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Multiclassifier System with Competence and Diversity Measures Applied to the Recognition of Multimodal Biosignals in the Control of Bioprosthetic Hand

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

Index Terms—**EMG signal, MMG signal, bioprosthetic hand, multiclassifier, competence, diversity**

I. Introduction

Loss of hand significantly reduces the activity of human life. The people who have lost their hands are doomed to permanent care. Restoring to these people even a hand substitute makes their life less onerous. The hand transplantations are still in a medical experiment, mainly due to the necessity of immune-suppression (permanent, to the end of patient's life). An alternative is to equip these people with cybernetics prostheses.

Existing active prostheses of hand (the bioprostheses) 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], [22].

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). The natural solution to overcome this error is to improve the recognition method [15]. Another approach consists in additional use of a different kind of modalities on recognition stage, i.e. to complement EMG signals with another type of biosignals. The authors studied the fusion of EMG signals and the mechanomyography signals (MMG signals). The MMG signals are mechanical vibrations propagating in the limb tissue as the muscle contracts.

According to the author's recent experience ([15], [16], [17]), increasing the efficiency of the recognition stage may be achieved through the following activities:

- by introducing the concept of simultaneous analysis of two different types of biosignals, which are the carrier of information about the performed hand movement – the EMG and MMG signals;
- through the use of multiclassifier system with the heterogeneous base classifiers dedicated to particular registered biosignals;
- through development of the paradigm of dynamic ensemble classifier selection system using measures of competence and diversity as results of appropriate optimization problems;
- by the appropriate choice of feature extraction methods (biosignals parameterization) justified by the experimental results of comparative analysis.

Taking into account above observations and suggestions, the paper aims to solve the problem of recognition of the patient's intention to move the multiarticulated prosthetic hand during grasping and manipulating objects in a skillful manner, by measuring and analyzing multimodal signals coming from patient's body. The adopted solution takes into consideration the advantages given by the fusion of the EMG and MMG signals. The concept combines the recognition (of EMG and MMG signals) performed by multiclassifier system working in the dynamic ensemble selection (DES) fashion with measures of competence and diversity of base classifiers.

The paper arrangement is as follows. Chapter 2 includes the concept of prosthesis control system based on the recognition of patient intention and provides an insight into steps of the whole decision control procedure. Chapters 3 and 4 present the key recognition algorithm based on the multiclassifier system with the dynamic ensemble classifier selection strategy. Chapter 5 presents experimental results confirming adopted solution and chapter 6 concludes the paper.

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II. Prosthesis Decision Control

The application of biological signals to control the prosthesis requires the development of three stages (types of actions) (vide Fig. 1):

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

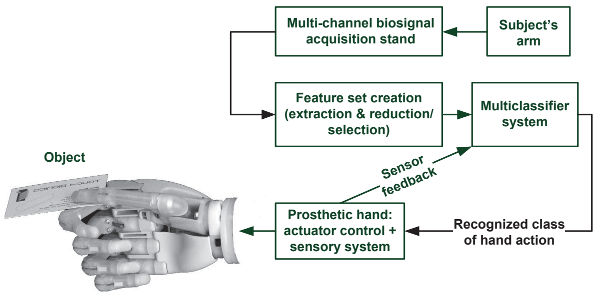

Fig. 1. Block diagram of the prosthesis decision control based on recognition process.

The acquisition must take into account the nature of the measured signals and their measurement conditions. A quality of obtaining information depends essentially on the ratio of the measured signal power to 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, to obtain a satisfactory SNR is a difficult issue [3]. Usually the noise amplitude exceeds many times the amplitude of the measured signal. For example, for electrical signals (which include EMG and EEG 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. This induces the need for careful design of measurement channels for different modalities, including the sophisticated circuits and high-quality components. New issue of bioprosthesis control is to include "feeling of grip" – i.e. the feedback about the posture of prosthesis fingers and their contact with the object being gripped. The focal point of this issue is choosing the type of sensors and their location on the artificial hand. Both types of indicated problems will be addressed in the design of the measuring stand and the method of conducting experiments.

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.

Former experimental research showed, that the best methods in respect of the recognition error and the calculation costs in the biosignal analysis are the following:

- For the feature extraction: Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT) and Autoregressive Model (AR) methods [2], [3], [7], [15];
- For the feature reduction/selection: Interpolation (IP), Principal Component Analysis (PCA) and Sequential Backward Selection (SBS) methods [13], [15], [17], [22].

