Hetero- and Homogeneous Multiclassifier Systems Based on Competence Measure Applied to the Recognition of Hand Grasping Movements

Marek Kurzynski and Andrzej Wolczowski

Wroclaw University of Technology, Department of Systems and Computer Networks
Wyb.Wyspianskiego 27, 50-370 Wroclaw, Poland,
marek.kurzynski@pwr.wroc.pl

Abstract. The paper presents an advanced method of recognition of patient's intention to move of multijoint hand prosthesis during the grasping and manipulating objects in a dexterous manner. The proposed method is based on a two-level multiclassifier system (MCS) with heterogeneous and homogeneous base classifiers dedicated to EMG and MMG biosignals and with combining mechanism using a dynamic ensemble selection scheme and probabilistic competence function. The performances of two MCSs with the proposed competence function and combining procedure were experimetally compared against three benchmark MCSs using real data concerning the recognition of six types of grasping movements. The systems developed achieved the highest classification accuracies demonstrating the potential of multiple classifier systems with multimodal biosignals for the control of bioprosthetic hand.

Keywords: Multiclassifier system, Competence measure, Hand grasping movements.

1 Introduction

Nowadays, many researchers focus on Multiple Classifier Systems (MCS) because this approach has been shown to outperform single classifiers for a wide range of classification problems. Two main approaches used for the combination of classifiers in the ensemble, are classifier fusion and classifier selection [7]. In the first approach, all classifiers in the ensemble contribute to the decision of the MCS, e.g. through sum or majority voting. In the second approach, a single classifier is selected from the ensemble for each test example and its decision is used as the decision of the MCS. The selection of a classifier can be either static or dynamic. In static classifier selection, a region of competence in the feature space is assigned for each classifier during the training phase and classification is made by the classifier assigned to the competence region that contains the test example. In dynamic classifier selection, competences of classifiers are calculated during the classification phase, i.e. at the time when the test example is presented. The classifier with the highest value of competence is used for the classification of the test example.

E. Pietka, J. Kawa, and W. Wieclawek (eds.), *Information Technologies in Biomedicine, Volume 4,* Advances in Intelligent Systems and Computing 284,
DOI: 10.1007/978-3-319-06596-0_15,

Recently, dynamic ensemble selection (DES) methods are intensively developed as an effective approach to the construction of multiple classifier systems ([12,23,24]). In these methods, first an ensemble of base classifiers is dynamically selected and then the selected classifiers are combined by majority voting. The most DES schemes use the concept of classifier competence on a defined neighbourhood or region, such as the local accuracy estimation, Bayes confidence measure, multiple classifier behaviour or probabilistic model, among others.

In this study the multiclassifier system was applied to the recognition of hand grasping movements, which is a fundamental problem in the control of the dexterous bioprosthetic hand [16]. The proposed method is based on a two-level multiclassifier system (MCS) with heterogeneous and homogeneous base classifiers dedicated to EMG and MMG biosignals and with combining mechanism using a dynamic ensemble selection scheme and original probabilistic competence function. This paper is a sequel to the authors' earlier publications [8,9,10] and it provides an extension of the results included therein.

The paper arrangement is as follows. Chapter 2 includes the concept of prosthesis control system based on the recognition of patient intent and provides an insight into steps of the whole recognition procedure. Chapter 3 presents the key recognition algorithm based on the multiclassifier system with the dynamic ensemble classifier selection strategy. Chapter 4 presents experimental results confirming adopted solution and chapter 5 concludes the paper.

2 Recognition of Hand Movements as a Tool for Bioprosthesis Decison Control

Existing active prostheses of hand are generally controlled on myoelectric way – they react to electrical signals that accompany the muscle activity (called electromyography signals – EMG signals). The control is feasible since after the amputation of the hand, there remain a significant number of the muscles in the arm stump that normally controlled the finger action. The tensing of these muscles still depends on the patient will and may express her/his intentions as to the workings of her/his prosthesis [13,26].

