2019 IEEE Region 10 Humanitarian Technology Conference
Depok, Indonesia | November 12-14, 2019

Finger Movement Recognition based on Muscle Synergy using Electromyogram

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***Abstract*— Motor functions of human hand during daily living activities involve multiple finger movements, which has not yet been fully explored for electromyogram (EMG) based prosthesis control. This paper presents a framework based on forearm muscle synergy for recognition of finger movement using four channel EMG. With five normal-limbed subjects, synergy of four forearm muscles was estimated for five finger movements through non-negative matrix factorization of EMG feature. Using leave-one-patient-out cross-validation, radial basis function support vector machine was implemented for recognition of finger movements. The framework exhibited an average recognition rate of 97%. This study offers feasibility of a finger movement recognition framework based on the inherent physiological mechanism of muscle synergy, which has potential for dexterous finger movement control in prosthetic hands.**

I. Introduction

Current prosthetic hands have multiple fingers with higher degrees of freedom (DoF) [1]. Higher DoF increases the functionality of prosthetic hands which otherwise have been one of the reasons for loss of interest in prosthetic hands by the amputees [2]. However, electromyogram (EMG) based control systems do not have comparable controllability [3], which is another one of the major causes for amputees to not use prosthetic hands regularly [2]. Machine learning techniques have made significant advances in recognition of hand movements [4], [5], [6], [7], [8] and grasping operations [9], [10], [11], [12] for EMG based prosthesis control. Although EMG based control for multiple DoF has been attempted in recent years, the number of simultaneously activated DoF is still limited to three [13].

For prosthetic hands with higher controllability, EMG based recognition of finger movements based on the inherent physiological mechanism is one of the important aspects in the area of rehabilitation robotics. Peleg et al. [9] are amongst the pioneers to report classification of finger movements for pressing a switch. Recognition of thumb, index, middle finger flexion and hand close movements with a recognition rate of 93% have been reported by Tsenov et al. [14]. Using envelop detection of EMG, classification of five finger movements with a recognition rate of 80-92% have been reported by Sebelius et al. [15]. Efforts have been made for continuous decoding of finger position using 15-channel EMG and it achieved a recognition rate of 90% [16]. Experiments with EMG collected from transradial amputees for 10-class finger movement classification with an accuracy of 93% have been reported by Tenore et al. [17]. Cipriani et al. [1] have reported continuous EMG based control of a dexterous hand prosthesis by transradial amputees through classification of finger movements. In [18], experiments for finger movement classification, with post-stroke subjects, using 89-channel EMG achieved an average recognition rate of 95%. Gijsberts et al. [19] have reported a recognition rate of 90% for classification of five finger movements using time domain features from 12-channel EMG. Although high recognition rate was a success of these experiments, these were subjected to the use of higher dimensional feature vectors for classification.

More recently, investigations of muscle synergy for recognition of EMG based hand gestures have appeared as one of the promising methods for prosthesis control. Ma et al. [20] suggested a muscle synergy model to transform commands of the central nervous system to realize the proportional control of multiple DoF. In this study, four hand/ wrist movements of the prosthesis: open, close, pronate, and supinate have been controlled. Muscle synergy based characterization and clustering of post-stroke patients in reaching movements have been reported in [21]. Five basic clusters were identified successfully as a function of shoulder elevation, elbow extension and normalized jerks. A case study on synergy based EMG controlled prosthetic hand has been reported in [22]. The experiments have been accomplished to control a robotic hand for grasping objects. Although classification of 18 finger movement tasks using muscle synergy have been reported by [23], it was using 32-channel EMG; which is higher in number and will lead to complex control systems. Synergistic EMG activities of forearm muscles have been explored for recognition of five gestures: pinch, fist, open hand, grip, and extension [24]. However, there is little research considering finger movement recognition with the inherent physiological mechanism of muscle synergy.

