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A novel approach of FMG sensors distribution leading to subject independent approach for effective and efficient detection of forearm dynamic movements

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ABSTRACT

In force myography (FMG) limb movement is detected by measuring muscle contraction intensity in terms of forces. In this work, FMG is used to detect forearm movements i.e. flexion, extension, pronation, supination and steady-state. In FMG, sensors are conventionally located at supinator/pronator muscles to detect forearm pronation/supination movement. In this paper, a new approach to detect forearm movements i.e. pronation/supination also including flexion/extension and steady-state posture, is proposed. This is achieved by designing a sensor distribution pattern on upper arm muscles and supported by bagged tree ensemble classification algorithm a unified classification model is obtained and tested on multiple subjects. Performance of the method is evaluated using accuracy, precision, and recall. Results have shown that with the proposed method a unified model can be developed for detecting forearm movements. An average of 0.91, 0.93 and 97.3% precision, recall and accuracy, respectively, is achieved.

1. Introduction

Human intention detection, i.e. movement type or assistance level detection, is one of the key component in the development of exoskeletons [1]. They provide the information that drives the exoskeleton according to user requirements. Therefore, in order to provide correct assistance accurate movement detection methods are required.

Many methods to detect limb movement have been proposed. Of those methods EMG is used to detect the muscle activity in terms of electrical signals. This method has been used to detect upper limb [2–4] and lower limb activities [5,6] and has also been applied for the control of assistive exoskeletons and prosthesis [7]. FMG is another method to detect muscle activity by measuring lateral forces caused by muscle contraction/relaxation [8]. This method has also been applied to detect both upper and lower limb activities for controlling exoskeletons and prosthesis. While comparing both techniques, studies have shown that FMG has better performance than sEMG for gesture classification [9,10], forearm motion classification [11] and fingers force estimation [12] in terms of accuracy and stability w.r.t time.

In the recent years many FMG based methods have been proposed to detect upper limb movements. The movements include hand gestures [13–19], grasps [15,20–22], grasp force [22,23], static and dynamic forearm gestures [24], joint torque [25], upper arm movements [26,27] and carried payload [28]. Besides, FMG has also been reported for detecting lower limb movements for the purpose of step counting [29], detecting ankle positions [30], estimating knee joint angle [31], locomotion detection [32,33] and gait phase detection [34–36].

In the existing literature forearm pronation/supination is detected by placing the sensors on forearm muscles [13,14,16,26,37]. As biceps brachii also acts as secondary muscle to perform supination, which implies that sensors placed on the upper arm muscles can also be used to detect pronation/supination.

This study aims to investigated the use of upper arm muscles for the detection of forearm movements i.e. pronation/supination, flexion/extension and steady-state posture. Furthermore, in order to reduce the time and effort used in the collection of training data a generalized model is developed and evaluated to detect these movements.

This paper is organized as follows: Contributions made in this study are presented in Section 2. Section 3 describes the materials and methods to detect muscle activity, collect data and perform experiments and analysis, whereas results are presented in Section 4. Discussion is presented in Section 5 and finally, the work is concluded in Section 6.

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2. Contributions

Following are the contributions/novelty of the presented work,

- Use of upper arm muscles, i.e. biceps and triceps, for detecting forearm pronation/supination movement.
- A unified classification model that,
  - Detects forearm dynamic movements across multiple subjects.
  - Reduces the need of training data, hence improving applicability of motion detection methods in real-time applications.
- Verification of the proposed approach by testing on multiple subjects.

3. Method and materials

3.1. Muscle activity detection with FMG sensors

In FMG muscle activity is measured in terms of lateral force that is caused by muscle contraction. In this work we have used this method to detect forearm movements i.e. pronation/supination, and flexion/extension and steady-state posture. Here, steady-state is defined as holding forearm in a fixed position.

Conventionally, forearm pronation/supination is detected by placing the sensors on forearm. In this work we have proposed an alternative approach to detect pronation/supination, which is by placing the sensors on upper arm muscles, as shown in Fig. 1(a). Upper arm muscles, i.e. biceps and triceps, are prime movers for elbow flexion/extension. Biceps Brachii, however, also assists in supination of the forearm. Therefore, by specific distribution of sensors on the upper arm, all of the aforementioned forearm motions can be detected.