Nevertheless, reliable recognition of intended movement using only the EMG signals analysis is a hard problem. A recognition error increases along with the cardinality of movement repertoire (i.e. with prosthesis dexterity). A natural solution to overcome this error and increasing the efficiency of the recognition stage may be achieved through the following activities:

1. by introducing the concept of simultaneous analysis of two different types of biosignals, which are the carrier of information about the performed hand movement – authors studied the fusion of EMG signals and the mechanomyography signals (MMG signals)[9];
2. through improving the recognition method – authors proposed to use the multiclassifier system with heterogeneous and homogeneous base classifiers dedicated to particular registered biosignals;

3. by the appropriate choice of feature extraction methods (biosignals parameterization) justified by the experimental results of comparative analysis.

The above analysis shows, that – according to authors' proposition – the bioprosthesis control is performed by recognizing its intended movement on the base of classification of EMG and MMG signals from the user arm stump. This requires the development of three stages:

1. acquisition of signals;
2. reduction of dimensionality of their representation;
3. classification of signals.

The acquisition must take into account the nature of the measured signals and their measurement conditions. A quality of the obtaining information depends essentially on the ratio of the measured signal power to the interfering signal power, defined as SNR (Signal to Noise Ratio). For the non-invasive methods of measurements carried out on the surface of the patient's body, it is difficult to obtain a satisfactory SNR [2]. The noise amplitude usually exceeds many times the amplitude of the measured signal. For the EMG signals the amplitude of voltages induced on the patient body as a result of the influence of external electric fields, may exceed more than 1000 times, the value of useful signals. To overcome this difficulty a differential measurement system was applied. The system encompasses two signal electrodes placed above the examined muscle and an reference electrode placed as far as possible above electrically neutral tissue (above a bone or a joint). Signals obtained from signal electrodes are subtracted from each other and amplified. The common components, including surrounding noise, are thus excluded and the useful signal is amplified.

The MMG signals are mechanical vibrations propagating in the limb tissue as the muscle contracts. They have low frequency (up to 200 Hz) and small amplitude and can be registered as a "muscle sound" on the surface of the skin using microphones [14,20]. This sound carries essential information about individual muscle group excitation. The basic problem when designing the MMG sensor is to isolate the microphone from the external sound sources along with the best acquisition of the sound propagating in the patient's tissue.

After the acquisition stage, the recorded signals have the form of strings of discrete samples. Their size is the product of measurement time and sampling frequency. For a typical motion, that gives a record of size between 3 and 5 thousand of samples (time of the order of 3-5 s, and the sampling of the order of 1 kHz). This "primary" representation of the signals hinders the effective classification and requires the reduction of dimensionality. This reduction leads to a representation in the form of a signal feature vector. To determine the algorithm of features extraction, the database records were analyzed in time and frequency using Short Time Fourier Transform (STFT). Fig. 1 shows the exemplary results.

As we can see, the MMG histogram has two amplitude peaks: at the beginning and at the end of the movement, and relatively low amplitude in the middle while the EMG histogram shows a peak in the middle of the movement time

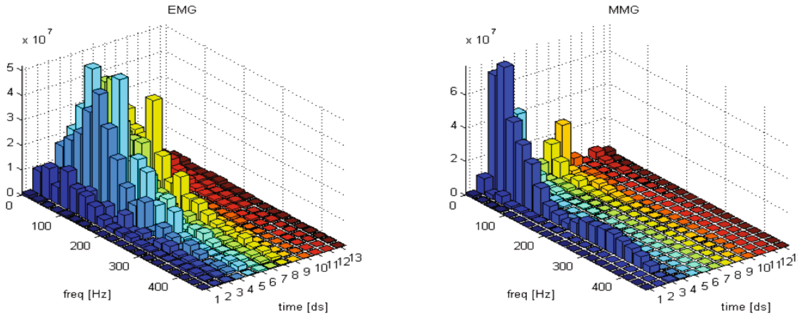

Fig. 1. Exemplary histograms for EMG signal (left) and for MMG signal (right)

span. The analyses of histograms for the tested movements allowed selecting the localization of the best signal features (the best points in time and frequency) securing the best differentiation of the movements.

