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Research article

An early force prediction control scheme using multimodal sensing of electromyography and digit force signals

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ABSTRACT

Different grasping gestures result in the change of muscular activity of the forearm muscles. Similarly, the muscular activity changes with a change in grip force while grasping the object. This change in muscular activity, measured by a technique called Electromyography (EMG) is used in the upper limb bionic devices to select the grasping gesture. Previous research studies have shown gesture classification using pattern recognition control schemes. However, the use of EMG signals for force manipulation is less focused, especially during precision grasping.

In this study, an early predictive control scheme is designed for the efficient determination of grip force using EMG signals from forearm muscles and digit force signals. The optimal pattern recognition (PR) control schemes are investigated using three different inputs of two signals: EMG signals, digit force signals and a combination of EMG and digit force signals. The features extracted from EMG signals included Slope Sign Change, Willison Amplitude, Auto Regressive Coefficient and Waveform Length. The classifiers used to predict force levels are Random Forest, Gradient Boosting, Linear Discriminant Analysis, Support Vector Machines, k-nearest Neighbors and Decision Tree. The two-fold objectives of early prediction and high classification accuracy of grip force level were obtained using EMG signals and digit force signals as inputs and Random Forest as a classifier. The earliest prediction was possible at 1000 ms from the onset of the gripping of the object with a mean classification accuracy of 90 % for different grasping gestures.

Using this approach to study, an early prediction will result in the determination of force level before the object is lifted from the surface. This approach will also result in better biomimetic regulation of the grip force during precision grasp, especially for a population facing vision deficiency.

1. Introduction

In daily life, the grasping and lifting tasks are performed multiple times by different gestures. However, multiple decision making complexities are involved within the human body to perform these tasks. The complexities include decision making for the type of gesture required to grasp the object, the selection of the grip force and feedback information from the sensory system of the hand and the visual sensory system of the eyes [1–4]. The decoding of the different muscle and brain signals has resulted in the designing of bionic devices. Most often, the bionic devices use the electrical activity from the muscles by electromyography (EMG) signals to actuate

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the assistive devices [5]. Despite the development of different bionic devices for upper limb amputees, more than 50 % of individuals reject bionic prosthetic devices [6]. It suggests the need for improvement of prosthetic devices especially its improved feedback and corrective algorithm to avoid slip of the object [7].

The signals acquired from the muscles are used to design different control schemes using machine learning and dynamic model designing. The dynamic model design involves mathematical modeling using EMG signals as the inputs most effectively used to estimate joint torques [8,9]. The machine learning control schemes use EMG signal properties as the input to recognize a particular action type from different possibilities [10]. Most recent studies focused on using machine learning-based pattern recognition of different gestures from the EMG signals of the muscles [11–14]. Researchers have frequently worked on this aspect in offline and online processing systems [15,16]. However, the prediction of the grip force required during grasping of the object is relatively less focused so far. The grip force and lift force estimation during grasping and lifting the object helps in taking corrective measures required during grasping [17,18]. It becomes more important when the object is fragile due to its shape, size and texture [19]. Any error in the force prediction may result in the slippage of the object or breakage of the object. The neurophysiological studies have shown the complexities and changes in the somatosensory system, related to the skin [4,7,20,21]. These studies have shown that a human hand possesses a strong feedback system to manipulate the force while grasping an object [20]. However, the EMG signal characteristics are dependent on the information acquired by motor units and their firing behaviour, resulting in a complex nature of muscles for activities of daily living [22]. The phenomenon of the grip force is more complex than the gesture type prediction phenomenon due to its wide of variation for different gestures. For instance, the grip force range is smaller during precision grasp as compared to the grip force range in the power grasp. Previous studies on the gesture type have shown that gesture types may range from 6 to 44 gestures [19,23,24]. Thus, the grip force range will also vary for each gesture, making grip force estimation a more complex phenomenon than realized.

The prediction of the grip force using pattern recognition algorithms has received lesser attention as compared to gesture type prediction [12,25,26]. The algorithm employed frequently for the grip force estimation is the proportional algorithm, where the grip force proportionally changes with the change in EMG activity [27]. Off late, researchers have employed different regression models for

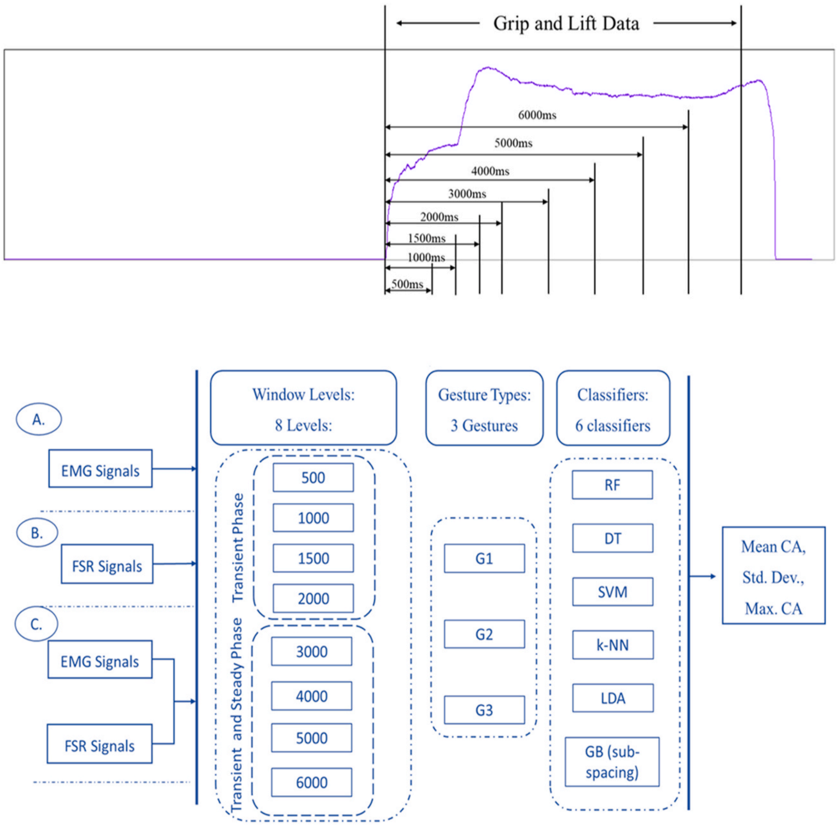

Fig. 1. Summarized Procedure of the Analysis Performed using sEMG and digit force signals acquired during pick and place activity. (a). The grip and lift section of the data was divided into small windows, broadly classed as transient and transient-steady phases. The signals acquired during experimentation were processed for different window durations for force level classification. (b). The parameters included were window durations, gesture type and classifier used. The three types of gestures for grasping the object were used during experimentation. Different window durations were used for each gesture, and each window duration was classified using different classifiers. The outcomes were obtained in terms of mean classification accuracy, standard deviation and maximum classification accuracy.

the discrete force estimation [28,29]. The outcomes have shown motivating results with an absolute error of 2.04 % and a coefficient of determination of 95 % [30,31]. Certain grip force classifications have shown that the grip force prediction can be achieved with an accuracy of more than 90 % [1,32]. An advantage of applying classification of force levels can be the ease in computation as compared to the regression algorithms, especially when applied for different gestures of grasping.

