Finger Movement Classification from EMG Signals Using Gaussian Mixture Model

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Abstract. Hands are the most used parts of the limbs while performing complex and routine tasks in our daily life. Today, it is an important requirement to determine the user's intention based on muscle activity in exoskeletons and prostheses developed for individuals with limited mobility in their hands due to traumatic, neurologic injuries, stroke etc. In this study, 5-finger movements were classified using surface electromyography (EMG) signals. The signals were acquired from forearm via the 8-channel Myo Gesture Control Armband. EMG signals from three participants were analyzed for the movements of each finger, and the activity levels of the channels were compared according to the movements. Following, movement classification was performed using the Gaussian mixture network, a statistical artificial neural network model. According to the experimental results, it was seen that the model achieved an accuracy of 73.3% in finger movement classification.

Keywords: finger movement classification · sEMG · Gaussian Mixture Model · artificial neural network

1 Introduction

Hands are used the most in daily life and are exposed to the biggest strain and trauma. Complete or partial loss of function in the hands may occur due to ageing, traumatic injuries and neurologic diseases. These movement limitations are tried to be eliminated as much as possible with various surgical interventions and rehabilitation processes. In amputation cases, solutions are found for the problems of patients with individually designed prostheses. Evaluation of muscle activities is extremely important both in treatment processes and in prosthesis

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applications. Measuring muscle contraction levels according to finger movements during hand rehabilitation is important in determining target position and force values. Especially in robotic rehabilitation, while the control parameters are determined by the doctor according to the patient's condition or automatically selected by the system, the evaluation of muscle contraction levels and providing optimum contraction of the muscles increase the effectiveness of the treatment. In exoskeleton robots, which are also used for therapeutic purposes or as motion supporters, movement classification is made with the signals received from the muscles, and the limbs are moved with various actuation systems. In upper limb prosthesis applications, the intended motion of the patient is determined by the muscle contraction signals received from the forearm or upper arm, and motors connected to the prosthetic fingers are moved accordingly. In order to achieve high success in these applications, it is necessary to determine the muscles and activity levels in each finger movement separately. After finding the critical features in the raw EMG signal, finger movements can be detected from muscle contraction levels with various classification algorithms [1].

There is a bundle of studies in the literature on movement classification from muscle contraction levels. These studies differ in terms of the target limb, the number of channels and the classification method preferred. While the number of channels is one of the most important parameters affecting classification accuracy, it creates a negative effect in terms of cost and complexity [2]. In the study conducted by Caesarendra et al. [3], the movement of the five fingers was tried to be estimated using the adaptive neuro-fuzzy input system method over an 8-channel EMG. In the system where the general classification accuracy is 72%, still, the accuracy of the thumb movement has a lower value of 20%. In the study conducted by Lee et al. [4], the signals received from the three-channel EMG device and nine different hand movements were classified with ANN-based classifiers and the results were compared. In the study conducted with 10 different subjects, accuracy values ranging from 54.4% to 67.5% were obtained. Bhattachargee et al. [5] used the dataset containing EMG data of 10 different hand movements to classify movements with the Gradient Boosting method. In this study, where an accuracy value of 98.5% was obtained, no experiment was done with real subjects. In the study published by Tuncer et al. [6], using the EMG dataset containing 15 different hand movements, classification was made with the multi-centred binary pattern method and an accuracy value of 99% was obtained. However, when the results are analysed in detail, it is seen that lower accuracy values are obtained in real-time motion classification applications with subjects.

In this study, activity levels of forearm muscles were determined during five different finger movements. Using the Gaussian Mixture Model developed by Tsuji et al. [7], the signals received from the 8-channel EMG device and finger movements were classified. It was tested with three participants and an average accuracy of 73.3% was obtained.

The paper is organized as follows. Section 2 contains a brief discussion of the EMG device, signal pre-processing steps and details of the Log-Linearized

Gaussian Mixture Network (LLGMN) model. Section 3 presents the experimental results along with relevant discussion. Lastly, Sect. 4 contains concluding remarks and some recommendations regarding future developments.

