet transform

The mother wavelet, $\Psi(t)$, determines a band-pass filter; we can thus generate a family of wavelets:

$$\Psi_{ab}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right), \quad a \in R^+, \quad b \in R, \quad (1)$$

where the a parameter is a scale and corresponds to frequency, while the b parameter scales a shift in time.

The continuous wavelet transform of signals $f(t) \in L^2(R)$ is given by the following equation:

$$CWT(a, b) = \int_{-\infty}^{+\infty} f(t) \Psi^*_{ab}(t) dt. \quad (2)$$

As a result of quantization of parameters $a = 2^m$ and $b = n2^m$ in Equation (1), we obtain:

$$\Psi_{mn} = 2^{-m/2} \Psi(2^{-m}t - n), \quad \text{where } (m, n) \in Z^2, \quad (3)$$

which is a dyadic orthonormal wavelet basis of L^2 space.

The discrete wavelet analysis of signal $f(t) \in L^2(R)$ consists in the calculation of wavelet coefficients for the expansion of Equation (2), after substitution (3). The one-dimensional signal $f(t)$ can be expressed as:

$$f(t) = \sum_m \sum_n d_m[n] \Psi_{mn}, \quad (4)$$

where the wavelet coefficients, $d_m[n]$, represent the common features of signal f and wavelet Ψ .

The fast wavelet transform is closely associated with the signal multidistributive analysis using the orthogonal basic functions for the spanning of the signal onto the suitable subspaces of the signal details and approximation. Such spaces have to fulfil the conditions given in [1, 3, 5].

The approximation of the function, $f(t)$, with resolution 2^m for scale, J , will be the orthogonal projection onto space V_j decomposed according to the equation:

$$V_j = V_{j_0} \cup \bigoplus_{j=l_0}^{J-1} W_j, \quad j_0 < J, \quad j_0 \in Z. \quad (5)$$

Spaces W_j are called the *spaces of details* and the V_{j_0} space – the space of approximation.

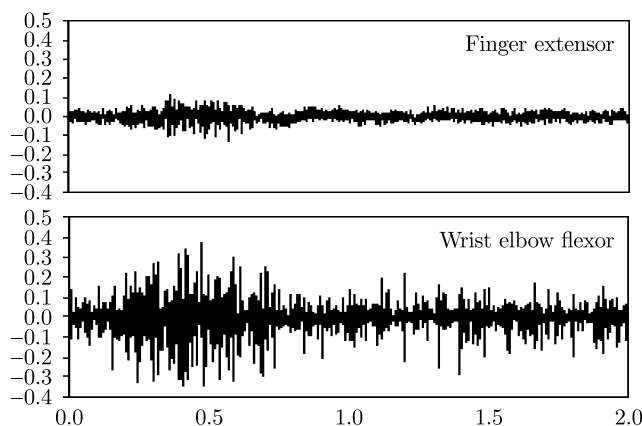


Figure 5. Exemplary EMG signals from the finger extensor and the elbow wrist flexor

The calibrating function, $\varphi(t)$, is then the function which is scaled and translated when it spans on V_j spaces:

$$\varphi_{j,k} = 2^{j/2} \varphi(2^j t - k), \quad k \in Z. \tag{6}$$

However, the $\psi(t)$ wavelet is a scaling and translating function, which spans W_j spaces:

$$\psi_{j,k} = 2^{j/2} \psi(2^j t - k), \quad k \in Z. \tag{7}$$

Finally, we can represent a one-dimensional signal as:

$$f(t) = \sum_{k=-\infty}^{\infty} c_{j_0,k} \varphi_{j_0,k}(t) + \sum_{j=j_0}^{J-1} \sum_{k=-\infty}^{\infty} d_{j,k} \psi_{j,k}(t), \tag{8}$$

where the wavelet coefficients are calculated as follows:

$$c_{j_0,k} = \int_{-\infty}^{\infty} f(t) \varphi_{j_0,k}(t) dt, \quad d_{j,k} = \int_{-\infty}^{\infty} f(t) \psi_{j,k}(t) dt. \tag{9}$$

Coefficients $c_{j_0,k}$ create approximations of the signal, $f(t)$, on the j_0 level, while coefficients $d_{j,k}$ represent the details of the signal, $f(t)$, on the given levels.

