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Multiclassifier System with Dynamic Model of Classifier Competence Applied to the Control of Bioprosthetic Hand

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Abstract

In this paper the problem of recognition of patient's intent to move hand prosthesis is addressed. The proposed method is based on recognition of electromiographic (EMG) and mechanomiographic (MMG) biosignals using a multiclassifier system (MCS) working with dynamic ensemble selection (DES) scheme and original concept of competence function. The competence measure is based on relating the response of the classifier with the decision profile of a test object which is evaluated using K nearest objects from the validation set (static mode). Additionally, feedback information coming from bioprosthesis sensors on the correct/incorrect classification is applied to the adjustment of the combining mechanism during MCS operation through adaptive tuning competences of base classifiers depending on their decisions (dynamic mode). Experimental investigations using real data concerning the recognition of five types of grasping movements and computer-simulated procedure of generating feedback signals are performed. The performance of MCS with the proposed competence measure is experimentally compared against 5 state-of-art MCS's in static mode and furthermore the MCS system developed is evaluated with respect to the effectiveness of the procedure of tuning competence. The results obtained indicate that the modification of competence of base classifiers during the working phase essentially improves performance of the MCS system. The system developed achieved the highest classification accuracy demonstrating the potential of MCS with feedback signals from prosthesis sensors for the control of bioprosthetic hand.

1 Introduction

Hands in a human life play a role not only of a skillful manipulator which allows grasping and manipulating a variety of objects, but also of the sensor in order to determine the type of object being touched or held and when there is no light also detect the object position. A loss of even a single hand significantly reduces the human activity. A possible solution is "cyborgization", i.e. equipment the armless patient with the prosthetic hand. At present, the construction of a multi-joint anthropomorphic mechanical structure that can copy even very complicated movements of the human hand poses no problem. Also the motion control of such a structure to accomplish defined finger postures is well known. The basic problem lies however in controlling the movement of prosthetic hands so as to enable their users to grasp and manipulate objects dexterously.

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At the decision level this control can be reduced to the recognition of the patient's intent on the basis of biosignals coming from the patient's body. Nevertheless, a reliable recognition of the intended movement is a serious problem. A natural solution to overcome this difficulty and increase the efficiency of the recognition stage may be achieved through the following actions [16]:

1. by introducing the concept of simultaneous analysis of different types of biosignals which are the carrier of information about the performed hand movement – the fusion of electromyographic signals (EMG signals) and mechanomyographic signals (MMG signals) is considered in this study;

2. through improving the recognition method – the author proposes to use the multiclassifier system with dynamic ensemble selection scheme and with supporting the process of biosignal recognition by taking into account the feedback signal derived from the prosthesis sensors for the correction of combining algorithm of MCS [15].

Multiclassifier systems (MCS) combine responses of a set of base classifiers. For the classifier combination two main approaches used are classifiers fusion and classifiers selection. In the first method, all classifiers in the ensemble contribute to the decision of the MCS, e.g. through sum or majority voting [9]. In the second approach, a single classifier is selected from the ensemble and its decision is treated as the decision of the MCS. The selection of classifiers can be either static or dynamic. In the static selection scheme a classifier is selected for all test objects, whereas the dynamic classifier selection (DCS) approach explores the use of different classifiers for different test objects [7].

Recently, dynamic ensemble selection (DES) methods have been developed which first dynamically select an ensemble of classifiers from the entire set (pool) and then combine the selected classifiers by majority voting [8]. In this way a DES based system takes advantage of both selection and fusion approaches. In most of the methods, the base classifiers are selected from the pool on the basis of their individual accuracy measure called competence in a local region of the feature space. These methods differ in algorithms for determining classifier competence and ways of defining the local regions [10], [17], [24], [28].

In this paper a new method for calculating the competence of a classifier in the feature space is developed and applied to the classifying user intent of upper-limb prosthesis motion based on EMG and MMG biosignals. In the proposed method, first the so-called decision profile of classified object is determined using K-nearest validation objects. The decision profile indicates the class with the greatest chance of being the true class together with the value of this chance. Next, the decision profile is compared with the response produced by the classifier and the competence is calculated according to the similarity rule: the closer is the response to the profile, the more competent is the classifier. In a nutshell, originality of the proposed approach consists in another use of the validation set. In the state-of-art methods the validation set is directly used for calculation of local accuracy of classifier, i.e. its local competence. However, in the proposed method, the validation set is used for estimate the classification profile of a test point and competence of a classifier is determined by relating its response to this estimation.