The pick and place activity is a compilation of several smaller activities, also called the phases. Among these phases, is the phase of gripping and lifting [33]. This phase can be further divided into two broader classes, named as the transient phase and the steady phase [31]. The transient state is when the grip force continuously varies during gripping and lifting. In contrast, the steady phase is the phase when the object is lifted and maintained at a height, resulting in the constancy of the grip force.

Based on these parameters, an exploratory study is performed where an EMG driven pattern recognition control scheme is designed for the early prediction of the grip force while grasping the object. The whole gripping region, consisting of the grip and lift of the object is divided into small windows classed into two types of window durations: transient phase and transient-steady phase on the basis of force distribution pattern as shown in Fig. 1(a). Using these two phases, the classification of force level required for lifting is performed using different classifiers, for 3 types of precision gestures usually preferred for picking and placing an object, such as glass. The classification procedure followed is described in Fig. 1(b).

The assistive devices are controlled by muscular activation using EMG activity and tactile sensation, by measuring grip force. The summarized procedure followed in this study is shown in Fig. 2. This study shows the idea of early prediction of the grip force classification level when objects with different weights are grasped.

This study is structured as follows: Section 2 details the experimental setup and experimentation procedure is explained. Section 3 and Section 4 includes the analysis and results respectively. Lastly, a detailed and comprehensive discussion based on the outcomes is made in Section 5.

2. Methodology of the experiment

The methodology of the experiment details the experiment setup and parameters designed for the experiment. This section also includes explanation on the protocols followed by the participants to perform experiment in the study.

2.1. Experiment setup

The EMG signals were acquired from the data acquisition system of Biometric Ltd. At a sampling rate of 1024 Hz. Four differential bipolar electrodes were positioned on forearm muscles and a ground electrode was placed on the mastoid bone. The forearm muscles selected in this study were Flexor Carpi Ulnaris (FCU), Flexor Carpi Radialis (FCR), Extensor Carpi Radialis (ECR) and Extensor Carpi Ulnaris (ECU). These muscles were most frequently selected muscles [1,34,35]. The real time transfer of acquired EMG signals to the computing system was done using the NI-USB-6211 DAQ card.

The fingertip force signals were acquired from the glove based digit force acquisition system as shown in Fig. 3. The sensors used for the acquisition of digit force signals were force sensitive resistors (FSRs) positioned on the fingertip of each finger. The FSRs were pasted on the fingertip region of the glove for each finger. A topping of the rough rubber surface was placed on the sensing region of each FSR. The force signals from the FSRs were acquired using the NI-myRIO system which was synchronized with EMG Data Acquisition (DAQ) system.

The computing system for force DAQ was considered the main/master computing system (HP-BS 180tx, i5, 8th Gen), connected to NI MyRIO, as shown in Fig. 3. For data recording, this computing system starts recording of the force signals and sends a command to

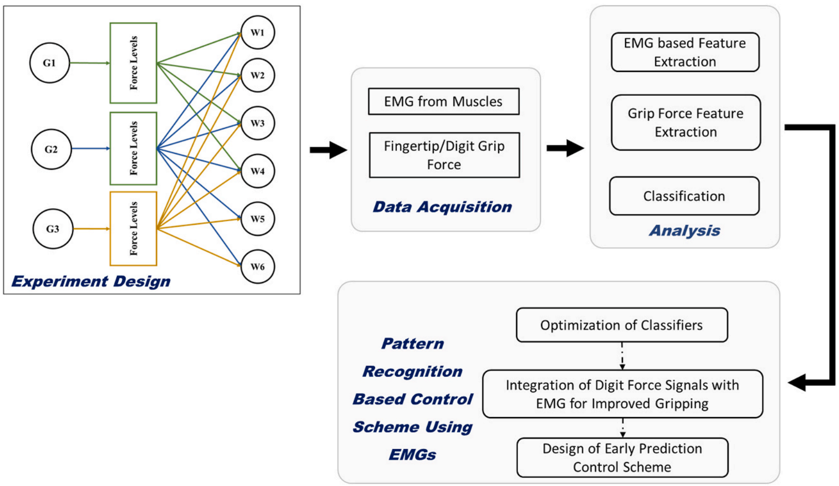

Fig. 2. Sequence of Steps followed in this Study.

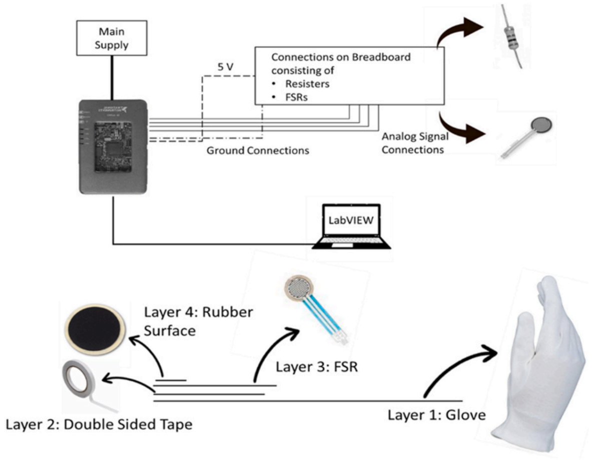

Fig. 3. Designing of Force Sensing Glove and its Interfacing with computing system.

the computing system acquiring EMG signals. The interfacing was performed by an Arduino Uno microcontroller. Similarly, a command was sent to the computing system, designed as an interface to assist the subjects using LabVIEW. This command was responsible for the initiation of the time log visible on the screen during experiment. The screen consisted of information on the gesture type to be performed, the weight level in the object and the time log. The time log described the start of the experiment, the time at which the gesture action is performed, the time duration of grasping, lifting and placing and the end of the experiment.

2.2. Design of experiment

The precision grasp type and weight of the object to be grasped were considered the two parameters for the experiment. Three different precision grasp types were considered for the study [19]. These are Palmer Pinch grasp (G1); Prismatic two Finger grasp (G2); and Prismatic three Finger grasp (G3). These grasp types were preferred more to grasp objects resembling a glass of water. For each grasp type, objects of different weights were designated as shown Table 1. Lesser weight levels were selected for the Palmer Pinch grasp.

2.3. Participants

For the experiment, the healthy right handed male subjects were recruited. Ten subjects (Age: 20–30; Mean: 23.5 Years) with no previous neurological and musculoskeletal disorders participated in the experimentation. The recruitment of subjects was ensured through the notices within the department. Prior to the experimentation, all subjects were informed about the procedure of the experiment. A written consent, in accordance with the Department ethics committee ((241(B), Dated: 20/02/2021) under supervision of Department of Mechanical Engineering), was obtained from all the subjects. It also included permission to take pictures during experiment. Different hand dimensions of all subjects were also recorded before the start of the experiment.

