On The Classification of Hand Movements with Electromyogram Signals Obtained From Arm Muscles for Controlling Hand Prosthesis

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Abstract: *The aim of the study is to generate control signals from surface Electromyography signals (EMGs) measured from four hand muscles; Extensor carpi radialis, Palmaris longus, Pronator quadratus and Flexor digitorum superficialis to navigate a prosthetic hand. The EMGs for five hand movements; finger flexion, wrist flexion, wrist extension, pronation, supination have been acquired. The right hand and left hand data recorded from two males and two females. The features have been computed from the windowed EMG of a 0.512 second interval. From each muscle, root mean square value, mean frequency and peak frequency are employed as features. These features and their pairwise combinations have been classified with support vector machine. The classifications have been done for two scenarios: 1. For each subject the right (left) hand movement is classified from the right (left) arm EMG data. 2. The left (right) hand movement of a subject is classified from the right (left) arm EMG data of the same subject. The average right-hand success of the classification was 82.0%, while the left-hand categorization was 83.5%. Interestingly, the left-hand versus right-hand and the right-hand versus left-hand classification success was obtained 65.7%.*

Keywords: *Electromyography, hand prosthesis, support vector machine, hand movement classification.*

1. Introduction

The natural disasters, accidents, wars, vascular diseases and congenital defects may cause loss of the hand. Loss of a hand can give negative consequences on the amputee’s ability to not completely participate in many works, those that involve hands. Although the hand is missing, the arm muscles can still be flexed. These muscle activities can be read from the skin surface as electromyography (EMG) signals by placing electrodes on the forearm and can be employed to generate control signals to navigate a hand prosthesis. There are many studies on concerning the classification of the EMG and generation of control signals from EMG to control a robot arm. In the following, some of these works are summarized.

Liu, Huang and Weng (2007) [1] employed a novel EMG classifier called cascade kernel learning machine (CKLM) for classifying EMG signals by employing autoregressive modelling (AR) and histogram of EMG. They reported the highest accuracy for an amputee subject and a normal subject, 93.54% and 96.76% respectively.

K. Momen et.al. (2007) [2] in their work studied real-time classification of forearm EMG signals corresponding to user-selected intentional movements for multifunction prosthesis control. They acquired EMG from fore arm flexors (two channels) of seven able budied and one below-elbow amputee. The natural logarithm of RMS value of 0.2 second EMG have been classified with fuzzy c-means clustering algorithm. An average accuracy 79.9% ± 16.8% for all classes and 92.7% ± 3.2% success for movements discernible at greater than 79% have been reported.

N. S. Rekhi, A. S. Arora, S. Singh and D. Sing (2009) [3] analyzed the EMG signals from the ten subject’s forearm using wavelet packet transform and extracted features using the singular value decomposition. The support vector machine (SVM) classifier accuracy is over 96% for identifying of six motions (open to close, close to open, supination, pronation, flexion and extension).

Ahsan, Ibrahimy and Khalifa (2011) [4] applied artificial neural network (ANN) for detecting left, right, up, down hand movements of 3 able bodied people. They also utilized a back-propagation (BP) network with Levenberg-Marquardt training algorithm. Their designed network was able to classify in average of 88. 4%.

Baspinar, Varol and Yildiz (2012) [5] classified seven different motions of four people by ANN and Gustafson Kessel algorithm. They found that ANN classifiers give 91.95% classification success.

As it is easily noticed the subjects, experiments and methods in these studies are different and unique.

The main goal of our research is to employ EMG signals obtained from the forearm to successfully identify which type of hand movements is done. The identification of the

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movement type (the features related to the movement type) can be used to generate control signals for a robotic arm.

By considering this goal the algorithm is realized with a minimum run time and maximum accuracy as possible [6, 7]. Block diagram of the process is sketched in Figure 1.