This paper is divided into five chapters and organized as follows. Chapter 2 provides an insight into biosignals acquisition procedure and the method of feature extraction. Chapters 3 presents the key recognition algorithm based on the multiclassifier system with tuning competence of base classifiers in a dynamic fashion. Chapter 4 presents experimental results confirming the adopted solution and Chapter 5 concludes the paper.

2 Control System of Bioprosthetic Hand via Classification of Patient Intent

The bioprosthesis control performed by recognizing patient's intention involves three stages:

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

As already mentioned, in this study the fusion of electromyography (EMG signals) and mechanomyography (MMG signals) is the basis for recognition of patient's intent. Myopotentials (EMG signals) can be detected through the skin by means of surface electrodes located above selected muscles. Myopotential phenomena result from ion movements in the sarcoplasma of activated muscle fibres. The group of fibres stimulated simultaneously by the same motoneuron (along with the neuron) is called a motor unit. EMG signals measured on skin are the superposition of electrical potentials generated by recruited motor units of contracting muscles.

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 [22]. This sound carries essential information about individual muscle group excitation. In the case of MMG signals the basic problem is to isolate the microphone sensor from the external sound sources along with the best acquisition of the sound propagating in the patients tissue.

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 noise 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 example, for electrical signals (which include 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. 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 [1], [21]. 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 [12], [13], [14], [20] that the effective method as regards to the recognition error and the calculation costs in the biosignal analysis are the sequence of two techniques: autoregressive (AR) model and principal component analysis (PCA).

The AR model belongs to a group of linear prediction methods that attempt to predict an value y_n of a time series of data $\{y_n\}$ based on the previous values $(y_{n-1}, y_{n-2}, \ldots)$.

Several estimators of AR coefficients are well known in the field of signal processing. In the experimental investigations we choose the Burg algorithm because of its many remarkable advantages (it does not apply window data, minimizes forward and backward prediction errors, gives high resolution for short data records, always produces a stable model) [18]. The Burg algorithm estimates the AR coefficients by fitting an auto-regressive linear prediction filter model of a given order to the signal.

Although as a classifier construction different methodological paradigms can be used, we suggest to use multiclassifier systems (MCS), with base classifiers dedicated to particular registered biosignals and with the dynamic ensemble selection method using procedure of fusion/selection based on original competence measure. Additionally, the competence measure is tuned in a dynamic fashion during the recognition process using feedback information coming from the bioprosthesis sensors. Details of the classification stage are presented in the next section.

3 Multiclassifier System

3.1 Preliminaries

Consider a classification problem with a set $\mathcal{M} = \{1, 2, \dots, M\}$ of class labels and a feature space $\mathcal{X} \subseteq \mathcal{R}^n$. Let a pool of classifiers, i.e. a set of trained classifiers $\Psi = \{\psi_1, \psi_2, \dots, \psi_L\}$ be given. Let

$$\psi_l : \mathcal{X} \to \mathcal{M} \tag{1}$$

be a classifier, that produces a vector of discriminant functions $[d_{l1}(x), d_{l2}(x), \dots, d_{lM}(x)]$ for an object described by a feature vector $x \in \mathcal{X}$. The value of $d_{lj}(x)$, $j \in \mathcal{M}$ represents a support given by the classifier ψ_l for the fact that the object x belongs to the j-th class. Assume without loss of generality that $d_{lj}(x) \geq 0$ and $\sum_j d_{lj}(x) = 1$. Classification is made according to the maximum rule

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

The ensemble Ψ_E 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 [9], [26]. The proposed multiclassifier systems use both dynamic classifier selection (DCS) and dynamic ensemble selection (DES) strategies with trainable selection/fusion algorithms. The basis for dynamic selection of classifiers from the pool is a competence measure $c(\psi_l, x)$ of each base classifier $(l = 1, 2, , L)$, which evaluates the competence of classifier ψ_l i.e. its capability of correct activity (correct classification) at a point x .

