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Comparison Evaluation of Machine Learning Regression Models for EMG-Based Hand Grip Prediction across Multiple MVC Levels

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ABSTRACT

Electromyography–based force prediction provides an intuitive control strategy for assistive and rehabilitation hand systems. This study investigates an EMG-based hand grip force prediction framework using machine learning techniques by modeling the relationship between forearm muscle activation and grip force at varying contraction levels. sEMG signals were obtained from the FDS and FCR muscles of ten healthy female participants (aged 20–25 years) during controlled grip tasks performed at five MVC levels ranging from 20% to 100%. The recorded signals were filtered, processed using RMS feature extraction, and normalized to MVC prior to regression modeling. LR, GPR, SVR, and kNN models were evaluated using offline analysis. Performance was evaluated using RMSE and prediction accuracy, defined relative to the measured grip force. The results indicate that GPR demonstrates the most consistent performance, achieving the highest average accuracy (85.84%) and the lowest average RMSE (10.54). In contrast, SVR and kNN exhibit higher prediction errors, particularly at higher MVC levels.

Keywords: Had Grip Force Prediction, Comparative Evaluation, Regression Models

INTRODUCTION

The human hand plays a central role in daily activities, particularly in tasks that require grasping, holding, and using force when interacting with objects. Effective control of grip force is essential not only for functional performance, but also for safety and comfort, especially in assistive and rehabilitation applications. In such systems, improper force usage may result in object slippage or excessive compression, which can limit usability and user confidence (Vredenbregt et al., 2015; Suppiah et al., 2020). Hand grip force is primarily generated through coordinated activation of forearm muscles and can be indirectly observed using surface electromyography (sEMG). sEMG is a non-invasive technique that records the electrical activity produced during muscle contraction and has been widely adopted in biomechanics and rehabilitation engineering studies. From a physiological standpoint, EMG amplitude reflects motor unit recruitment and firing behaviour, both of which contribute to muscle force generation. This underlying relationship has motivated extensive research into EMG-based force prediction, particularly under controlled isometric conditions (McManus et al., 2021).

However, the relationship between EMG activity and force output is not straightforward. Previous studies have shown that EMG–force behaviour is often nonlinear and strongly influenced by contraction intensity, muscle fatigue, electrode placement, and individual physiological differences (Simão et al., 2019; Nguyen et al., 2025). During sustained or high-level contractions, EMG amplitude may continue to increase even when force output remains relatively constant. Such effects complicate direct force prediction and reduce the reliability of simple linear modelling approaches.

While EMG-based gesture recognition and movement classification have been widely studied, continuous and proportional force prediction has received comparatively less attention, particularly across a wide range of contraction levels (Secciani et al., 2019). Many existing studies focus on limited force ranges or single operating conditions, without explicitly analysing how prediction accuracy varies at different levels of Maximum Voluntary Contraction (MVC). This limitation is important in assistive applications, where users are required to apply varying levels of effort during daily activities.

In response to these challenges, this study examines EMG-based hand grip force prediction across multiple MVC levels ranging from 20% to 100%. Surface EMG signals recorded from the flexor digitorum superficialis (FDS) and flexor carpi radialis (FCR) muscles are processed using root mean square (RMS) feature extraction and normalised to MVC. Several regression-based machine learning models, including Linear Regression (LR), Support Vector Regression (SVR), k-Nearest Neighbour (kNN), and Gaussian Process Regression (GPR), are evaluated. Subject-wise and MVC-wise analyses are conducted to assess model robustness and consistency, with particular emphasis on their suitability for proportional force prediction in assistive and rehabilitation contexts (Sade, J., 2026). Estimating muscle force from EMG signals has long been explored in the context of assistive and rehabilitation systems, particularly in situations where direct force sensing is impractical due to hardware constraints or system complexity (Sittiruk et al., 2025). Although EMG does not provide a direct measurement of force, it reflects neuromuscular activation associated with motor unit recruitment and firing behaviour, which are closely related to force generation under controlled conditions (Li et al., 2023).

Previous studies have established that EMG amplitude generally increases with muscle activation through motor unit recruitment and firing rate modulation. However, the EMG force relationship is nonlinear and influenced by factors such as contraction intensity, fatigue, muscle physiology, and between subject variability (Li et al., 2023). As a result, simple linear models are often insufficient for force prediction across different operating conditions. To address these limitations, more recent work has shifted towards machine learning-based regression methods capable of modelling nonlinear EMG–force relationships (Singh et al., 2025; Özbek et al., 2025). Approaches such as SVR, kNN methods, and GPR have been reported to outperform simple linear models, particularly when force prediction is analysed across varying contraction levels. Among these methods, kernel-based and example-based models have shown improved robustness to signal variability, although their performance is often sensitive to data distribution and experimental conditions.