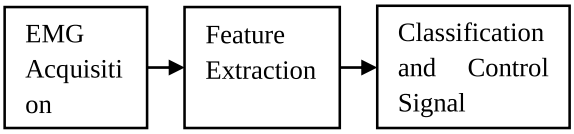

Figure 1. The signal processing components of a robotic hand

The rest of the paper is organized as follows. In section two experiment and approach are described. Results of the algorithm are given in section three. And finally the outcomes are discussed and the paper is concluded in section four.

2. Material and Method

In this study EMG signal are acquired by placing bipolar Ag/AgCl electrodes on the left and the right forearm surface, then features are extracted for classifying, five hand movements; finger flexion, wrist flexion, wrist extension, pronation, supination (see Figure 2). Many variants of movements of a hand prosthesis may be considered. However the wrist is capable of only three sets of distinct movements: flexion and extension, supination and pronation and, ulnar deviation and radial deviation. For this reason, the basic five hand movements have been recorded and classified. We used a four-channel EMG device (ME3000P8 muscle tester, Mega Electronics Ltd, Finland) for recording simultaneously four muscle groups; extensor carpi radialis, palmaris longus, pronator quadratus, flexor digitorum superficialis. These muscles have been chosen since they are responsible for producing the five hand movements. The EMG signals have been recorded in laboratory of sport physiology of medicine faculty of Çukurova University. The EMGs are read from right and left arms of two females whose are 20,23 and two males (four able bodied people) whose are 27 years old. The EMGs were recorded in bipolar configuration. Before acquiring we used muscle stimulator for correctly specifying muscle locations and then electrodes was placed on the specified locations. The locations of electrodes on the hand for the identified muscles of a subject are shown in Figure 3. For each hand movement, start and stop of the recording were marked. The hand movements; finger flexion, wrist flexion, wrist extension, pronation, supination were performed sequentially by the subjects. Equal number of samples for each class was acquired. The total number of trials for each subject has been different (see Table 1 and Table 2). The EMG signal from electrodes was amplified using a preamplifier with a band pass of 8Hz to 500Hz. Sampling frequency was f_s=*1000 Hz* and the resolution was 12 bits/sample (about 3 mV/bit). All algorithms have been implemented by using MATLAB® release R2011 on a personal computer (equipped with an Intel® Core™ i5-3317U CPU@1.70 GHz and a 4 GB RAM). The processing and classification have been applied on offline data.

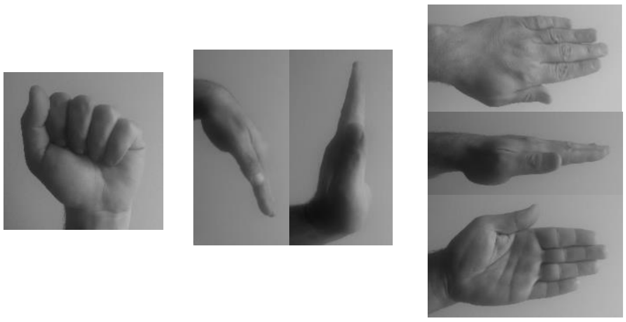

Figure 2. Five hand movements; from left to right finger flexion, wrist flexion, wrist extension, and in the first and third row of the last column illustrates pronation, supination movements respectively.

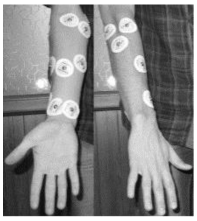

Figure 3. Electrode positions for bipolar EMG reading from four muscles on the hand.

2.1. Pre-processing

As it is well known medical signals are subject to the power line noise. Therefore, it is required to suppress the power line signal added in the EMG. A notch filter does the removal of the power line frequency. We have employed a second-order discrete IIR notch filter with the transfer function [8]:

$$H(z) = \frac{1-2\,cos(2\pi f_n/f_s)z^{-1} + z^{-2}}{1-2r\,cos(2\pi f_n/f_s)\,z^{-1} + r^2\,z^{-2}} \tag{1}$$

and a bandwidth = *0.02* f_s. The notch frequency is $f_n = 50\,Hz$ and *r = 0.97*. The first 101 samples of the impulse response have been used to obtain its FIR approximation. This allows to specify the filter boundaries; the first and the last 50 samples of the filter output are removed.