The classification of the feature vector in bioprosthesis control system is of great importance. Prosthesis dexterity implies huge repertoire of movements (between a dozen or so and several dozens of movements). Because recognition error increases with the extension of movement repertoire (i.e. with prosthesis dexterity) [17], the reliable recognition of intended movement is a hard problem. This is a reason, why existing commercial prostheses can perform just a few movements. There is still a need for developing new ways of increasing reliability of identifying muscle activity. The existing research focuses mainly on developing methods of better EMG signal identification. But the distinguishing capabilities of EMG signal features turn out insufficient for reliable recognition with many classes. Possible approach is reinforcement of the algorithm using another kind of signals that occur during muscle activity, such as mechanomyography (MMG) signals (vibrations) or electroencephalography (EEG) signals that arise in cerebral cortex.

Although as a classifier construction different methodological paradigms can be used, we suggest to use multiclassifier systems, which have proved to be an effective approach in the problem of EMG signal recognition [10]. We will aply a multiclassifier system with heterogeneous base classifiers dedicated to particular registered biosignals and with the dynamic ensemble classifier selection method using original procedure of fusion/selection based on competence and diversity measures.

III. Multiclassifier System

A. 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

$$\psi_l(x) = i \Leftrightarrow d_{li}(x) = \max_{j \in \mathcal{M}} d_{lj}(x), \tag{1}$$

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 $\sum_j d_{lj}(x) = 1$.

Now, our purpose is to determine the following characteristics, which will be the basis for dynamic selection of classifiers from the pool:

1) 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 $x \in \mathcal{X}$.
2) a diversity measure $D(\Psi_E|x)$ of any ensemble of base classifiers Ψ_E, considered as the independency of the errors made by the member classifiers at a point $x \in \mathcal{X}$.

In this paper trainable competence and diversity functions are proposed using a probabilistic model. It is assumed that a validation set

$$\mathcal{S} = \{(x_1, j_1), (x_2, j_2), \ldots, (x_N, j_N)\}; \quad x_k \in \mathcal{X},\ j_k \in \mathcal{M} \tag{2}$$

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is available for the training of competence and diversity measures.

In the next section the original concept of a reference classifier will be presented, which – using probabilistic model – will state the convenient and effective tool for determining both competence and diversity measures.

B. Randomized Reference Classifier - RRC

A classifier[1] ψ from the pool Ψ is modeled by a randomized reference classifier (RRC) [19] which takes decisions in a random manner. A randomized decision rule (classifier) is, for each $x \in \mathcal{X}$, a probability distribution on a decision space [1] or – for the classification problem (1) – on the product $[0,1]^M$, i.e. the space of vectors of discriminant functions (supports).

The RRC classifies object $x \in \mathcal{X}$ according to the maximum rule (1) and it is constructed using a vector of class supports $[\delta_1(x), \delta_2(x), \ldots, \delta_M(x)]$ which are observed values of random variables (rvs) $[\Delta_1(x), \Delta_2(x), \ldots, \Delta_M(x)]$. Probability distributions of the random variables satisfy the following conditions:
(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. In other words, class supports produced by the modeled classifier ψ are equal to the expected values of class supports produced by the RRC.

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

$$P^{(RRC)}(i|x) = Pr[\forall_{k=1,\ldots,M,\ k\neq i}\ \Delta_i(x) > \Delta_k(x)]. \quad (3)$$

In particular, if the object x belongs to the i-th class, from (3) 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 can be found in [20] and furthermore the MATLAB code for calculating probabilities (3) was developed and it is freely available for download [21].

Applying the RRC to a validation point x_k and putting in (3) $i = j_k$, we get the probability of correct classification of RRC at a point $x_k \in \mathcal{S}$, namely

$$Pc^{(RRC)}(x_k) = P^{(RRC)}(j_k|x_k), \quad x_k \in \mathcal{S}. \quad (4)$$

Similarly, putting in (3) a class $j \neq j_k$ we get the class-dependent error probability at a point $x_k \in \mathcal{S}$:

$$Pe^{(RRC)}(j|x_k) = P^{(RRC)}(j|x_k), \quad x_k \in \mathcal{S}, \quad j(\neq j_k) \in \mathcal{M}. \quad (5)$$

In next sections probabilities of correct classification (4) and conditional probabilities of error (5) for validation objects will be utilized for determining the competence and diversity functions of base classifiers.