2.4. Procedure

The subject was seated on a chair in front of the table as shown in Fig. 4. Four EMG bipolar electrodes were placed on the forearm muscles. The subjects were also asked to wear the glove on their right hand and place their right forearm on the in-house designed armrest. The object of wooden texture was placed beside the hand for grasping. It allowed the minimal redundant motion of the subject's hand. The subjects were offered the flexibility to move the object a little left or right for their convenience.

Table 1
Design of experiment showing different levels of Gestures and Weights.

Weight / Gesture	200 grams	300 grams	400 grams	500 grams	600 grams	700 grams
G1	✓	✓	✓	✓		
G2	✓	✓	✓	✓	✓	✓
G3	✓	✓	✓	✓	✓	✓

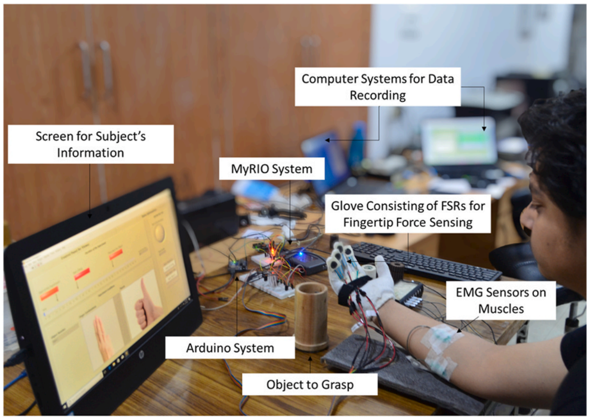

Fig. 4. Subject Performing an Experiment with the Fingertip Force Sensing Glove and EMG signals pasted on the forearm. The Image shows Two Computing Systems used for the Recording of Two Signal Types. The Third Computing System acts as the Screen to Provide Useful Information to the Subjects. The Three Computing systems are Synchronized Together using Arduino Uno.

The time span of one single trial of the experiment was 14–16 s. A time log was designed to restrict different activities performed during different time intervals. With the start of the data acquisition and recording from the computing system, the time log also started. Based on this time log, the subject was asked to perform a pick and place task, divided into different sections, as shown in Fig. 5. The different sections included getting ready for the experiment, grasping the object, lifting it, maintaining its height and placing it back. When the object was lifted to a particular height, the subject was asked to maintain the object at a height for 5 s. The task ended by placing the object at its original place and putting a hand on the table.

All the details described in the procedure were explained to the subjects, and each subject was asked to perform repeated practice trials before performing main experimental trials. All subjects performed according to the random order as per a full factorial experimental design. Each combination of the experiment parameter was repeatedly (3 times or more) performed by all the subjects.

3. Analysis of the acquired signals

The signals acquired from forearm muscles and digit force signals were processed to remove artifacts. The processed EMG signals were used for feature extraction to form a feature set. Lastly, the digit force signals were also processed to compute features.

3.1. Preprocessing of EMG signals

The raw EMG signals acquired from the 4 muscles were initially filtered. The EMG signals of each muscle were subjected to Notch filtering at 50 Hz, followed by the Butterworth filtering. The bandpass Butterworth filtering was applied in the range of 30–450 Hz. As mentioned previously, the object was grasped 5 s from the initiation of the experiment. Thus, force based analysis on two signal types

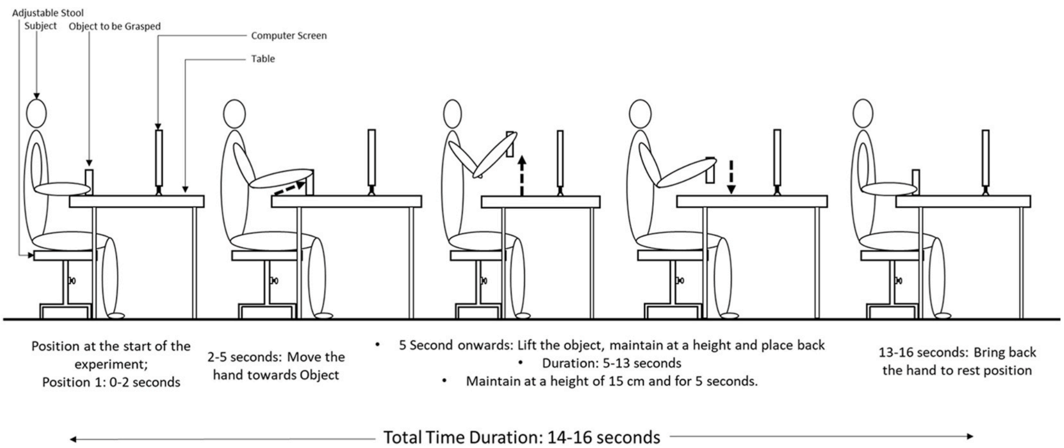

Fig. 5. Procedure of the pick and place activity followed by the subjects. In initial 0–2 s, the subject was asked to prepare himself. After 2 s, the subject was asked to grasp the object. After 5 s, 3 sets of activities were performed, including lifting objects to a height and placing back. Lastly, the hand was removed from the object.

was performed on the signals beyond 5 s. To separate the EMG activity for gesture and grip force, the EMG and force signals were visually correlated and point of separation was obtained for each trial to avoid discrepancies, as shown in Fig. 6. The increment in grip force from zero value was marked as the start point of the grip force. The timestamp concurrent to this point was selected as the marker for EMG dataset selection for grip force estimation.

3.2. Feature extraction of EMG signals

The parameters selected for feature extraction, segmentation and feature set were based on study performed by Khan et al. [32,36]. Before the features were extracted, the filtered EMG signals were subjected to overlapped segmentation. The overlapped segmentation was performed with a segment length of 150 ms and an overlap of 100 ms. The raw EMG signals acquired from the muscles were processed further to extract features. The feature extraction converts the signals into different forms by mathematical computation. In this study, time domain features found optimal in a previous in-house study [32] were extracted to form a feature set. For each segment, the features were extracted as shown in Table 2. The features extracted in this study are as follows: Willison Amplitude, Slope Sign Change, Waveform Length, Auto-Regressive Coefficient and Absolute Value of the Summation of Square root (ASS).

3.3. Preprocessing of force signals

The force signals from FSRs were subjected to multiple processing steps: pre-processing, feature extraction and feature selection. The force signals were filtered using median filtering, performed with left and right ranks as 25. The section beyond the zero value of the force signal was selected for further analysis, while the signal before it was removed. This point value showing deviation from zero was visually observed and marked as the start point for data selection for each trial performed by different subjects. Thus, the selected region included the period of the object grasping and lifting, followed by the duration for which the lift is maintained.