2 Material and Method

In this study, the finger movements are detected using muscle contraction signals from the forearm. LLGMN model [7] is used for the movement classification process. MYO Armband device was used to measure muscle contraction levels (Fig. 1).

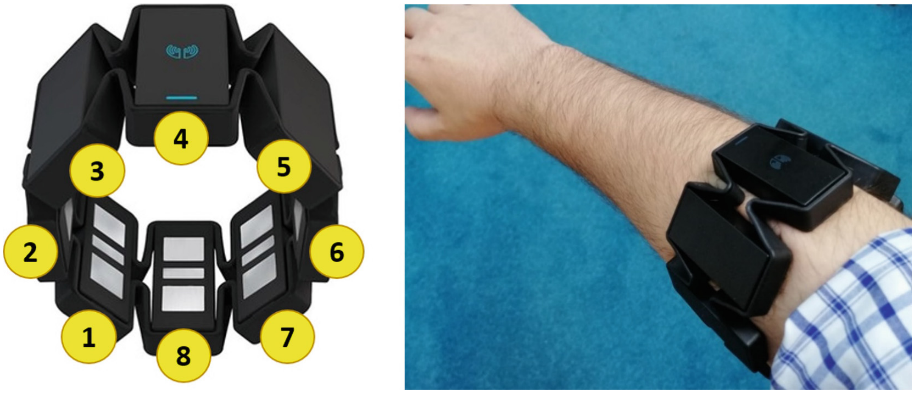

Fig. 1. MYO Armband channels and placement on the arm

Raw signals were received through the 8-channel electrodes on the MYO Armband and subjected to various pre-processing steps. In the first step, the raw EMG signals from the 8 electrodes were amplified, rectified and filtered, respectively. Since the amplitude of the raw EMG signals was very low; first, the 20 dB amplification was performed. Then, the values in negative alternance were converted into positive by rectification. Finally, filtering was done to eliminate unwanted noise in the EMG signal. For this, a 2nd order low-pass Butterworth filter was used. The corner frequency of the filter was chosen as 3 Hz. These filtered signals were sampled. The sampled signals were identified as $EMG_i(t)(i = 1, 2, 3...8)$. The $EMG_i(t)$ parameter was normalized so that the sum of the signals from the 8 channel electrodes was 1. The normalized EMG signal was defined in Eq. 1.

$$EMG_i'(t) = \frac{EMG_i(t) - EMG_i^{rest}}{\sum_{i=1}^{L}(EMG_i(t) - EMG_i^{rest})} \tag{1}$$

Here, $EMG_i'(t)$ represents normalised EMG signals, EMG_i^{rest} represents the mean value of $EMG_i(t)$ in the rest position of the relevant limb. The detailed diagram for the processing of EMG signals was given in Fig. 2.

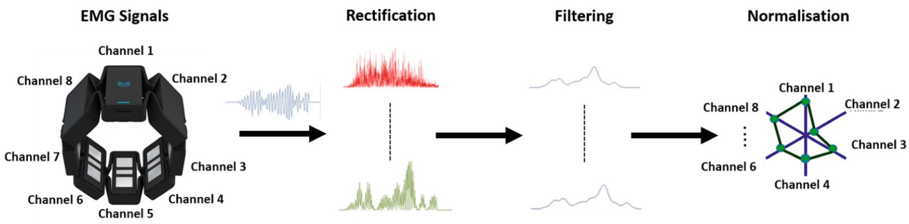

Fig. 2. EMG signal processing steps

In order to perform the movement classification, the muscular contraction level (MCL) must be calculated using the processed EMG signals. The equation used for the MCL calculation is given in Eq. 2.

$$MCL(t) = \frac{1}{2}\sum_{n=1}^{N}(\frac{EMG_n(t) - EMG_n^{rest}}{EMG_n^{max} - EMG_n^{rest}}) \quad (2)$$

Here, EMG_n^{rest} and EMG_n^{max} represent the muscular contraction level at rest and at maximum contraction, respectively. n is the number of channels (n = 8). For rest and maximum contraction, a 30 kg adjustable hand grip strengthener was used. Pictures taken during maximum contraction and rest are shown in Fig. 3.