[1]Throughout this subsection, the index l of classifier ψ_l and class suppports $d_{lj}(x)$ is omitted for clarity

C. 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 (4) as the competence of the classifier ψ_l at the validation point $x_k \in \mathcal{S}$, i.e.

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

The competence values for the validation objects $x_k \in \mathcal{S}$ can be then extended to the entire feature space $\mathcal{X}$. To this purpose the following normalized Gaussian potential function model was used ([20]):

$$C(\psi_l|x) = \frac{\sum_{x_k \in \mathcal{S}} C(\psi_l|x_k) exp(-dist(x, x_k)^2)}{\sum_{x_k \in \mathcal{S}} exp(-dist(x, x_k)^2)}, \quad (7)$$

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

D. Measure of Diversity of Classifiers Ensemble

As it was mentioned previously, the diversity of a classifier ensemble Ψ_E is considered as an independency of the errors made by the member classifiers. Hence the method in which diversity measure is calculated as a variety of class-dependent error probabilities is fully justified [12].

Similarly, as in competence measure, we assume that at a validation point $x_k \in \mathcal{S}$ the conditional error probability for the class $j \neq j_k$ of the base classifier ψ_l is equal to the appropriate probability of the equivalent RRC, namely:

$$Pe^{(\psi_l)}(j|x_k) = Pe^{(RRC)}(j|x_k). \quad (8)$$

Next, these probabilities can be extended to the entire feature space $\mathcal{X}$ using Gaussian potential function (7):

$$Pe^{(\psi_l)}(j|x) = \frac{\sum_{x_k \in \mathcal{S}, j_k \neq j} Pe^{(\psi_l)}(j|x_k) exp(-dist(x, x_k)^2)}{\sum_{x_k \in \mathcal{S}, j_k \neq j} exp(-dist(x, x_k)^2)}. \quad (9)$$

According to the presented concept, using probabilities (9) first we calculate pairwise diversity at the point $x \in \mathcal{X}$ for all pairs of base classifiers ψ_l and ψ_k from the pool Ψ:

$$D(\psi_l, \psi_k|x) = \frac{1}{M} \sum_{j \in \mathcal{M}} |Pe^{(\psi_l)}(j|x) - Pe^{(\psi_k)}(j|x)|, \quad (10)$$

and finally we get diversity of ensemble of n ($n \leq L$) base classifiers $\Psi_E(n)$ at a point $x \in \mathcal{X}$ as a mean value of pairwise diversities (10) for all pairs of member classifiers, namely:

$$D(\Psi_E(n)|x) = \frac{2}{n \cdot (n-1)} \sum_{\psi_l, \psi_k \in \Psi_E(n); l \neq k} D(\psi_l, \psi_k|x). \quad (11)$$

IV. Dynamic Ensemble Selection System

A. Method

The proposed DES competence and diversity based classification system (DES-CD) is constructed in the procedure consisting of two steps:

1) For the test object $x \in \mathcal{X}$ and for given ensemble size n and the competence threshold α first the ensemble of classifiers $\Psi^*_E(n)$ is found as a solution of the folowing optimization problem:

$$D(\Psi^*_E(n)|x) = max_{\Psi_E(n)} D(\Psi_E(n)|x) \quad (12)$$

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subject to $C(\psi_l|x) \geq \alpha$ for $\psi_l \in \Psi_E^*$. This step eliminates incompetent (inaccurate) classifiers and keeps the ensemble maximally diverse.

2) The selected classifiers are combined by weighted majority voting where the weights are equal to the competence values. The weighted vector of class supports of DES-CD system is given by

$$d_j(x) = \sum_{\psi_l \in \Psi_E^*(n)} C(\psi_l|x)\, d_{jl}(x). \tag{13}$$

B. Solution of Optimization Problem

The key moment in the method developed is the optimization problem (12). As a solution method we propose suboptimal procedure which is followed sequential forward feature selection method [8]. In this method first the set of competent classifiers (better than threshold α) is created and next classifiers are sequentially selected from this set: at first the classifier with the highest competence is chosen, next to the already selected classifier we add another one so as to create the couple with the best diversity, then the three classifiers with the highest diversity, including the selected first and second ones are chosen and so one. This procedure is continued up to n classifiers are selected.