Following our continuous effort for an EMG based prosthetic hand with higher controllability [11], [25], this paper presents a framework for finger movement recognition based on muscle synergy using EMG. Five able-bodied subjects took part into the experiment. Surface EMG were recorded for five finger movements using four channel EMG. Non-negative matrix factorization (NMF) of EMG feature: root mean square (RMS) have been accomplished to estimate the muscle synergy. Radial basis function (RBF) kernel support

978-1-7281-0834-6/19/$31.00 ©2019 IEEE

vector machine (SVM) was used for recognition of finger movements. Using leave-one-patient-out cross-validation, an average recognition rate of 97% was achieved.

II. Materials and Methods

A. Subject Preparation

Five normal-limbed subjects (mean age: 26±1.5 years, height: 165±10 cm, weight: 63±2 kg) volunteered for the experiment. Following the case study on myoelectric control reported in [26], the number of subjects have been kept five. The consideration of normal-limbed subjects was based on the fact that amputees are able to generate similar forearm EMG to that of the healthy subjects [27], [28]. All subjects were informed with the details of experimental study and they signed an informed consent form before the experiment. This is in line with the institutional ethical committee approval. Prior to the start of the experiment, the participants were asked to be seated comfortably. Subjects were seated with the forearm extended at the side; palm facing upward and wrist placed on the arm rest of the chair. The forearm skin of the participants was cleaned with alcohol pad followed by the placement of EMG electrode. Ag/AgCl button type surface floating EMG electrodes were used. They typically consist of a metal or conductive polymer disc of diameter 5-30 mm with adhesives. Surface electrodes measure the potential of the muscles available from the surface of the skin. Table I shows the placement of EMG electrodes on the specific muscles and the muscle compartments on the forearm. The distance between the center of the electrodes were 1-2 cm and the electrodes were arranged along the longitudinal midline of the muscles to detect improved superimposed EMG [29].

TABLE I
Placement of Four Channel EMG Electrodes on the Subjects' Forearm for EMG Acquisition

Electrodes	Muscles	Muscle Compartment
Channel 1	Brachioradialis	Posterior
Channel 2	Extensor Digitorium	Posterior
Channel 3	Flexor Carpi Radialis	Anterior
Channel 4	Flexor Carpi Ulnaris	Anterior
Reference	Ulnar Styloid	

B. Experimental Protocol

On preparation of the subjects, they were instructed to perform the flexion-extension movement by the thumb, index, middle, ring, little fingers with intermediate relaxing period. The subjects performed the tasks following the visual instruction on a computer screen. The time-line activities of the experimental protocol is as tabulated in Table II. EMG were recorded for 10 trials of each movement in two sessions. Fig. 1 shows the finger movement during the acquisition of EMG following the experimental protocol.

C. EMG Acquisition and Data Set

EMG generated following the experimental protocol in section II-B were acquired using AD Instruments power lab 4/26T bio-amplifier. The specification settings of the bio-amplifiers during EMG acquisition was as tabulated in Table III.

TABLE II
Time-line Activities of the Experimental Protocol

Enumeration	Activity	Duration
M0	Hand Relax	10 seconds
M1	Thumb Flexion-Extension	2 seconds
M2	Hand Relax	10 seconds
M3 - M14	Repeat M0 to M2 for Index (M3-M5), Middle (M6-M8), Ring (M9-M11) and Little (M12-14)	88 seconds

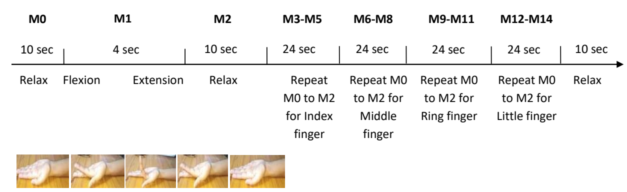

Fig. 1. Schematic of Experimental Protocol Time Line Activities

TABLE III
Specifications of the Settings of the EMG Unit during Acquisition

Parameter	value
High Cut-off Frequency	500 Hz
Low Cut-off Frequency	10 Hz
Notch Cut-off frequency	50Hz
Amplification range	$\pm$ 5
Common Mode Rejection Ratio	110 db

A total of (5 subjects $\times$ 5 finger movements $\times$ 10 trials $\times$ 2 sessions =) 500 four-channel EMG have been collected for the experiment. The EMG were sampled at 1 kHz. Sufficient relaxation time between each session ($\approx$30 minutes in total) was allowed. EMG during hand relaxation was recorded as relaxing EMG in a different class.

