Analyzing Muscle Synergies for Finger Movement Recognition using sEMG Signals

***Abstract*—The study focuses on extracting muscle synergy from electromyographic (EMG) signals for recognition of finger movement. The process involves using a non-negative matrix factor (NNMF) to decompose the EMG signal matrix into muscle synergies and their corresponding activation coefficients. The synergy obtained from this process reveals the underlying patterns in the EMG data that help in the classification of finger movements. Other steps include hyperparameter tuning using grid search, feature selection using sequential forward selection (SFS), and classification using support vector machine (SVM). The proposed method shows the effectiveness of NNMF in detecting muscle synergy for accurate classification of finger movements. A classification accuracy of 97.5±1.67% is obtained.**

***Index Terms*—Muscle Synergy, NNMF, SVM**

I. Introduction

The hand plays a major role for fulfilling the activities of daily life of a person [1]. A lot of researches are being carried out to analyze the human hand and how it is being controlled. The control of the hand is done by the central nervous system (CNS), which is a complex process involving multiple areas of the brain and spinal cord [2]. The CNS coordinates the activation of specific groups of muscle to produce movements for interaction with the environment and perform various tasks [3]. The process of hand control begins with sensory information from the hand being transmitted to the brain via sensory nerves. The brain then processes this information and sends signals to the motor neurons in the spinal cord that control the hand muscles. The motor neurons in the spinal cord activate specific muscle groups to produce the desired movement [4]. The CNS also regulates the force [5] and speed of the movement to ensure that the hand movements are precise and coordinated. Additionally, the CNS can modulate hand control based on the context of the task. For example, if we are holding a fragile object, the CNS will adjust the force and speed of our grip to prevent us from breaking the object. The control of the hand by the CNS is a dynamic and adaptable process that allows us to perform a wide range of tasks with precision and coordination.

Muscle synergy is the concept of the nervous system coordinating the activation of groups of muscles rather than individual muscles to perform a movement or required muscle forces [3], [6]. Research has shown that the CNS controls the activation of specific muscle synergies for different movements [7]. The nervous system organizes these muscles into functional units that work together to generate a specific movement. This allows for efficient and coordinated movements and reduces the need for the nervous system to control each individual muscle. For example, the CNS activates different muscle synergies for grasping an object with a power grip, compared to manipulating an object with a precision grip. The specific muscle synergies activated by the CNS depend on the task demands, the context of the task, and the individual's motor abilities. Furthermore, studies have found that the CNS is able to combine and reorganize muscle synergies to adapt to different tasks and environments. For instance, when we switch from holding a heavy object to a lighter one, the CNS will adjust the muscle synergies used to control the hand to produce the appropriate force. Understanding the role of the CNS in the control of muscle synergies for the hand is essential for developing strategies to restore or enhance hand function in individuals with disabilities or injuries [8]. For instance, neural interfaces can be used to connect the CNS to a hand exoskeleton or prosthetic device, allowing individuals to control the activation of specific muscle synergies to produce desired hand movements. In the context of hand function, muscle synergies are essential for performing tasks such as grasping, manipulating objects, and fine motor movements. By studying the patterns of muscle activity during these tasks, researchers have identified several muscle synergies that are consistently used across individuals [3].

The musculoskeletal system is complex and involves the interactions between bones, joints, muscles, and nerves. Understanding and controlling these interactions is essential for developing musculoskeletal disorder treatments and designing more effective biomedical devices. The Bernstein problem has important implications in the field of control of the musculoskeletal system. In the context of musculoskeletal control, the Bernstein problem can be formulated as follows: given a desired movement trajectory, how can we determine the control signals (i.e., the activation levels of the muscles) from an infinite number of solutions that produce the desired movement? It can also be termed Bernstein's DOF problem, where multiple choices exist for carrying out one particular task [9]. One approach to solving this kind of problem in robotics is to use optimization techniques to find the optimal control signals. Creating muscle synergies is an optimization technique where the CNS encodes the synergies and combines them to generate muscle contractions for the desired movement [7]. By understanding these muscle synergies, researchers have been able to develop strategies for controlling hand function using assistive devices [2] through neural interfaces. For example, a person with a spinal cord injury may be able to control a hand exoskeleton device by using signals from their remaining muscles to activate specific muscle synergies for controlling the device. Overall, muscle synergies are an important aspect of hand function and can be used to develop new technologies for restoring or enhancing hand function in individuals with disabilities or injuries. With this motivation, in this paper muscle synergies are being identified using EMG signals and these are used for the recognition of finger movements or grasp postures.