The pseudo-code of the algorithm is as follows [12]:

Input data: $\mathcal{S}$ – validation set; Ψ_L – the pool of classifiers;
n – the size of enesemble; $x \in \mathcal{X}$ – the testing point;
α – the threshold of competence
1. For each $\psi_l \in \Psi_L$ calculate competence $C(\psi_l|x)$ at the point x
2. Create temporal set of competent classifiers at the point x
$\Psi(x) = \{\psi_l \in \Psi_L \,:\, C(\psi_l|x) \geq \alpha\}$
3. $\Psi_E^*(n) = \{\psi_{(1)}\}$ and $\Psi(x) = \Psi(x) - \psi_{(1)}$ where $\psi_{(1)} \,:\, C(\psi_{(1)}|x) = max_{\psi \in \Psi(x)} C(\psi|x)$
4. For $i = 2$ to n do
a) Find $\psi_{(i)} \in \Psi(x)$ for which $D(\Psi_E^*(n) \cup \psi_{(i)}|x) = max_{\psi \in \Psi(x)} D(\Psi_E^*(n) \cup \psi|x)$
b) $\Psi(x) = \Psi(x) - \psi_{(i)}$
c) $\Psi_E^*(n) = \Psi_E^*(n) \cup \psi_{(i)}$
endfor

C. Fusion Procedure at the Second Level

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: $\Psi^{(EMG)}$ and $\Psi^{(MMG)}$ – 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 combining procedure at the second level is consistent with the continuous-valued dynamic fusion scheme.

At the second level of MC, supports (13) are combined by the weighted sum:

$$d_j^{(MC)}(x) = c^{(EMG)} d_j^{(EMG)}(x) + c^{(MMG)} d_j^{(MMG)}(x), \tag{14}$$

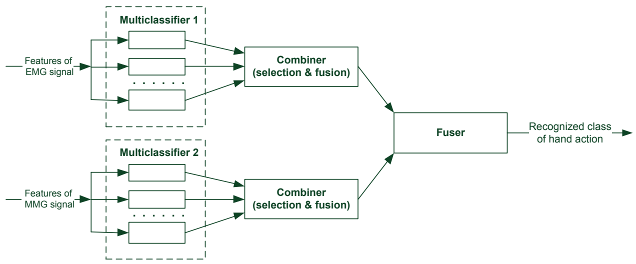

Fig. 2. Block diagram of the proposed multiclassifier system.

where weight coefficients $c^{(EMG)}$ and $c^{(MMG)}$ denote mean competence of base classifiers from $\Psi^{(EMG)}$ and $\Psi^{(MMG)}$.

Finally, the MC system classifies $x = (x^{(EMG)}, x^{(MMG)})$ using the maximum rule:

$$\psi_{MC}(x) = i \;\Leftrightarrow\; d_i^{(MC)}(x) = \max_{j \in \mathcal{M}} d_j^{(MC)}(x). \tag{15}$$

V. Experiments

A. Experimental Setup

In order to study the performance of the proposed method of EMG signal recognition, some computer experiments were made. The experiments were conducted in MATLAB using PRTools 4.1 [6].

In the recognition process of the 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 one 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 [15].

The experiments were carried out on healthy persons. Biosignals were registered using 3 EMG electrodes and 3 MMG microphones located on a forearm above the appropriate muscles (vide Fig.3). EMG and MMG signals were registered in specially designed 16-channel biosignals measuring circuit (Bagnoli Desktop EMG System made by DELSYS Inc.) with sampling frequency 1 kHz.

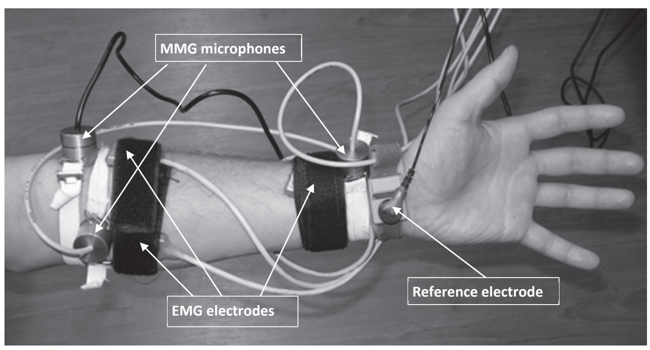

Fig. 3. The layout of the EMG electrodes and the MMG microphones on the forearm

The dataset set used to test of proposed classification method was acquired in the Biomedical Laboratory of the Dept. of Systems and Computer Networks of Wroclaw Technical University. The dataset consisted of 400 measurements, i.e. pairs "EMG signal segment/movement class".

