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Dependency Independency measure for posterior and anterior EMG sensors used in simple and complex finger flexion movements: Evaluation using SDICA

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***Abstract*— Identification of simple and complex finger flexion movements using Surface Electromyography (sEMG) and muscle activation strategy is necessary to control Human Computer Interfaces (HCI) such as prosthesis and orthoses. In order to identify these movements, sEMG sensors are placed on both anterior and posterior muscle compartments of the forearm. In general, the accuracy of myoelectric classification depends on several factors, which include number of sensors, features extraction methods and classification algorithms. Myoelectric classification using a minimum number of sensors and optimal electrode configuration is always a challenging task. Sometimes, using several sensors including high density electrodes will not guarantee high classification accuracy. In this research we investigated the dependency and independency nature of anterior and posterior muscles during simple and complex finger flexion movements. The outcome of this research shows that posterior parts of the hand muscles are dependent and hence responsible for most of simple finger flexion. On the other hand this study shows that anterior muscles are responsible for most complex finger flexion. This also indicates that simple finger flexion can be identified using sEMG sensors connected only on anterior muscles (making posterior placement either independent or redundant), and vice versa is true for complex actions which can be easily identified using sEMG sensors on posterior muscles. The result of this study is beneficial for optimal electrode configuration and design of prosthetics and other related devices using a minimum number of sensors.**

***Index Terms*— Surface Electromyography (sEMG); Subband Decomposition ICA (SDICA); Blind Source Separation (BSS); Anterior; Posterior; simple and complex flexion.**

I. Introduction

Surface Electromyography (sEMG) represents the level of muscle activity recorded from the skin surface. It provides rich motor control information and is closely related to the strength of muscle contraction [1, 2]. In the recent past myoelectric signals were extensively used for prosthetics [3-6], wheel chairs [7, 8], exoskeleton robotics [9, 10], silent speech recognition [11] and rehabilitation applications [9, 12].

Myoelectric classification depends on several factors which include electrode selection [13], placement of electrodes [14-17], feature extraction methods, selection of appropriate classifier algorithms [18] and computational complexity associated with myoelectric classification [19, 20]. Researchers have been working extensively to improve the myoelectric classification accuracy by improving the above factors; however, cross talk and noise makes it difficult to achieve higher rate of recognition. The most significant elements that contribute to the amount of detected crosstalk signal are: (i) sensor placement on the surface of the muscle and (ii) the spacing between the electrodes on the sEMG sensor [21]. The electrode placements and effect of electrode shift on sEMG pattern recognition has been previously investigated with varied results [22, 23]. In a recent study, Hargrove et al. [23], found different results using five electrodes that are connected parallel to the muscle fibers. Another study conducted by the same authors investigated the placement of electrode poles and concluded that transverse orientation of electrodes are more sensitive to shift than longitudinal orientation [14]. A previous version of our proposed method on sEMG electrode sensor placement concentrated mainly on simple gestures [15]. However, issues remain to be resolved such as selection and placement of electrodes for identification of simple and complex gestures [1, 18].

Anterior and posterior hand muscles are responsible for simple and complex finger flexions and actions. However, it is known phenomenon that while muscles in the anterior compartment are contracting there is co-activation of muscles in the posterior compartment [24, 25]. In general, these (anterior and posterior) muscles are not contributing to flexion but are impeding movement to better control the action by muscles in the anterior compartment [24]. Hence, there is a need for proper signal processing and pattern recognition methods, which can evaluate and identify approximate location for placement of electrodes in identifying gestures. By doing the above, we can identify different simple and