3.4. Feature extraction and selection of force signals

In a previous study by Agriomallos et al. [22], time and time-frequency domain features showed better classification accuracies for force signals. Thus, different time domain features were extracted while the FSRs were used for force sensations. The features used in this study are listed in Table 3. Thus, 11 features were extracted from three fingers. Since; the experiment was performed using 3 gestures, a different feature matrix was obtained for 3 gestures. For gesture G1, the features were extracted for the index finger only, while features extracted for gesture G2 involved signals from the index finger and middle finger. For gesture G3, signals from the index finger and middle finger were used.

Prior to the feature extraction, overlapped windowing was performed. The window selected for the overlapped window was 45 ms with an overlap of 30 ms. A shift of 15 ms was decided so that the data count in a signal set remains equivalent with respect to the EMG signals. The equal data points in the two data sets allowed easier comparison of the two parameters. Once the features were extracted, the selection of the optimal feature set was performed using Neighborhood Component Analysis (NCA). The NCA is a non-parametric algorithm, based on the Mahalanobis distance. NCA computes the feature weights to select the best fit subset of features [40]. The feature weighing vectors are learned by maximizing the leave-one-out classification accuracy with an optimized regulation parameter

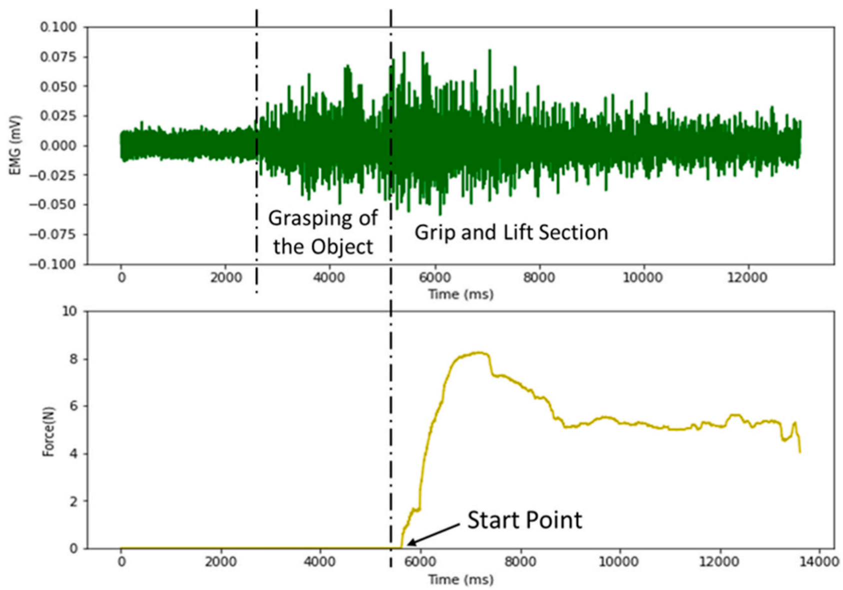

Fig. 6. Graphical interpretation of the relation between EMG and force signals.

Table 2
Different EMG features extracted and their equations.

Features	Equation
Willison Amplitude (WAMP) [37]	$\sum_{i=1}^{N-1}[f(\lvert x_i - x_{i+1}\rvert)]$ $f(x) = \begin{cases} 1 & x \geq threshold \\ 0 & otherwise \end{cases}$
Slope Sign Change (SSC) [37]	$\sum_{i=2}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$ $f(x) = \begin{cases} 1 & x \geq threshold \\ 0 & otherwise \end{cases}$
Waveform Length (WL) [23]	$\sum_{i=1}^{N-1}\lvert x_{i-1} - x_i\rvert$
Autoregressive Coefficient (AR) [38]	$\sum_{p=1}^{P} a_p x_{i-p} + w_i$ $P \rightarrow$ *order of the AR model*; a_p : *coefficients of AR model used as feature vector*
Absolute Value of the Summation of Square root (ASS) [39]	$\sum_{i=1}^{p}\left\lvert \lvert x_i\rvert^{1/2}\right\rvert$

Table 3
List of different features extracted for FSR based force level classification.

Time Domain Features
Mean, Root Mean Square (RMS), Maximum (Max), Minimum (Min), Standard Deviation (Std Dev.), Variance (Var), Skewness (Skw), Kurtosis (Kurt), Waveform Length (WL), Median, Auto-Regressive Coefficient (AR).

[41]. The optimal feature sets obtained for different fingers during feature selection, as shown in Table 4, were used for classification.

3.5. Classification procedure

To maintain the realistic motion of the assistive devices while avoiding slippage of the object, the earliest determination of force class is important. Here, the EMG recording during the grasping and lifting phase is considered as the transient phase EMG data, and the EMG recorded while the object is maintained at a particular height is called the steady phase EMG data. A continuous change in the digit force signals is observed in the transient phase, whereas the change is minimal and reduced in the later phase.

Based on the above observations, it was hypothesized that the force level classification could be performed using EMG signals or digit force signals. Another possibility is the design of the control scheme consisting of both EMG signals and force signals as input. To maintain the synchronization of the two signal types, the EMG signals from the onset of the force signals are regarded as the starting point of the transient EMG phase. The first window is designed for a window length of duration 500 ms, referred as window duration in the manuscript. The 3 following windows are designed with an increment of 500 ms. Based on the experiment designed, the transient phase was completed in 2 s in most of the trials performed by different subjects. Followed by it, different window durations of a combination of transient and steady EMG data are prepared. The designed window durations are used for force classification to inspect the degree of increment in classification when a window duration is added to the transient data. Beyond the last window of the transient EMG phase, 4 windows were designed, with a gap of 1000 ms.

For each window duration, EMG signals, digit force signals, and EMG + force signals were three separate input feature sets, used to perform force level classification. Initially, the classification of force levels is performed using different classifiers mentioned below over the entire duration of the gripping and lifting. The classifiers computing better accuracy in this set of study were further applied for different window durations.

3.5.1. Classifiers

The classifiers used in the study are Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), Decision Tree (DT), Linear Discriminant Analysis (LDA) and Gradient Boosting (GB). The optimal classifier among all the classifiers were selected for the Pattern Recognition (PR) control scheme. The parameters obtained after hyper parameter tuning of each classifier are listed in Table 5.

3.5.2. Performance metrics

The input used consisted of EMG signals from the 4 muscles. The cross-validation of the data allows a more assured outcome as the repeated classification is performed using different training and testing data on a particular set of data. The mean Classification

Table 4
Features found optimal for different fingers and gestures.

S. No.	G1	G2		G3	
	Index Finger	Index Finger	Middle Finger	Index Finger	Middle Finger
1	Max, Min, Skw, AR, Median	Max, Min, Var	Mean, RMS, Max, Min	Max, Min	RMS, Max, Min,

Accuracy of 10 subjects obtained from the k-fold cross-validation (CV) are computed, along with the standard deviation and maximum of the CV outcomes. The output was computed in three forms. These were Mean Classification Accuracy (Mean CA), Standard Deviation (Std. Dev.) and Maximum Mean Classification Accuracy (Max CA).