Fig. 3. EMG measurement at maximum contraction and rest position

After signal processing, normalization and MCL calculation, motion classification was performed. Motion classification is the detection of human limb motion using EMG signals. After the signal processing stages, the data was given to LLGMN, a statistical artificial neural network model, where motion classification was performed. With the movement information obtained at the output of the network, it was decided which finger to move. The structure of the LLGMN network is demonstrated in Fig. 4.

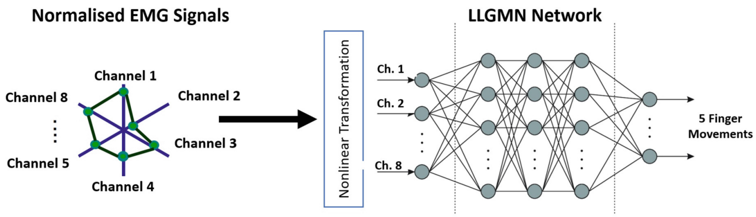

Fig. 4. LLGMN network structure

3 Results and Discussion

EMG signals obtained via the defined system were analysed for the movement of each finger, and which channels were more active in which movement, and movements that could affect each other and negatively affect the result of movement classification were determined. Data collection was done with 3 healthy subjects with the permission of the Istanbul University-Cerrahpasa Ethical Committee (ID: E-83045809). The exclusion criteria were having history of upper limb fracture, upper limb nerve injury, upper limb peripheral neurophaty, diabetes mellitus, hypo or hyperthyroidism, cervical radiculopathy, rheumatologic diseases, and kidney or liver failure. The personal information of the subjects is given in Table 1.

Table 1. Personal information of the subjects

	Subject A	Subject B	Subject C
Gender	Male	Male	Male
Age (year)	34	26	21
Height (cm)	175	170	180
Weight (kg)	78	72	69
Dominant Hand	Right	Right	Right

The 8-channel EMG signals from Subject A for each finger movement are given in Figs. 5, 6, 7, 8 and 9.

When the figures were examined, it was seen that channels 3, 4 and 8 were dominant in thumb movement. Also, channels 3, 4 and 8 are active in the index finger, middle finger and ring finger movements, and channel 7 was also active in addition to these. In the ring finger movement, channels 7 and 8 seemed more dominant than the other fingers. In addition to channels 3, 4 and 8, channels 1, 2 and 5 were also dominant in the little finger movement. Root mean square-RMS values of EMG signals from three subjects were calculated and averaged. Thus, the activity levels of 8-channels were expressed numerically in each finger movement. The results are in Table 2.