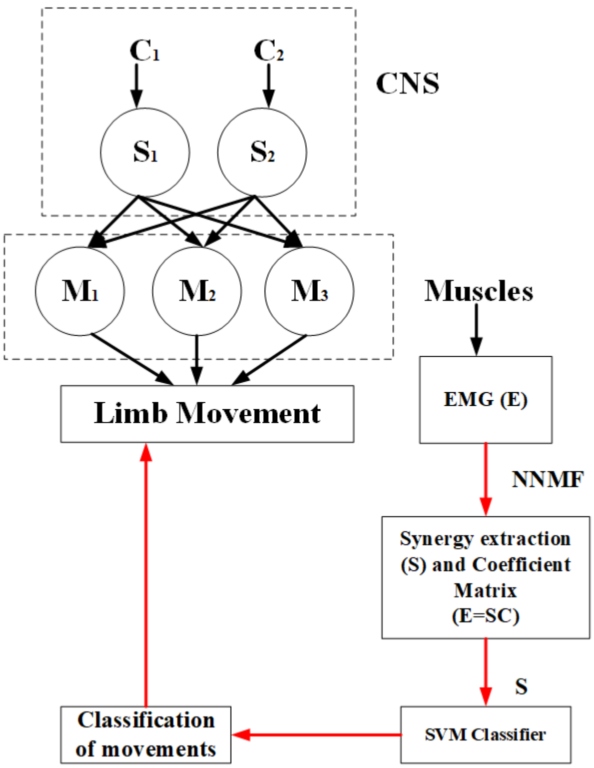

Fig. 1: The schematic of muscle synergy theory and extraction process. The coactivation of a group of muscles by CNS for limb movement is represented by the black arrows. Extraction of Muscle synergy from the recorded EMG signals for finger movement recognition represented by the red arrows

Fig 1 shows that the CNS determines the synergies S_1 and S_2 which works in conjunction to activate a set of muscles M_1, M_2 and M_3. C_1 and C_2 are the activation coefficients that combines with synergies for activating the muscle groups. These activations leads to the movement of the limbs. But when an individual suffers from impairments due to various factors like injuries, neurological disorders etc, they are unable to perform these movements voluntary. Then the muscle signals are collected from the individual in the form of EMG signals and muscle synergies are extracted. The extracted synergies are used for the recognition of movements of the individual which can further be used to perform its movements through various assistive devices. The computational work performed in this paper is shown by the red arrows in Fig 1. Muscle synergies are estimated from surface electromyography (sEMG) signals applying Non-negative Matrix Factorization (NMF) technique. Muscle synergy extracted by this method follows time invariant muscle synergy model [10].

II. Methodology

A. Experimental Protocol and Data Preprocessing

The dataset used for the analysis is drawn from Khushaba et al [11]. It has EMG signals extracted from eight subjects for 15 finger movements: individual finger flexion movements of the index (ii), middle (mm), ring (rr), little (ll), thumb (tt), and the pinch of the combined thumb-index (ti), thumb-middle (tm), thumb-ring (tr), thumb-little (tl), index-middle (im), middle-ring (mr), ring-little (rl), index-middle-ring (imr), middle-ring-little (mrl) and finally, the Hand close (hc). An auditory cue was used to collect the EMG signals from the forearm where the electrodes are placed as shown in Fig 2. The subjects were asked to move a particular finger from extension to flexion position and hold that finger posture for 20 secs. These finger movements are repeated three times for a subject with a resting period of 3-5 secs. The sampling frequency is considered to be 4000 Hz. The collected EMG signal is then amplified with a total gain of 1000. To improve the signal-to-noise ratio of the EMG signals, filtering is done. The amplified EMG signal is then bandpass filtered between 20 Hz and 450 Hz, and then a notch filter is applied to remove the 50 hz-line interference. Wavelet decomposition of the filtered signal is then performed using , Daubechies wavelet of order five as the mother wavelet. The signal is further rectified using full wave rectification that involves evaluating the absolute value of the EMG signal and then normalized. The experimental investigation involves recognition of finger movement of the individual based on EMG signals extracted. The features for classifying the movement are based on muscle synergies.