Besides, a closer examination of the literature reveals that many studies evaluate force prediction performance over relatively narrow force ranges or focus on a single contraction condition. Systematic analysis across multiple MVC levels is less commonly reported, even though contraction level has a direct impact on EMG signal characteristics and force generation behaviour. In addition, subject-wise variability is frequently underemphasised, despite its known influence on EMG-based modelling performance (Simão et al., 2019; Nguyen et al., 2025). From these observations, further investigation is required to understand how different regression models behave across a wide range of contraction intensities and between subjects. Evaluating model consistency and robustness across multiple MVC levels is particularly important for assistive and rehabilitation applications, where users are expected to apply varying levels of effort during daily activities. This study addresses this need by conducting a comparative evaluation of several regression-based machine learning models for EMG-based hand grip force prediction across MVC levels ranging from 20% to 100% (Singh et al., 2025; Bhadauria et al., 2025).

METHODOLOGY

System Overview and Research Framework

This study presents an EMG-based hand grip force prediction approach using regression-based machine learning for assistive and rehabilitation applications (Martinez et al., 2020; Kizyte et al., 2023). EMG signals are recorded from selected forearm muscles while subjects perform controlled grip tasks at fixed MVC levels. Grip force is measured simultaneously using a hand dynamometer and used as the reference output for model development and evaluation. The recorded EMG signals are pre-processed, RMS features are extracted and normalised, and the resulting feature set is used to estimate grip force using several regression models. Model outputs are then compared with the measured force to evaluate prediction error and robustness across MVC levels, as pictured in Figure 1 below (Li et al., 2023; Sittiruk et al., 2025).

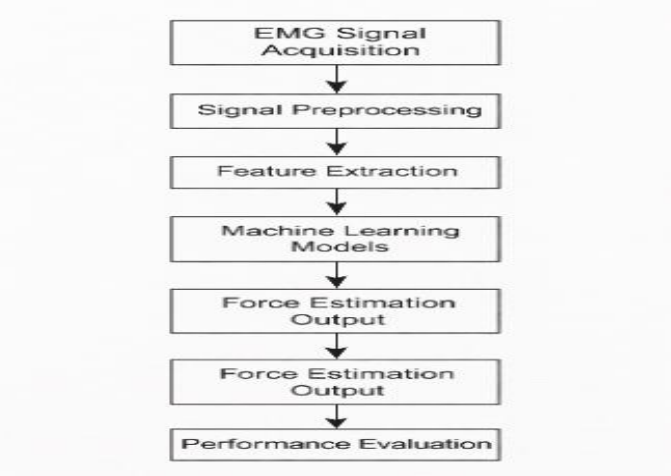

Figure 1: Overall framework of the proposed system

Experimental Setup and Subject Information

EMG signals were recorded using non-invasive Vernier EMG sensors, while grip force was measured simultaneously using a hand dynamometer. Signal acquisition was synchronized through Vernier Logger Lite software to maintain temporal alignment between EMG activity and force output. During data collection, subjects were seated with the forearm maintained in a neutral position to reduce motion-related artefacts and promote consistent muscle activation (Kizyte et al., 2023). The scope of this study only focused on ten healthy female participants aged between 20 and 25 years. None of the participants reported a history of neuromuscular disorders or having any upper-limb injury. Before the experiment, participants were informed of the experimental procedure and provided written consent. All measurements were conducted in accordance with established ethical guidelines for human subject research. The experimental configuration is illustrated in Figure 2, showing the placement of surface EMG sensors over the FDS and FCR muscles alongside the hand dynamometer used for grip force measurement. Electrode placement and subject posture were maintained consistently across trials to limit signal variability and minimize motion artefacts during acquisition.

Figure 2: Experimental setup and surface EMG electrode placement for FDS and FCR muscles during hand grip force measurement.

Muscle Selection and Electrode Placement

Two forearm muscles were selected for EMG acquisition: FDS and FCR which may not fully represent the contribution of other synergistic muscles involved in grip force. These muscles play a key role during hand grip, with the FDS contributing directly to finger flexion and grip force generation, while the FCR provides wrist stabilisation during force exertion (Nguyen et al., 2025). Surface EMG electrodes were positioned over the muscle belly following established electrode placement guidelines to minimise signal contamination and crosstalk. Anatomical muscles positioning was used to maintain consistent electrode positioning across subjects, supporting reliable and comparable EMG recordings. The electrode placement used in this study is illustrated in Figure 3.

