Control of Bioprosthetic Hand Based on EMG and MMG Signals Recognition Using Multiclassifier System with Feedback from the Prosthesis Sensors

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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 fuction. Additionally, the feedback signal derived from the prosthesis sensors is applied to the correction algorithm of classification results. The performance of two MCSs with 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.**

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 [10], [21].

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 [13]. 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. The new concept is to exploit the feedback signal derived from the prosthesis sensors for the correction of erroneous and/or confirmation of the proper recognition.

According to the author's recent experience ([13], [14], [15], [16]), 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;
- by taking into account in classification algorithm the feedback signal derived from the prosthesis sensors for the correction of erroneously classified hand motion and/or confirmation of the proper recognition (at a lower level of the classification procedure) as well as to adapt learning algorithm (at a higher level of classification);
- 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 and from prosthesis sensors. 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 two-level

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structure, with tuning the classifier competence measure in dynamic manner by data coming from prosthesis sensors.

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. 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.

II. PROSTHESIS DECISION CONTROL

As mentioned above, the bioprosthesis control is performed by recognizing its intended movement on the base of classification of EMG and MMG signals from user arm stump. This requires the development of three stages (vide Fig. 1):

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

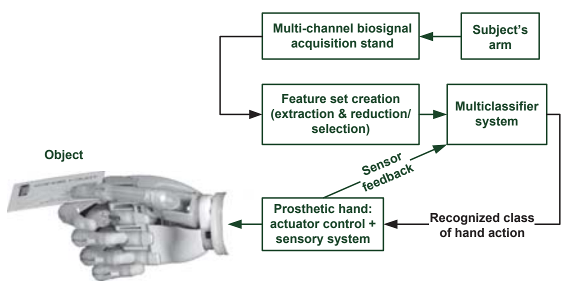

Fig. 1. Block diagram of the prosthesis decision control based on recognition process.

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 [2]. Usually the noise amplitude 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 [11], [17]. 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 patients tissue.

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 [15]. 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. To determine the algorithm of features extraction, the database records were analyzed in time and frequency using Short Time Fourier Transform (STFT). Fig. 2 shows the exemplary results.

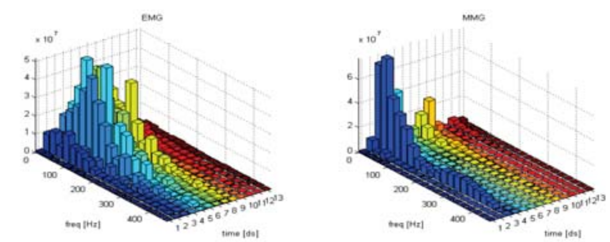

Fig. 2. Exemplary histograms for EMG signal (left) and for MMG signal (right).

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 EMG histogram shows the peak in the middle of the movement time span. The analyses of histograms for the tested movements allowed to select the localization of the best signal features (the best points in time and frequency) securing the best differentiating 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 for each segment the STFT;
Step 3. Choose as a signal features the values from STFT product corresponding to the k (most representative) time slices;
Step 4. Repeat the steps 2 and 3 for every channel;

Step 5. Use all obtained (in the steps 2 and 3) values as elements of feature vector representing the analyzed signal segment.

This procedure allows to create input vectors with an adjustable size. The structure of these 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 as a classifier construction different methodological paradigms can be used, we suggest to use 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.

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

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

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

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

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 as 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.

B. 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. From the above definition it follows that the RRC can be considered as 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 an object x to the i-th class:

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

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 [20].

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 $x_k \in V$:

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

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 [20].

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 (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 ([19]):

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

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

D. 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 combining procedure at the second level is consistent with the continuous-valued dynamic fusion scheme.

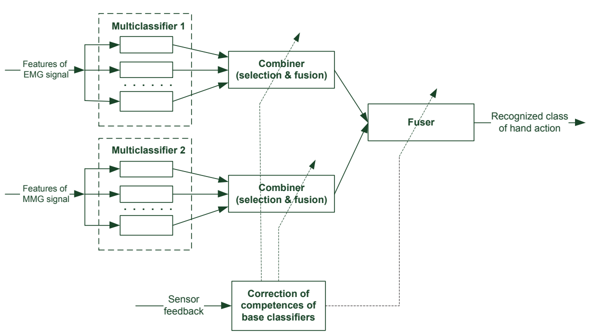

Fig. 3. Block diagram of the proposed multiclassifier system.

1) 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 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 [9]. 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.

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

2) 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:

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

E. Tuning of Competence Measures

The feedback signal from the bioprosthesis sensors can be the source of information about a correct class of hand movement. This signal contains the data defining relation between the finger postures during the grasp, univocally connected with the classification result and the grasping object which in turn explicitly determines the correct type of hand action (class of hand movement) [17]. In other words, the feedback signal coming in the course of recognition of testing hand movement $\bar{x}$, can help us answer the question if the classifiction result is correct or – if not – what is the set of classes into which the correct classification belongs. This proposition is the basis of an additional sequential learning procedure through the tuning of competence measures of base classifiers. The suggested algorithm for a base classifier ψ_l is the following.