Each measurement lasted 3 s and was preceded with a 10 s break. The root mean square (RMS) values of 250-sample frames of EMG signal and 8 harmonics were considered as features, which gave a total of 324 primary features. Next, primary features were subjected to the PCA feature extraction procedure for different numbers of principal component ($p = 2, 4, 6, 8, 10$). Consequently, we got 5 datasets each containing 400 objects desribing by different number of features. The training and testing sets were extracted from each dataset using two-fold cross-validation. A half of 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 differ in the biosignals used for classification (EMG signals, MMG signals, both EMG and MMG signals). The experiments were conducted using the set of the following ten base classifiers [5] : (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) naive Bayes classifier (8) decision-tree classifier with Gini splitting criterion, (9-10) feed-forward back-propagation neural network with 1 hidden layer (with 2 hidden layers).

The performances of the DES-CD system was compared against the following four multiple classifier systems:

1) The single best (SB) classifier in the ensemble [9].
2) Majority voting (MV) of all classifiers in the ensemble [9].
3) DES-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 [14].
4) DES-C system: this system classifies x using selected classifiers with the competences (7) higher then random guessing method [11].

TABLE I

CLASSIFICATION ACCURACIES OF CLASSIFIERS COMPARED IN THE EXPERIMENT (DESCRIPTION IN THE TEXT). THE BEST SCORE FOR EACH DATASET IS HIGHLIGHTED. (NPC – NUMBER OF PRINCIPLE COMPONENTS)

	Classifier / Mean (SD) accuracy [%]				
NPC	SB (1)	MV (2)	LA (3)	DES-C (4)	DES-CD (5)
EMG signals					
2	77.2/2.3	74.5/1.5	78.3/1.6	78.5/2.3	**79.8**/1.7 1,2
4	79.3/1.7	80.5/2.3	**84.6**/1.9	82.5/2.3	84.3/1.9 1,2,4
6	**85.7**/1.9	83.2/1.3	85.1/1.8	85.4/2.5	85.5/2.0 2
8	87.2/2.3	85.7/2.5	88.6/1.8	91.1/1.6	**91.6**/1.6 1,2,3
10	90.5/2.2	92.6/1.8	91.8/1.7	93.1/2.3	**93.8**/1.7 1,2,3
MMG signals					
2	47.8/1.1	43.5/1.5	46.8/1.6	45.9/1.3	**48.1**/0.9 2,3,4
4	**49.8**/1.4	46.8/0.8	45.3/1.1	48.4/0.9	49.6/1.3 2,3
6	52.4/1.3	51.2/1.2	50.6/0.8	54.2/0.9	**55.6**/0.9 1,2,3
8	57.3/1.5	58.4/1.3	62.3/1.6	61.1/1.3	**63.5**/0.9 1,2,4
10	65.8/1.1	63.9/0.7	65.4/0.9	67.2/1.3	**68.5**/1.0 1,2,3
MMG and EMG signals					
2	82.5/2.1	81.8/1.5	83.1/1.6	84.3/1.5	**84.5**/1.8 1,2,3
4	87.4/1.8	87.6/1.3	88.2/1.5	**89.6**/1.3	89.0/1.8 1,2,3
6	92.7/1.7	92.1/1.3	91.9/2.0	93.8/2.1	**95.3**/1.5 1,2,3,4
8	92.7/1.6	93.2/2.1	93.8/2.1	95.4/2.1	**96.6**/1.6 1,2,3
10	95.9/1.3	95.1/0.7	94.7/0.9	96.8/1.1	**97.9**/1.3 1,2,3

B. Results and Discussion

Classification accuracies (i.e. the percentage of correctly classified objects) for methods tested are listed in Table I. The accuracies are average values obtained over 10 runs (5 replications of two-fold cross validation). Statistical differences between the performances of the DES-CD and the four MC systems were evaluated using Dietterich's 5x2cv test [4]. The level of $p < 0.05$ was considered statistically significant. In Table I, statistically significant differences are given under the classification accuracies as indices of the method evaluated, e.g. for the dataset with $p = 8$ and EMG signals the DES-CD system produced statistically different classification accuracies from the SB, MV and LA methods.