In this work, FMG of upper arm muscles is performed by using two similar sensor bands (Fig. 1(c)). Each is constructed by an array of eight force sensing resistor (FSR) sensors. One sensor band is placed at the center of the upper arm, SB_a, where the deformation is maximum when the arm is flexed. The second sensor band is placed near elbow joint SB_b, as shown in Fig. 2. FSR sensor is mounted on the sensor band as shown in Fig. 1(b). The inner most layer is the FSR. Afterwards, the layer beneath FSR is the "FSR base", which is comprised of both hard and soft material. It ensures the proper contact of FSR with the skin. Finally, on the outermost side it is band that is wrapped around the arm.

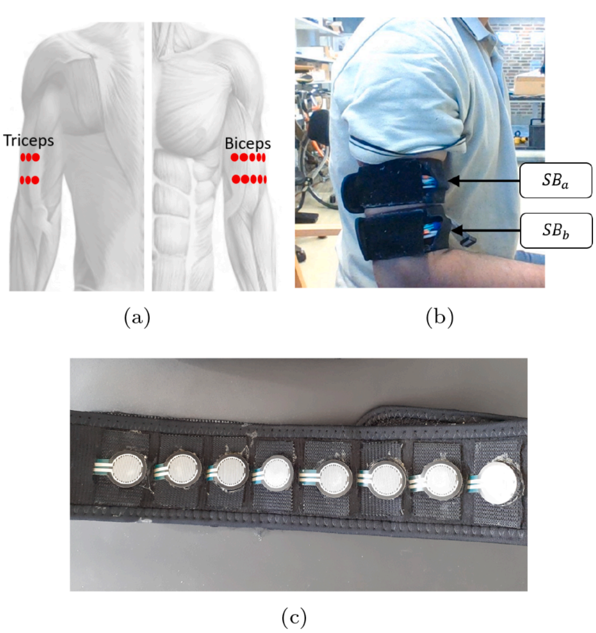


Fig. 1. (a, b) Placement of sensors on upper arm and (c) FSR sensors placed inside the band.

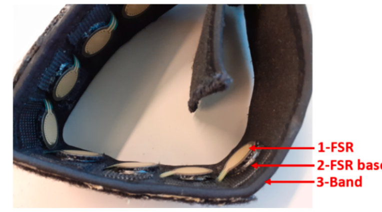


Fig. 2. Mounting of FSR sensor on the sensor band.

FSR sensors used in the sensor bands are FSR402, which are developed by Interlink electronics. They can measure the forces in the range of 0.1–10 N. To acquire force data, FSR sensor is interfaced with Arduino, where the data is fetched and transmitted to MATLAB at the rate of 80 Hz.

3.2. Data Processing

3.2.1. Data collection protocol

To collect data for each movement subjects were asked to stand with their upper arm positioned parallel to the body as shown in Fig. 1(b). Moreover, they were instructed to keep the upper arm as steady as possible while performing experiments.

Steady-State data was recorded by keeping the forearm steady in three positions, i.e. at elbow joint angle approximately 10°, 45° and 90°. To collect data for flexion/extension, subjects were asked to perform flexion and extension of forearm between fully flexed position and neutral position of forearm. This movements sequence was performed repeatedly 16 times. The speed was kept normal as per subject's perspective. The data for pronation/supination was obtained by performing them in a continuum between fully pronated and supinated position, repeatedly for 16 times. These movements were performed at four different elbow joint angles, starting at neutral elbow position and at approximately 30°, 60° and 90°. At each of the aforementioned elbow joint angle pronation/supination was performed four times, hence making it 16 in total. All of the aforementioned movements are illustrated in Fig. 3.

3.2.2. Features extraction

RMS and slopes features obtained from raw data are shown in Fig. 4. In each figure, data samples 0–166 are of steady-state, from 167 to 332 are of flexion and from 333–498, 499–664 and 665–830 are of extension, pronation and supination, respectively. Data shown for steady-state is from two different elbow joint angles. Whereas, for all the other movements several repetitions are shown together.

Observing the data visually, it can be seen that signal amplitudes and patterns for RMS are quiet similar between the movements, whereas, very distinctive patterns can be observed for slope feature. Furthermore, signal amplitude is different from subject to subject, however, muscle contraction/relaxation behaviour is same e.g. to perform forearm flexion biceps will always contract resulting in positive slope for data read by FSR sensor and same is the case for other movements. Hence slope can provide more meaningful information to perform classification and develop a unified movement detection algorithm. Therefore, slope is used as input feature for the classifier training. Mathematically, slope is computed using the following equation,

$$\kappa = \frac{R^i - R^{i-1}}{t_{ws}} \tag{1}$$

here κ represents the slope feature, R^i represents the newest sample of RMS data and t_{ws} is the window time to extract features.