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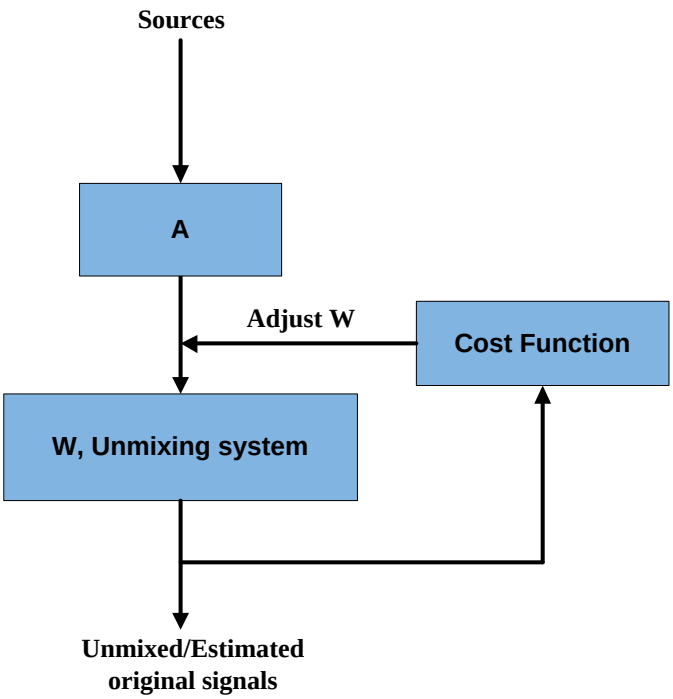

Fig. 1. ICA source separation system.

complex gestures efficiently using minimum number of sensors.

One approach is to select/reduce the number of sensors (used for simple and complex gestures) based on independency and dependency among different sensors/ muscles. However, noise and cross talk make this task tedious. This opens an opportunity to use Blind Source Separation (BSS) techniques such as Independent Component Analysis (ICA) for this task. This research reports pattern recognition based on Subband Decomposition ICA (SDICA) system that is able to identify dependency and independency among sensors/muscles placed on posterior and anterior compartment of muscles while doing simple and complex finger flexions.

One of the main aims of this research is to measure dependency and independency among sEMG sensors/muscles, which helps in the identification of suitable muscles responsible for each finger/hand actions. The specific aim of this study is to reduce the necessary number of sEMG channels presented in a sEMG pattern recognition system. There are two main reasons for this reduction. Firstly, if we reduce the number of physical sEMG channels we make the sEMG-recording device simpler and cheaper. Secondly, if we diminish the number of channels and features we reduce the dimension of the vector of variables presented to the classifier, hence, less training examples are needed and, furthermore, the classifier requires less memory and computational power.

II. Subband Decomposition ICA and Global Matrix Computation

ICA has been found very effective in solving BSS problems. It is a statistical technique for decomposing a complex data set into independent sub-elements. It develops from BSS and tries to transform an observed multidimensional vector into factors that are statistically independent from each other as much as possible [26, 27]. For a linear ICA model, the recordings are a linear combinations of the sources, and also that the original sources are independent from each other. In fact, it factorizes the observation vector x into mixing matrix A and source matrix s by searching the most non-Gaussianity distributions, i.e. $x = As$, where x and s are n-dimensional real vectors, and A is a mixing matrix. ICA strives to find a separation matrix W (up to permutation and scaling) that maximizes the non-Gaussian features of the data x, thus optimally separating the original signals s to make estimated sources u, i.e., $u = Wx$ [27].

The key assumption used in ICA is that (i) the sources should be as statistically independent as possible; (ii) the sources should not have Gaussian distributions. The performance of the estimated sources is determined by cost functions such as kurtosis, mutual information, negentrophy etc. Hence, ICA is considered as an optimization technique, which maximizes the cost function under the condition $u = Wx$. An example of the ICA source separation process is shown in Fig. 1.

For traditional ICA, one of the major requirements is that the sources are linear and independent. This option is relaxed somewhat in SDICA, where we assume that only a certain set of sub components are independent from each other. The main idea here is to divide the signal into its subspectra or subbands, and then process individual subbands using traditional ICA algorithms. These subbands can then be ranked and processed independently by ICA/BSS algorithms, provided that some of the time/frequency subbands (at least one) are temporally decorrelated or mutually independent [28-30].