Input data:
 $\bar{x}$ – the testing point;
 ψ_l – the base classifier;
 i – the result of classification of $\bar{x}$ by ψ_l;
 $\mathcal{I}_{\bar{x}}$ – the subset of classes determined by feedback information from bioprosthesis sensors.
If $i \notin \mathcal{I}_{\bar{x}}$ then do
Begin
 1. Calculate competence of ψ_l at the point $\bar{x}$:

$$C(\psi_l|\bar{x}) = \frac{1}{|\mathcal{I}_{\bar{x}}|} \sum_{k \in \mathcal{I}_{\bar{x}}} P^{(RRC)}(k|\bar{x}) \tag{12}$$

where $P^{(RRC)}(k|\bar{x})$ is given in (4);

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  2. Calculate new competence measure
     c(ψ_l|x) for ψ_l according to (7) with
     V = V ∪ {x̄}.
End
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IV. EXPERIMENTS

A. 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 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 [13].

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.4). 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. The results of classification were the basis of control of actuation system of artificial hand constructed in the Biocybernetics Laboratory of Wroclaw University of Technology presented in Fig. 5. During experiments its sensors located at tips and joints of digits produced feedback signals.

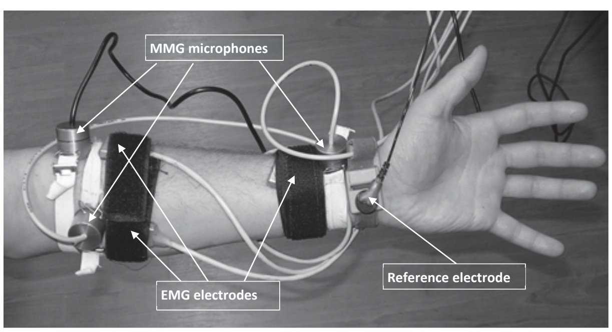

Fig. 4. The layout of the EMG electrodes and the MMG microphones on the forearm

The dataset set used to test of proposed classification method consisted of 400 measurements, i.e. pairs "EMG and MMG signals segment/movement class". Each measurement lasted 6 s and was preceded with a 10 s break. The values from 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 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

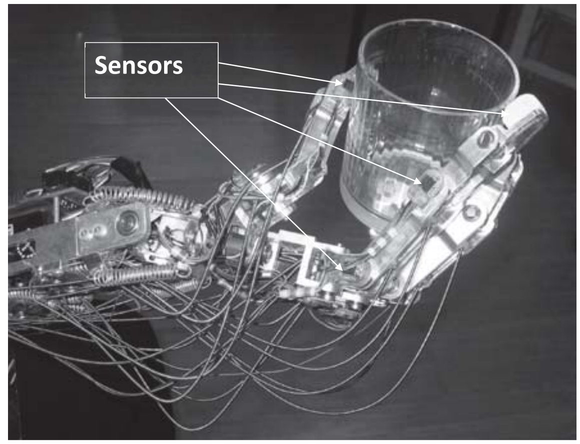

Fig. 5. The laboratory artificial hand with sensors

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 ensembles Ψ_1 and Ψ_2 consisted of the following ten base 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) 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 systems constructed (MC-, MC+ – without using and with using the signals from the bioprosthesis sensors) 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 [12].

B. Results and Discussion

Classification accuracies (i.e. the percentage of correctly classified objects) for methods tested are listed in Table I (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 DCS-MC and DES-CS systems and the four MCS's were evaluated using Dietterich's 5x2cv test [3]. 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 $k = 3$ and EMG signals the MC+ system produced statistically different classification accuracies from the SB

TABLE I

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- (4)	MC+ (5)
	EMG signals				
3	77.2/2.3	74.5/1.5	78.3/1.6	78.5/2.3 1,2	**79.2**/1.8 1,2
4	**85.7**/1.9	83.2/1.3	85.1/1.8	85.4/2.5 2	84.9/2.1 2
5	90.5/2.2	92.6/1.8	91.8/1.7	93.1/2.3 1,3	**93.3**/1.7 1,2,3
	MMG signals				
3	**47.8**/1.1	43.5/1.5	46.8/1.6	45.9/1.3 2	45.6/0.8 2
4	52.4/1.3	51.2/1.2	50.6/0.8	54.2/0.9 1,2,3	**54.5**/0.7 1,2,3
5	65.8/1.1	63.9/0.7	65.4/0.9	67.2/1.3 1,2,3	**67.7**/1.2 1,2,3
	MMG and EMG signals				
3	82.5/2.1	81.8/1.5	83.1/1.6	84.3/1.5 1,2	**84.8**/1.8 1,2,3
4	92.7/1.7	92.1/1.3	91.9/2.0	**93.8**/2.1 2,3	93.2/1.7 2,3
5	95.9/1.3	95.1/0.7	94.7/0.9	96.8/1.1 2,3	**97.1**/1.5 1,2,3

and MV methods.

These results imply the following conclusions:

1) The both MC- and MC+ systems produced statistically significant higher scores in 39 out of 54 cases (9 datasets $\times$ 3 classifiers $\times$ 2 systems developed);
2) There are no statistically significant differences between scores of MC- and MC+ systems.
3) The multiclassifier systems using both EMG and MMG signals achieved the highest classification accuracy for all datasets.

V. CONCLUSION

Experimental results indicate, that proposed methods of grasping movement recognition based on the dynamic ensemble selection with probabilistic model of competence function, produced accurate and reliable decisions, especially in the cases with features coming from the both EMG and MMG biosignals. Unfortunately, experimental tests did not confirm that proposed algorithm for tuning of competence measure is an effective tool for recognition of patient's intent in the bio-prosthesis control systems. This results from the fact, that presented concept of using feedback signals from bioprosthesis sensors has preliminary character and the proposed procedure of additional adaptive learning requires both theoretical analyses and experimental investigations.

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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