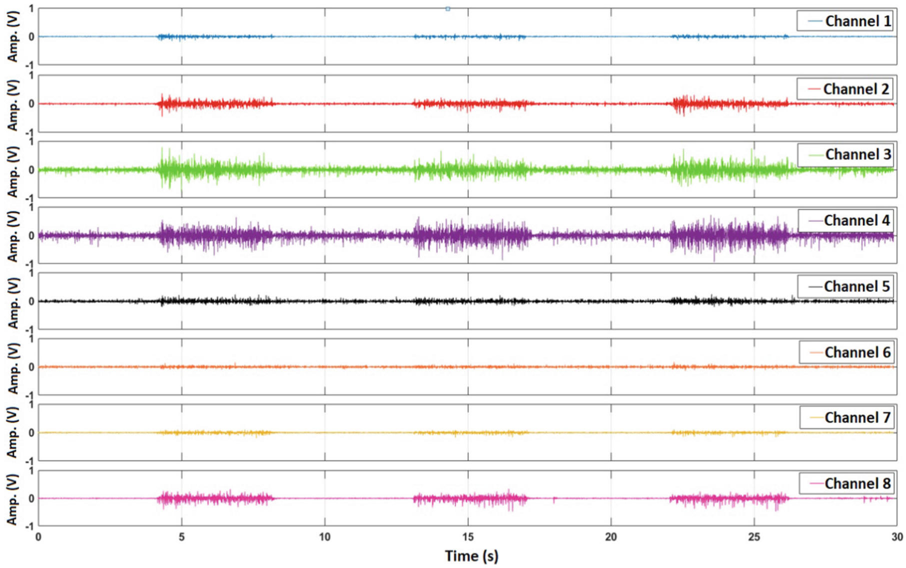

Fig. 5. Muscle contraction levels during thumb flexion and extension movement

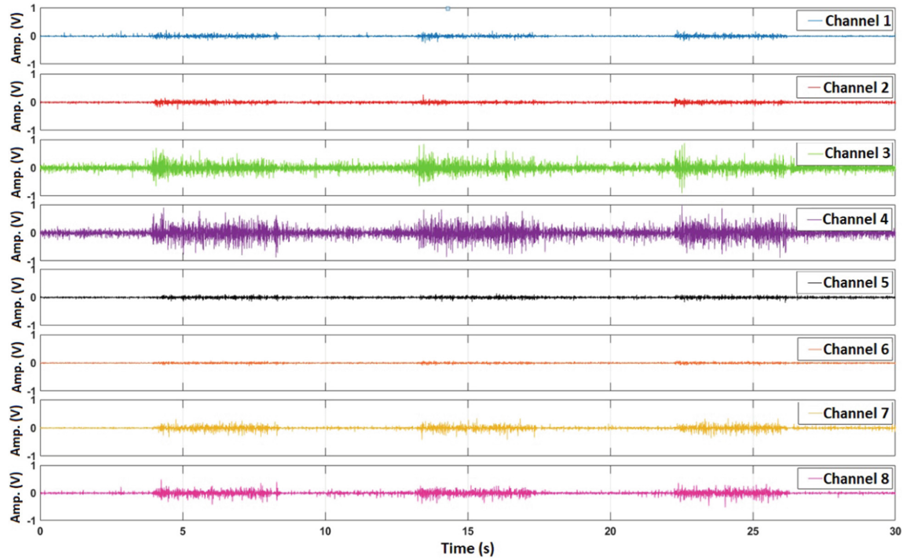

Fig. 6. Muscle contraction levels during index finger flexion and extension movement

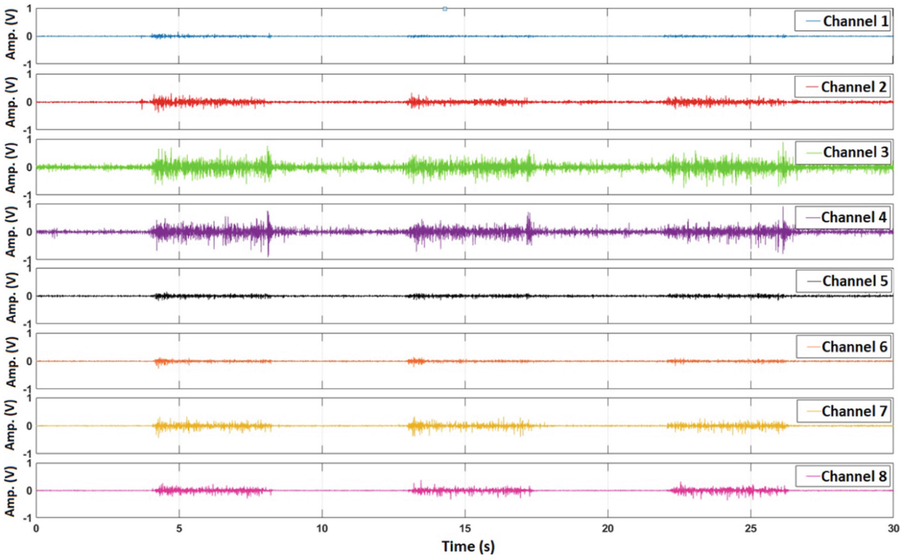

Fig. 7. Muscle contraction levels during middle finger flexion and extension movement