3.6. Statistical analysis

To determine the effect of the classifier type and gesture on classification accuracy, a two-way repeated measures analysis of variance (ANOVA) test was performed. The subjects were the random effect, and the gesture type and classifier were selected as fixed parameters. Post hoc comparisons were made using a Bonferroni correction factor to determine the significance of the classifier. The statistical analyses were performed using IBM SPSS 25, with a significance value of 0.05.

4. Results

The results obtained in this study are divided into 2 sections. In 1st section, the classification is performed using different classifier for a dataset consisting of grasp and lift. The classification is performed using 3 different sets of input; EMG signals, Force signals and EMG + Force signals. The optimal classifiers found were used in Section 2. 8 transient and transient steady windows were used for pattern recognition classification using RF, LDA, and GB (sub-spacing). The 1st and 2nd input type consisted of EMG signals and Force signals only. The 3rd input type consisted of the feature sets of EMG signals along with the force signals as the input for the force level classification.

4.1. Comparison of classifiers with different signal datasets

4.1.1. Classification of force level using EMG signals

The statistical comparison showed that there is a significant effect of the classifier (significance value of 0.027). On the contrary, no effect of the gesture type was found during statistical analysis. From Table 6, it is found that the classification accuracy was obtained highest by using RF and GB classifiers. The standard deviation for different classifiers ranged more than 10 % in most cases, depicting variable mean CA for different subjects. The standard deviation was as high as 17.71 % and 16.56 % for DT and SVM classifiers, respectively. A relatively smaller standard deviation was found while using GB and RF classifiers compared to the rest of the classifiers. Among the three gestures, the accuracies for different output weight levels were highest for G1 and G2 gestures. The accuracies obtained for G1 and G2 gestures were 89.33 ± 8.7 % and 86.25 ± 14.3 %, respectively, using the GB classifier. The classification accuracies G1 and G2 gestures using the RF classifier were 89.05 ± 9.19 % and 86.32 ± 15.43 % respectively. Statistical analysis also showed that performance of the classifiers was comparable except that the GB and RF performance was moderately better than DT and k-NN classifiers.

4.1.2. Classification of force level using FSR signals

For digit force signals, the significant effect was found for the classifier type (p value = 0.000) and gesture type (p value = 0.002). The mean classification accuracies using digit force signals were significantly less for all gestures as shown in Table 7 as compared to the mean CAs using EMG signals. The mean CAs of 51.34 %, 53.11 % and 55.11 % were obtained using an RF classifier for gestures G1, G2 and G3, respectively. Lesser CAs were obtained for different gestures using the rest of the classifiers. The classification accuracies were also computed for different subjects and different window types using 8 classifiers. Post hoc test based on Bonferroni showed that GB, k-NN and RF classifiers were comparable except that LDA and SVM computed least CAs. Among gesture types, gesture type G3 was significantly different from gesture G1 and G2 with a p-value of 0.005 and 0.009 respectively.

4.1.3. Classification of force level using EMG + FSR signals

Lastly, the sEMG and force signals were combined as inputs, and the classification accuracy for force levels was computed for different gestures. The mean classification accuracy and standard deviation were computed from 10 cross-validated results using different classifiers and gestures. From Table 8, it was evident that the classification accuracy was obtained highest when Random Forest (RF) and gradient boosting classifiers were used. The outcomes from the results suggest that the classification accuracy was obtained close to 90 % for all gestures. The statistical analysis on CAs of different subjects showed significant effect of the classifier type

Table 5
Properties of various classifiers used in the following Pattern Recognition (PR) analysis.

Classifiers	Characteristics
Random Forest (RF)	Number of Trees in the Forest = 70
Decision Tree (DT)	Max Leaf Nodes = 8, Class Weights = balanced
Support Vector Machines (SVM)	Kernel Type = Radial Basis Function, Regularization Parameter = 5
k- Nearest Neighbors (k-NN)	Number of Neighbors = 1
Linear Discriminant Analysis (LDA)	Type of Solver = Singular Value Decomposition
Gradient Boosting (GB)	Level Number of the Boosting = 70, Number of samples to be used for fitting the base learners (sub-sample level) = 0.85, Learning Rate = 0.1

Table 6
Classification Results obtained from the EMG Signals over a range of grasping and lifting for different Gestures and Classifiers.

Classifier	Gesture G1		Gesture G2		Gesture G3	
	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)
RF	89.05	9.19	86.32	15.43	84.60	13.20
DT	76.42	17.71	78.24	17.59	74.69	13.21
SVM	82.62	16.56	81.75	16.33	75.75	16.51
k-NN	83.34	10.53	77.67	18.70	71.58	20.74
LDA	81.48	14.55	82.73	14.30	79.72	11.78
GB	89.33	8.73	86.25	14.30	84.82	12.58

Table 7
Mean CA and its Standard Deviation obtained for different Gestures and Classifiers obtained for Dataset consisting grasping and lifting duration when Digit Force Signals are used as inputs.

Classifier	Gesture G1		Gesture G2		Gesture G3	
	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)
RF	51.34	8.37	53.11	12.39	55.11	6.94
DT	39.84	10.06	52.05	12.24	43.67	8.01
SVM	44.96	10.66	40.54	10.30	48.80	10.28
k-NN	51.27	6.86	44.39	9.02	54.89	5.77
LDA	32.54	6.02	38.70	10.95	39.27	11.77
GB	49.92	9.49	52.58	12.25	53.88	7.38

only. The LDA classifier was comparable to all the classifiers whereas GB and RF classifiers were comparable to each other apart from LDA.

4.2. Early prediction using optimal classifiers

The classification accuracy using EMG + Force signals, along with statistical analysis shows that the RF and GB are better classifiers than the rest. Thus, early prediction of the grip force was computed with RF and GB classifier. Fig. 7 lists the classification accuracy of different force levels for a designated transient period. While using RF as a classifier and EMG signals as input, the classification outcomes shows highest accuracy in gesture G1 for all periods, as shown in Fig. 7(a). Numerically, the classification accuracy of the force was found highest in a dataset of time-period of 5000 ms and 6000 ms for all gestures. However, statistical analysis showed no significant change in CA with increase in window duration. Compared to the transient phase, the classification accuracy was obtained more than 80 % after a window duration of 500 ms. In the transient phase, the highest accuracy was obtained for the window size of 2000 ms. When GB was used as the classifier, the accuracy was obtained beyond 80 % from the 2nd level of the transient phase for all gestures, as shown in Fig. 7(b). The accuracy obtained at a window duration of 5000 ms was 89.09 %, 86.58 % and 84.40 % for gestures G1, G2 and G3, respectively. In the transient phase, the accuracy was best obtained at a window durations of 2000 ms for gestures G1 and G2 and 1500 ms for gesture G3.

In Fig. 7(c), the mean classification accuracy using force signals shows that the highest mean classification accuracy was obtained at the transient window duration RF classifier for all the gestures. Among different window types, the highest classification accuracy was obtained in the case of window size of 500 ms from the onset of the force application. The highest classification accuracy was 75 % for a window size of 1000 ms and gesture G3. Fig. 7(d) shows the classification accuracies for the different gesture and window types while using GB as the classifier. Statistical analysis showed that the mean CAs changed significantly with change in window duration for digit force signals.