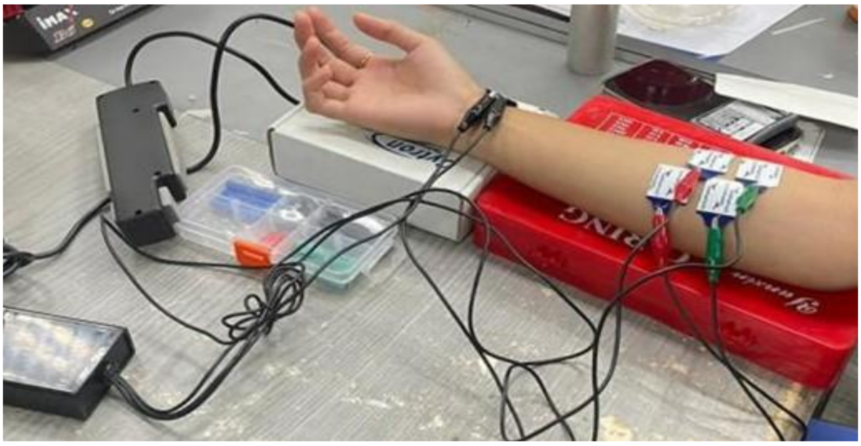

Figure 3: Surface EMG electrode placement on the forearm for FDS and FCR muscle signal acquisition

Data Acquisition Protocol and MVC Measurement

Subjects performed repeated hand grip tasks following a designed experimental procedure. Each trial involved maintaining grip force at agreed levels corresponding to different percentages of MVC, with rest periods introduced between trials to limit the influence of fatigue. For each subject, three trials were recorded to support repeatability and data reliability (Bardizbanian et al., 2020). Characteristic examples of the raw EMG signals from the FDS and FCR muscles, together with the corresponding grip force signals at different MVC levels, are presented in Figure 4, 6 and 7. MVC was recorded prior to the main experimental trials by asking subjects to perform their maximum grip force for a short duration. The highest recorded EMG amplitude was taken as the MVC reference value. This reference was subsequently used to normalise extracted EMG features, allowing meaningful comparison across subjects and contraction levels on a similar scale.

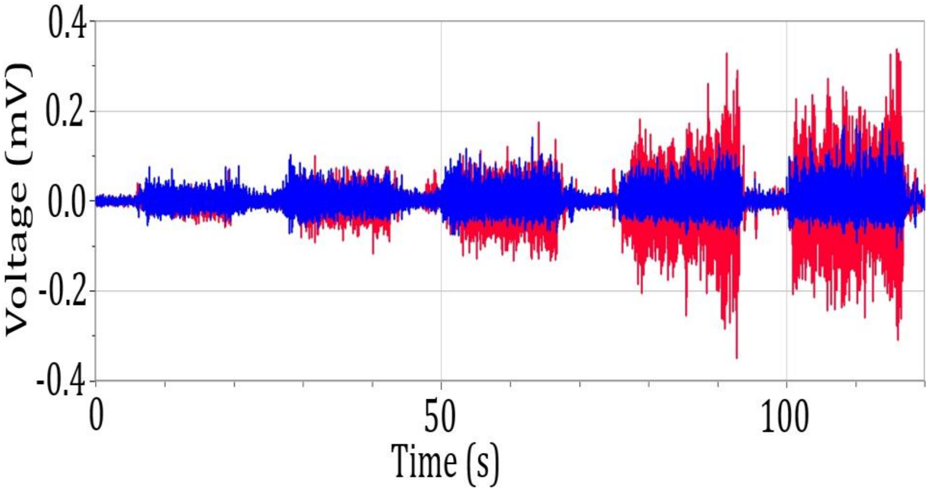

Figure 4: Raw EMG signals from the FDS (red) and FCR (blue) muscles at different MVC