III. Proposed Framework

Fig. 2 shows the framework of finger movement recognition based on muscle synergy using EMG.

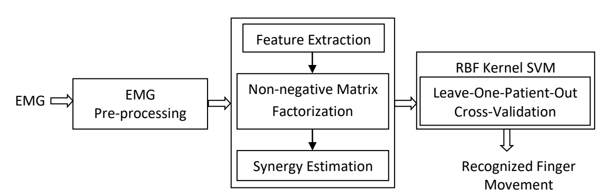

Fig. 2. Schematic of Finger Movement Recognition based on Muscle Synergy using EMG

A. EMG Pre-processing

On acquisition, EMG were subjected to onset detection. EMG acquired during hand relaxation have very small amplitude and do not carry any information about the finger movements [30]. EMG onset detection technique extracts the EMG generated during the individual finger movements. During onset detection, EMG with amplitude less than three times of the standard deviation of the EMG at rest position were removed. This threshold was following the discussion in [31]. In line with [32], a Hamming window of size 100 samples was used on the onset detected EMG. This size of Hamming window was to meet the real-time constraint of myoelectric control system [33]. Fig. 3 shows the four channel pre-processed EMG generated during one trial of five finger movements.

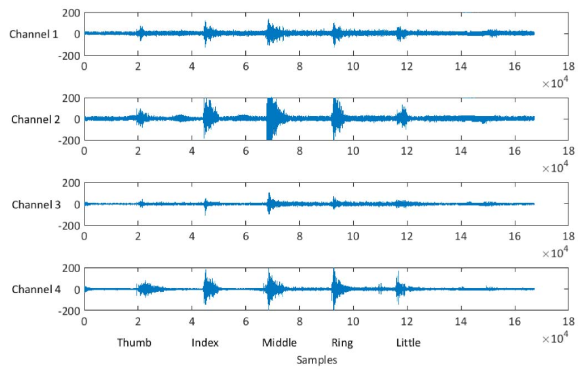

Fig. 3. Four channel pre-processed EMG generated during one trial of five finger movements. The four EMG channels are in Y-axis with amplitude in milliVolt and five fingers are in X-axis with the number of EMG samples

The EMG activity intensity was estimated through RMS value of the pre-processed EMG. It is related to the muscle force involved during the movements [34] and was calculated as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{1}$$

where x_i represents the i^{th} sample of EMG with N as the total number of samples in each EMG trial during flexion-extension movement.

B. Non-negative Matrix Factorization

NMF algorithm is one of the many methods used for extraction of muscle synergy along with their corresponding activation coefficients. This synergy matrix is the result of decomposition of the selected EMG time-domain feature. The decomposition method was carried out as follows:
Let V be the RMS feature matrix of size $r \times s$ where r is the number of muscles involved (i. e. r = 4) and s is the number of trials for which each movement have taken place (i. e. s = 10). V is decomposed into two non-negative matrices:

$$V_{r\times s} = W_{r\times k} \times H_{k\times s} \tag{2}$$

W is the synergy matrix of size $r \times k$ with k being the number of muscle synergies (1≤k<4). It represents synergy pattern of the four muscles. H is the $k \times s$ matrix representing the activation weights of the specific muscle synergy. The NMF decomposition for the middle finger flexion-extension movement is shown in Fig. 4. Fig. 4(a) shows the pre-processed EMG for one trial flexion-extension movement of the middle finger. Fig. 4(b) represents the RMS feature vector of EMG. Fig. 4(c) shows the normalized synergy of the four muscles (1: Brachioradialis, 2: Extensor Digitorium, 3: Flexor Carpi Radialis, 4: Flexor Carpi Ulnaris). It represents the co-activation of the four muscles during the middle finger flexion-extension movement. Fig. 4(d) shows the activation function representing weights of the synergy.