The resulting algorithm has the following form:

Step 1. Extract from the recorded signal, the signal segments representing the specified movements (using video information). Each extracted segment has new time span ($t \in [0, T]$);
Step 2. Apply the STFT to each segment;
Step 3. Choose as signal features the values from the STFT product corresponding to the k (most representative) time slices;
Step 4. Repeat steps 2 and 3 for every channel;
Step 5. Use all the obtained (in steps 2 and 3) values as elements of the feature vector representing the analyzed signal segment.

This procedure allows creating input vectors with an adjustable size. The structure of this feature vector used as an input in the classifier is given by:

$$(A_{t_1}^{CH_i}, A_{t_2}^{CH_i}, \ldots, A_{t_k}^{CH_i})_{i=1,2,\ldots,n}, \tag{1}$$

where k is the number of time slices and n denotes the number of signal channels.

Although different methodological paradigms can be used as a classifier construction, we suggest using multiclassifier systems (MCS) with base classifier dedicated to particular registered biosignals and with the dynamic ensemble selection method using original procedure of fusion/selection based on competence measure.

3 Multiclassifier System

3.1 Preliminaries

In the multiclassifier (MC) system we assume that a set of trained classifiers $\Psi = \{\psi_1, \psi_2, \ldots, \psi_L\}$ called base classifiers is given. A classifier ψ_l is a function

$\psi_l : \mathcal{X} \to \mathcal{M}$ from a feature space to a set of class labels $\mathcal{M} = \{1, 2, \ldots, M\}$. Classification is made according to the maximum rule

$$\psi_l(x) = i \Leftrightarrow d_{li}(x) = \max_{j \in \mathcal{M}} d_{lj}(x), \tag{2}$$

where $[d_{l1}(x), d_{l2}(x), \ldots, d_{lM}(x)]$ is a vector of class supports (classifying function) produced by ψ_l. Without loss of generality we assume that $d_{lj}(x) \geq 0$ and $\sum_j d_{lj}(x) = 1$.

The ensemble Ψ is used for classification through a combination function which, for example, can select a single classifier or a subset of classifiers from the ensemble, it can be independent or dependent on the feature vector x (in the latter case the function is said to be dynamic), and it can be non-trainable or trainable [7]. The proposed multiclassifier system uses dynamic ensemble selection (DES) strategy with trainable selection/fusion algorithm. The basis for dynamic selection of classifiers from the pool is a competence measure $c(\psi_l|x)$ of each base classifier ($l = 1, 2, \ldots, L$), which evaluates the competence of classifier ψ_l, i.e. its capability to correct activity (correct classification) at a point $x \in \mathcal{X}$. For the training of competence it is assumed that a validation set

$$\mathcal{V} = \{(x_1, j_1), (x_2, j_2), \ldots, (x_N, j_N)\}; \;\; x_k \in \mathcal{X}, \; j_k \in \mathcal{M} \tag{3}$$

containing pairs of feature vectors and their corresponding class labels is available.

The construction of the competence measure consists of the two following steps. In the first step, a hypothetical classifier called a randomized reference classifier (RRC) is constructed. The RRC can be considered to be equivalent to the classifier ψ_l and its probability of correct classification $Pc^{(RRC)}(x_k)$ can be used as the competence $C(\psi_l|x_k)$ of that classifier. In the second step, the competences $C(\psi_l|x_k), \; x_k \in \mathcal{V}$ are used to construct the competence function $c(\psi_l|x)$. The construction is based on extending (generalizing) the competences $C(\psi_l|x_k)$ to the entire feature space $\mathcal{X}$. The next two subsections describe the steps of the method in detail.