3.3. Experiments

Ten subjects participated in this experiment. Each of them was

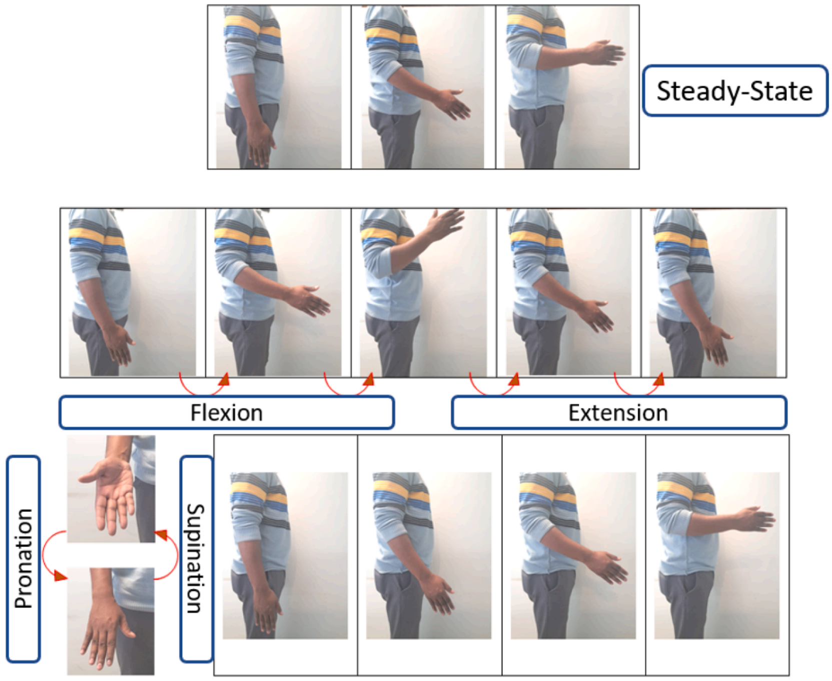


Fig. 3. Movements performed for data collection.

healthy and belonged to age group of 25 to 40 years. Ethical approval to conduct these experiments was obtained from ethical committee, Region Nordjylland, Denmark. Prior the experiments, subjects were instructed about the tasks and were asked to sign consent forms.

Three experiments are performed in this study. **(a) Experiment A:** In first experiment, data recorded from ten subjects was divided into two subsets. Data from first five subjects was used as training dataset and data from other five subjects was placed under testing dataset. 25 ms window was used for feature extraction and ensemble learning algorithm bagged trees was used to perform classification. **(b) Experiment B:** In second experiment, effect of window size for features extraction is studied. To perform this experiment classification technique, and training and testing dataset used are same as that of **Experiment A**. However, window size is varied from 25ms to 125ms with the step of 25ms. **(c) Experiment C:** In third and last experiment, testing dataset, window size for features extraction and classification technique used is same as that of **Experiment A**. The motion detection performance is investigated by varying the size of training data.

3.4. Analysis

The performances of above mentioned experiments are analyzed by computing precision, recall and accuracy. Correctly detected samples from total number of samples detected as a movement gives precision. Whereas, in recall it is calculated that from the number of times a task was performed, how many times the classifier was able to detect it correctly. Finally, accuracy is the measure of correct samples from total number of samples collected. Mathematically these parameters are calculated as

$$P_{\text{pre}} = \frac{N_{\text{TP}}}{N_{\text{TP}} + N_{\text{FP}}} \tag{2}$$

$$P_{\text{rec}} = \frac{N_{\text{TP}}}{N_{\text{TP}} + N_{\text{FN}}} \tag{3}$$

$$P_{\text{acc}} = \frac{N_{\text{TP}} + N_{\text{TN}}}{N_{\text{TP}} + N_{\text{TN}} + N_{\text{FP}} + N_{\text{FN}}} \tag{4}$$

here TP, TN, FP and FN are true positive, true negative, false positive and false negative samples, whereas N_{TP}, N_{TN}, N_{FP} and N_{FN} represents the number of samples that are true positive, true negative, false positive and false negative respectively. P_{pre}, P_{rec} and P_{acc} represents precision, recall and accuracy respectively. Precision and recall are defined in the range of 0–1, whereas, accuracy is expressed in percentage.

4. Results

4.1. Experiment A

The results of the experiment are shown in Tables 1, 2, and Figs. 5, 6.