The numerical realization of the fast discrete wavelet transform does not use wavelets $\psi(t)$ or the calibrating function, $\varphi(t)$, but the filters associated with them. The calibrating function is connected with the low-pass filter giving the signal's approximation, while the wavelet is connected with the high-pass filter giving signal details.

An example course of wavelet decomposition of an EMG signal is shown in Figure 6.

3. Multistage recognition with wavelets

The algorithm of multistage recognition with the teaching set is shown in Figure 7.

The considered problem of recognition has been split into sub-problems. A description of the method and the algorithm of multistage recognition are given in papers [1, 2]. We have modified the basic algorithm as follows.

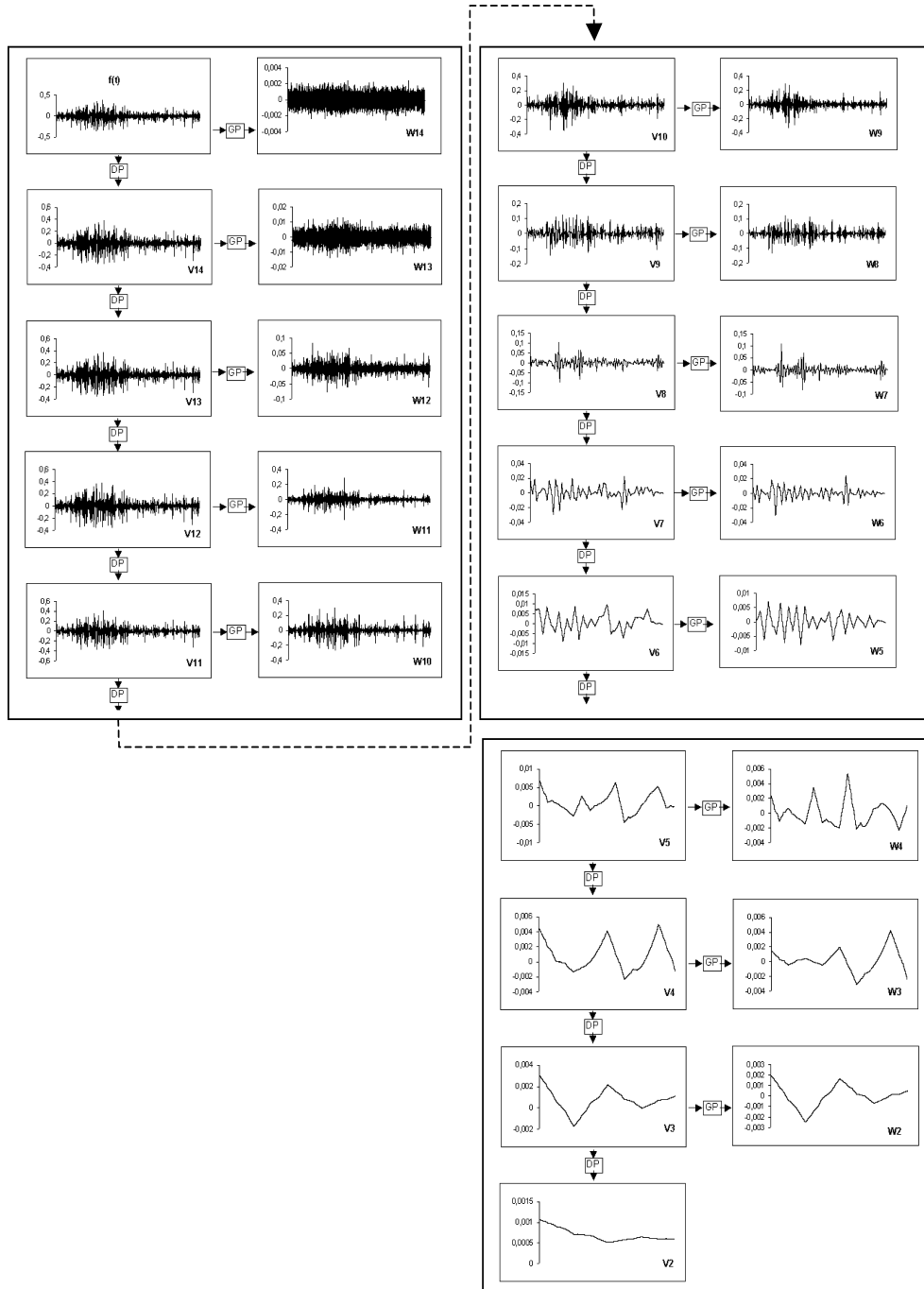


Figure 6. EMG signal wavelet decomposition for the elbow wrist flexor $f(t)$ from Figure 5 using the **db3** wavelet; the spaces of details, W_j , are shown on the right and the spaces of approximation, V_j , of the signal, for scale $j=2$ to 14 – on the left