In this paper a trainable competence function is proposed that leads to the assumption that a validation set containing pairs of feature vectors and their corresponding class labels is available, viz:

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

The next subsection describes the procedure of determining the competence measure $c(\psi_l, x)$ of classifier ψ_l using validation set (3) in detail.

3.2 Competence Measure

For the calculation of the classifier competence $c(\psi_l, x)$ at a point x, the so-called K-neighborhood of x, i.e. the K nearest neighbors of x from validation set $\mathcal{V}$ is used in the following way [11]. First, we calculate the so-called decision value of an object x which determines the class number with the greatest chance of being the true class together with the normalized (from the interval $[0, 1]$) value of this chance. For the probabilistic model of classification task the decision profile can be interpreted as the greatest *a posteriori* probability of a class at a point x. Next, the decision value is compared with the support produced by classifier ψ_l at a point x for the same class. Finally, the competence is calculated according to the following rule: the competence is maximum and equal to 1 if the decision value and the classifier support are identical and the competence decreases with increasing difference between the decision value and classifier support.

In order to determine the decision value of x let first define the decision value of a validation object x_k $(k = 1, 2, , N)$ as follows:

$$D_j(x_k) = \begin{cases} 1 & \text{for } j = j_k, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Decision values (4) of validation objects from the jth class ($j \in \mathcal{M}$) belonging to the K-neighborhood $V_K(x)$ of a point $x \in \mathcal{X}$ create the class-dependent decision values $D_j(x)$ ($j \in \mathcal{M}$). The class-dependent decision value $D_j(x)$ is a result of the cumulative influence of validation objects from $V_K(x)$ and from the jth class where the influence of each validation object $x_k \in V_K(x)$ decreases as the distance between x and x_k increases. This interpretation allows for using the potential function model [26] to determine the class-dependent decision values of x as follows:

$$D_j(x) = \sum_{x_k \in V_K(x); j_k = j} D_j(x_k) G(x, x_k), \ j \in \mathcal{M}, \tag{5}$$

where $G(x, x_k)$ is a non-negative potential function decreasing with the increasing distance between x and x_k. Although any given metric can be used in the definition of the distance $dist(x, x_k)$ and the potential function $G(x, x_k)$ can have any form, in this study we propose the Euclidean distance:

$$dist(x, x_k)^2 = (x - x_k)^T (x - x_k) \tag{6}$$

and the Gaussian potential function:

$$G(x, x_k) = \exp(-dist(x, x_k)^2). \tag{7}$$

Putting (7) into (5) and normalizing the result in order for the $D_j(x)$ to take values in the interval $[0, 1]$ we get:

$$D_j(x) = \frac{\sum_{x_k \in V_K(x); j_k = j} D_j(x_k) G(x, x_k)}{\max_{j \in \mathcal{M}} D_j(x)}, \ j \in \mathcal{M} \tag{8}$$

The decision value of x is calculated as a greatest value of class-dependent decision values (8), namely:

$$dv(x) = D_i(x), \ \text{where} \ \ D_i(x) = \max_{j \in \mathcal{M}} D_j(x). \tag{9}$$

Finally, the normalized competence $c(\psi_l, x) \in [0, 1]$ of base classifier $\psi_l \in \Psi$ at a point x is defined as follows:

$$c(\psi_l, x) = 1 - |dv(x) - d_{li}(x)|. \tag{10}$$

3.3 DCS and DES Systems

The proposed measure of competence can be incorporated in virtually any multiclassifier system in selection/fusion algorithm provided that the feature space $\mathcal{X}$ is a metric space. In this subsection we describe two multiclassifier systems based on the proposed measure of competence employing both DCS and DES strategies.

3.3.1 DCS-Most Competent System (DCS-MC)

In this system, first the competence $c(\psi_l, x)$ is calculated for each base classifier $(l = 1, 2, , L)$. Then the DCS-MC system selects the most competent classifier from the ensemble and uses it for the classification of x:

$$\psi^{MC}(x) = i \Leftrightarrow d_{ki}(x) = \max_{j \in \mathcal{M}} d_{kj}(x), \tag{11}$$

where

$$c(\psi_k, x) = \max_{l=1,2,\ldots,L} c(\psi_l, x). \tag{12}$$

The DCS-MC system uses a selection strategy, i.e. for each object described by a feature vector x it selects a single classifier to be used for classification.