In order to apply ICA algorithms to any application, it is assumed that the sources $s_i(t)$ are non-Gaussian and mutually independent. For biomedical applications such as EMG, Electroencephalography (EEG) and Electrocardiography (ECG) this assumption may not be true. Hence, we assume that all sources $s_i(t)$ are not essentially independent (this could be due to cross-talk or artefacts) and can be represented as

$$s_i(t) = s_{i,1}(t) + s_{i,2}(t) + s_{i,3}(t) + \cdots + s_{i,M}(t) \qquad (1)$$

where $s_{i,p}$ $p = 1,\ldots,M$, are narrow band subcomponents. In practical applications, we must find at least two groups of sub-component which are mutually independent [28, 30]. Similarly, the observed signals are represented as

$$x_i(t) = x_{i,1}(t) + x_{i,2}(t) + x_{i,3}(t) + \cdots + x_{i,M}(t) \qquad (2)$$

where, $x_{i,p}$ $p = 1,\ldots,M$, are narrow band subcomponents which are obtained from the filter bank (refer to Fig. 2).

In general, subbands are chosen based on high pass or Bandpass filtering methods. The basic structure of the subbands are illustrated in Fig. 2, where the transform consists

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of a set of bandpass filters whose transfer functions are $B_1(z), \ldots, B_M(z)$ with the associated impulse responses $b_1, \ldots, b_M$, respectively. In the ICA/BSS, the global matrix **G** is computed as: $G = WA$. We apply traditional ICA/BSS algorithm such as FastICA [27] on each subband signals and obtain the series of separating matrices: $W_1, W_2, W_3, \ldots W_M$, where W_1 is the separation matrix estimated for subband $x_1(t)$

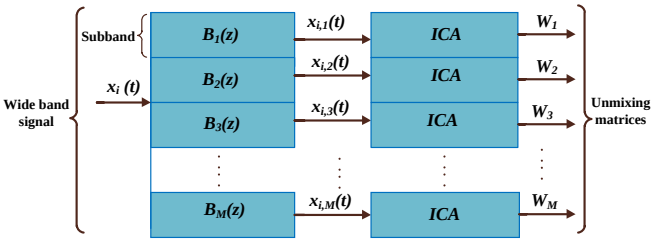

Fig. 2. Subband decomposition: A filter bank structure and computation of unmixing matrices.

and W_M is the separation matrix estimated for subband $x_M(t)$. If the specific subband components are mutually independent for at least two subbands, say subband p and subband q, then global matrix $G_{p,q}$ can be represented as

$$G_{p,q} = W_p * W_q^{-1}, p \neq q \quad (3)$$

$G_{p,q}$ is a sparse generalised permutation matrix P with only one non-zero component in the diagonal of the matrix (each row and column). In this way we can identify independent components for any linearly transformed signals in time, frequency and time-frequency representations [28, 30, 31].

III. Methodology and Data Acquisition

For this research study, required sEMG data was taken from the Khushaba et al. [32] EMG data repository. The sEMG data acquisition and experimental procedures are described in detail in Khushaba and Kodagoda [32]. A brief description of their data acquisition procedure is explained below: the EMG data were acquired from 8 normally limbed individuals (6 males and 2 females) with no muscular disorders. During the experiment, subjects were seated on an armchair, with their arm supported and fixed in one position. The sEMG data was recorded using eight EMG sensors (DE 2.x series EMG sensors) mounted across the circumference of the forearm and processed by the Bagnoli desktop EMG system (Delsys Inc). In their research study, Khushaba et al. [32] placed four sEMG channels (ch1, ch2, ch7 and ch8) on posterior compartment of the hand and the other four channels (ch3, ch4, ch5 and ch6) were placed on anterior part of the participant's hand. Based on the location of the forearm surface electrodes numbered 1-8, it is possible to identify the muscles located immediately beneath each of these electrodes. The approximate location of the sEMG sensor placement used by Khushaba et al. [32] is explained in Table I.