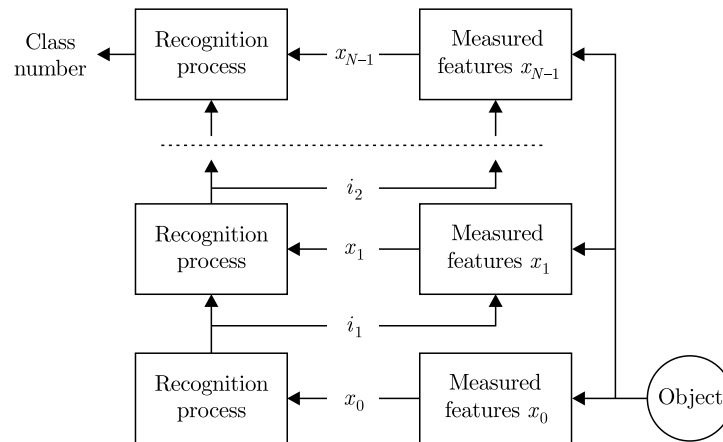


Figure 7. The scheme of the multistage recognition [2]

Let us use the following symbols and descriptions: M – the set of all classes; M_{i_n} – the set of numbers of classes (terminal nodes) attainable from the i_n node; D_{i_n} – the set of direct successors of the node i_n ; $D(n)$ – the set of nodes distant from a root about n , that is the set of decisions possible for stage $n-1$, $D(n) = M$; $x \in X$ – the vector of features describing the object; $x_{i_n} \in X_{i_n} \in X$ – the vector of features used in the i_n node.

The modification consists in that the consecutive decomposition levels determine the set of features for undertaking a successive decision. Discriminating the signals onto detail levels and the approximation level we can choose scales j in such a way that the interesting waveband will cover the levels of details, that is they are captured by $\{d_{j,k}\}$, for $j = j_0, \dots, J-1$. Sets X_{W_j} are the sets of signal features on given levels of decomposition. The adopted approach simplifies the algorithm of multistage recognition, as it imposes the set of features used in the succeeding stages of the decision process. The next stages already serve as corrections of the decisions from the previous levels.

It is known that with the growth of scale j the quantity of features increases and it is not profitable to use them in the next stages. One should rather choose subsets X_{W_j} , dependent on the already taken decisions. The use of wavelet approximation imposes the structure of the multistage recognition algorithm. We have established the structure of a decision tree (see Figure 8), as well as the set of features used in the next stages. The closest neighbour algorithm is used as a classifier at each stage. Two classes have been accepted: 1 – for images connected with forefinger flexion and 2 – for the middle finger. The method of cross-validation described in papers [12, 13] has been used for feature set reduction and to evaluate the recognition algorithm in succeeding stages.

A set of features which improved the quality of discrimination between different classes has been distinguished for feature subsets X_{W_j} . The distinguishing procedure was as follows: one feature in subset X_{W_j} was chosen and another rejected, then the number of wrong classifications was estimated by the cross validation method. This was repeated for each feature. Finally, the feature whose rejection gave the best

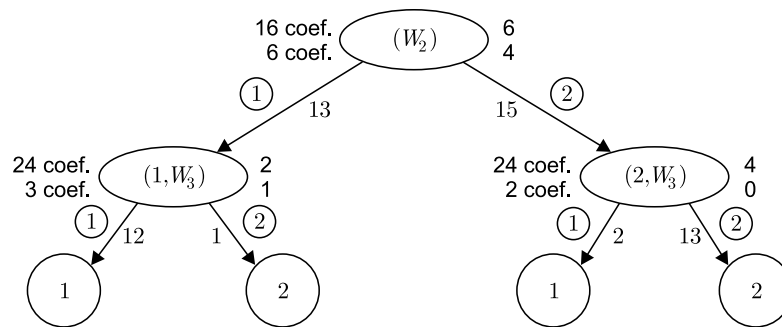


Figure 8. A decision tree of multistage recognition using wavelet coefficients as representations of signal features

improvement for classification was rejected permanently. The procedure was repeated until the rejection of any feature deteriorated the quality of classification.