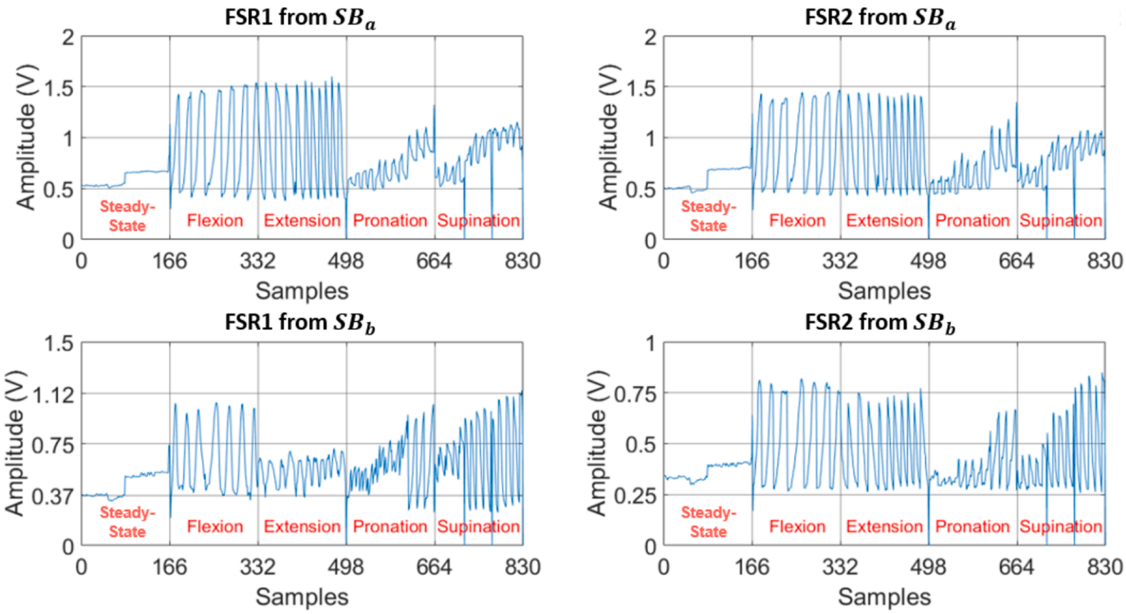
4.1.1. Results w.r.t subjects

Results shown in Table 1 and Fig. 5 presents movement detection performance w.r.t each subject. From these results it can be seen that precision is lowest i.e. 0.86, for subject 2 and highest i.e. 0.94 for subject 5. Similarly, recall is achieved lowest for subject 2 and highest for subject 5 i.e. 0.89 and 0.96 respectively. However, best results for accuracy are seen for subject 4 and lowest for subject 2, which are 95.35% and 98.37% respectively. In these results it can be noticed that for each subject the results of recall are better than precision. Eqs. (2) and (3) depicts that performance of recall depends upon FN samples and precision depends on FP samples. The less the FN samples are the better is the recall and similarly, the less the FP samples are the better is the precision. It implies that for each subject FN were less then FP samples. Therefore, results of recall were better than precision.