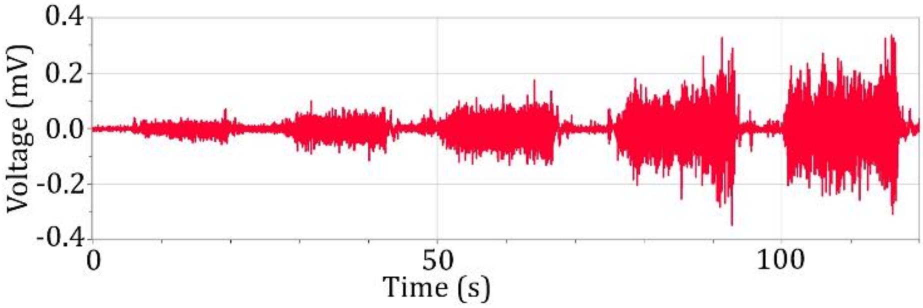

Figure 5: Raw EMG signal from FDS muscle across different

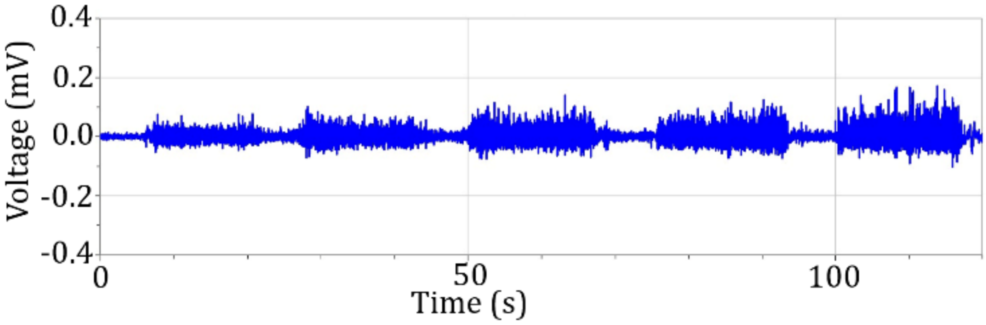

Figure 6: Raw EMG signal from the FCR muscle across different MVC levels

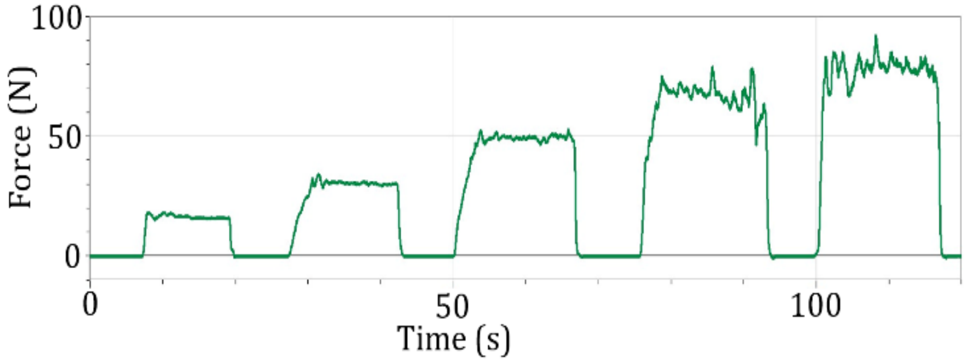

Figure 7: Corresponding grip force signal during hand grip at different MVC levels

EMG Signal Preprocessing and Feature Extraction

Prior to force prediction, the recorded EMG signals were processed to improve signal quality and reduce the influence of noise and motion artefacts (Nguyen et al., 2025). Band pass filter was applied to maintain the dominant physiological frequency components of the EMG signal while suppressing low frequency movement artefacts and high frequency noise (Li et al., 2023). Following filtering, the EMG signals were full wave rectified and smoothed to obtain the signal envelope, which provides a more stable representation of muscle activation over time. RMS features were then extracted, as they offer a reliable measurement of signal amplitude and have been shown to correlate well with muscle force during isometric contractions. To counter for inter-subject variability, the extracted features were normalised using MVC values, improving comparability across subjects and contraction levels (Bardizbanian et al., 2020).

Dataset Preparation

For each subject, three experimental trials were recorded. Two trials were used for model training, while the remaining trial was reserved for testing. This process was repeated such that each trial served as the testing dataset once. This trial rotation strategy ensures fair evaluation and reduces dependency on a single data split.

Machine Learning Based Force Prediction Methods

The EMG to force prediction framework was implemented in MATLAB and follows a structured flow consisting of signal preprocessing, feature extraction, model training, force prediction, and performance evaluation. sEMG signals from the forearm muscles were first filtered, segmented, and converted into RMS features. These features were then normalised using MVC to reduce between subject variability.

(A) Method 1: Linear Regression (LR)

Linear Regression was used as a baseline model to establish a reference for EMG-based grip force prediction. RMS-normalised features extracted from the FDS and FCR muscles were used as input variables, while the measured grip force served as the target output. For each subject, data from two experimental trials were combined for model training, and the remaining trial was reserved for testing. Model parameters were estimated using least squares fitting implemented through MATLAB’s fitlm function with default settings. The trained model was then applied to the unseen testing data to generate force estimates. While LR offers a straightforward and interpretable linear mapping between EMG activity and force, its performance is expected to degrade when nonlinear muscle activation behaviour becomes dominant, particularly at higher contraction levels (Manickaraj et al., 2025).

(B) Method 2: Support Vector Regression (SVR)

Support Vector Regression was adopted to account for nonlinear relationships between EMG features and grip force. As with the LR approach, RMS normalised EMG features from two trials were used for training, while the remaining trial was used for evaluation. SVR was implemented using MATLAB’s fitrsvr function with default parameter settings to maintain consistency across models. The solver automatically applied a nonlinear kernel to project the EMG feature space into a higher-dimensional domain, enabling the model to capture nonlinear EMG–force mappings (Zhang et al., 2025). In practice, SVR produced smoother force estimates than LR, particularly at moderate MVC levels. However, performance tended to decrease when abrupt force changes occurred at higher contraction levels.