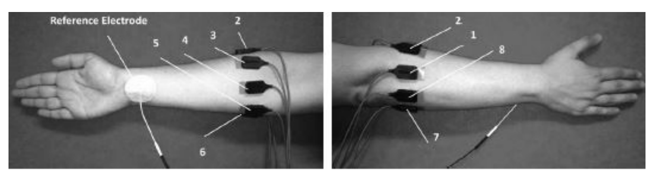

Fig. 2: Position of EMG sensors placed on the circumference of forearm for collection of signals while performing finger movement [11]

B. Recognition of finger movements

The process undertaken to classify finger movements using muscle synergies is outlined in Fig 3. Further elaboration on executing these steps is provided below.

1) Extraction of muscle synergies: The decomposition to synergy is carried out by recording the EMG signals from the individuals while performing the task. The synergies obtained can be either posture-dependent or posture-independent. Studies have shown that posture-independent synergies have the advantage of being easier to implement. Also, more synergies are required for posture-dependent synergies to capture the maximum variation in muscle activity patterns. In our study, the EMG signal profile of the eight muscles are

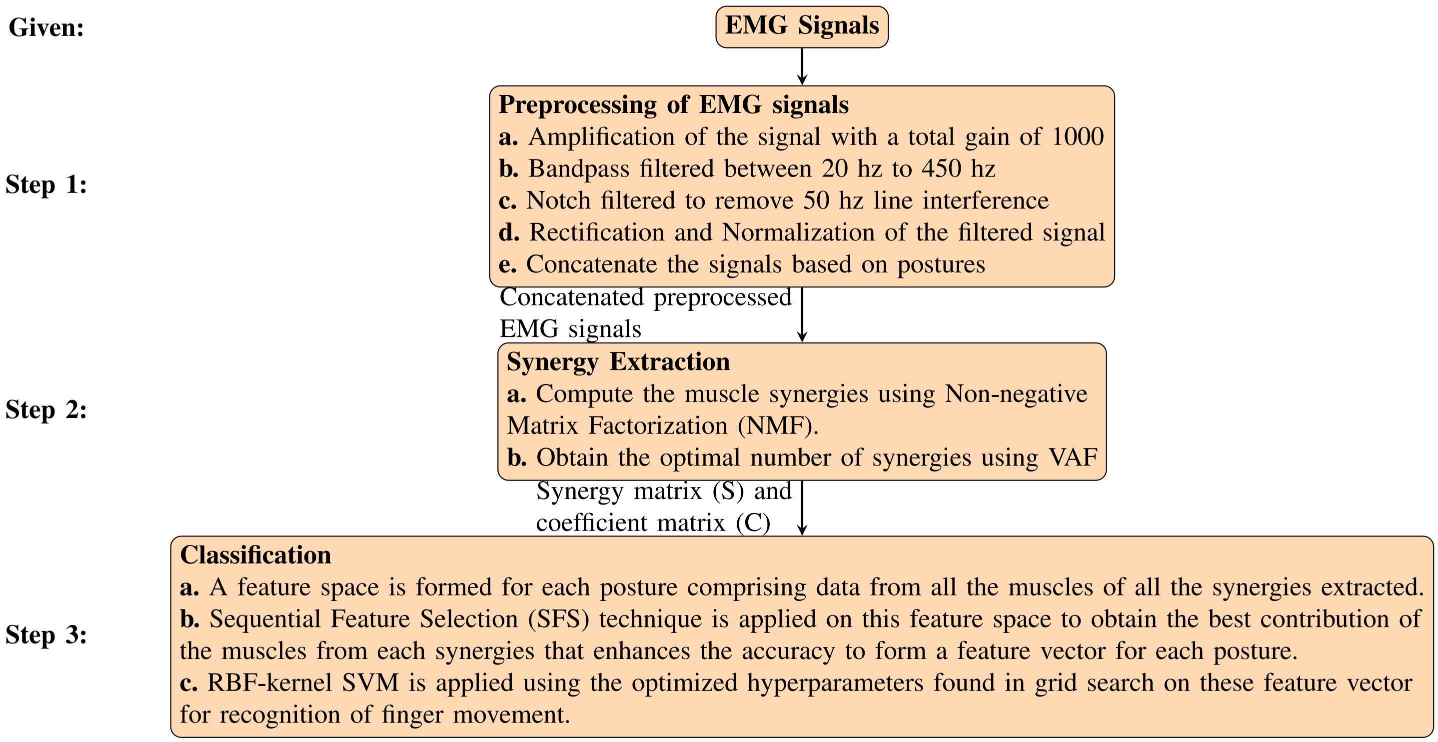

Fig. 3: Flowchart of the steps followed for recognition of finger movement based on muscle synergy