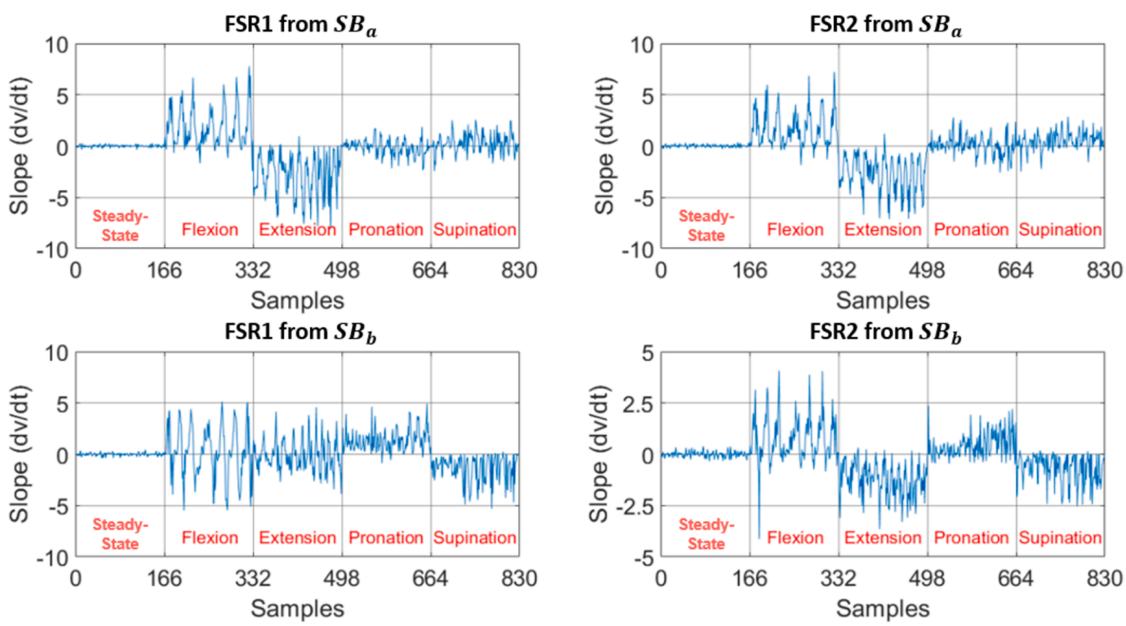
4.1.2. Results w.r.t motion type

In previous section the results showed that FP samples were higher then FN samples. This means that relatively larger number of samples detected as a movement were miss-classifications. In this section the results are analyzed from the perspective of each motion type, in order to investigate which movements were miss-classified and reasons for it by studying the confusion matrix shown in Table 2.

Steady-State: The results from confusion matrix exhibits that none of the steady-state data sample was miss-classified as any other motion type. In other words there were no FN samples detected for steady-state dataset. Hence, the recall of steady-state was 1, which can also be seen in



(a)



(b)

Fig. 4. Example dataset of sensor data for forearm motions, (a) RMS and (b) slope.

Table 1
Average results for each subject from the testing dataset.

Subjects	1	2	3	4	5
Precision	0.90	0.86	0.94	0.92	0.94
Recall	0.92	0.89	0.95	0.95	0.96
Accuracy %	96.59	95.35	98.08	98.37	98.22

Fig. 6(b). However, data samples from other motion types i.e. flexion, extension, pronation and supination were miss-classified as steady-state. These samples are termed FP, affecting the precision of predicting steady-state, which can be visualized in Fig. 6(a). Among all the motion types, flexion contributed the most and supination contributed the least number of FP samples for steady-state.

Flexion: Confusion matrix show that from total of 3323 flexion samples approx. 7% were miss-classified as other movements. Therefore, recall of flexion was 0.93. On the other hand, from total number samples that were predicted as flexion approx. 4% were FP, hence precision is 0.96. Of all the FP samples majority of them were of pronation.

Extension: Approx. 9% of the samples were miss-classified as FN, resulting in recall of 0.91 for extension. Whereas, samples that were predicted as extension 5% were FP, resulting in 0.95 precision. In contrast to flexion, majority of the FP extension samples actually were of supination.

Pronation: The lowest performance in terms of precision is seen while detecting pronation. 16% of the samples predicted as pronation were FP, therefore precision of predicting pronation was 0.84. The

Table 2
Confusion matrix computed for all the data samples from testing dataset.

Actual \ Predicted	Steady-State	Flexion	Extension	Pronation	Supination
Steady-State	1230	0	0	0	0
Flexion	25	3089	27	39	143
Extension	19	30	2327	131	57
Pronation	17	63	25	1034	2
Supination	2	26	73	34	1160