High frequency noise is also suppressed by linear phase FIR low-pass filter. The FIR filter is designed by the Fourier series method with the hamming window. The coefficients of the low-pass filter with a cut-off frequency $\boldsymbol{f_0}$ *Hz* and the length *2N + 1* is [9]:

$$h(n) = (0.5 + 0.46\,cos\,(\pi n/N))\,.\frac{sin(2\pi f_0\,n/\,f_s)}{\pi n}$$
$$n = -N \ldots N \tag{2}$$

where *N=10* and cut off frequency is $\boldsymbol{f_0}$ *=180 Hz.* A sample of notch and low-pass filtered EMG signals of a finger flexion movement are also given in Figure 4. From top to bottom EMGs of extensor carpi radialis, palmaris longus, pronator quadratus and flexor digitorum superficialis muscles are plotted respectively.

After removal of high frequency components, the EMG signal from each four muscles are segmented.

2.2. Signal segmentation

We have four channels and five different hand movement. Initially the EMG signal of four channels between the start and stop markers is extracted. The channel with the highest power (mean square value) is used to decide the midpoint of the segmentation; namely the reference point. The position of the peak value of the envelope of this dominant channel used as the reference point for the segmentation and is denoted by the sample index t_i. All four channels are segmented based on this reference point (see Figure 4).

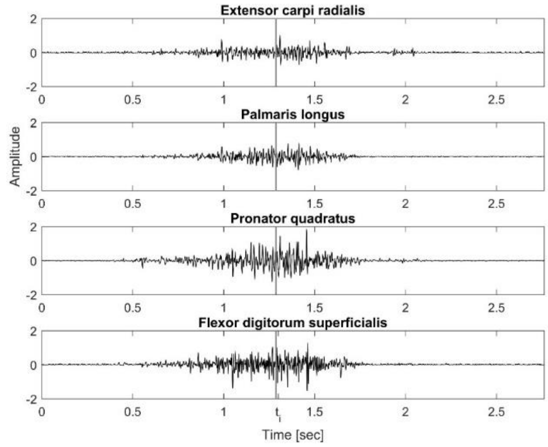

Figure. 4. EMGs of four muscles corresponding to a finger flexion movement. The vertical line marks the reference point of this finger flexion movement.

The range of the segmentation is chosen $[t_i - L/2 + 1\ ,\ t_i + L/2]$ with $L = 2^R$, (512 in this study) is the length of the segment. The window or interval of the burst signal of the dominant channel is computed by succeeding the following steps:

- RMS signal of the EMG is obtained.

$$RMS(n) = \sqrt{\frac{1}{11}\sum_{k=0}^{10} EMG^2(n-5+k)} \qquad (3)$$

- A threshold value is computed

$$THR = \min(EMG) + 0.25(\max(EMG) - \min(EMG)) \qquad (4)$$

- Envelope of the EMG is computed by employing the Hilbert transformation [10].

$$ENV = \frac{1}{2}\sqrt{EMG^2(n) + \widehat{EMG}^2(n)} + \frac{1}{2}\sqrt{EMG^2(n) + (-\widehat{EMG})^2(n)} \qquad (5)$$

where $\widehat{EMG(n)}$ and $\left(-\widehat{EMG}\right)(n)$ are Hilbert transforms of $EMG(n)$ and $-EMG(n)$ respectively.

- The window is the region (interval) where $ENV > THR$.

The outcome of this approach for a sample EMG signal is shown in Figure 5.

2.3 Feature extraction

This phase involves extracting those features of the signal that display certain characteristic properties of EMG signal that are unique to the signal and are thus suitable for the classification purpose. Below the features used in this study are listed.

RMS value:
It is the root of the average power of the signal.