While using RF as a classifier, the higher accuracy was obtained when the transient phase was used as input, as shown in Fig. 7(e). The classification accuracy for all gestures was obtained highest at a window duration of 2000 ms. The accuracy for all gestures was

Table 8
Mean CA and its Standard Deviation obtained for different Gestures and Classifiers obtained for Dataset consisting grasping and lifting duration using EMG and Force Signals as Input.

Classifier	Gesture G1		Gesture G2		Gesture G3	
	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)
RF	91.16	7.31	88.56	12.17	87.20	10.94
DT	77.24	17.81	78.47	15.47	76.64	11.29
SVM	83.90	15.86	81.95	15.93	79.16	12.99
k-NN	84.12	10.83	78.50	17.83	73.92	18.10
LDA	84.40	12.76	83.79	13.21	83.20	10.20
GB	90.52	7.92	87.70	12.14	86.85	10.13

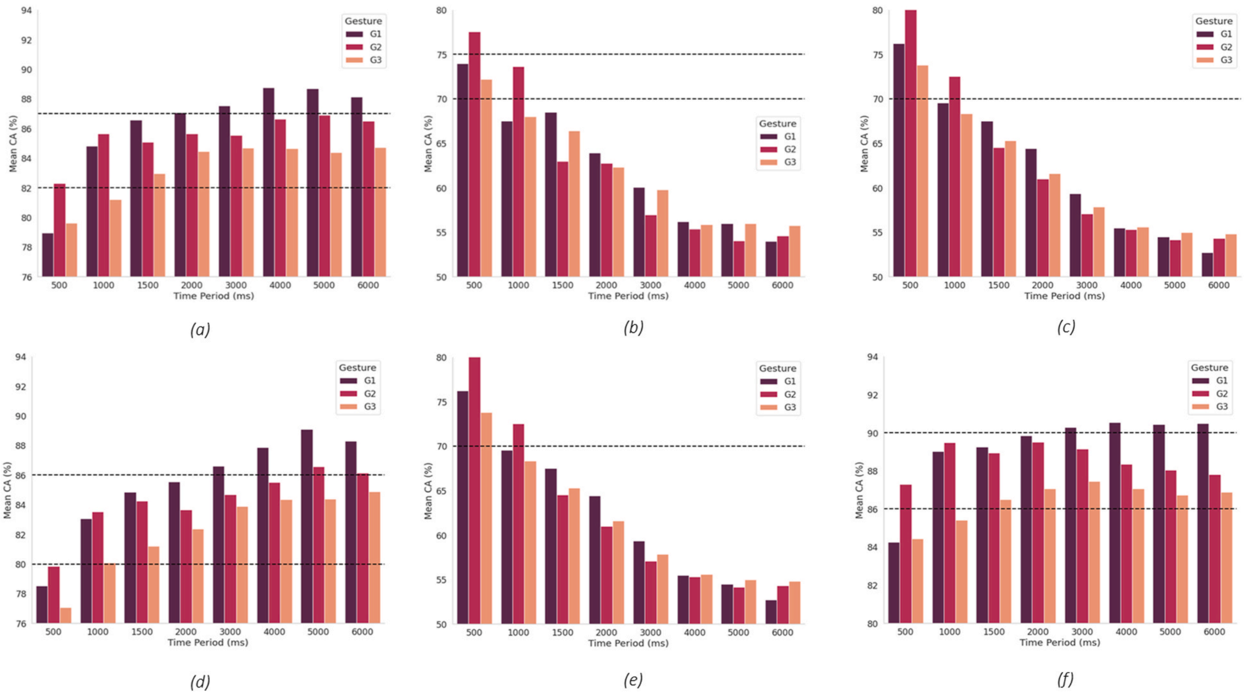

Fig. 7. Graphical Representation of the Mean CA obtained at different window durations for each gesture using (a) RF while using EMG as input, (b) GB while using EMG as input, (c) RF while using Force Signals as input, (d) GB using Force Signals, (e) RF using EMG + Force Signals, and (f) GB while using EMG + Force Signals as input.

obtained at around 90 % at this window duration. In the transient and steady phase, the classification accuracies for gestures G1, G2 and G3 were highest at a window duration of 3000 ms. With gradient boosting, the highest mean accuracy for all gestures was found in the transient and steady phase, at the window duration of 4000 ms for gesture G1 and 3000 ms for gesture G2 and G3. The mean classification accuracy with the GB classifier was found close to 90 % in the transient phase for all gestures as shown in Fig. 7(f). The highest mean classification accuracies in the transient phase were found at a window duration of 2000 ms. The mean CA ranged 87%–90 % for all gestures at this window duration. Beyond that, only small increments in the mean CA were observed. Lastly, the statistical analysis showed that no significant change in mean CAs was found with increase in window duration for all gestures.

5. Discussion

This section includes the exploration of the results obtained by discriminating 2 aspects. These are the classifier types best suited to obtain the best outcomes and the signal type and window duration to determine the earliest force class level.

5.1. *Effect of classifier type on classification accuracy*

The highest classification accuracies were obtained using Ensemble classifiers among various classification schemes. For all signal types, the mean classification accuracy was obtained highest using RF and GB classifiers. Using EMG signals over a gripping and lifting period, the highest classification accuracy of more than 80 % for 3 gestures was obtained using the Random Forest classifier. The other classifiers, such as GB and LDA, also computed classification accuracy of more than 80 %, but lesser than RF classifier. However, statistical analysis showed that the lower bound of the LDA were comparable with upper bound of LDA and k-NN classifiers. Similarly, the mean CA was obtained highest using the RF classifier when force signals were used as input for classification. When EMG + Force signals were used as inputs, the highest mean classification accuracy was obtained using RF and GB classifiers. Post-hoc analysis also showed that the CAs from RF and GB were significantly different than the rest of the classifiers. Previous studies based on comparison of classifiers for upper limb studies have also suggested that ensemble classifiers, especially RF classifier compute better accuracy as compared to rest of the classifiers [42–44].

5.2. *Effect of window duration and signal type on classification accuracy*

The comparison of signal type and window duration was performed by comparing the mean classification accuracy and its standard deviation. The change in mean classification accuracy with the change in window duration suggest different patterns for different signal types. Among different signal types, the highest classification accuracy was obtained when EMG feature set was fused with a feature set of digit force were input of the model.