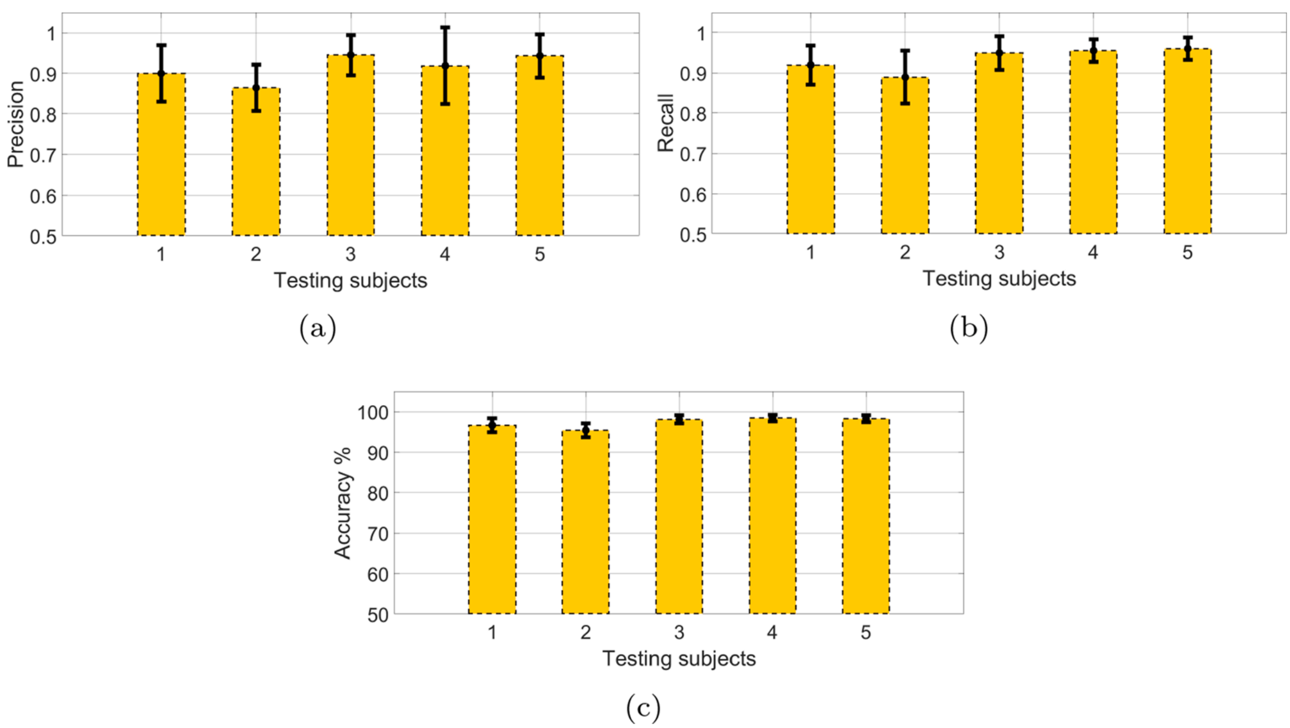


Fig. 5. Results of motion detection w.r.t each subject, (a) Precision, (b) Recall and (c) Accuracy.

performance was mostly affected by extension samples, a total of 64% FP samples were actually of extension. 9% of pronation samples were predicted as FN, which resulted in recall of 0.91.

Supination: Precision of predicting supination was slightly better than pronation. 15% of the total samples predicted as supination were FP. In contrast to pronation, mostly FP samples, i.e. 71%, were of flexion. On the other hand, recall for supination was slightly lower in comparison to pronation, 10% of supination samples were FN.

The output of the FSR sensors placed at the center of the upper arm has different amplitudes but similar pattern for flexion/supination and extension/pronation, which can also be seen in Fig. 4. That explains why majority of the FP samples of supination are from flexion and for pronation are from extension. Overall trend shows that precision is better than recall for flexion/extension movement. Whereas, recall of predicting steady-state, pronation and supination is better. However, if results are compared in perspective of each subject, Fig. 5, recall is found to be higher than precision of predicting all movements.

4.2. *Experiment B*

The results presented in the previous experiments were performed by keeping the window size fixed for features extraction process. In this section the performance of movement classification is briefly analyzed by varying the window size. Training and testing data is kept same as explained for **Experiment A** and window size is varied from 25ms to 125ms with the step of 25ms. The results of the experiments are shown in Fig. 7.

Results show that best performance is achieved when features are extracted using window size of 25ms. As, window size is increased the performance is degraded gradually for each parameter i.e. precision, recall and accuracy.

4.3. *Experiment C*

In all of the experiments reported earlier, training dataset comprised of the data from five subjects. Here performance of the motion detection is analyzed by varying the amount of training data, while keeping the testing data same as used for the previous experiments. Five combinations of training data are tested i.e. data from one, two, three, four and finally from all five subjects. The results of this experiment are shown in Fig. 8.

A significant change in performance can be seen when the training data is increased from 1 subject to 2 subjects. All three parameters i.e. precision, recall and accuracy showed improvement. However, as more and more training data is added the change in performance is almost similar, which implies that for the given test group training data from only two subjects is sufficient for detecting movements effectively and efficiently.