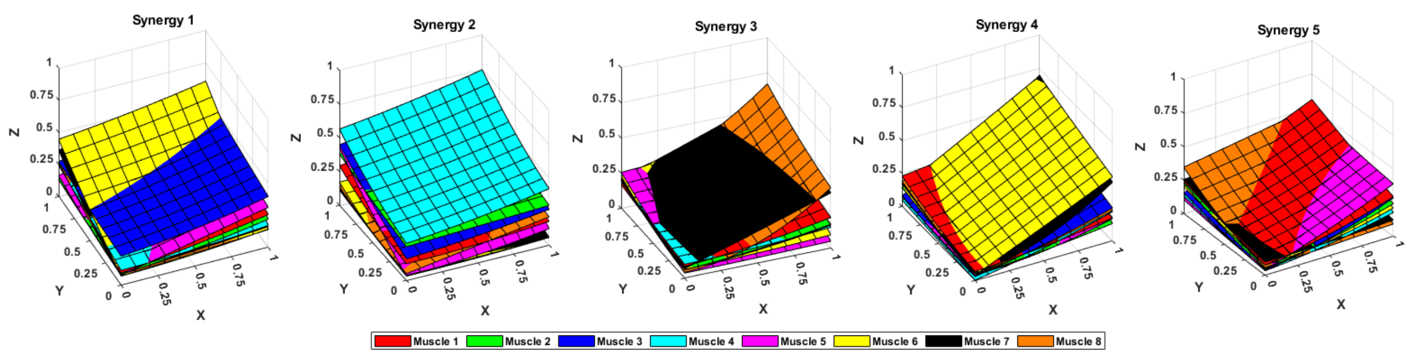

Fig. 4: Activation level of each muscle in a synergy represented by coloured surface.

cascaded for a particular finger movement vertically. Finally, a matrix is formed with fifteen rows, each representing a particular finger movement for a subject. The posture matrix for each subject is obtained in the form of E_{con} as shown below

$$[E]_{con} = \begin{bmatrix} E^1_{mn} \\ E^2_{mn} \\ . \\ . \\ . \\ E^P_{mn} \end{bmatrix}_{mP \times n}$$

where P is the number of postures, m is the number of muscles and n is the data samples.

$$[W]_{con} = \begin{bmatrix} W^1_{mn} \\ W^2_{mn} \\ . \\ . \\ . \\ W^P_{mn} \end{bmatrix}_{mP \times k}$$

Non-negative Matrix Factorization (NMF) is used to extract muscle synergies from Electromyography (EMG) signals. The mathematical formulation of NMF for this purpose involves factorizing a non-negative matrix E into two non-negative matrices W and H. Given an EMG signal matrix E of size m×n, where m represents the number of muscles and n represents the number of samples, NMF factorizes this matrix into W and H as follows:

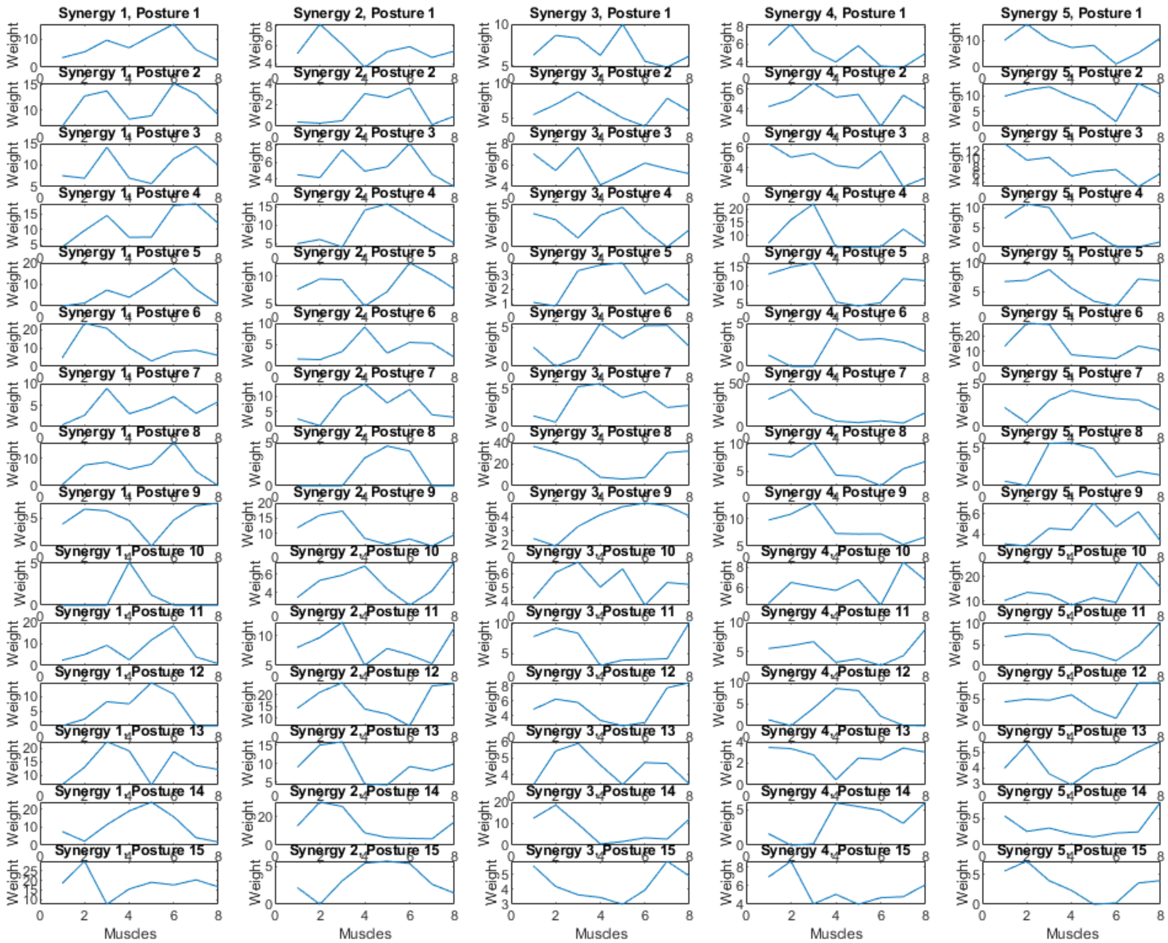

Fig. 5: Muscle activations with respect to each posture; x-axis represents the muscles and y-axis represents the activation weight

$E \approx W \times H$,
where,
W is the matrix of muscle synergies of size m×k,
H is the matrix of coefficients or activations of the synergies of size k×n (k represents the number of synergies)

Applying NMF to $[E]_{con}$, a concatenated posture-independent synergy matrix, $[W]_{con}$ and a coefficient matrix, H will be obtained. $[W]_{con}$ therefore contains k muscle synergies for all postures. These muscle synergies captures the underlying fundamental patterns of muscle activation for each movement. The next step is labelling these extracted synergies for each movement that acts as an identifier for the pattern obtained from corresponding movements. It is an important step before performing the classification.

2) Optimal number of synergies: Selecting the optimal number of synergies (k) is another step to be performed before the classification step. A parameter Variance Accounted For (VAF) is evaluated between E and the product W × H which is a quantitative measure used for obtaining the optimal number of synergies [2]. The VAF is calculated using the formula

$$VAF = (1 - \frac{(E - WH)^2}{E^2}) \times 100\%$$

3) Recognition rate evaluation: Hyperparameter tuning is an important step and is performed initially as the hyper-parameters are used in feature selection technique. The best set of hyperparameters for a model is evaluated from a grid of values. `GridSearchCV` is employed that utilizes cross-validation to train the data on different subsets for evaluating the model's performance. It identifies the optimal values of hyperparameters that yields the best performance metric. After performing a grid search, the most relevant features among the extracted synergies are computed employing Sequential Forward Selection (SFS). It iteratively selects the set of synergies that contributes most to recognition rate. SFS configuration initializes an SVM model with hyperparameters obtained from grid search. The iteration process evaluates the performance of a model; starts with one feature and then new features are added sequentially in each iteration. This process is continued until a subset of optimal features are obtained that enhances model performance.