4. Experiment

One healthy person took part in the experiment. Electrodes were placed on the forearm over the muscles of the finger extensor and the wrist elbow flexor. The measuring system included two pairs of dry electrodes located over the selected muscles and a reference electrode situated in an electrically neutral place, an arrangement of amplifiers and galvanic separators of analogue signals, eight-channel analogue input device NI4472 with the maximum frequency of sampling of 102.4kS/s for each channel and 24-bit resolution. The NI4472 was equipped with an anti-aliasing filter automatically tuned to the Nyquist frequency (half of the sampling frequency). The acceptable input voltages for each channel were $\pm 10V$. The device cooperated with a Pentium 4 PC with LabView6 for recording signals.

The measurements were conducted for isotonic flexion movement of forefinger and the middle finger. 13 and 15 pairs of EMG signals were registered for the forefinger and the middle finger, respectively. The signals were recorded with sampling frequency $f_s = 11025\text{Hz}$ and 16-bit resolution and period length of about 2s, which gave about 22000 samples for one signal. The useful band for EMG signals was included into the range of 0Hz to 500Hz. Basing on this parameter, wavelet decomposition was performed on the scale level from $j = 2$ to 10 using the Daubechies wavelet, db3. This gave about 2000 coefficients. With the scale range selected in this way, the wavelet coefficients described every signal in the band from 2Hz to 350Hz.

Let us mark the i^{th} EMG signal registered from the elbow wrist flexor and from the finger extensor as $f_1^i(t)$ and $f_2^i(t)$, respectively. Further more, $\{d_{j,k}^{i,1}\}$ and $\{d_{j,k}^{i,2}\}$ are the sets of wavelet coefficients representing $f_1^i(t)$ and $f_2^i(t)$, respectively. As image x_i , the joint set of wavelet coefficients calculated for both signals for every pair i :

$$x_i = \{d_{j,k}^{i,1}, d_{j,k}^{i,2}, j, k\}, \quad j = 2, \dots, 10, \quad k \in K_\psi(j, [t_0, t_1]) \quad (10)$$

was accepted, where t_0 and t_1 mark the beginning and the end of registration, respectively.

The prepared images contain about 4000 features. From the signal images, $f_1^i(t)$, prepared in this way and $f_2^i(t)$, a teaching sequence, S_N , was created with the length of $N = 28$. The closest neighbour recognition rule was used for each stage, given by the following equation:

$$\Psi_{i_n}(x_{w_{n-1}}) = m_l, \\ l = \min \sum_{k \in K_\varphi(n-1, [t_0, t_1])} \left[\left(d_{n-1,k}^1 - d_{n-1,k}^{l,1} \right)^2 + \left(d_{n-1,k}^2 - d_{n-1,k}^{l,2} \right)^2 \right], \quad (11)$$

where m_l is a class including image x_l of teaching sequence S_N and $x_{w_{n-1}}$ is the subset of the recognised image: $x = \{d_{j,k}^1, d_{j,k}^2, j, k\}$, $j = 2, \dots, 10$, $k \in K_\psi(j, [t_0, t_1])$.

In the basis on this sequence, the building of an algorithm of finger movement recognition was approached according to the algorithm concept discussed above.

5. Conclusions

The conducted experiment is preliminary in character. The aim of the experiment has been to distinguish the movements of flexion of two fingers – the forefinger and the middle finger. The developed algorithm of multistage recognition numbered a given image into one of the two classes, with a 3.5% error. The wavelet representation of signals was used to extract features. Next, a considerable reduction of features was done for the consecutive recognition stages according to the cross-validation method. Out of 4000 enumerated features (wavelet coefficients) the algorithm used only 10. Moreover, they were not used simultaneously. The calculation of recognition rules was done off-line on a PC. Figure 8 shows the multistage recognition tree of EMG signals. The amount of features before (above) and after (below) optimisation of the feature set is shown on the left side of every node. On the right side of every node there are numbers of wrong recognitions before (above) and after (below) the optimisation. Below every branch the amount of images classified at the given node to class 1 and 2 is given.

Current research aims at increasing the set of classes (so as to increase the number of recognized movements). It is necessary to examine the movements of flexion and extension of three fingers: the thumb, the forefinger and the middle finger. The final goal of this research is to develop a control system of dexterous prosthesis, so the experiments should be conducted first of all with the participation of persons disabled by an amputation at the forearm level.

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