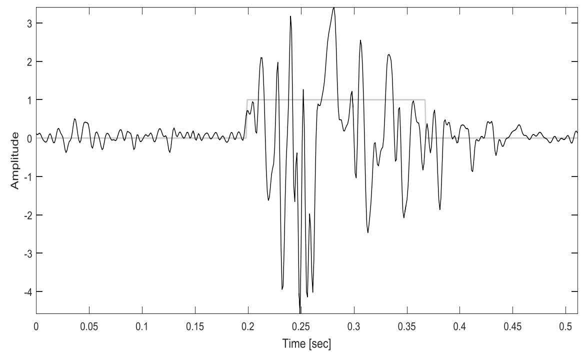

Figure 5. A burst of an EMG signal (solid black line) and the window (solid gray line) used to segment the burst signal.

$$\mathrm{RMSV} = \sqrt{\frac{1}{\mathrm{L}}\sum_{n=0}^{L-1} EMG^2(n)} \qquad (6)$$

Mean-frequency:
It is computed by calling three approaches:

1. The discrete Fourier transform:
The mean frequency is extracted from discrete Fourier transform of the signal.

$$\boldsymbol{f_a} = \frac{\sum_{k=0}^{\frac{L}{2}-1} |X(k)|^2 . k}{\sum_{k=0}^{\frac{L}{2}-1} |X(k)|^2} \cdot \frac{f_s}{L} \qquad (7)$$

$$X(k) = \sum_{n=0}^{L-1} EMG(n)\ \omega(n) e^{-i\frac{2\pi}{L}k\,n}$$

where f_a is the average frequency, f_s denotes the sampling frequency and $\omega(n)$ is the Hamming window [11].

2. Sub-space method
The minimum norm is an Eigen decomposition based frequency estimation method and is employed to guess the dominant frequency. Suppose that the signal contains are p

complex exponentians, then p Eigen vectors the auto-correlation matrix of the signal corresponding to p highest eigen-values are linked to the signal and the remaining $M-p$ Eigen vectors form noise sub-space. The minimum norm is peak-frequency of the frequency estimation function

$$P(e^{j\omega}) = \frac{1}{|\underline{e}^H \underline{a}|^2} \tag{8}$$

where $\underline{a}$ is a vector which lies in the noise sub-space of the signal and has minimum norm and its first element is unity. The $\underline{e}$ vector is the frequency vector with M components:

$$\underline{e}^H = [1 \quad e^{-j\omega} \quad \cdots \quad e^{-j(M-1)\omega}] \tag{9}$$

Because a real frequency contains two complex-conjugate exponentials $p = 2$ in this study. And the dimension of the noise sub-space has been chosen $M - p$ =6. This frequency will be denoted as f_{sub}.

3. Number of zeros crossings
The frequency is predicted by the following formula:

$$f_{est} = f_s \frac{k}{2L} \tag{10}$$

with k is the total number of zero crossings and L is the signal length.

Peak Frequency:
Peak frequency of frequency spectrum of the signal computed by discrete Fourier transform is extracted. It is denoted as f_p.

These features are computed from the windowed 512 length segment to generate feature vector for classification. For each trial the highest RMSV of four channels is scaled the unity and, hence RMSVs become less than or equal to one. And the frequency range $[0, \quad 500]$ is also scaled to $[0, \quad 25]$ to reduce 40 Hz to unity. The features used for the classification are $RMSV$, $\boldsymbol{f_a}$, $\boldsymbol{f_{sub}}$, $\boldsymbol{f_{est}}$, f_p and, ($RMSV$, $\boldsymbol{f_a}$), ($RMSV$, $\boldsymbol{f_{sub}}$), ($RMSV$, $\boldsymbol{f_{est}}$) and ($RMSV$, f_p) subsequently. The feature vectors obtained from the EMGs of the four channels are concatenated. Consequently we have features of length four when a single attribute is used, and eight when a pair of attributes are employed from the four muscles. The classification performance is examined for each of these feature vectors.

2.4 Classification

As a next step of the procedure the features are fed to a classifier. A support vector machine (SVM) is utilized for decoding the movement type. The SVM does not require computation of the covariance matrix of the data as in the statistical classifiers. This is an advantage of SVM over the statistical classifier.

