Performance of Force Myography and surface Electromyography in Level of Muscle Activity Classification: A Preliminary Study

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1. Introduction

Features extracted from signals recorded from a muscle, namely surface Electromyography (sEMG), hold significant hidden information. These features are commonly used for signal classification using machine learning techniques for several purposes. Recent study showed that customized Force Sensing Resistors (FSR) may precisely track muscle force myography (FMG) (Baklouti et al. 2021). Indeed, features extracted from FMG were reported to have a strong linearity relationship with those extracted from sEMG. Within this preliminary comparative study, we will evaluate different machine learning algorithms performance in muscle level of contraction classification based on the two technologies, namely the FMG and the sEMG.

2. Methods

2.1 Instrumentation and experimental protocol

The study group consisted of 10 healthy adults with a mean age of 27 ±3 years, height of 170 ± 12 cm and body mass of 70 ± 14 kg. Inclusion criteria was being intact and without any musculoskeletal disorders. For the experiment, subjects were asked to perform hand power grip at 4 different level: Weak, Moderate, Important, and Maximal effort. For the data collection, volunteers were asked to perform 10 repetitions of each level at a self-chosen comfortable pace with rest breaks in-between. sEMG and FMG linear envelopes were recorded using DELSYS TRIGNO system and a customized FSR, respectively. The FSR was customized using a mechanical couple (rigid dome and rigid back in figure 1A, a constant input voltage as, and a current to voltage converter (Baklouti et al. 2021). The devices sensor nodes were placed on the center of the belly of the Flexor Digitorum Superficialis (FDS) muscle. This muscle was reported by Johanson et al. (1998) to have the highest activity percentage during power grip.

2.2 Machine Learning Classification Model

The sEMG and FMG data collection were performed separately. Then, a normalization by maximal voluntary contraction (MVC) was performed to allow comparisons between volunteers (Fig 1A).

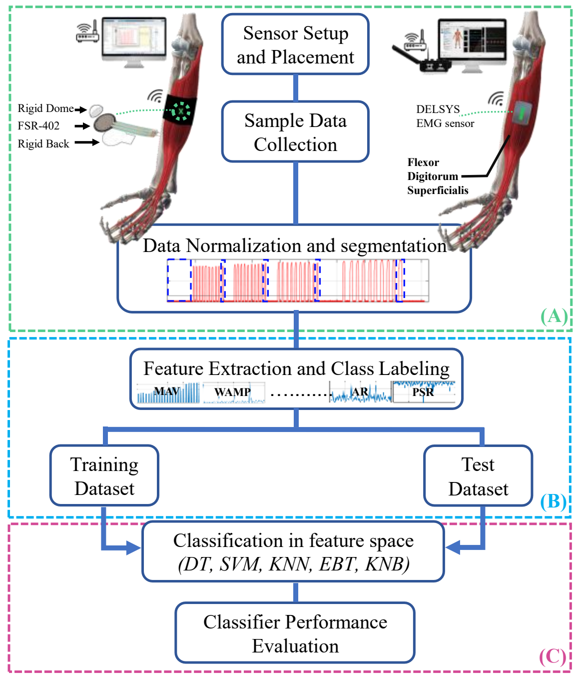

Figure 1 Experimental Process

The recorded signals are undisturbed and stable; therefore, activity regions were identified using a 15% MVC threshold (Staude and Wolf 1999). Since myoelectric signals may rapidly fluctuate between voltages, we considered window-based feature extraction. These features are listed in table 1 and were recommended by Phinyomark et al. (2012) for EMG classification.

Feature	Description	Value
MAV	Mean Absolute Value	Real
MAV_i	Modified MAV type i; i = 1,2.	Real
WL	Waveform length	Real
WAMP	Willison amplitude	Real
AR	Auto-regressive coefficients	Real
MAVS	Mean absolute value slope	Real
MNF	Mean frequency	Real
PSR	Power spectrum ratio	Real

Table 1 Feature List

As illustrated by figure 1B, features and their class labelling will serve as input for the selected ML algorithms. ML classifications algorithms considered in this study are Decision Tree (DT), Support Vector Machine (SVM), K Nearest Neighbors (KNN), Ensemble Bagged Tree (EBT), and Kernel Naïve Bayes (NB). The learned ML models are tested with leave-one-out five-fold cross validation. To evaluate the performance of classifiers, we considered accuracy, precision, and recall criteria. All computations were performed using Matlab software. The classification data were over-sampled using Synthetic Minority Over-sampling Technique (SMOTE) to have a more balanced dataset (Chawla et al. 2002).

3. Results and discussion

The accuracy, recall and precision of DT, SVM, KNN (k = 10), EBT, and KNB algorithms for sEMG and FMG are illustrated by figure 2.

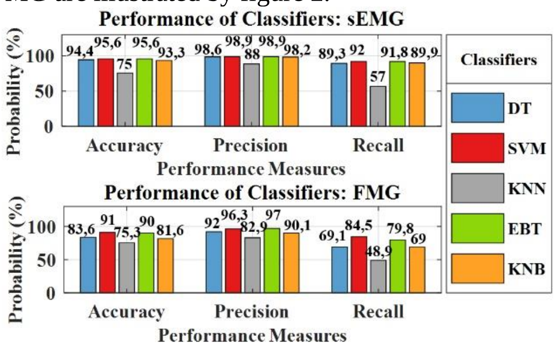

Figure 2 Performance of classifiers

SVM and EBT present the highest accuracy of 95.6%, precision of 98,9% each, and recall of 91.9% ±0.1 for sEMG. This result is in coherence with the findings of (Bian et al. 2017). An interesting result of our study is the performance of EBT and SVM to predict the level the muscle contraction from FMG. EBT (SVM) performed classification with an accuracy of 90% (91%), precision of 97% (96.3%) and recall of 79.8% (84.5%). This indicates that EBT (SVM) models return 79.8% (84.5%) correct predictions with a 97% (96.3%) precision. Conversely, KNN (k = 10) shows the lowest accuracy of 75% (75.3%), precision of 88% (82.9%), and recall of 57% (48.9%) for sEMG (FMG). This implies that KNN classified only 57% (48.9%) of the results correctly with a precision of 88% (82.9%) for sEMG (FMG). Indeed, KNN was reported by (Bukhari et al. 2020) to be an inconsistent classifier for EMG time domain features because of the signal high variability. As a result, we do not recommend KNN for level of muscle activity classification. Overall, the studied classifiers perform better when applied to sEMG than FMG by an average difference of 5.7%, 4.8%, and 15.1% for accuracy, precision, and recall, respectively. Despite that, SVM, EBT, DT, and KNB present high accuracy, precision, and recall when applied on FMG data.

4. Conclusions

This research is a preliminary study on the performance of ML classification algorithms in muscle level of contraction prediction using sEMG and FMG. FMG sensing device based on FSR-402 was prototyped and used for data collection. Experimental results have shown that SVM and EBT outperform the other classifiers. Nevertheless, DT and KNB offer high classification accuracies with both technologies. However, we do not recommend KNN because of its low recall. Even though sEMG serves as a better input for the ML classifiers, FMG offers a high accuracy that can be improved with a larger dataset. This study can be used to choose the classifier for predicting muscle level of contraction. In a future work, we aim to generate dataset at large scale and integrate the ML classification model to monitor muscle contractions during performing tasks in a work environment.

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