3.2 Randomized Reference Classifier

The RRC is a stochastic classifier and therefore it is defined using a probability distribution over the set of class labels $\mathcal{M}$ or, assuming the canonical model of classification, over the product of class supports $[0, 1]^M$. In other words, the RRC uses the maximum rule and a vector of class supports $[\delta_1(x), \delta_2(x), \ldots, \delta_M(x)]$ for the classification of the feature vector x, where the j-th support is a realization of a random variable (rv) $\Delta_j(x)$. The probability distributions of the rvs are chosen in such a way that the following conditions are satisfied (throughout this description, the index l of the classifier ψ_l and its class supports is dropped for clarity):

(1) $\Delta_j(x) \in [0, 1]$;
(2) $E[\Delta_j(x)] = d_j(x), \; j = 1, 2, \ldots, M$;
(3) $\sum_{j=1,2,\ldots,M} \Delta_j(x) = 1$,

where E is the expected value operator. The above definition denotes that the RRC can be considered to be equivalent to the classifier ψ for the feature vector x since it produces, on average, the same vector of class supports as the modeled classifier.

Since the RRC performs classification in a stochastic manner, it is possible to calculate the probability of classification of an object x to the i-th class:

$$P^{(RRC)}(i|x) = Pr[\forall_{k=1,\dots,M,\ k\neq i}\ \Delta_i(x) > \Delta_k(x)]. \tag{4}$$

In particular, if the object x belongs to the i-th class, from (4) we simply get the conditional probability of correct classification $Pc^{(RRC)}(x)$.

The key element in the modeling presented above is the choice of probability distributions for the rvs $\Delta_j(x), j \in \mathcal{M}$ so that the conditions 1-3 are satisfied. In this paper beta probability distributions are used with the parameters $\alpha_j(x)$ and $\beta_j(x)$ $(j \in \mathcal{M})$. The justification of the choice of the beta distribution, resulting from the theory of order statistics, can be found in [23].

Applying the RRC to a validation point x_k and putting in (4) $i = j_k$, we get the probability of correct classification of RRC at a point $x_k \in V$:

$$Pc^{(RRC)}(x) = \int_0^1 b(u, \alpha_1(x_k), \beta_1(x_k)) \\ [\prod_{j=2}^{M} B(u, \alpha_1(x_k), \beta_1(x_k))]du, \tag{5}$$

where $B(\dot{})$ is a beta cumulative distribution function. The MATLAB code for calculating probabilities (5) was developed and it is freely available for download [25].

3.3 Measure of Classifier Competence

Since the RRC can be considered equivalent to the modeled base classifier $\psi_l \in \Psi$, it is justified to use the probability (5) as the competence of the classifier ψ_l at the learning point $x_k \in \mathcal{S}$, i.e.

$$C(\psi_l|x_k) = Pc^{(RRC)}(x_k). \tag{6}$$

The competence values for the validation objects $x_k \in \mathcal{V}$ can be then extended to the entire feature space $\mathcal{X}$. To this purpose the following normalized Gaussian potential function model was used ([22]):

$$c(\psi_l|x) = \frac{\sum_{x_k \in \mathcal{V}} C(\psi_l|x_k) exp(-dist(x, x_k)^2)}{\max_{x \in \mathcal{X}} \sum_{x_k \in \mathcal{V}} C(\psi_l|x_k) exp(-dist(x, x_k)^2)}, \tag{7}$$

where $dist(x, y)$ is the Euclidean distance between two objects x and y.

3.4 Dynamic Ensemble Selection System

Since recognition of the patient's intent is made on the basis of analysis of two different biosignals (EMG and MMG), the multiple classifier system – according to the proposed concept of the recognition method – consisits of two submulticlassifiers, each of them dedicated to particular types of data. It leads to the two level structure of MC system presented in Fig. 2, in which the DES method is realized at the first level, whereas the combining procedure at the second level is consistent with the continuous-valued dynamic fusion scheme.