(C) Method 3: k-Nearest Neighbour (kNN)

The k-Nearest Neighbour algorithm was implemented as a non-parametric, example based method for force prediction. Unlike LR and SVR, kNN does not rely on explicit model training. Instead, force prediction is performed by comparing testing samples directly with stored training data (Boka et al., 2024; Çelik et al., 2025). In this study, RMS normalised EMG feature vectors from two trials formed the reference dataset. For each testing sample, Euclidean distances to all reference samples were computed, and the five nearest neighbours ($k = 5$) were identified. The estimated grip force was calculated as the mean of the corresponding force values of these neighbours. The value of k was selected to balance sensitivity to local EMG patterns and prediction stability. Although kNN is capable of capturing nonlinear EMG–force relationships through local data structure, its performance remains sensitive to noise, data density, and inter-subject variability.

(D) Method 4: Gaussian Process Regression (GPR)

Gaussian Process Regression was employed as a probabilistic nonlinear modelling approach for EMG-based force prediction. RMS normalised EMG features from two trials were used for training, while the remaining trial was used for testing. GPR was implemented using MATLAB’s fitrgp function with default kernel and hyperparameter settings to avoid bias introduced by aggressive tuning. Unlike deterministic regression models, GPR defines a distribution over possible functions that map EMG features to force output. This formulation enables the model to capture nonlinear behaviour while explicitly accounting for uncertainty in the input data (Wang et al., 2023). As a result, GPR produces smooth force estimates and demonstrates strong robustness to signal variability and measurement noise, which is particularly relevant in EMG-based applications where physiological variability is unavoidable.

System Workflow and Implementation

The system workflow follows a structured sequence from EMG signal acquisition to force prediction and performance evaluation. EMG preprocessing, feature extraction, dataset preparation, model training, force prediction, and evaluation were conducted sequentially to ensure consistency and repeatability. All signal processing, model training, and performance evaluation were implemented using MATLAB. Additional software tools were used only for visualization purposes and did not involve real-time system implementation. The overall workflow of the proposed EMG-based hand grip force prediction system is summarized in Figure 8.

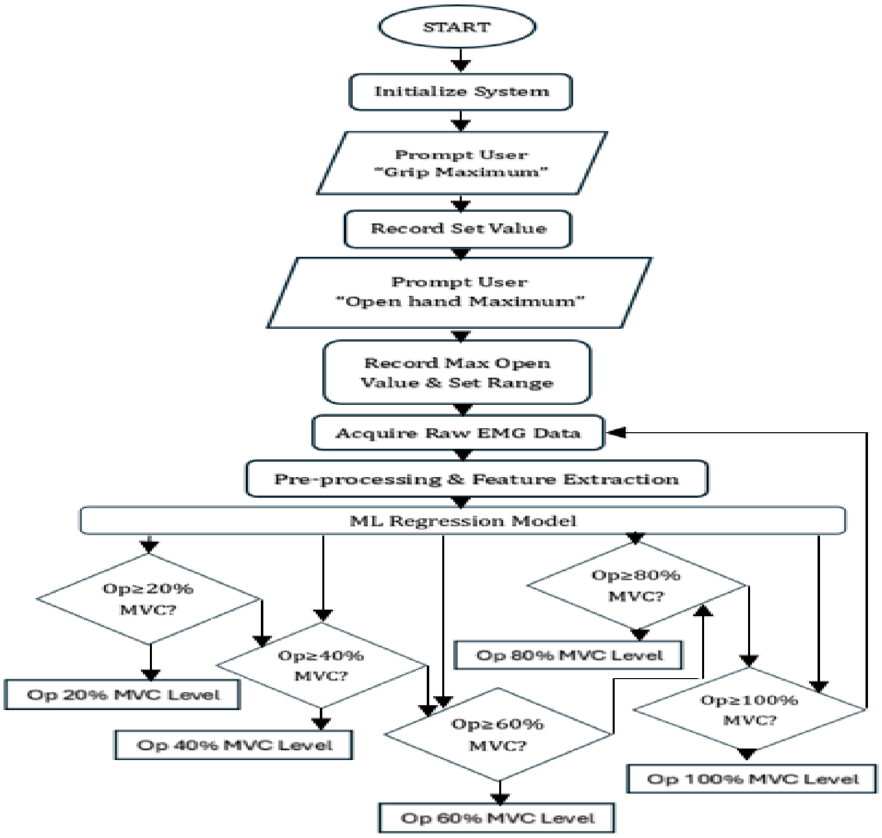

Figure 8: Flowchart of the EMG-based hand grip force prediction process

Performance Evaluation and Validation

Model performance was evaluated using quantitative metrics, including RMSE, prediction accuracy, and percentage error. to characterise prediction error and consistency across MVC levels and subjects (Li et al., 2023; Sittiruk et al., 2025). Validation was carried out using offline analysis of recorded EMG and force data, enabling systematic comparison of model behaviour without the constraints of real-time implementation.