These results imply the following conclusions:

1) The DES-CD system produced statistically significant higher scores in 42 out of 60 cases (15 datasets $\times$ 4 classifiers compared);
2) The multiclassifier systems using both EMG and MMG signals achieved the highest classification accuracy for all datasets.

VI. CONCLUSION

Experimental results indicate, that proposed methods of grasping movement recognition based on the dynamic ensemble selection with probabilistic model of competence and diversity functions, produced accurate and reliable decisions, especially in the cases with features coming from the both 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 signal recognition, thereby contributing to the comprehensive development of civilization. But more importantly, these results will also find practical application in the design of 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 a hand transplantation [18].

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REFERENCES

[1] Berger J.O.: Statistical Decision Theory and Bayesian Analysis, Springer Verlag, New York 1987

[2] Boostanl B., and Moradi M.: Evaluation of the forearm EMG signal features for the control of a prosthetic hand, Physiolog. Measurement 24, 309-319 (2003)
[3] De Luca C: Electromyography. Encyclopedia of Medical Devices and Instrumentation, (John G. Webster, Ed.) John Wiley Publisher, 98-109 (2006)
[4] Dietterich T.: Approximate statistical tests for comparing supervised classification learning algorithms, Neural Computation 10, 1895-1923 (1998)
[5] Duda R., Hart P., Stork D.: Pattern Classification, John Wiley and Sons, New York (2000)
[6] Duin R, Juszczak P, et al.: PRTools4. A Matlab Toolbox for Pattern Recognition, Delft University of Technology (2007)
[7] Englehart K.: Signal representation for classification of the transient myoelectric signal, Ph.D. Thesis, University of New Brunswick, Fredericton, New Brunswick (1998)
[8] Kanal L.: Patterns in pattern recognition. IEEE Trans. Information Theory 20, 697 – 722 (1974)
[9] Kuncheva I.: Combining Pattern Classifiers: Methods and Algorithms, Wiley-Interscience (2004)
[10] Kurzynski M., Wolczowski A.: Dynamic selection of classifier ensemble applied to the recognition of EMG signal for the control of bioprosthetic hand, Proc. 11 th Int. Conf. on Control, Automation and Systems, Seoul, 175-182 (2011)
[11] Kurzynski M,, Wolczowski A., Amaral T.: Control of bioprosthetic hand based on EMG and MMG signals recognition using multiclassifier system with feedback from the prosthesis sensors, 2nd International Conference on Systems and Control, Marrakech, Morocco, 280-285 (2012)
[12] Lysiak R., Kurzynski M., Woloszynski T.: Probabilistic approach to the dynamic ensemble selection using measures of competence and diversity of base classifiers, Lecture Notes in Artificial Intelligence 6679, 229-236 (2011)
[13] Nishikawa D.: Studies on Electromyogram to Motion Classifier, Ph.D. Thesis, Graduate School of Engineering, Hokkaido University, Sapporo (2001)
[14] 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)
[15] Wolczowski A., Kurzynski M.: Human – machine interface in bioprosthesis control using EMG signal classification, Expert Systems 27, 53-70 (2010)
[16] Wolczowski A., Kurzyski M.: Control of artificial hand via recognition of EMG Signals, LNCS 3337, Springer Verlag, 356-367 (2004)
[17] Wolczowski A., Krysztoforski K.: Artificial hand control via EMG signal classification - experimental investigation of alghoritms. Progress in robotics [ed.] K. Tchon. Warszawa WKL, 97 - 122 (2008)
[18] 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, Journal of Medical Informatics and Technologies, 85 - 91 (2012)
[19] Woloszynski T., Kurzynski M.: A measure of competence based on randomized reference classifier for dynamic ensemble selection. In: 20th Int. Conf. on Pattern Recognition, 4194 - 4197, IEEE Computer Press, Istanbul (2010)
[20] Woloszynski T., Kurzynski M.: A probabilistic model of classifier competence for dynamic ensemble selection. Pattern Recognition 44, 2656-2668 (2011)
[21] Woloszynski T., Matlab Central File Enchange, URL: http://www.mathwork.com/matlabcentral/ fileenchange/28391-classifier-competence-based-on- probabilistic-modeling (2010)
[22] Zecca M., Micera S., Carrozza M., and Dario P.: Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal, Critical Reviews in Biomedical Engineering 30, 459-485 (2002)