The classification model employed in our study is Support Vector Machine (SVM) as it is obtained to give higher accuracy for classification of movements. SVM classifier is trained using the optimized hyperparameters and the selected features. Further cross validation technique is employed to ensure robustness of the model. Performance metric of the classifier is evaluated to assess its performance in recognition of the postures based on muscle synergies.

III. Results and Discussion

A. Extraction of muscle synergies

The synergies are extracted using Non-negative matrix factorization (NNMF) . The subjects performed 15 different postures and each posture having three trials. Each posture formed a data matrix representing $E_{8\times 80000}$ with size in the form muscles $\times$ data points. Since the data was collected for 15 postures the concatenated data matrix formed is represented by $E_{(15\times 8)\times 80000}$. NNMF is applied to this concatenated matrix to obtain posture-dependant synergies (W) and activation coefficients (H) as seen below

$E_{(15\times 8)\times 80000} = W_{(15\times 8)\times k} H_{k\times 80000}$

k represents the number of synergies and is considered to be 5. The reason for choosing $k = 5$ is described in the next section. Fig 4 shows how moving in x and y directions affects the muscle activations in the synergies. The eight coloured surfaces represents the variation of a muscle share in a synergy across various postures. Fig 5 shows the muscle activation level of each synergy for every postures.

B. Optimal number of synergies

The investigation into determining the optimal number of muscle synergies from the EMG signals revealed crucial insights. Employing Non-negative Matrix Factorization (NNMF) resulted in a systematic decomposition of the EMG data, enabling the identification of distinct muscle synergies underlying finger movements. Through an iterative process, varying the number of synergies, the analysis highlighted an intriguing pattern. The VAF value with respect to the number of synergies displayed an increasing trend with an increasing number of synergies. The blue curve in Fig 6 shows the trend of the curve. This observation suggested an optimal number of muscle synergies as five that effectively captured the essential information within the EMG signals having a VAF value of 0.83. Figure also shows the variation of computational time to classify the movements with respect to number of synergies. It is observed that when the number of synergies is five, the computational time is almost equal to the time when the number of synergies is six. But when five synergies are taken, the recognition rate is observed to be more compared to when six synergies are taken. Further, increasing the number of components increases the VAF value but is not very significant compared to computational time and accuracy. So, the number of synergies considered for the classification process is five.

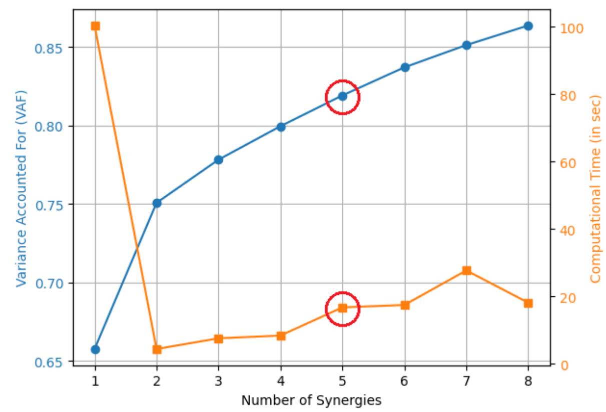

Fig. 6: Number of synergies vs VAF values and computational time required for recognition of movement

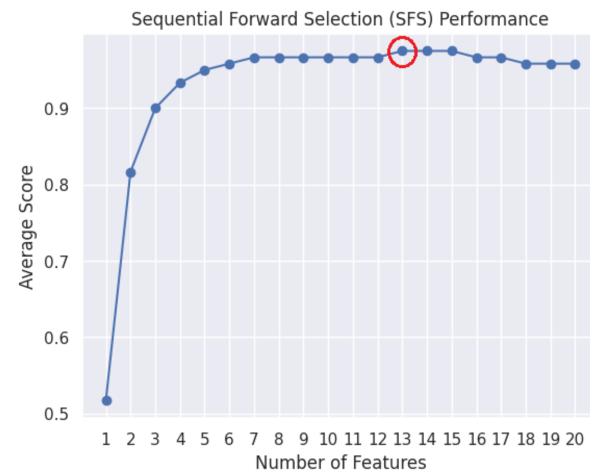

Fig. 7: Classification accuracy changes on applying Sequential Forward Selection (SFS)