An SVM constructs a separating hypersurface between two categories of data, which can be used for classification, separation and detection of two classes. In case of linear SVM the hypersurface is a hyperplane. For linearly separable features, a linear SVM achieves a good separation by choosing the hyperplane that has the largest distance to the nearest training data point of any class [12].

We employ linear SVM and because it is much simpler than non-linear SVM and summarize it below.
The optimal hyperplane is given by:

$$w^T x - b = 0 \tag{11}$$

where *w* represents a weight vector and *x* represents an input (feature) vector. A particular set of input vectors is used to define the optimal hyperplane, called support vectors. Suppose x_i is the *i-th* sample and y_i is the *i-th* output (the class label). The linear support vector machine maximize margin; $2/\|w\|$ between support-vectors (boundaries of two classes): $w^T x_i + b = 1$ for the class labeled $y_i = 1$ and $w^T x_i + b = -1$ for the class labeled $y_i = -1$. For any new sample x_i, classification is then performed based on the following conditions [8,13,14].

$$\begin{array}{lll} \text{if} \quad w^T x_i - b \geq 0, & & y_i = +1 \\ \text{if} \quad w^T x_i - b < 0, & & y_i = -1 \end{array} \tag{12}$$

SVM is never designed as multiclass classifier. In this study, we have five hand movements and classes. For solving this problem one class is classified versus others (one versus all classification). The five classes mean five binary classifiers and therefore five results. From these five outputs movement types is decided [14]. The class indices 0 and 1 used to indicate a non-class and a class member respectively. It is experimentally observed that, for a feature input to the classifiers, one classifier output is 1 while the others are 0. Consequently, the error correction matrix for classifying five hand movements is an identity matrix of dimensions five-by-five.

3. Results

In this section we report the classification results for right hand, left hand and left versus right (and right versus left) classification performances of the features.
In case of right hand and left hand classification trials of each subject are randomly divided into the two equal size groups (training and test data are selected randomly). The first group is used for training and the second group is employed for testing and then the role of testing and training is changed and finally average success of this process is obtained (2-fold cross validation). This procedure is repeated twenty times and the average success is reported.

For obtaining left versus right and right versus left classification outcome, left hand data of subject is used for training and right hand data is employed for testing and then the role of testing and training data is changed and finally average success of this process is obtained.

The results for every nine types of feature vectors for the classification arrangements are provided in Tables 1-3. Table 1 shows right hand classification accuracies and table 2 list left hand classification rates of the subjects. Table 3 contains performances for right versus left and left versus right classification.

Statistical significance of the results have also been investigated and reported. In case of right and left hand classifications, the classification is repeated twenty times for each subject, therefore in total it accounts eighteen results for each feature type. The p-value of ANOVA is computed based on these eighteen outcomes for every feature type. The p-values for Table 1, 2 have been less than 0.05. The paired ttest for pairs of features has also been computed. In case of right hand classification, the features f_a and f_{sub} are statisticly dependent (p-value = 0.64). Although the average accuracies for the features $RMSV$ and $(f_a, \;\; RMSV)$ are almost equal, p-value is obtained less than 0.05 which indicates no statistical dependence. When paired ttest of the left hand classification is investigated the features $(f_p, \;\; RMSV)$ and $(f_{sub}, \;\; RMSV)$ are found to be statistically dependent (p-value = 0.26). The confusion matrix of right hand and left hand classification for feature type $(f_{est}, RMSV)$ which provides the highest average accuracy are also given in Table 4 and 5 respectively. The abbreviations FFLEX, WFLEX, WEXT, PRON and SUP in the tables stand for finger flexion, wrist flexion, wrist extension, pronation and, supination in that order.

For the right versus left and left versus right classification, there are two measurements for each subject (one for right versus left and one for left versus right) and average of these for every subject are accepted which makes four results in total for each feature type. Four results for a feature type may not be statistically sufficient nevertheless the p-value of ANOVA analysis is computed and found to be 0.06 which is higher than significance level 0.05. This indicates that at least one of the feature type is statistically dependent with the others. The paired ttest has also been run and the outcomes (p-values) of the paired ttest have supported this result. The confusion matrix (in percent) for feature type $(f_{est}, RMSV)$ for comparision with the right and left hand categorization is also been reported in Table 6.