Khushaba et al. [32] collected fifteen classes of movements from eight individuals, which included both simple and complex finger movements. The simple flexions include the movement of just one finger flexion at a time, they are:

TABLE I
sEMG SENSOR PLACEMENT AND MUSCLES USED FOR DATA ACQUISITION [32]

Sensors	Muscles
Electrode 1	Extensor digitorum
Electrodes 2 and 3	Brachioradialis
Electrode 4	Flexor carpi radialis
Electrodes 5, 6 and 7	Flexor carpi ulnaris
Electrode 8	Extensor carpi ulnaris

Thumb (T), Index (I), Middle (M), Ring (R) and Little (L). The complex finger flexions include the following: Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (T-L), Index-Middle (I-M), Middle-Ring (M-R), Ring-Little (R-L), Index-Middle-Ring (I-M-R), Middle-Ring-Little (M-RL), and finally the Hand Close (HC). The surface EMG data were collected at the rate of 4000 samples/sec and were amplified with a gain of 1000 using Delsys Bagnoli Desktop EMG measurement system.

For this research, the original data (Khushaba et al. [32]) was re-sampled to 1000 samples/sec. Movement artefact (<20 Hz), power-line interference (50 Hz) and high-frequency noise (>450 Hz) were also removed. In total, 2880 recordings with a length of 20000 samples (5s) were available for analysis (8 subjects × 8 channels × 15 motions × 3 sets). These sEMG signals were further processed using SDICA and normalised determinant values of global matrices were computed. The entire feature extraction and data analysis process is shown in Fig. 3 and is explained in the next section.

IV. Feature Extraction and Data Analysis

Initially, anterior and posterior (4 sensors each) sEMG subbands were computed using bandpass filters in the frequency range 10Hz to 450Hz. For each subband, we applied the traditional ICA/BSS algorithm and extracted succession of separating matrices $W_1, W_2, W_3, \ldots W_M$, where W_1 is the separation matrix estimated for subband $x_1(t)$ and W_M is the separation matrix estimated for subband $x_M(t)$. The most independent/dependent anterior and posterior sEMG subbands were chosen based on Band Performance Index (BPI). BPI is given by

$$\text{BPI} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{i=1}^{n}|g_{ij}|^2}{\max_i|g_{ij}|^2} - 1\right) + \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{i=1}^{n}|g_{ij}|^2}{\max_j|g_{ij}|^2} - 1\right) \quad (4)$$

where g_{ij} represents the ijth element of the matrix G. The term $max_j g_{ij}$ specifies the maximum value among the elements in the ith row vector of G. The minimum value of BPI will give independent pair of subbands [28, 31]. For each finger flexion, BPI indices were computed for all global matrices $BPI(G_{l,m})$, for $l, m = 0, \ldots, L$ (up to 8 sub bands). Among them (series of Global matrices), for each finger flexion task, two subbands l_l and l_m that correspond to the minimal BPI were selected. A rigorous empirical study was employed to select subbands with minimum BPI values, which has ensured the selection of best subband combination for further analysis.

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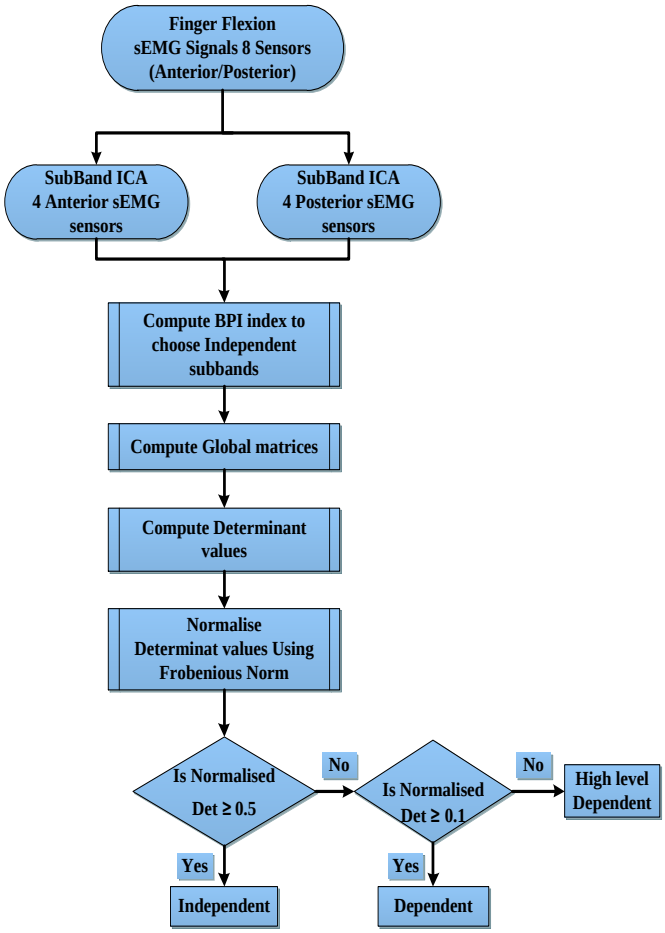