3.3.2 DES-Competence Based System (DES-CS)

This system is based on continuous-value outputs and a weighted majority voting procedure. First, a subset $\Psi^*_x(\alpha)$ of base classifiers with the competences greater than the adopted threshold value α is selected for a given x:

$$\Psi^*_x(\alpha) = \{\psi_{l1}, \psi_{l2}, \ldots, \psi_{lT}\}, \text{ where } \ c(\psi_{lt}, x) > \alpha. \tag{13}$$

The selected classifiers are combined using the weighted majority voting rule where the weights are equal to the competences. This results in the following vector of class supports:

$$d_j^{CS}(x) = \sum_{t=1}^{T} c(\psi_{lt}, x) d_{lt,j}(x). \tag{14}$$

The DES-CS system ψ^{CS} classifies x using the maximum rule:

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

The DES-CS system represents a fusion approach where the final classification is based on responses given by all competent base classifiers.

3.4 Feedback Information and Tuning Procedure

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) [22]. In other words, the feedback signal coming in the course of recognition of testing hand movement, can help us answer the question if the classifiction result is correct

Table 1: Pseudocode of the tuning algorithm.

```
Input data:
  x̄ - the testing point;
  ψ_l - the base classifier;
  i - the result of classification of x̄ by ψ_l;
  information if i is the correct class, whereas if not:
  M(x̄) - the subset of classes determined by feedback information
  from the sensors into which the correct class belongs.
If i is the correct class then
  V := V ∪ {x̄};
  D_j(x̄ = 1 for j = i and 0 otherwise;
  If x̄ ∈ V_K(x) then
    Calculate c(ψ_l, x) according to (10);
    c(ψ_l, x) := c(ψ_l, x) + 1/K
  End If
End If
If i ∈ M(x̄) then
  V := V ∪ {x̄};
  D_j(x̄ = 1/|M(x̄)| for j ∈ M(x̄) and 0 otherwise;
End If
```

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 in dynamic mode through the adding new objects into validation set (3) with appropriate decision profile (4) and through tuning competence of base classifiers depending on their decisions. The suggested algorithm is presented in Table 1.

4 Experiments

4.1 Experimental Setup

The performance of the systems developed was evaluated in experiments using real data. The experiments were conducted in MATLAB using PRTools 4.1 [5] and Signal Processing Toolbox. In the recognition process of the grasping movements, 5 types of grips (hook, power, column, pinch and tripoid grip) presented in Fig. 1 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 pronation/supination, however for the dexterous hand these functions differ depending on grasped object [20].

The experiments were carried out on healthy persons. Biosignals were registered using 8 integrated sensors (containing EMG electrode and MMG microphone in one casing) located on a forearm (vide Fig.2). EMG and MMG signals were registered in specially designed 16-channel biosignals measuring circuit with sampling frequency 1 kHz.

The dataset used to test the proposed classification methods consisted of 1625 measurements, i.e. pairs EMG and MMG signals and segment/movement class. Each measurement lasted 6 s and was preceded with a 10 s break. The coefficient of the AR function for different orders of the AR model ($p = 20, 50, 80$) were considered as primary feature vector. Next, primary features were subjected to the PCA feature extraction procedure set to preserve 95% of variance threshold.

The training and testing sets were extracted from each dataset using 5×2 cross-validation technique. Additionally, the training fold was divided into two subfolds whose cardinality was 80 and 20 percent of the fold. One was used to learn base classifiers, while the other one was employed to calculate competence measure for base classifiers (validation set). 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 heterogeneous ensemble (the same for each MCS) consisting 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 neighbors classifiers with $k = 1; 5; 15$; (7) nearest mean 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).