For both right hand and left hand categorization combination of RMSV and average frequency estimated with number of zero crossings and RMS value provides the best accuracy. The right versus left and left versus right hand classification accuracy is less than the single right and left hand categorization however it is greater than the chance level; since there are 5 classes the change level is $100/5 = 20\%$ and 65.7% average success is quite higher than this chance level.

4. Conclusions

The loss of arms can give negative consequences on the amputee’s ability to fully participate in daily life. Helping to the amputees to get them back to their normal life is the motivation of studies on prosthetic arm controlled with EMG signals.

In this study SEMGs acquired from four muscles; extensor carpi radialis, palmaris longus, pronator quadratus, flexor digitorum superficialis from three subjects (two females and two male) for five hand movements; finger flexion, wrist flexion, wrist extension, pronation, supination have been classified. The common segmentation window for channels has been chosen as to cover burst signal of the SEMG channel with the highest average power. A multi-class classifier obtained with the union of binary SVM (support vector machine) classifiers is employed to distinguish the movements from the several combinations of features; frequency measures (average, peak value, minimum norm estimation and number of zero crossings) and RMS value.

Among the feature combinations right hand and left hand classifications attains the highest accuracy with average number of zero crossing and RMS value. The accuracy is 82% for right hand classification and is 83% for left hand categorization. This feature produces the best success also for right versus left and left versus right classification with 65.7% accuracy. Since there are five categories the chance level is 20% and these rates are above the chance level. Accordingly, the results look satisfactory.

In the study, the decision of left hand movement from the right arm muscles and right hand movement from the left arm muscles has also been considered. To our knowledge this approach does not exist in the literature. The 65.7% classification rate achieved is promising. It shows that the identification of a left hand movement from the right arm muscles and a right hand movement from the left hand arm muscles is possible.

The studies involving the classification of SEMG/EMG related to a hand movement in the literature [1, 2, 3, 4, 5, 13] are different in terms of the subject group, data, experiment and method. Therefore the comparison of this study with these works may not be appropriate and significant. If it is compared the results obtained in this study are not outstanding among the performances of the similar studies in the literature, nevertheless it is not far from the average or nearby or better from some of them.

The classification performance of each category has also been explored individually by computing confusion matrix. It is observed that the right hand and left hand supination movement is classified as wrist extension erroneously with 25.3% and 30.6% respectively. In the case of right versus left and left versus right hand classification the classifier confuses supination movement with wrist extension and finger flexion and it also mixes pronation movement with wrist extension and flexion and finger flexion. Consequently it does not perform well in the classification of supination and pronation movements when right/left and left/right hand classification is involved.

We have employed commonly used features types. The average number of zeros crossing with RMS value produced the best accuracies. The results suggest that average number of zero crossings with RMS value should be employed as feature in hand movement classification. It may possible to increase the classifier recognition rate by using different features. Alternative multi-class classifiers may also improve the performance.

As a result, the classification rates obtained for classification of right and left hand movements show that the method used in the study can be employed to generate control signals from the arm to control a hand prosthesis.

Table 1. Classification rates (%) for right hand classification obtained with of 2-fold cross validation

SBJ	#TRS	f_a	f_p	f_{sub}	f_{est}	$RMSV$
S1	90	45.5	42.9	52.9	54.0	68.2
S2	200	57.5	53.5	56.6	73.6	74.7
S3	250	46.9	36.5	47.5	56.2	45.1
S4	320	55.0	33.0	49.1	50.7	64.1
Average		51.2	42.2	51.5	58.6	63.0
Standard deviation		5.9	8.6	4.1	10.2	12.7

		Feature combined with $RMSV$			
SBJ	#TRS	f_a	f_p	f_{sub}	f_{est}
S1	90	68.2	79.6	81.3	81.3
S2	200	74.8	78.8	74.5	74.5
S3	250	46.4	70.0	76.1	76.1
S4	320	64.1	68.2	73.7	73.7
Average		63.4	74.2	76.4	82.0
Standard deviation		12.1	5.9	3.4	4.9