RESULTS

Subject-Wise Force Prediction Results

Subject-wise force prediction results are presented to provide a qualitative view of how well each regression model tracks the measured hand grip force across different contraction levels. The subject-wise plots illustrate the correspondence between estimated and measured force signals over the full range of MVC levels. Figure 9 shows representative EMG-force prediction results, where the measured grip force is compared with force estimates produced by LR, SVR, kNN, and GPR. Across subjects, the estimated force profiles generally follow the overall trend of the measured force signal. This agreement indicates that the extracted EMG features preserve relevant information related to grip force generation, allowing all evaluated models to capture the main force variation across MVC levels.

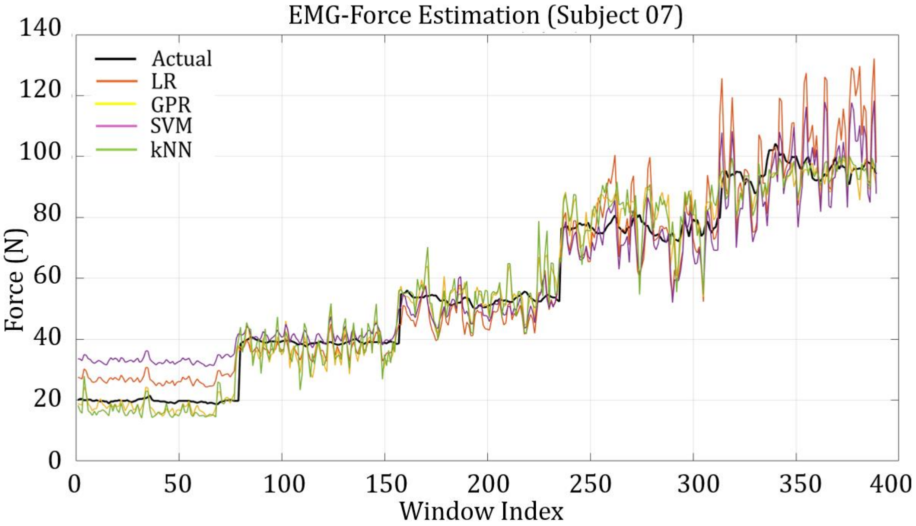

Figure 9: EMG-to-Force prediction graph

The variations of force changes with respect to the different MVC levels are shown for measured and predicted forces. At low MVC small amplitude variations can be seen due to low EMG amplitudes and possibly a higher level of noise. As MVC increases, the amplitude of the variations of the estimated force increases as well in association with the increase in the level of the EMG signal. These plots provide a first insight in each subject's model performance in terms of model smoothness, stability and accuracy. The subject-wise behaviour obtained for all subjects confirms that the proposed EMG modelling approach provides an acceptable representation of the grip force activity over the whole range of MVCs and supports the fact that the used EMG variables are applicable in this context. In addition, the observed similar trends for all subjects support that the force activity underlying the designed experimental protocol was properly reproduced and that the modelling approach enables a consistent representation of the muscle behaviour throughout the whole range of MVCs.

Subject-Wise Mean Performance Across All MVC Levels

Figure 10, 11 and 12 show the mean subject-wise performance of each of the ML algorithms in terms of normalized accuracy, normalized percentage error and RMSE for each MVC levels from 20% to 100% averaged together. This bar chart was plotted to increase the understanding towards overall performance of each of the models regardless of the specific muscle activation level (MVC).