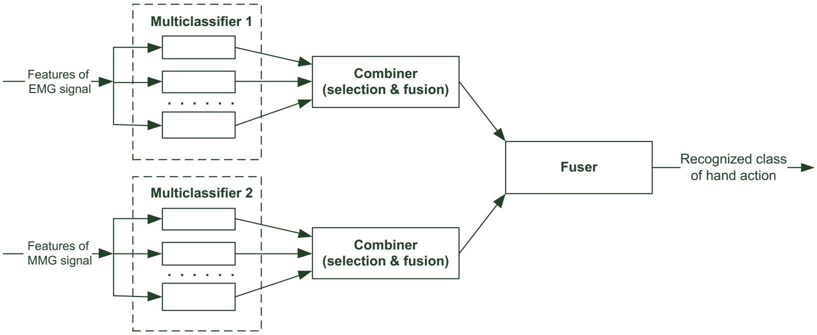

Fig. 2. Block diagram of the proposed multiclassifier system

DES Systems at the First Level. Let Ψ_1 and Ψ_2 denote sets (ensembles) of base classifiers dedicated to the EMG and MMG signals, respectively. The DES system for the ensemble Ψ_i $(i = 1, 2)$ is constructed using the developed measure of competence and classifies the feature vector $x^{(i)}$ ($x^{(1)}$ and $x^{(2)}$ denote the vector of features obtained from the EMG and MMG signal, respectively) in the following manner.

First, the competence function $c(\psi_k^{(i)}|x)$ $(k = 1, 2, ..., L_i)$ are constructed for each classifier in the ensemble. Then, a subset $\Psi_i^*(x)$ of base classifiers with the competences greater than the probability of random classification is selected. This step eliminates inaccurate classifiers and keeps the ensemble relatively diverse [11]. The selected classifiers are combined on the continuous-valued level [7], i.e. class suports are calculated as the weighted sum of supports given by base classifiers from $\Psi_i^*(x)$,viz.

$$d_j^{(i)}(x) = \sum_{\psi_k^{(i)} \in \Psi_i^*(x)} c(\psi_k^{(i)}|x) d_{k,j}^{(i)}(x). \tag{8}$$

Fusion Procedure at the Second Level. At the second level of MC, supports (8) are combined by the weighted sum:

$$d_j(x) = \sum_{i=1,2} c^{(i)}(x) d_j^{(i)}(x), \tag{9}$$

where weight coefficients ($i = 1, 2$)

$$c^{(i)}(x) = \frac{1}{|\Psi_i^*(x)|} \sum_{\psi_k^{(i)} \in \Psi_i^*(x)} c(\psi_k^{(i)}|x). \tag{10}$$

denote mean competence of base classifiers from $\Psi_i^*(x)$.

Finally, the MC system classifies $x = (x^{(1)}, x^{(2)}, x^{(3)})$ using the maximum rule:

$$\psi_{MC}(x) = i \;\Leftrightarrow\; d_i(x) = \max_{j \in \mathcal{M}} d_j(x). \tag{11}$$

4 Experiments

4.1 Experimental Setup

In order to study the performance of the proposed method of EMG and MMG signals recognition, some computer experiments were made. The experiments were conducted in MATLAB using PRTools 4.1 [5] and Signal Processing Toolbox. In the recognition process of grasping movements, 6 types of objects (a pen, a credit card (standing in a container), a computer mouse, a cell phone (laying on the table), a kettle and a tube (standing on the table)) were considered. Our choice is deliberate and results from the fact that the control functions of simple bioprosthesis are hand closing/opening and wrist pronantion/supination, however for the dexterous hand these functions differ depending on grasped object [16].