When EMG signals were used as the input, the classification accuracy increased as the windows were shifted towards steady phase data set. The major increments in the mean CA were observed in the initial window durations. However, no significant change was observed in the CAs on change of window duration, irrespective of gesture. It suggests that the transient phase of the grasping consisted of sufficient differential information for the decision making of the force output. The transient phase can be considered as the dynamic period of grasping, consisting of sub activities of gripping and lifting, such as the period of touching the object, forming a grip, the intention of lift, predicted application of force to lift and varying force levels during lifting. Lesser classification accuracy increment in the transient and static phase suggests that the differentiation of the EMG activity in the static phase for different force levels were not much different from each other. It indicated an overlapping phenomenon of the EMG activity during precise grasping with smaller weight differences. The highest mean CA and its standard deviation for different subjects in transient and transient + steady window type is shown in Table 9. The accuracy was obtained highest at a window duration of 6000 ms. Not many changes were observed in the standard deviation computed.

When digit force signals were used as input for classification, a declining pattern in the mean CAs was observed with the increase in window duration. The maximum mean CA was found at the window duration of 500 ms. It indicates that the initial information in the transient phase obtained from the force signals contain differential information for different weight levels. The differential information can be based on the gripping pattern initially performed when the subject is unaware of the force required to apply for different weight levels. The statistical analysis showed that the gesture also played a significant role in mean CA. It was not observed in the case when EMG signals were used as inputs.

The mean accuracy increased when the feature set of EMG muscles and the feature set for different fingers were used as inputs for classification as compared other signal types. While using ensemble classifiers, the mean CA increased as the window durations in the transient phase were increased for all the gestures. However, very small increments in mean CA were observed beyond transient window level as shown in Table 10. Also, statistical analysis showed no significant change in mean CA with change in window durations.

The increments in mean CA with increase in the transient-steady phase were not observed, largely due to the negative effect of the force signals previously observed during FSR based classification. The reduction in accuracy between two window types seen in certain classifiers was negligible in most cases. The higher mean accuracy was observed in force-based classification in the transient phase. It plays a pivotal role in improving accuracy while using EMG and force signals as inputs. More significantly, the classification accuracies with RF and GB were obtained at around 90 % in the transient phase with a relatively smaller standard deviation. It was not possible when only EMG signals were used as inputs for classification.

Also, the maximum of accuracy for different window durations in the transient phase was found more than 95 % when RF and GB (sub-spacing) were used as classifiers as shown in Fig. 8(a) and (b) respectively. Thus, better classification accuracy can be obtained if precise and better data acquisition is performed on more subjects.

5.3. Comparison of this study with previous studies

This study shows that optimal force level classification was performed using 4 EMG sensors and force sensors for different gestures. Most of the previous studies have incorporated more number of EMG sensors or high density EMG sensors, resulting in high accuracy outcomes [27,43,44]. A previous study by Itzel et al. [30] showed that significant outcomes can be obtained at 500 ms from the onset of the gripping, using EMG signals only. However, the EMG signals were acquired from high density EMG sensors, showing better outcomes as compared to present study. However, the application of more number of EMG sensors and high density EMG sensors results in a more complicated and bulky system. Eventually, this leads to discomfort among the amputees, resulting in rejection of the assistive devices.

Another key aspect of discussion is the difference in the level of forces. Most studies preferred to class the force in 3 levels; low, medium and high [45,46]. The maximum level of forces was 5 in a study by Jitaree et al. where levels were force amplitude measured by a sensor [1]. Other studies of the force level classification incorporated a lesser number of levels as compared to the levels incorporated in this study [47–49]. The force levels designated in this study were more complex for another reason. The force level classification was performed for low level forces. It meant that the classification of the force levels was performed for very small changes in EMG signals.

The muscle count selected in the previous studies was much higher than the muscles selected in this study as shown in Table 11 [1,

Table 9
Tabulated correlation of the Window Durations and Gestures among GB, RF and LDA Classifiers when EMG Signals were used as Inputs.

Window Type	Window Duration	Gesture	GB		RF	
			Mean CA (%)	Std. Dev (%)	Mean CA (%)	Std. Dev (%)
Transient	2000	G1	85.53	9.99	87.07	10.12
Transient-Steady	6000	G1	88.3	10.37	88.14	10.89
Transient	2000	G2	83.67	12.95	85.64	13.54
Transient-Steady	6000	G2	86.13	14.66	86.49	15.1
Transient	2000	G3	82.35	11.72	84.44	11.87
Transient-Steady	6000	G3	84.89	12.8	84.71	13.72

Table 10
Highest Mean CA, Standard Deviation and Max. CA was obtained in the Transient and Transient-Steady Phase using GB and RF for different Gestures.

Window Type	Gesture	Window Duration	GB		Window Duration	RF	
			Mean CA (%)	Std. Dev. (%)		Mean CA (%)	Std. Dev. (%)
Transient-Steady	G1	4000	90.53	7.23	5000	91.41	7.01
Transient-Steady	G2	3000	89.15	7.28	3000	90.84	7.1
Transient-Steady	G3	3000	87.44	10.01	3000	88.21	10.66
Transient	G1	2000	89.85	5.22	2000	91.46	5.52
Transient	G2	2000	89.5	8.5	2000	91.54	7.19
Transient	G3	2000	87.07	8.66	2000	89.32	9.2

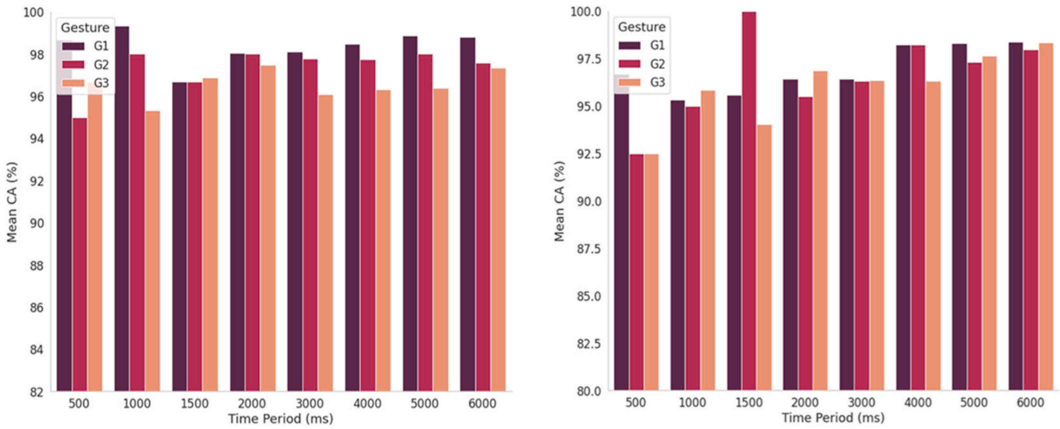

Fig. 8. Maximum Classification Accuracy obtained using (a) Random Forest and (b) Gradient Boosting.

47,50,51]. Only one study by Kamavuako et al. selected only one muscle [52]. However, an intramuscular EMG electrode was used as compared to the rest of the studies in which surface EMG signals were used in this study. Only a few studies have used a small number of EMG electrodes previously. One such instance is the study by Karasoulis et al., in which the classification of grip types was performed using EMG signals from 2 muscles [46]. The count of features obtained EMG muscle activity used in this study was relatively higher as compared to previous studies [48,53]. However, computation of a few more features using 4 muscles won't impact much on the computation power. Also, the total number of muscle-feature combinations was relatively the same or higher except the studies by Hajian et al. where a deep learning algorithm was applied for classification purposes in this study [49,54].