5. Discussion

Exoskeletons [38,39] and prosthesis [40] are the devices to help

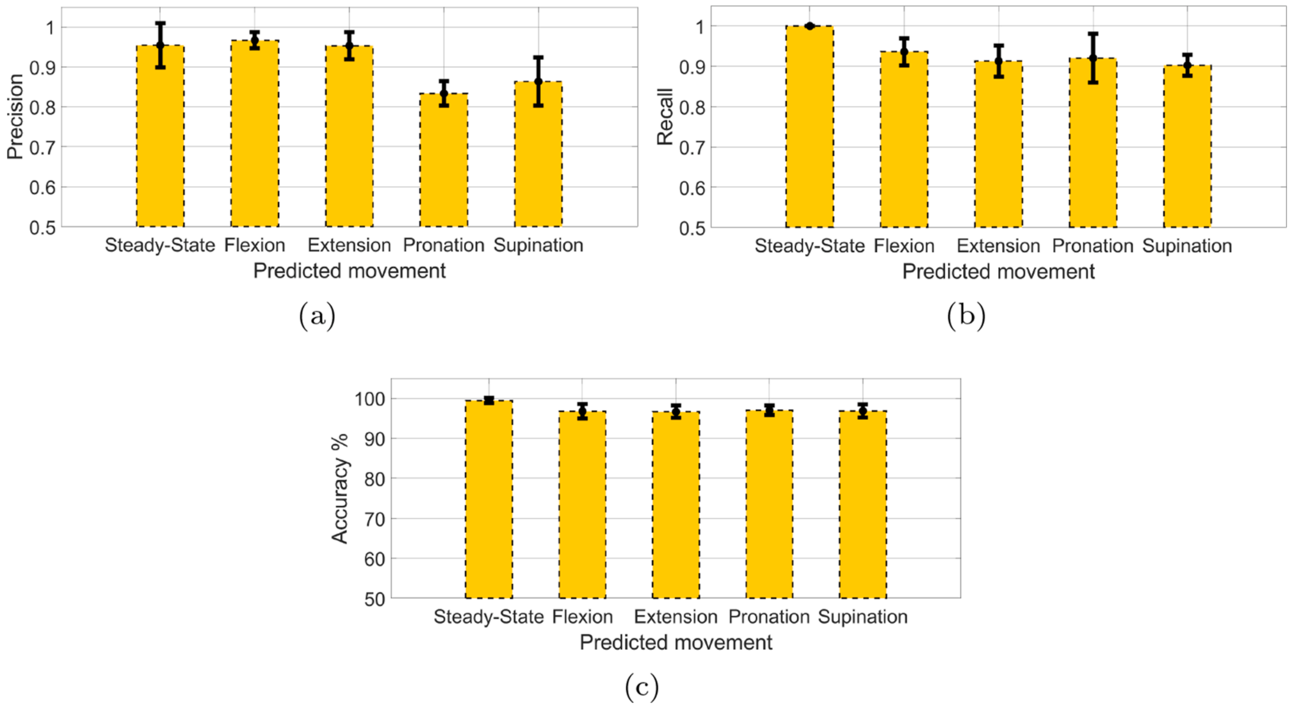


Fig. 6. Results of motion detection w.r.t each motion type, (a) Precision, (b) Recall and (c) Accuracy.

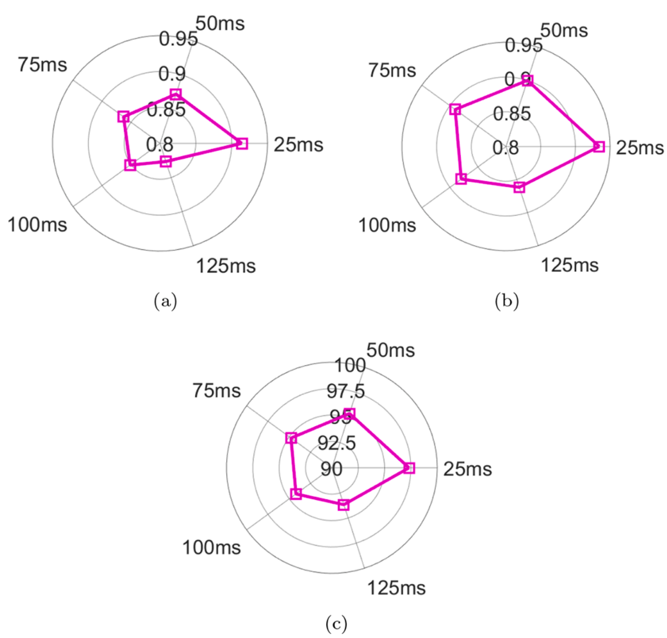


Fig. 7. Results of motion detection by varying window size for features extraction, (a) Precision, (b) Recall and (c) Accuracy.