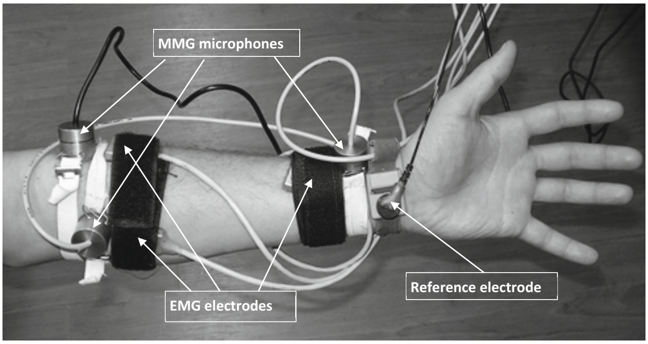

Fig. 3. The layout of the EMG electrodes and the MMG microphones on the forearm

The dataset used to test the proposed classification methods consisted of 400 measurements, i.e. pairs "EMG and MMG signals segment/movement class". Each measurement lasted 6 s and was preceded by a 10-second break. The values from the STFT product (1) corresponding to the $k = 3, 4, 5$ most representative time slices were considered as feature vector. Consequently, we got 3 datasets each containing 400 objects desribed by a different number of features.

The training and testing sets were extracted from each dataset using two-fold cross-validation. One half of the objects from the training dataset was used as a validation dataset and the other half was used for the training of base classifiers. Three experiments were performed which differed in the biosignals used for classification (EMG signals, MMG signals, both EMG and MMG signals).

The experiments were conducted using two types of ensembles Ψ_1 and Ψ_2: homogeneous and heterogeneous. The homogeneous ensemble consisted of 20 feed-forward backpropagation neural network classifiers with one hidden layer (containing 10 neurons) and the number of learning epochs set to 100. The heterogeneous ensemble consisted of the following 10 classifiers [4]: (1, 2) linear (quadratic) classifier based on normal distributions with the same (different) covariance matrix for each class, (3) nearest mean classifier, (4 – 6) k-nearest neighbours classifiers with $k = 1, 5, 15$, (7, 8) Parzen density based classifier with the Gaussian kernel and the optimal smoothing parameter h_{opt} (and the smoothing parameter $h_{opt}/2$), (9) pruned decision tree classifier with Gini splitting criterion, (10) support vector machine classifier with radial basis kernel function. For both ensemble types, classifiers were trained using bootstrapping of the training set.

The performances of the systems constructed (MC_{Hetero} and MC_{Homo} (with hetero-and homogeneous base classifiers,respectively) were compared against the following three multiple classifier systems: (SB) – The single best classifier in the ensemble [7]; (MV) – Majority voting (MV) of all classifiers in the ensemble [7]; (LA) – DCS-local accuracy (LA) system: this system classifies x using selected classifier with the highest local competence (the competence is estimated using k nearest neighbours of x taken from the validation set [15].

4.2 Results and Discussion

Classification accuracies (i.e. the percentage of correctly classified objects) for methods tested are listed in Table 1 (k denotes the number of time slices per signal channel). The accuracies are average values obtained over 10 runs (5 replications of two-fold cross validation). Statistical differences between the performances of the MC_{Hetero} and MC_{Homo} systems and the three MCS's were evaluated using Dietterich's 5x2cv test [3]. The level of $p < 0.05$ was considered statistically significant. In Table 1, statistically significant differences are given under the classification accuracies as indices of the method evaluated, e.g. for the dataset with $k = 3$ and EMG signals the MC_{Homo} system produced statistically different classification accuracies from the SB and MV methods.

These results imply the following conclusions:

1. The both MC_{Hetero} and MC_{Homo} systems produced statistically significant higher scores in 37 out of 54 cases (9 datasets $\times$ 3 classifiers $\times$ 2 systems developed);
2. There are no statistically significant differences between scores of MC_{Hetero} and MC_{Homo} systems.
3. The multiclassifier systems using both EMG and MMG signals achieved the highest classification accuracy for all datasets.