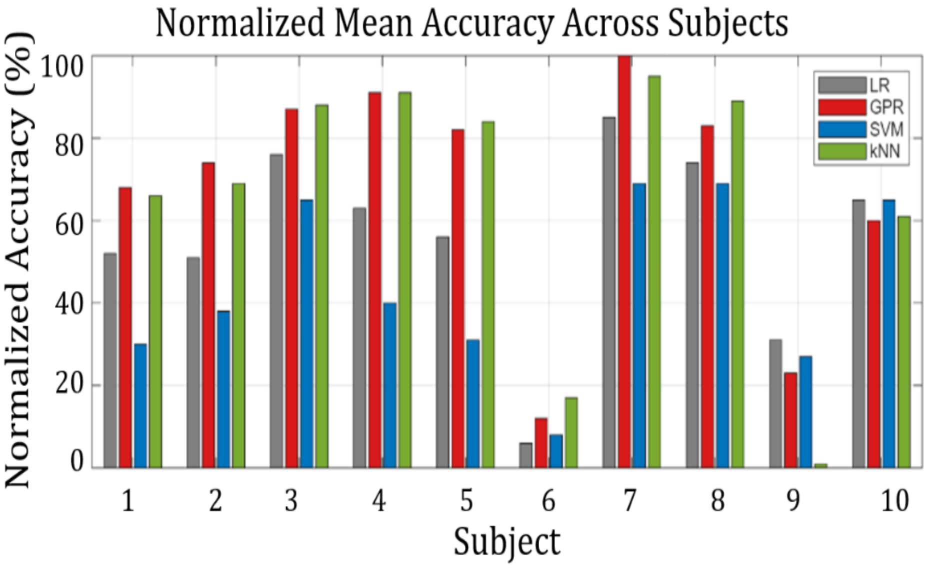

Figure 10: Normalized mean accuracy across subjects

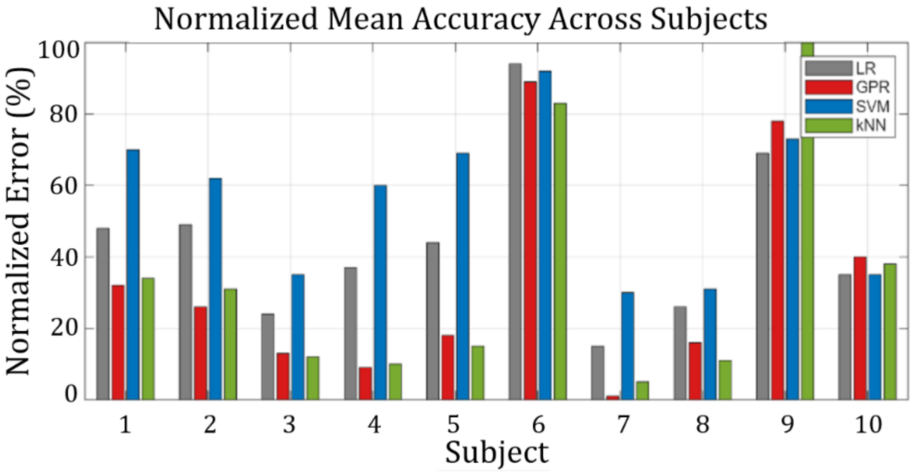

Figure 11: Normalized mean percentage error across subjects

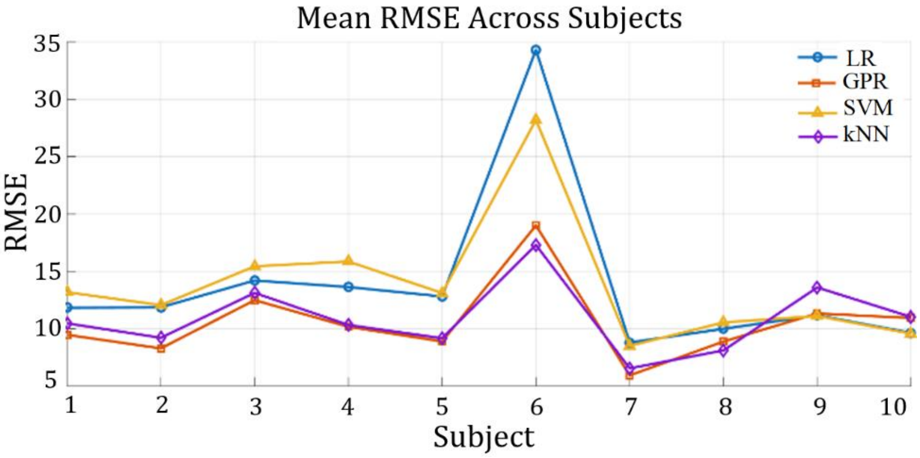

Figure 12: Mean RMSE across subjects

To compare the performance across the models, the accuracy and percentage error were normalized (subject-wise min–max normalization) and represented as bar chart plots. The RMSE is plotted in the original scale using line plots in order to analyse the magnitude of the errors and the intersubject variability. From the normalized accuracy plots, it seems that, on average over the MVCs, the GPR and kNN models generally obtain higher mean accuracy for almost all subjects, while the LR model obtains lower mean accuracy values for several subjects, suggesting that it is unable to represent the nonlinear relationship between EMG and force. The SVR model gives intermediate accuracy values for all subjects. Also from the RMSE plots, the GPR and kNN models seem to obtain generally lower mean RMSE values. Peaks are clearly visible in all the RMSE plots indicating large variability among the subjects possibly due to differences in muscle physiology, in the EMG characteristics or electrode positioning. The RMSE for the GPR model has less fluctuation among the subjects. The performance of the models for each subject over the MVCs is summarized in Table 1, providing the MVCs at which the maximum accuracy is achieved for each model as well as the MVCs corresponding to the minimum RMSE values.