C. Recognition rate evaluation

The synergies extracted are posture dependant synergies. For every subject with respect to each synergy, data from all eight muscles are obtained for a particular posture. So considering all the five synergies a feature space is formed that contains a total of 8×5=40 elements for a particular posture. Similar feature space is formed for all the 15 postures. Sequential Feature Selection (SFS) technique is applied to this feature space to obtain a feature vector that best describes the contribution of muscles in a synergy for classifying a posture. The technique sequentially combines the feature starting with one element and then gradually increasing the number of elements in the feature vector at each step and evaluates the average accuracy score. The accuracy score at each step is evaluated based on the best combination of elements for that particular step from the feature space available. From Fig 7, it is evident that on applying this technique the classification accuracy increases abruptly on adding two features and then it becomes steady. But after adding 13 features the classification

TABLE I: Contribution of muscles in a synergy to a feature vector

Synergy number	Muscle number
1	2, 7
2	3, 4, 5, 6, 7, 8
3	1, 2, 5
4	2, 8

accuracy increases to 97.5±1.67% and then it remains steady for sometime before decreasing again. So, 13 features are considered for classification of the finger movements. Table I shows the 13 elements that form the feature vector represents the contribution of which muscle group of a particular synergy is considered for recognition of finger movement.

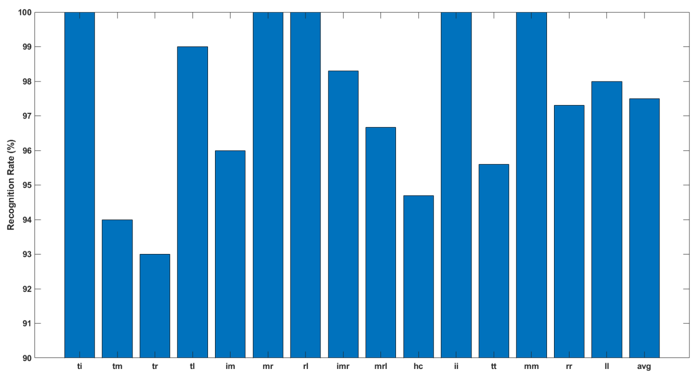

Fig. 8: Finger movement recognition rate for all 15 postures with an accuracy of 97.5±1.67%

The assessment of classification accuracy following the extraction of muscle synergies from EMG signals yielded promising outcomes. Employing a Radial Basis Function (RBF) kernel Support Vector Machine (SVM) classifier with optimized hyperparameters demonstrated robust performance in accurately categorizing finger movements. The model, configured with the determined optimal number of muscle synergies, exhibited a high accuracy rate of 97.5±1.67%. This high classification accuracy suggests that the muscle synergies extracted through Non-Negative Matrix Factorization (NNMF) encapsulated distinctive patterns inherent to various finger movements. Furthermore, the use of Sequential Forward Selection (SFS) for feature selection, refining the feature set used in classification, notably contributed to improving the model's accuracy. This finding emphasizes the importance of identifying and selecting relevant features in enhancing classification performance. The achieved high accuracy rates validate the efficacy of the proposed approach in characterizing and discriminating finger movements based on EMG-derived muscle synergies.

IV. Conclusion

A muscle synergy-based classification method for detecting finger movements using EMG signals is a robust and efficient method for accurate movement characterization. The non-negative matrix factorization (NNMF) extracted discrete muscle synergies that encapsulated the significant patterns of the EMG signals. Exploiting these synergies in a support vector machine (SVM) classifier resulted in a high classification accuracy of 97.5±1.67%. Optimizing hyperparameters and feature selection using sequential forward selection (SFS) significantly improved model accuracy, highlighting the importance of identifying significant features. This research and progress highlights the potential of muscle synergy-based methods for decoding finger movements and shows their applicability for controlling various human-machine interfaces (eg hand exoskeleton devices, prostheses, etc.).

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