Table 2. Classification rates (%) for left hand classification obtained with of 2-fold cross validation

SBJ	#TRS	f_a	f_p	f_{sub}	f_{est}	$RMSV$
S1	100	55.2	43.5	53.6	56.1	73.3
S2	220	47.2	42.3	34.2	46.8	79.7
S3	190	50.2	35.9	46.7	52.0	72.3
S4	250	48.8	39.7	41.6	50.3	50.4
Average		50.3	40.3	44.0	51.3	68.7
Standard deviation		3.5	3.3	8.2	3.9	12.7

		Feature combined with $RMSV$			
SBJ	#TRS	f_a	f_p	f_{sub}	f_{est}
S1	100	72.3	74.0	80.1	81.2
S2	220	79.7	84.0	81.0	87.6
S3	190	72.3	76.2	80.7	85.6
S4	250	50.5	69.9	65.3	79.7
Average		68.7	76.1	76.8	83.5
Standard deviation		12.6	5.9	7.7	3.7

Table 3. 2-fold cross validation results for left hand versus right hand and right hand versus left hand classification

SBJ	f_a	f_p	f_{sub}	f_{est}	$RMSV$
S1	40.7	36.7	51.7	46.1	49.9
S2	50.8	43.8	31.4	47.1	70.7
S3	36.4	30.7	29.3	36.6	20.5
S4	25.7	22.0	28.9	29.9	33.4
Average	38.4	33.3	35.3	40.0	43.6
Standard deviation	10.4	9.2	11.0	8.2	21.7

	Feature combined with $RMSV$			
SBJ	f_a	f_p	f_{sub}	f_{est}
S1	49.9	69.4	74.1	70.2
S2	70.7	77.8	70.5	80.9
S3	21.3	58.4	55.4	70.6
S4	33.4	34.6	35.7	40.9
Average	43.8	60.1	58.9	65.7
Standard deviation	21.4	18.7	17.5	17.2

Table 4. Confusion matrix of right hand classification obtained using feature $(f_{est}, RMSV)$. Columns denote predicted and rows indicate actual values.

FFLEX	WFLEX	WEXT	PRON	SUP	
8.7	1.5	25.3	8.8	55.7	SUP
5.3	0.1	15.0	76.4	3.2	PRON
3.7	0.0	95.5	0.1	0.6	WEXT
18.3	81.7	0.0	0.0	0.0	WFLEX
93.2	4.2	0.8	1.0	0.8	FFLEX

Table 5. Confusion matrix of left hand classification obtained using feature $(f_{est}, RMSV)$. Columns denote predicted and rows indicate actual values.

FFLEX	WFLEX	WEXT	PRON	SUP	
12.5	3.3	30.6	0.5	53.2	SUP
3.1	1.9	14.4	79.7	0.9	PRON
5.7	0.1	93.3	0.3	0.8	WEXT
4.0	95.8	0.2	0.0	0.0	WFLEX
96.4	0.0	3.3	0.3	0.1	FFLEX

Table 6. Confusion matrix of right versus left hand and left versus right hand classification obtained using feature $(\boldsymbol{f_{est}}, \boldsymbol{RMSV})$. Columns denote predicted and rows indicate actual values.

FFLEX	WFLEX	WEXT	PRON	SUP	
19.8	4.6	35.6	5.5	34.7	SUP
22.2	21.6	17.9	33.7	4.6	PRON
4.9	0.0	92.7	0.6	1.8	WEXT
11.9	85.7	0.3	2.1	0.0	WFLEX
66.6	9.7	15.5	1.8	6.4	FFLEX

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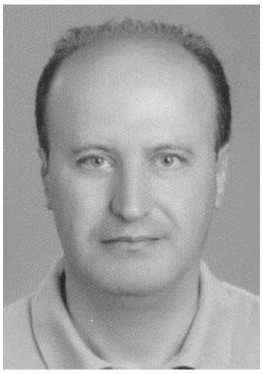

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