In the first experiment the DCS-MC and DES-CS systems were compared in static mode against six multiclassifier systems:

1. **SB system** [9]. This system selects the single best classifier in the ensemble.
2. **MV system** [9]. This system is based on majority voting of all classifiers in the ensemble.
3. **LA system** [28]. In this system the competence at a testing point x is calculated as the percentage of the correct recognition of the k-nearest validation samples of x. $k = 10$ was chosen since for this value the DCS-LA system had the best overall performance in previous studies.
4. **KE system** [8]. This system dynamically selects a subset of classifiers with the perfect classification accuracy of k nearest neighbours of the test object x. The k nearest neighbours are taken from the validation dataset V. If there is no classifier with the perfect classification accuracy of all k nearest neighbours, the value of k is decreased until at least one such classifier is found. $k = 8$ was chosen since for this value the DES-KE system had the best performance.
5. **DCS-RRC system** [25], [26]. In this system first the competence of base classifiers is calculated using the concept of randomized reference classifier (RRC) and next the most competent classifier is selected for the classification of x.
6. **DES-RRC system** [25], [26]. This system is the same as the DCS-RRC except that the set of classifiers with the competence greater than the probability of random classification is selected for an object x. Decision is made using weighted majority voting rule.

Figure 1: Types of grips.

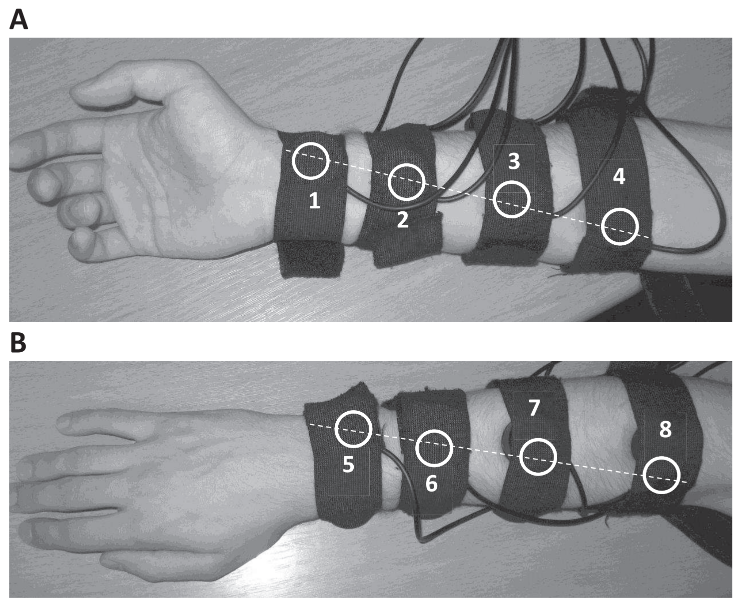

Figure 2: The layout of the integrated sensors (EMG electrodes and MMG microphones) on the underside (A) and top side (B) of the forearm.

The second experiment was conducted in order to evaluate the ability of the proposed MC systems to utilize feedback information. The performances of DCS-MC and DES-CS systems without feedback information and DCS-MC(F) and DES-CS(F) systems with feedback information were compared in the dynamic mode.

4.2 Results

Classification accuracies (i.e. the percentage of correctly classified objects) for methods tested in the first experiment are listed in Table 2. The accuracies are average values obtained over 10 runs (5 replications of two-fold cross validation). Statistical differences between the performances of DCS-MC and DES-CS systems and the six MC systems were evaluated using 5x2cv F test [3]. The level of $p < 0.05$ was considered statistically significant. In Table 2, statistically significant differences are given under the classification accuracies as indices of the method evaluated, e.g. for the dataset with $p = 50$ and EMG signals the DCS-MC system produced statistically better classification accuracies from the SB, MV, DCS-LA and DCS-RRC methods.

Results of the second experiment, i.e. comparison of DCS-MC and DES-CS systems and their tunable versions are provided in Table 3.

These results imply the following conclusions:

1. The DCS-MC and DES-CS system produced statistically significant higher scores in 63 out of 108 cases (9 datasets $\times$ 6 classifiers compared $\times$ 2 MC systems);
2. The DCS-MC classifier:
   - for EMG signals outperformed, on average, the SB, MV, DCS-LA, DES-KE and DCS-RRC systems by 2.2%, 2.9%, 3.7%, 0.5% and 0.1%, respectively;

Table 2: Classification accuracies of classifiers compared in the experiment (description in the text). The best score for each dataset is highlighted. (p denotes the order of AR model).