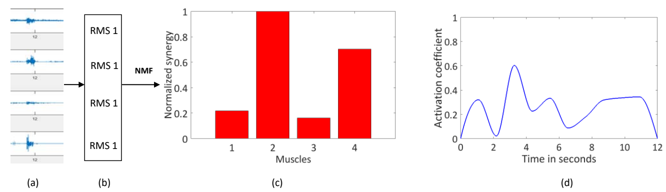

Fig. 4. Non-Negative Matrix Factorization of EMG (a) pre-processed EMG during one trial of flexion-extension movement (b) RMS value of EMG during each trial of movement (c) Normalized synergy representing the co-activation of four muscles during the middle finger flexion-extension movement (d) Activation co-efficient pattern of the muscle synergy during the middle finger flexion-extension movement

1) Selection of optimal number of synergies: The optimal number of synergies to be selected was determined by calculating a parameter called Variance Accounted For (VAF) [24]. VAF between the RMS feature matrix V and the reconstructed matrix (W×H) was calculated using the following equation:

$$VAF = (1 - \frac{(V-(W\times H))^2}{V^2}) \times 100\% \tag{3}$$

For keeping information regarding the movements in original form, the optimum number of synergies can be determined when the minimum number of synergies satisfied the two main criteria:

- Criterion 1: VAF > 95%
- Criterion 2: VAF increases by less than 1% when one synergy is added.

C. EMG Feature Matrix and Recognition

Finger movements were characterized by a synergy feature matrix i. e. A. This was comprised of the co-activation of the muscles in the synergy matrix for each finger movement and is represented as follows:

$$A = [W_{i,j}] \tag{4}$$

where W = Synergy matrix representing the co-activation of four muscles
i = 1, 2, 3, 4, 5 representing five finger movements
j = 1, 2, 3, 4 representing the four muscles

RBF kernel SVM was used for recognition of finger movements. SVM regularization constant (c) and kernel parameter (γ) were found through grid search [35] and set as c $=2^{-4}$ and $\gamma = 2^{3.2}$. The choice of RBF kernel was based on the fact that it can map features into infinite spaces, simultaneously controlling the training error, and computational complexity of classifier is based on a fewer number of hyper-parameter as compared to the limited feature spaces in polynomial kernel [35], [36].

To make the experimental results clinically applicable, leave-one-patient-out cross-validation was used for recognition of finger movements. Accordingly, the SVM classifier was trained with EMG feature matrix from four subjects and tested with remaining one subject. This is repeated for each subject as test subject and the average of all the test results have been estimated as the average recognition rates [37]. The splitting of the data being accomplished in a way independent of the data, the recognition results avoid any effect of bias or over-fitting [38].

IV. Experimental Results

A. Optimal Number of Muscle Synergies

Fig. 5 shows three sets of muscle synergy patterns while adding one synergy each time for the middle finger movement of one subject. Each time a set of synergy is added, new synergy patterns were observed with new activation coefficients. To estimate the optimal number of synergy sets to be used for recognition of finger movements, criteria mentioned in section III-B.1 was followed.

Table IV through VIII shows the VAF for three sets of synergy during five finger movements for 10 trials across the five subjects.

TABLE IV

VAF in % for Three Sets of Synergy during Five Finger Movements of Subject 1

	Index	Middle	Ring	Little	Thumb
k=1	98.7	98.6	98.1	98.3	98.8
k=2	98.9	98.8	98.5	98.6	99.1
k=3	99.5	99.9	99.6	99.8	99.9
k=4	100	100	100	100	100

TABLE V

VAF in % for Three Sets of Synergy during Five Finger Movements of Subject 2

	Index	Middle	Ring	Little	Thumb
k=1	98.4	98.8	97.9	97.1	98.5
k=2	98.7	99.1	98.4	97.7	99.2
k=3	99.9	99.9	99.9	99.9	99.9
k=4	100	100	100	100	100

The VAF corresponding to Fig. 5 is shown in Fig. 6. As in Fig 5, the synergy pattern is consistent with k = 1 for all the finger movements. Further, observing the VAF in Table IV through VIII; it has been found that the VAF is more than 95% for all the finger movements across all the subjects satisfying criterion 1 mentioned in section III-B.1. While analyzing the second criterion, it has been found that for k = 1, VAF increases by less than 1% when one synergy is added. According to [24], the minimum number of synergy should be selected when the above two criteria are satisfied. Accordingly, synergy with k = 1 was selected for recognition of finger movements.