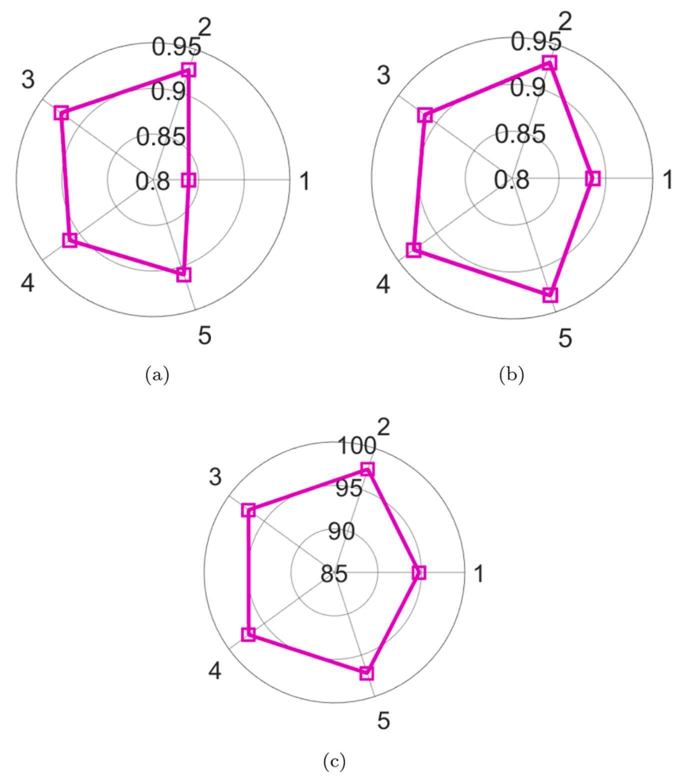


Fig. 8. Results of motion detection by varying training data, (a) Precision, (b) Recall and (c) Accuracy.

humans in gaining extra strength or restoring DOF lost due to amputation. In this paper, FMG based upper arm motion detection method is presented for exoskeleton control. It is shown that by placing FSR sensors on upper arm muscle in a specific configuration, forearm flexion, extension, pronation, supination and steady-state can be detected. Moreover, using slope feature a generalized model can be developed to detect all these motions.

Biceps brachii governs the movement of flexion and supination of forearm. Therefore, any assistive device designed to support elbow flexion/extension should be able to detect the muscle activity caused by pronation/supination, so that the assistance is provided correctly. For example, elbow exoskeleton presented in [41] is designed for power assist task during forearm flexion/extension movement. In many daily routine activities forearm pronation or supination is also performed e.g. during drinking, pouring or tightening, which can change the biceps muscle activity level and cause incorrect estimation of assistance level. The developed method can detect the bicep activity change due to pronation/supination. This information can be used in a way so that the assistive torque is primarily adjusted only for flexion/extension movement.

The method presented in this study has many more advantages. Obtaining training data for all the tasks can be challenging. By using the developed method effort and time in collecting training data can be reduced significantly. Conventionally, forearm pronation/supination is detected by placing the sensors on forearm. Forearm muscles are also prime movers of fingers, hand and wrist motions. Designing an algorithm to detect all of these motion is computationally complex. This study has shown that pronation/supination can also be detected through biceps. Hence, the complexity of forearm, hand and wrist motion detection algorithms can be reduced because of additional sensory information obtained from biceps.

In this study all the experiments were performed offline. In future studies, real-time testing will be performed to analyze online detecting performance. Moreover, the method will also be tested by integrating it with assistance control for elbow exoskeleton. Furthermore, In each of the experiment a contrasting performance is seen for flexion/extension and pronation/supination in terms of precision and recall. Beside, large number of FP samples that were observed in case of pronation and supination were hypothesized as the result of similarity in data patterns. There can be many other factors that are causing this effect, which needs further analysis and testing. The other limitation of this study is validation on diverse age group and physical condition of a user. All of the experiments were performed on young and healthy subjects. However, results of generalized model might deviate when algorithm is tested with obese or weak users. It might happen that for the given physical conditions or age group a different detection model is needed. Future experiments will also cover these aspect.

6. Conclusion

In this work FMG of upper arm muscles is studied to detect forearm movements i.e. flexion, extension, pronation and supination, and steady-state posture. Moreover, a generalized model is developed and its performance is investigated to detect all of the aforementioned movements. The objectives are achieved by placing FSR sensors on upper arm, at the center and near elbow joint.

The results show that upper arm muscle can provide very clear activity levels for classifying forearm motions. It is also shown that slope feature contributes significantly towards development of a generalized model.

Furthermore, the results obtained in this study have great significance while considering human effort and time to collect training data. The new method indicates that using slope feature a generalized model can be developed and effort in collecting right and enough amount of training data can be saved, which improves the usability in actual environment. Moreover, performance of detecting hand motions though forearm muscle can be improved by adding more sensors on upper arm near elbow joint. However, the validation of this method through real-time testing while performing routine activities is needed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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