5.4. Implications of the early grasping

From the above discussion, it is found that the early decision making of the force level can be performed at the transient phase using surface EMG sensors. It would result in the early feedback information for grip force required for grasping the objects, eventually resulting in less chance of slipping the objects. The transient phase consists of several smaller activities combined, which can be divided into the intention and execution sections as shown in Fig. 9(a). In the intention section, the subject only intends to grip and lift the object from the surface by predicting the force required to lift the object. Thus, it consists of two sub-activities in which the touching of the object and forming of the grip are performed at first, followed by the application of the force high enough to remove the contact between the object and the table surface.

In the intention section, humans apply force much more than the required force, especially in cases of objects with a weight of less than 250 g as shown in Fig. 9(b). It results in a bump where the excess force is reduced in a few milliseconds. In the execution section, the subject manipulates the force by deciding the force nominally required at a particular height. The execution section becomes more complex due to changes in force level while the object's height is varied. It can be better understood by imagining the activities required to grasp and lift the water glass. Once the water glass is lifted from the surface, an individual continues to lift the object at a required height. It is well understood that the force required will increase with the increase in height. Thus, it is realized that the two sets of activities are simultaneously taking place during the execution section, decrease or increase in force level due to force applied in the intention section; increase in the force level due to an increase in height. The overall state of force variation mentioned above demarcates the complexities of the force applied while grasping and lifting the object. An early force level classification will result in predefined force computation. It may reduce the chance of the slip of the objects as compared to open loop bionic devices. The combination of the early determining force classifier with the force regression model can also be explored in future.

Table 11
Comparison of this study with previous studies.

S. No.	Ref. No.	Input/ output	Level of Force	Type of EMG Sensors	No of Muscles	No of Features	Features in Feature Set	Type of Algorithm	Algorithm Used
1	Jitaree et al. [1]	EMGs/ Force	5 Levels	sEMG	12	12	DASDV, MFL, and WL	Classification	SVM
2	Ali H. Al-Timemy et al. [47]	EMGs/ Force	3 levels	sEMG	12	5	4th order AR, RMS	Classification	LDA
3	Leone et al. [48]	EMGs/ Force	3 levels	sEMG	6	5	MAV, RMS, SSC, WL, VAR	Classification	LDA
4	J. Luo et al., 2019 [55]	EMG/ Force	NA	sEMG	6	1	MAV	Regression	fuzzy wavelet neural network algorithm
5	Ruyi Ma et al., 2020 [50]	EMG/ Force	4 levels		16	1	RMS	Classification	NN
6	He Mao et al., 2021 [51]	EMG-ACC/ Force	NA	sEMG	12	4	RMS, WL, SampEn and CC	Regression	GRNN
7	Gelareh Hajian et al., 2021 [49]	EMG/ Force	3 Levels	HD EMGs	3	1	Power Spectral Densities	Regression	Deep CNN
8	Y. Yamanoi et al., 2017 [53]	EMGs/ Force	3 Levels	sEMG	5	2	MAV and PS	Regression	Linear Modeling
9	This Study	EMGs/ Force	4/6 Levels	sEMG	4	9	6th order AR, WAMP, SSC, ASS	Classification	RF

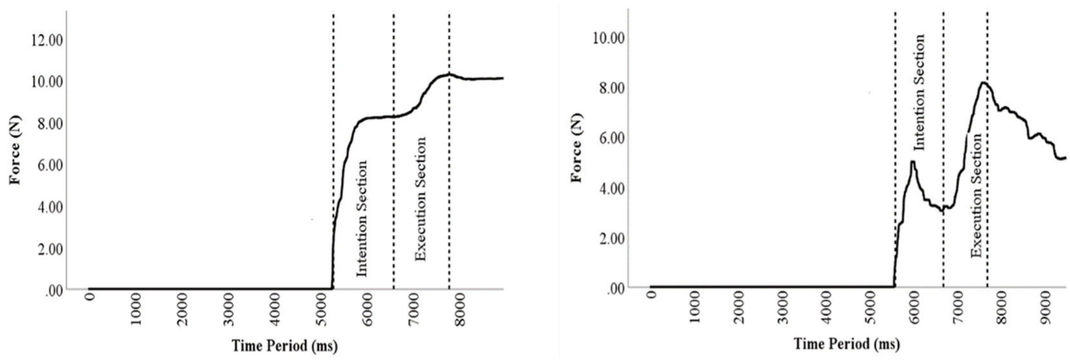

Fig. 9. Representation of the Intention Section and Execution Section found in the Transient Phase when the Index Finger and Thumb are used for Grasping (a) Gesture: G1, (b) Gesture G2 and Gesture G3.

5.5. Advantages of the proposed algorithm

When a bionic device is developed, the objective is to develop a precise, repetitive and optimal system. Based on these objectives, the key takeaways from this study are as follows:

- The designed algorithm will result in early prediction of the force level required to grasp and lift the object. The designed algorithm was designed using pattern recognition control scheme where a feature set (6th order AR, WAMP, SSC, and ASS) was used with a RF classifier.
- Most previous studies used 5 or more muscles for EMG data acquisition. In this study, four forearm muscles were selected for EMG data acquisition. Eventually, lower number of muscles will result in lesser hardware as well as lower computation power.
- Lastly, most studies used 3 levels of force levels as the output of machine learning algorithm. However, this study was performed with higher level of complexity, suggesting more complex but realistic model are possible in the future.

5.6. Limitations

The current control scheme design was an exploratory study in which the signals from the able bodied subjects were acquired and processed. However, the behaviour of the control scheme from the amputees was not acquired to implement on the control scheme design. Another key factor is that most studies preferred to apply regression based control schemes [13,49,54]. The force level classification control scheme design in this study was not compared with the regression control schemes. In this study, the regression analysis was avoided because the application of regression control schemes results in the need to have more robust hardware motor systems. Eventually, it results in high cost, contradicting the objective of this research.

6. Conclusion

In this study, a pattern recognition-based approach was designed to early predict the force level to overcome the chance of slippage. The control scheme was designed best using Random Forest Classifier when EMG signals from the forearm and digit force signals from index finger and middle finger were combined as inputs. This scheme provided highest prediction rate at the 500 ms and 1000 ms from the onset of the grasping using EMG signals and digit force signals, implying that the force level required to pick and place the object is computed before the object is lifted from the surface. However, the designed control scheme was not evaluated on the vulnerable population. In future studies, the real time control scheme will be applied on the amputees to demarcate the effective application of this control scheme.

Data availability statement

The dataset generated during and/or analysed during the current study will be made available on request.

CRediT authorship contribution statement

Salman Mohd Khan: Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Abid Ali Khan:** Writing – review & editing, Supervision. **Omar Farooq:** Writing – review & editing, Supervision.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e28716.

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