Fig. 3. Algorithm to compute dependency and independency of sEMG signals.

Source dependency and independency of simple and complex finger flexions of sEMG signals were computed using determinant of global matrix. Like other matrix factorization techniques such as Principal Component Analysis (PCA), ICA has a scaling problem. Hence, prior to the measure of dependency and independency, the determinant of *G* need to be normalized. Frobenius norm is one of the widely used matrix norm found in the literature and is explained as:

$$\|G\|_F = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left|g_{ij}\right|^2} = \sqrt{trace\, G^* G} = \sqrt{\sum_{i=1}^{\min\{m,n\}}\sigma_i^2} \qquad (5)$$

where, G^* denotes the conjugate transposition of G and σ_i represents the singular values of G [33].

According to mathematical principle, determinant values are zero for linear dependency and closer to one for linear independency [34]. Based on the above principle, normalised global matrix determinant values are mapped as independent ($0.5 \le \|G\| \le 1$), dependent ($0.1 \le \|G\| \le 0.5$) and high level dependent ($0.01 \le \|G\| \le 0.1$) values. The rationale for the above selection is explained in detail in [35, 36].

TABLE II
TWO SUBBANDS l_l AND l_M THAT CORRESPOND TO THE MINIMAL BPI (PERFORMANCE INDEX OF SUBBANDS) COMPUTED FOR EACH FINGER FLEXION

FINGER MOVEMENTS	SUBBANDS l_l AND l_m (POSTERIOR)	BPI VALUE	SUBBANDS l_l AND l_m (ANTERIOR)	BPI VALUE
Thumb (T)	l_2, l_3	0.0184	l_1, l_3	0.126
Index finger (I)	l_1, l_2	0.125	l_2, l_5	0.0150
Middle finger (M)	l_3, l_4	0.163	l_1, l_4	0.0153
Ring finger (R)	l_1, l_2	0.161	l_2, l_6	0.0151
Little finger (L)	l_4, l_5	0.125	l_3, l_7	0.0182
Thumb – Index(TI)	l_2, l_3	0.091	l_3, l_5	0.258
Thumb – Middle (TM)	l_5, l_6	0.085	l_4, l_7	0.218
Thumb – Ring (TR)	l_4, l_5	0.064	l_6, l_7	0.216
Thumb – Little (TL)	l_5, l_6	0.248	l_4, l_8	0.095
Middle – Ring (MR)	l_7, l_8	0.213	l_1, l_3	0.097
Ring – Little (RL)	l_5, l_6	0.216	l_4, l_5	0.094
Index – Middle (IM)	l_6, l_7	0.225	l_2, l_4	0.093
Index-Middle-Ring (IMR)	l_7, l_8	0.0276	l_1, l_5	0.127
Middle-Ring-Little (MRL)	l_6, l_7	0.0240	l_2, l_6	0.114
Hand Close (HC)	l_5, l_6	0.0235	l_1, l_7	0.135

V. RESULTS

The performance indexes (BPI values) and the relevant subbands computed for posterior and anterior sensors of each finger flexion are listed in Table II. The results show consistency and are significant with *p* value, $p < 0.001$. The dependency independency results for posterior and anterior muscles (mean and standard deviation) are shown in Table III. Based on the results obtained from this study, muscles responsible for simple and complex actions were mapped and the results are explained in Table IV.