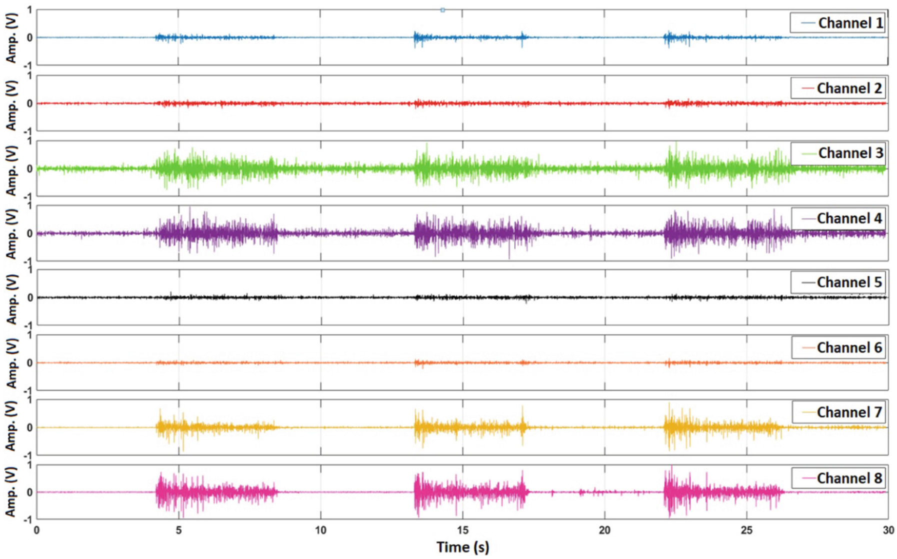

Fig. 8. Muscle contraction levels during ring finger flexion and extension movement

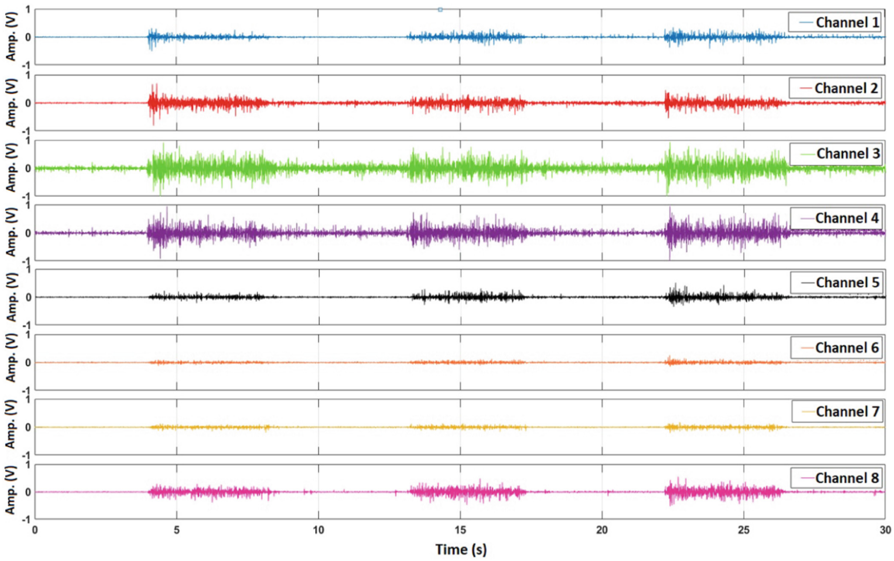

Fig. 9. Muscle contraction levels during little finger flexion and extension movement

Table 2. RMS values of EMG signals according to finger movements

	Thumb	Index Finger	Middle Finger	Ring Finger	Little Finger
Channel 1	0,0222	0,0332	0,0178	0,0329	0,0528
Channel 2	0,0546	0,0338	0,0494	0,0352	0,0816
Channel 3	0,1235	0,1337	0,1403	0,1557	0,1724
Channel 4	0,1624	0,1833	0,1186	0,1603	0,1432
Channel 5	0,0476	0,0327	0,0310	0,0333	0,0517
Channel 6	0,0284	0,0216	0,0259	0,0245	0,0251
Channel 7	0,0254	0,0588	0,0534	0,0928	0,0308
Channel 8	0,0579	0,0654	0,0457	0,1298	0,0761