Fig. 7 shows the individual muscle synergy patterns for

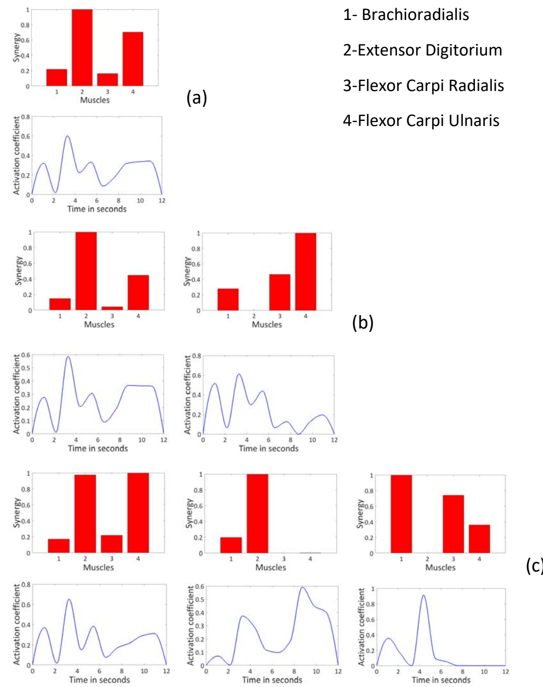

Fig. 5. Muscle Synergy Patterns and Activation Co-efficients for the Middle Finger Movement of One Subject as the Number of Synergies Increase from k = 1 to k = 3 (sub-figure (a) for k=1, sub-figure (b) for k=2 and sub-figure (c) for k=3)

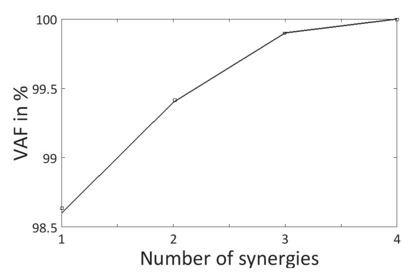

Fig. 6. Relationship between mean VAF of Five Finger Movements and Number of Muscle Synergy (k = 1, 2, 3)

TABLE VI

VAF in % for Three Sets of Synergy during Five Finger Movements of Subject 3

	Index	Middle	Ring	Little	Thumb
k=1	98.4	98.5	98.5	98.1	98.7
k=2	98.8	98.9	98.8	98.7	99.2
k=3	99.9	99.9	99.9	99.9	99.9
k=4	100	100	100	100	100

TABLE VII
VAF IN % FOR THREE SETS OF SYNERGY DURING FIVE FINGER MOVEMENTS OF SUBJECT 4

	Index	Middle	Ring	Little	Thumb
k=1	98.4	98.7	98.3	98.4	98.8
k=2	98.8	99.1	98.7	98.9	99.3
k=3	99.9	99.9	99.9	99.9	99.9
k=4	100	100	100	100	100

TABLE VIII
VAF IN % FOR THREE SETS OF SYNERGY DURING FIVE FINGER MOVEMENTS OF SUBJECT 5

	Index	Middle	Ring	Little	Thumb
k=1	98.1	95.6	98.9	96.3	95.2
k=2	98.7	96.2	99.2	96.8	95.7
k=3	99.9	99.8	99.8	99.6	99.8
k=4	100	100	100	100	100

each finger movement for five subjects. The sub-figure (a), (b), (c), (d) and (e) in Fig. 7 represent the synergy values of thumb, index, middle, ring and little fingers respectively. Each sub-figure consists of the synergy patterns of the four groups of muscles for five subjects. These synergy patterns are the coordination among the muscles while performing finger flexion-extension movement. It can be observed that the normalized synergy of the extensor digitorium muscle is maximum followed by the flexor carpi ulnaris muscle over the other two. It complies with the physiological fact that extensor digitorium and flexor carpi ulnaris muscles are mostly involved in finger extension and flexion movement respectively [39].