Table 1. Classification accuracies of MSCs compared in the experiment (description in the text). The best score for each dataset is highlighted

Classifier / Mean (SD) accuracy [%]					
k	SB (1)	MV (2)	LA (3)	MC_{Hetero} (4)	MC_{Homo} (5)
EMG signals					
3	77.2/2.3	74.5/1.5	78.3/1.6	78.5/2.3 1,2	**78.7**/1.9 1,2
4	**85.7**/1.9	83.2/1.3	85.1/1.8	85.4/2.5 2	85.1/1.9 2
5	90.5/2.2	92.6/1.8	91.8/1.7	93.1/2.3 1,3	**93.5**/1.6 1,2,3
MMG signals					
3	**47.8**/1.1	43.5/1.5	46.8/1.6	45.9/1.3 2	44.8/1.1 2
4	52.4/1.3	51.2/1.2	50.6/0.8	**54.2**/0.9 1,2,3	53.8/1.2 1,2,3
5	65.8/1.1	63.9/0.7	65.4/0.9	**67.2**/1.3 1,2,3	66.8/0.9 2,3
MMG and EMG signals					
3	82.5/2.1	81.8/1.5	83.1/1.6	**84.3**/1.5 1,2	83.9/1.8 1,2
4	92.7/1.7	92.1/1.3	91.9/2.0	**93.8**/2.1 2,3	93.0/1.5 2,3
5	95.9/1.3	95.1/0.7	94.7/0.9	96.8/1.1 2,3	**97.0**/1.2 1,2,3

5 Conclusion

Experimental results indicate that the proposed methods of grasping movement recognition based on the dynamic ensemble selection with probabilistic model of competence function, produced – regardless of the type of base classifiers – accurate and reliable decisions, especially in the cases with features coming from both the EMG and MMG biosignals.

The problem of deliberate human impact on the mechanical device using natural biological signals generated in the body can be considered generally as a matter of "human – machine interface". The results presented in this paper significantly affect the development of this field and the overall discipline of biosignal recognition, thereby contributing to the comprehensive development of biocybernetics and bioengineering. But more importantly, these results will also find practical application in designing a dexterous prosthetic hand – in the synthesis of control algorithms for these devices, as well as development of computer systems for learning motor coordination, dedicated to individuals preparing for a prosthesis or waiting for hand transplantation [21].

Acknowledgement. This work was financed from the National Science Center resources in 2012-2014 years as a research project No ST6/06168.