In order to determine the movement classification performance of the developed system, subjects were asked to perform some targeted experiments. In the test process, the subjects were informed about the project and the operation of the system was explained. The MYO Armband was placed on the right forearm. Each subject was asked to make 20 independent finger movements randomly. It was ensured that each finger movement was applied for 3 s, waiting for 10 s between movements. The timing was performed by the subjects themselves. During this test, the output of the LLGMN model for each movement of the subject was noted. It was planned to record the movements of the subject with the flex sensor, but it was not applied since it was thought that attaching any element (sensor, glove, etc.) to the subject's hand could affect the movement and muscle contractions [8,9], and it was recorded by observation. Accordingly, the movement classification results obtained from the three subjects are given in Table 3. The results shown in red in the table indicate the movements that the system detected incorrectly.

Table 3. Movement classification test resultsm

	Subject A		**Subject B**		**Subject C**	
	Movement	**Output**	**Movement**	**Output**	**Movement**	**Output**
1	Ring	Ring	Thumb	Thumb	Thumb	Thumb
2	Index	Middle	Little	Little	Middle	Middle
3	Thumb	Thumb	Middle	Index	Little	Little
4	Thumb	Index	Index	Index	Thumb	Thumb
5	Middle	Middle	Thumb	Thumb	Index	Middle
6	Little	Little	Ring	Ring	Ring	Ring
7	Ring	Ring	Index	Middle	Middle	Middle
8	Index	Middle	Little	Little	Little	Little
9	Thumb	Thumb	Thumb	Thumb	Thumb	Middle
10	Little	Little	Middle	Middle	Middle	Middle
11	Little	Index	Ring	Ring	Little	Little
12	Thumb	Thumb	Thumb	Thumb	Thumb	Thumb
13	Index	Index	Little	Little	Index	Index
14	Middle	Middle	Index	Index	Middle	Middle
15	Ring	Little	Thumb	Thumb	Thumb	Index
16	Little	Little	Ring	Ring	Ring	Ring
17	Middle	Middle	Little	Ring	Little	Little
18	Thumb	Middle	Index	Index	Middle	Ring
19	Index	Middle	Middle	Middle	Ring	Ring
20	Little	Little	Thumb	Middle	Index	Middle

When the movement classification results in Table 3 were examined, it revealed 13 correct, 7 wrong results for Subject A; 16 correct, 4 wrong results for Subject B; 15 correct and 5 wrong results for Subject C. When the test performance checked according to the movements for all subjects, 11 correct, 5 incorrect results for thumb; 5 correct, 6 incorrect results for index finger; 9 correct, 3 incorrect results for middle finger; 8 correct, 1 incorrect results for ring finger and 11 correct, 1 incorrect results for little finger has been obtained. When the results were examined according to the movements, it was seen that the most incorrect output was in the index finger. The most incorrect results for the index finger were given inappropriately as the middle finger. The reason for this can be shown that the dominant channel numbers in Table 2 were similar for the index and middle fingers. The most successful results were obtained for the little finger. Again, when Table 2 was examined, it was seen that the most distinctive movement according to EMG channels was in the little finger. The same was true for the ring finger. Accordingly, the similarity of dominant signals in the EMG channels affected the results of the LLGMN model. Similar movements could be confused with each other. As a solution, the number of channels should be increased, and different muscles should be evaluated. When the overall performance of the system regarding motion classification was calculated, it was seen that an accuracy rate of 73.3% was obtained.

4 Conclusion

In this study, EMG signals from the forearm were examined according to different finger movements, and the dominant muscle groups in each finger movement were determined and compared. By measuring muscular contraction levels, movement classification of the five fingers of the hand was made. According to the results obtained in the experiments with three subjects, it was seen that the system achieved an accuracy rate of 73.3% in the relevant classification. A high accuracy rate could not be obtained in the classification of index finger movements due to the nonlinearity of the human musculature, EMG measurements being made from the forearm, and the inability to differentiate the muscle groups responsible for the index and middle finger movements by the current system. In the next study, measurements can be taken from points close to the hand by increasing the number of EMG channels in order to increase the accuracy of movement classification of the index finger. The classifier results have a big potential to be transferred to an exoskeleton mechanism and used for therapeutic purposes at the clinical site.

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