One of the main objectives of this study was to reduce the number of sensors in sEMG based finger movement studies. Based on the results (independency and dependency of muscles) obtained from this study (Table III and Table IV), we can map the muscles and identify the minimum number of sensors needed for each action; the results are given in Table V.

VI. DISCUSSION

The use of surface electrodes to record myoelectric signals is extremely difficult due to large variation in EMG features [25]. Although surface electrodes are less reliable and precise than fine-wire electrodes [2, 37], the former are self-evidently superior for practical purposes, where invasive procedures are inappropriate or ill-advised. Therefore, it is not surprising that a number of the results in Table III and IV are counter-intuitive. For example, despite only anterior forearm muscles having the capacity to cause flexion of the hand and fingers, posterior muscles are frequently either 'dependent' or 'high-level dependent'. Furthermore, out of the electrodes placed

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over the muscles (described in Table I), only electrode 1 on extensor digitorum is able to cause finger movement: brachioradialis assists with elbow flexion and the remainder all act on the hand at the wrist. Of the forearm muscles, only flexor digitorum superficialis (no electrode), flexor digitorum profundus (no electrode), extensor digitorum (electrode 1), extensor indices and extensor digiti minimi are able to flex or extend the medial four digits. With regard to the thumb, flexor pollicis longus and extensor pollicis longus are primarily responsible for thumb flexion and extension. A possible explanation for myoelectric signals from muscles acting on the elbow and wrist is coactivation to stabilize these joints during finger movement [24, 38].

A. Simple finger movements

Recording of myoelectric signals from the thumb showed that the signal for the anterior muscles was dependent (see Table III), implying that the anterior muscles of the forearm were active during thumb flexion. With regard to the other digits, the myoelectric signal from the anterior muscles was independent for the index, middle, ring and little fingers whereas the signal from the posterior muscles was dependent suggesting the posterior muscles were active during flexion of these fingers. Therefore, of the recordings of the digits acting unilaterally only the thumb is dependent for the anterior muscles, with the remaining digits showing greater activity for the posterior muscles.

It is difficult to explain the correlation of 'dependent' with 'anterior' for the thumb. The primary muscle causing thumb flexion is flexor pollicis longus. This muscle is a deep flexor and its electrical activity is unlikely to be recorded by an electrode on the anterior surface of the forearm. Although extensor pollicis longus is probably coactivated during thumb flexion, this muscle is also located deeply in the posterior compartment of the forearm until near the wrist where it is more superficial and it is seen 'outcropping' from under extensor carpi radialis and extensor digitorum. In any case there are no electrodes in the proximity of either flexor pollicis longus or extensor pollicis longus.

With regard to individual flexion of the index, middle, ring and little fingers there is consistent correlation of 'dependent' with 'posterior' for recordings of myoelectric signals including those from extensor digitorum muscle (electrode 1). This may indicate coactivation of extensor digitorum muscle during flexion of these fingers by flexor digitorum superficialis. Similarly, myoelectric signals from the other two muscles mentioned in Khushaba and Kodagoda [32], extensor carpi ulnaris (electrode number 8) and flexor carpi ulnaris (electrodes 5, 6 and 7), may be due to stabilization of the wrist by these muscles while the long finger flexor muscle flexor digitorum superficialis contracts. Furthermore, there is a possibility that flexor carpi radialis muscle (electrode 4) and extensor carpi radialis (no electrode) may also stabilize the wrist during finger flexion.