References

1. Boostanl, B., Moradi, M.: Evaluation of the forearm EMG signal features for the control of a prosthetic hand. Physiolog. Measurement 24, 309–319 (2003)
2. De Luca, C.: Electromyography. In: Webster, J.G. (ed.) Encyclopedia of Medical Devices and Instrumentation, pp. 98–109. John Wiley Publisher (2006)
3. Dietterich, T.: Approximate statistical tests for comparing supervised classification learning algorithms. Neural Computation 10, 1895–1923 (1998)
4. Duda, R., Hart, P., Stork, D.: Pattern Classification. John Wiley and Sons, New York (2000)
5. Duin, R., Juszczak, P., et al.: PRTools4. A Matlab Toolbox for Pattern Recognition. Delft University of Technology (2007)
6. Englehart, K.: Signal representation for classification of the transient myoelectric signal. Ph.D. Thesis, University of New Brunswick, Fredericton, New Brunswick (1998)
7. Kuncheva, I.: Combining Pattern Classifiers: Methods and Algorithms. Wiley-Interscience (2004)
8. Kurzynski, M., Wolczowski, A.: Dynamic selection of classifier ensemble applied to the recognition of EMG signal for the control of bioprosthetic hand. In: Proc. 11 th Int. Conf. on Control, Automation and Systems, Seoul, pp. 175–182 (2011)
9. Kurzynski, M., Wolczowski, A., Tito, A.: Control of bioprosthetic hand based on EMG and MMG signals recognition using multiclassifier system with feedback from the prosthesis sensors. In: Proc. 2nd Int. Conf. on Systems and Control, Marrakech, Morocco, pp. 280–285 (2012)
10. Kurzynski, M., Wolczowski, A.: Control of bioprosthetic hand based on multimodal biosignals recognition and feedback signals from the prosthesis sensors. In: Int. Conf. Biological Engineering and Natural Science, Bangkok, pp. 315–322 (2013)
11. Lysiak, R., Kurzynski, M., Woloszynski, T.: Probabilistic approach to the dynamic ensemble selection using measures of competence and diversity of base classifiers. In: Corchado, E., Kurzyński, M., Woźniak, M. (eds.) HAIS 2011, Part II. LNCS, vol. 6679, pp. 229–236. Springer, Heidelberg (2011)
12. Lusiak, R., Kurzynski, M., Woloszynski, T.: Optimal selection of ensemble classifiers using measures of competence and diversity of base classifiers. Neurocomputing 126, 29–35 (2014)
13. Nishikawa, D.: Studies on Electromyogram to Motion Classifier. Ph.D. Thesis, Graduate School of Engineering, Hokkaido University, Sapporo (2001)
14. Orizio, C.: Muscle sound: basis for the introduction of a mechanomyographic signal in muscle studies. Critical Reviews in Biomedical Engineering 21, 201–243 (1993)
15. Smits, P.: Multiple classifier systems for supervised remote sensing image classification based on dynamic classifier selection. IEEE Trans. on Geoscience and Remote Sensing 40, 717–725 (2002)
16. Wolczowski, A., Kurzynski, M.: Human – machine interface in bio-prosthesis control using EMG signal classification. Expert Systems 27, 53–70 (2010)

17. Wolczowski, A., Kurzynski, M.: Control of artificial hand via recognition of EMG Signals. In: Barreiro, J.M., Martín-Sánchez, F., Maojo, V., Sanz, F. (eds.) ISBMDA 2004. LNCS, vol. 3337, pp. 356–367. Springer, Heidelberg (2004)
18. Wolczowski, A.: Smart hand: The concept of sensor based control. In: Proc. of 7th IEEE Int. Symposium MMAR, Miedzyzdroje, pp. 783–790 (2001)
19. Wolczowski, A., Krysztoforski, K.: Artificial hand control via EMG signal classification - experimental investigation of alghoritms. In: Tchon, K. (ed.) Progress in Robotics, pp. 97–122. WKL, Warszawa (2008)
20. Wolczowski, A., Suchodolski, T.: Bioprosthesis control: human-machine interaction problem. In: Eizmendi, G., Azkoitia, J.M., Craddock, G. (eds.) Challenges for Assistive Technology, pp. 558–560. IOS Press, Amsterdam (2007)
21. Wolczowski, A., Kurzynski, M., Zaplotny, P.: Concept of a system for training of bioprosthetic hand control in one side handless humans using virtual reality and visual and sensory biofeedback. Medical Information Technologies 18, 85–91 (2011)
22. Woloszynski, T., Kurzynski, M.: A measure of competence based on randomized reference classifier for dynamic ensemble selection. In: 20th Int. Conf. on Pattern Recognition, pp. 4194–4197. IEEE Computer Press, Istanbul (2010)
23. Woloszynski, T., Kurzynski, M.: A probabilistic model of classifier competence for dynamic ensemble selection. Pattern Recognition 44, 2656–2668 (2011)
24. Woloszynski, T., Kurzynski, M., Podsiadlo, P., Stachowiak, G.: A measure of competence based on random classification for dynamic ensemble selection. Information Fusion 13, 207–213 (2012)
25. Woloszynski, T.: Matlab Central File Enchange (2010), `http://www.mathwork.com/matlabcentral/fileenchange/28391-classifier-competence-based-on-probabilistic-modeling`
26. Zecca, M., Micera, S., Carrozza, M., Dario, P.: Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal. Critical Reviews in Biomedical Engineering 30, 459–485 (2002)