	Classifier / Mean accuracy [%]							
p	SB (1)	MV (2)	LA (3)	KE (4)	DCS-RRC (5)	DES-RRC (6)	DCS-MC (7)	DES-CS (8)
					EMG signals			
20	77.2	75.5	74.3	79.8	80.4	**82.2**	80.2 1,2,3	81.1 1,2,3,4
50	79.9	80.5	80.7	**83.8**	81.7	82.9	82.4 1,2,3,5	83.6 1,2,3,5,6
80	84.0	83.2	81.7	82.6	85.3	**87.1**	85.0 2,3,4	86.3 1,2,3,4
Av.	80.4	79.7	78.9	82.1	82.5	**84.1**	82.6	83.7
					MMG signals			
20	45.8	47.3	48.8	50.9	49.9	**51.6**	49.8 1,2	50.6 1,2,3
50	47.9	48.8	47.9	51.6	50.6	**52.9**	50.9 1,2,3	51.8 1,2,3,5
80	52.2	51.2	50.1	59.1	57.8	57.3	56.8 1,2,3	**59.9** 1,2,3,5,6
Av.	48.6	48.8	48.9	53.9	52.8	53.9	52.5	**54.1**
					MMG and EMG signals			
20	84.5	85.8	84.7	**88.2**	86.5	88.4	86.5 1,3	87.2 1,2,3
50	86.4	87.6	86.9	90.3	89.5	92.8	91.6 1,3,5	**93.1** 1,2,3,4,5
80	90.7	91.1	91.9	92.7	93.6	**95.2**	93.2 1,2,3	93.9 1,2,3,4
Av.	87.2	88.2	87.8	90.4	89.9	**92.1**	90.5	91.4
Av. rank	7.5	6.7	6.8	3.2	4.2	1.6	4.1	2.0

- for MMG signals outperformed, on average, the SB, MV and DCS-LA systems by 3.9%, 3.7% and 3.6%, respectively;
- for EMG and MMG signals outperformed, on average, the SB, MV, DCS-LA, DES-KE and DCS-RRC systems by 3.3%, 2.3%, 1.7%, 0.1% and 0.6%, respectively;

3. The DES-CS classifier:
   - for EMG signals outperformed, on average, the SB, MV, DCS-LA, DES-KE and DCS-RRC systems by 3.3%, 4.0%, 4.8%, 1.6% and 1.2%, respectively;
   - for MMG signals outperformed, on average, the SB, MV, DCS-LA, DES-KE, DCS-RRC and DES-RRC systems by 5.5%, 5.3%, 5.2%, 0.2% 1.3% and 0.2%, respectively;
   - for EMG and MMG signals outperformed, on average, the SB, MV, DCS-LA, DES-KE and DCS-RRC systems by 4.2%, 3.2%, 3.6%, 1.0% and 1.5% respectively;
4. Multiclassifier systems using DES scheme achieved higher classification accuracy than MC systems with DCS scheme;

Table 3: Classification accuracies of DCS-MC and DES-CS systems and their tunable counterparts.

	EMG signals				MMG signals				EMG and MMG signals			
p	20	50	80	Avg	20	50	80	Avg	20	50	80	Avg
DCS-MC	80.2	82.4	85.0	82.6	49.8	50.9	56.8	52.5	86.5	91.6	93.2	90.5
DCS-MC(F)	80.4	82.8	85.6	82.9	50.5	51.4	57.4	53.1	87.2	92.3	93.9	91.1
DES-CS	81.1	83.6	86.3	83.7	50.6	51.8	59.9	54.1	87.2	93.1	93.9	91.4
DES-CS(F)	81.9	84.4	87.0	84.4	51.8	52.5	60.6	55.0	87.9	93.9	95.1	92.3

5. The multiclassifier systems using both EMG and MMG signals achieved the highest classification accuracy for all datasets;
6. When the order of AR model increases then the accuracy of all methods investigated also increases.
7. The DCS-MC(F) system outperformed, on average, the DCS-MC system by 0.3%, 0.6% and 0.6% for EMG signals, MMG signals and EMG + MMG signals, respectively;
8. The DES-CS(F) system outperformed, on average, the DES-CS system by 0.7%, 0.9% and 0.9% for EMG signals, MMG signals and EMG + MMG signals, respectively.

5 Final Remarks

The experimental results indicate, that the proposed methods of grasping movement recognition based on the dynamic ensemble selection with using feedback information for tuning competence 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. 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 [23].

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