B. Combined finger movements

Correlation of 'dependent' with 'posterior' for combined flexion of the thumb with the index (TI), middle (TM) and ring (TR) fingers fit the pattern described above for these three fingers individually. Furthermore, there is a correlation of

TABLE III
INDEPENDENCY AND DEPENDENCY MEASURE (AVERAGE GLOBAL MATRIX VALUES) OF POSTERIOR AND ANTERIOR MUSCLES USING ICA

Finger movements	**Independent ($\|G\|$>0.5)**	**Dependent ($\|G\|$<0.5)**	**High level dependent ($\|G\|$<0.1)**
Thumb (T)	Posterior (0.7±0.05)	Anterior (0.2±0.03)	
Index finger (I)	Anterior (0.7±0.036)	Posterior (0.3±0.04)	
Middle finger (M)	Anterior (0.65±0.03)	Posterior (0.25±0.04)	
Ring finger (R)	Anterior (0.81±0.04)	Posterior (0.23±0.03)	
Little finger (L)	Anterior (0.75±0.04)	Posterior (0.31±0.05)	
Thumb – Index (TI)		Posterior (0.3±0.03)	Anterior (0.07±0.01)
Thumb – Middle (TM)		Posterior (0.2±0.02)	Anterior (0.06±0.01)
Thumb – Ring (TR)		Posterior (0.3±0.02)	Anterior (0.06±0.02)
Thumb – Little (TL)		Anterior (0.2±0.03)	Posterior (0.07±0.01)
Middle – Ring (MR)		Anterior (0.3±0.02)	Posterior (0.06±0.02)
Ring – Little (RL)		Anterior (0.2±0.03)	Posterior (0.07±0.01)
Index – Middle (IM)		Anterior (0.3±0.03)	Posterior (0.05±0.02)
Index-Middle-Ring (I-M-R)		Anterior (0.25±0.02)	Posterior (0.06±0.01)
Middle-Ring-Little (M-RL)		Anterior (0.3±0.01)	Posterior (0.05±0.02)
Hand Close (HC)		Anterior (0.26±0.03)	Posterior (0.04±0.01)

TABLE IV
MUSCLES RESPONSIBLE FOR SIMPLE AND COMPLEX ACTIONS (BASED ON THE RESULTS OBTAINED FROM THIS STUDY)

Finger movements	**Posterior**	**Anterior**	**Muscles responsible for digit flexion**
Thumb (T)	**X**	✓	a
Index finger (I)	✓	**X**	b
Middle finger (M)	✓	**X**	b
Ring finger (R)	✓	**X**	b
Little finger (L)	✓	**X**	c
Thumb–Index(TI)	✓	✓	a + b
Thumb–Middle (TM)	✓	✓	a + b
Thumb–Ring(TR)	✓	✓	a + b
Thumb–Little(TL)	✓	✓	a + b + c
Middle–Ring (MR)	✓	✓	a + b
Ring – Little (RL)	✓	✓	b + c
Index–Middle (IM)	✓	✓	a + b
Index-Middle-Ring (IMR)	✓	✓	a + b
Middle-Ring-Little (MRL)	✓	✓	b + c
Hand Close (HC)	✓	✓	a + b + c

a = *flexor pollicis longus* and *flexor pollicis brevis*; b = *flexor digitorum superficialis*, *flexor digitorum profundus* and *lumbricals*; c = *flexor digiti minimi brevis*.

Note: Here ✓ indicates the dependency (muscles responsible for finger flexion) and X indicates independency (muscles either inactive or not contributing for finger flexion).

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TABLE V
NUMBER OF SENSORS RESPONSIBLE FOR SIMPLE AND COMPLEX ACTIONS (BASED ON THE RESULTS OBTAINED FROM THIS STUDY)

Finger movements	Number of Sensors needed for each flexion
Thumb (T)	1
Index finger (I)	1
Middle finger (M)	1
Ring finger (R)	1
Little finger (L)	1
Thumb – Index(TI)	2
Thumb – Middle (TM)	2
Thumb – Ring (TR)	2
Thumb – Little (TL)	2
Middle – Ring (MR)	2
Ring – Little (RL)	2
Index – Middle (IM)	2
Index-Middle-Ring (IMR)	2
Middle-Ring-Little (MRL)	2
Hand Close (HC)	2

'high level dependent' for the thumb and little fingers (TL), middle and ring (MR), ring and little (RL) and index and middle (IM) fingers, presumably for the same reason. However, the reason for the reversal of 'anterior' and 'posterior' between the categories of 'dependent' and 'high-level dependent' is not known. From Table III and IV it is evident that there is a correlation of dependency and high level dependency between the three-finger movements (IMR and MRL) and hand closure. It is possible that this correlation is related to the fact that hand closure consists primarily of flexion of the index, middle, ring and little fingers which are extensively represented in both the three-finger movements.