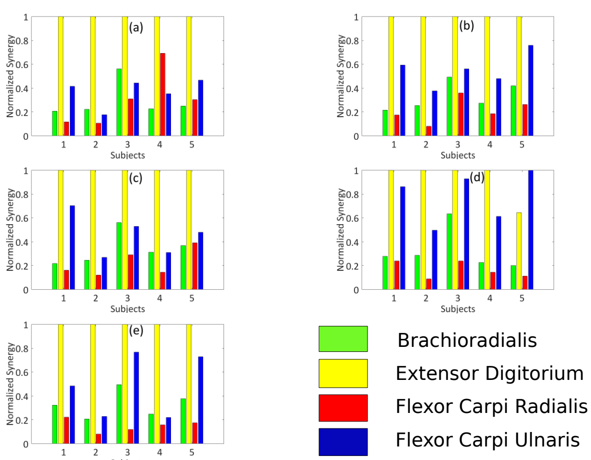

Fig. 7. Muscle Synergy Patterns of Five Finger Movements of Five Subjects. Muscle synergy of (a) thumb (b) index (c) middle (d) ring (e) little finger

B. Recognition Performance

EMG feature matrices of muscle synergy as in Fig. 7 were used as input to the RBF kernel SVM. The recognition results through leave-one-patient-out cross-validation are shown in Fig. 8. It shows the recognition results for each finger movement across 10 trials with the average recognition rate for the respective subjects. An average recognition rate of 97% was achieved across all the subjects.

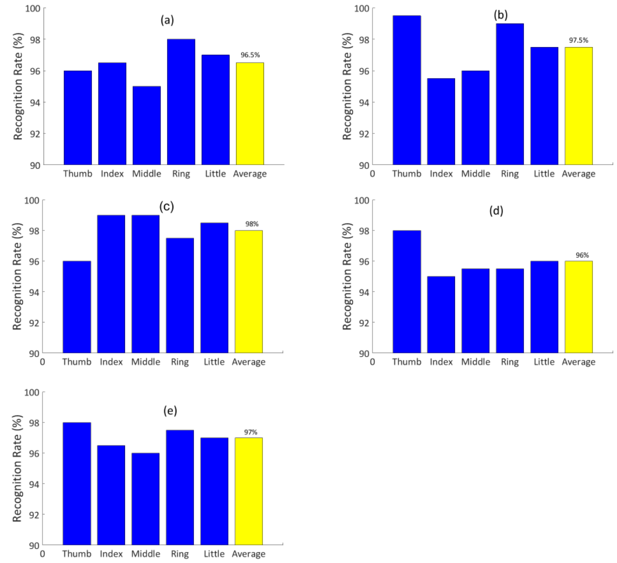

Fig. 8. Finger Movement Recognition Rates for (a) Subject 1 with an average recognition rate 96.5% (b) Subject 2 with an average recognition rate 97.5% (c) Subject 3 with an average recognition rate 98.0% (d) Subject 4 with an average recognition rate 96.0% (e) Subject 5 with an average recognition rate 97.0% through leave-one-patient-out cross-validation

V. CONCLUSIONS

We presented a framework for finger movement recognition based on muscle synergy using EMG. Non-negative matrix factorization was applied on the EMG feature for estimating co-activation of forearm muscles during finger movements. RBF kernel SVM was used as the classifier. Leave-one-patient-out cross-validation was applied to avoid any overfitting in the recognition results. An average recognition rate 97% was achieved. The present study suggested that, by means of the mechanism of muscle synergy, finger movement recognition can be achieved with lower feature vector dimensionality i. e. only with RMS of EMG as feature. The muscle activity contribution to the finger movements as depicted by the synergy patterns are in line with the physiological evidence. A recognition rate of 97% using minimum EMG feature offers potential for robust finger movement control in prosthetic hands.

The limitation of the presented work is that off-line recognition of finger movements is presented. The focus of our future work will lead to real-time implementation of the presented finger movement recognition results for control of prosthetic hands.

ACKNOWLEDGMENTS

The support received under the ASEAN-India R&D Scheme, SERB-DST, Government of India for the project No. CRD/2018/000049 and NECBH, DBT, Government of India for the project No. NECBH/2019-20/144 are gratefully acknowledged.

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