From the subject-wise mean results, it can be seen that that all the contraction levels have been predicted more accurately using non-linear regression models compared to linear regression. For the non-linear regression models, it can be seen that the mean value of GPR is constant for all the subjects, while there is a large scattering of error values for kNN in subject-wise mean values indicating its capability of modeling EMG signal for a better estimation of grip force at different MVC levels for different subjects. From all evaluated MVC levels, the prediction error of all the models changes with different MVC stages. Non-linear regression models have smaller prediction errors at higher MVC levels, while the linear regression model has smaller prediction error at the middle MVC levels. Table 1 summarises the behavior of non-linear regression models.

Table 1: Performance comparison of all machine learning models.

Model	MVC Levels (Accuracy)	MVC Levels (Lowest RMSE)	Mean Percentage Error (%)	Average RMSE
GPR	20%, 80%	20%, 80%	85.84	10.54
kNN	20%, 100%	100%	85.09	10.89
SVR	60%	60%	83.72	13.76
LR	40%	40%	83.71	13.83

DISCUSSION

EMG based hand grip force prediction was experimentally investigated and the results suggest that the force prediction depends on the level of the contractions and on the muscular activity of the subjects. The force predictions from the force signals for all subjects were following the same pattern as the measured grip force and the RMS values from the EMG signals contained information about the force production due to the relation between EMG and motor unit recruitment and the force produced by the muscle. At low contractions (20% MVC) the amplitudes of the EMG signals are small and the noise is large. Between the modelling techniques used in this study, the non-linear modelling techniques (GPR and kNN) gave the most accurate prediction while the linear model (least square method) gave the largest error. It is assumed that at low levels the non-linear parts of the EMG signal have a greater influence on the total signal and therefore that the linear model is not following the signal accurately.

At moderate to moderately strong contractions (40% to 60% MVC) the EMG–force relationship became more organised and the prediction error decreased in all models. The linear regression model performed the best at 40% MVC, while the non-linearity in the EMG-force relationship appeared to be sufficiently large for the SVR to provide a better fit than the linear model at 60% MVC for some subjects. At high contractions (80% to 100% MVC) the non-linearity in the EMG–force signal is greater and the force signal may approach saturation. In addition, muscle fatigue at the late stages of the contraction cycle may also affect the performance of the models. Under these conditions, the limitations of linear regression become more clear, with higher RMSE values observed. In contrast, there was a significant variation in performance between subjects for the other two models, the GPR model provided a smoother prediction trajectory and appeared to deal with a higher degree of non-linearity and variability in the EMG–force signal at high force levels as well as with the associated uncertainty better than the SVR.

The kNN works best at high levels of contraction and at 100% MVC because the EMG signals tend to be the farthest apart in amplitude in these cases. It is a bit more sensitive to noise at mid-level MVCs because the EMG signals tend to be more overlapped and therefore noisier in these cases. Between the nonlinear models, the performance of kNN can vary more from subject to subject. Possible sources of this variation could include differences in the muscle strength of the subjects, the shapes of their forearms, the positions in which they placed their electrodes, etc. In some cases for some subjects, RMSE peaks at higher MVCs, indicating that the models were not highly accurate for predicting force at those levels for that particular subject. However, the trend is clear and the nonlinear models generally work better at higher MVCs. Nevertheless, GPR is the most stable model over the whole range of contraction levels that have been tested here, and therefore, it is likely to be the model of choice for predicting an equally proportional and stable grip force for any given level of user effort.

CONCLUSION

The main aim of this work is to investigate the potential of regression based machine learning approaches in the context of EMG-based estimation of hand grip force for assistive and rehabilitation technologies. The surface EMG signals of FDS and FCR muscles were recorded during a set of controlled isometric grip force tasks while the subject attempted to exert the grip force at different MVC levels. The collected EMG signals were preprocessed using RMS feature extraction and MVC normalization and were then related to the corresponding actual grip force. In this work, LR, SVR, kNN and GPR models are used and the performance of the regression models is investigated for different MVC levels. The obtained results show that the performance of the regression models depends on the level of contraction of the muscles. In general, Linear models work well for the moderate levels of contractions while the non-linear models provide higher robustness in cases of high signal variability and nonlinearity. Among the non-linear models, GPR provides the most consistent performance with respect to all the subjects and MVC levels investigated in this work. The force estimated using GPR for different MVC levels of the subjects remain almost consistent.

This comparative analysis provides practical view into model selection for proportional grip force prediction across varying contraction levels used for proportional force prediction. This study is based on an offline analysis using data collected from a small homogeneous group of subjects acting on a small number of muscles. Future work will focus on development of a real-time control system, include the effects of synergy muscles chosen, additional EMG channels and the validation on a larger group of subjects are on going.

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