Very few muscles are directly involved in flexion of the thumb: these are flexor pollicis longus and flexor pollicis brevis. Similarly, there are relatively few muscles directly involved in finger flexion: chiefly flexor digitorum superficialis and flexor digitorum profundus. On the other hand, a large number of muscles may be coactivated during both normal flexion of the thumb and fingers, and forced flexion of these digits (see list above). However, since myoelectric signals can only be recorded from superficial muscles directly under each electrode, only those specific muscles identified for each electrode can be responsible for the EMG recordings discussed in the present study and hence the same (minimum number of sensors needed for each flexion) is justified in Table V.

Despite the difficulties associated with myoelectric signals from surface electrodes, this remains the only pragmatic method of recording muscle activity with real-world applications such as myoelectric and prosthetic control. These difficulties may contribute to the seemingly anomalous activation of posterior muscles during finger flexion. However, coactivation of muscles acting on the wrist in order to stabilize finger movement may explain myoelectric signals from muscles such as flexor carpi radialis, flexor carpi ulnaris and extensor carpi ulnaris. Similarly, either coactivation or cross-talk may be responsible for recording of myoelectric signals from extensor digitorum (a finger extensor) during flexion of the index, middle, ring and little fingers. Only a few specific anterior forearm muscles cause thumb and finger flexion. In contrast, a larger number of anterior and posterior muscles may be coactivated during thumb and finger flexion. With forceful thumb and finger flexion more proximal muscles may also be recruited for coactivation of muscles stabilizing the thumb, fingers, wrist and even elbow. The dependency nature of posterior (during simple flexion) and anterior (during complex finger flexions) muscles highlighted the importance of sEMG sensor placement during simple and complex finger flexion movements.

VII. CONCLUSION

In myoelectric prostheses design, it is normally assumed that the necessary control information can be extracted from the surface myoelectric signal. In order to extract valuable sEMG features, it is essential to place the sensors in optimum location so that the best features can be extracted without any artifacts or cross-talk. Moreover, it has been acknowledged in the literature that the classification accuracy in a pattern recognition framework is more affected by the location of the electrodes and choice of the feature set than by the classification algorithm itself. Hence, in order to get higher classification accuracy and robustness, prior to myoelectric and prosthetic design, it is essential to investigate the optimum sensor placement.

Classification of simple and complex gestures using minimum number of sEMG sensors is always a challenging task. Due to the complex nature of human hand muscle anatomy, the placement of sEMG electrodes in a correct position is very difficult. Artefact and cross-talk from adjacent muscles also make it very hard to identify the optimum location of the myoelectric sensors. In this study an attempt has been made to identify the dependency and independency of sEMG muscles/sensors which are used for identification of simple and complex gestures. The study has identified the redundant nature of some of the posterior and anterior muscles and hence, helps in optimizing the number of sensors required for myoelectric and prosthetic control applications.

From this study, it can be concluded that, it is possible to obtain most of the simple finger flexion movements by using sEMG sensors connected to posterior part of the muscles only. On the other hand, most of the complex finger flexions can be identified using sEMG sensors connected to the anterior part of the muscles. The proposed research study will certainly help in optimization of sEMG sensors and also help researchers and scientists who want to design prosthetic and myoelectric control systems for simple and complex gestures. Results from this study show that both simple and complex finger flexions can be recognized using only a few number sensors (up to 2 sensors). This requires careful study of hand muscles, choice of electrodes and the signal processing methods used to achieve the task. We believe that the outcome of this study (dependency/independency) could be used as one of the important pre-processing steps (electrode/muscle configuration) in myoelectric control, stroke rehabilitation and other prosthetic applications. In the near future, the authors would like to investigate the above-mentioned concept for prosthetics and stroke rehabilitation applications using a

minimum number of sensors.

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