Enhancing User Experience Via Calibration Minimization using ML Techniques

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***Abstract*—Electromyogram (EMG) signals are used to recognize gestures that could be used for prosthetic-based and hands-free human computer interaction. Minimizing calibration times for users while preserving the accuracy, is one of the main challenges facing the practicality, user acceptance and spread of upper limb movements' detection systems. This paper studies the effect of minimized user involvement, thus user calibration time and effort, on the user-independent system accuracy. It exploits time based features extracted from EMG signals. One-versus-all kernel based Support Vector Machine (SVM) and K Nearest Neighbors (KNN) are used for classification. The experiments are conducted using a dataset having five subjects performing six distinct movements. Two experiments performed, one with complete user dependence condition and the other with the partial dependence. The results show that the involvement of at least two samples, representing around 2% of sample space, increase the performance by 62.6% in case of SVM, achieving accuracy result equal to 89.6% on average; while the involvement of at least three samples, representing around 3% of sample space, cause the increase by 50.6% in case of KNN, achieving accuracy result equal to 78.2% on average. The results confirmed the great impact on system accuracy when involving only small number of user samples in the model-building process using traditional classification methods.**

Keywords*—EMG signals; user independence; EMG user acceptance; HCI; movement classification; calibration minimization

I. Introduction

Human computer interaction is highly relying on measuring and recording the signals produced by human body. Electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG) and electromyogram (EMG) are electrical signals used in various HCI systems either separated or fused. EEG signals measures the brain electrical behavior from the surface of the scalp [1]. EMG signals are the biological signals generated as a result of the potential difference caused by skeletal muscular contractions [2]. EOG signals are used for detection of involuntarily or intended eye movements that could be used in a verity of applications [3]. ECG signals are acquired to evaluate the heart functionality and detect its related diseases [4].

Monitoring and detecting the changes in the EMG signals are beneficial to the researchers in the medical field in order to recognize neuromuscular diseases and help out in the rehabilitation process [5]. As claimed by Turgunov in [6], the muscular disabilities are spreading for various reasons causing the increase in demand for prosthetic limbs and assisting robots. They could help the parallelized patients to be able to achieve their daily activities with minor or no involvement from others using sensors that measure the EMG signals and act accordingly through gesture recognition systems [7].

Those systems are also used for moving a remote robot and encouraging the distant rehabilitation process that is intensively needed after having strokes caused by a diversity of reasons [8]. Automated EMG signals translation offers great contribution in the success of remote monitoring for ALS patient using the measured physiological signals [9] and the availability of distant therapy and achieving high improvements in muscular responsiveness and motor functionality [2], [10]. EMG based gesture recognition is also used for explaining the sign language used by deaf people helping them to be easily engaged in the society [11] . EMG signals can be used also in fatigue detection [12], [13] and emotion identification systems [14] that could be beneficial for ergonomic and entertainment applications. Gamification therapy [15] as well as virtual reality and augmented reality [10], [16], [17] could be developed and evolved by enhancing the automated understanding muscle non-spoken language.

The muscular activity recognition systems start by collecting the EMG signals from relevant human parts. EMG signals do not only carry information about the movement itself but also contain other internally interfering signals such as muscle fatigue and emotional involuntary movements as well as external conditions like sensor placement or other sources of noise. So preprocessing component takes place to clean, filters noise and unwanted signals, performs segmentation and does normalization [18]. The feature engineering and classification for biological is described in [19], [20].

Muscular movement recognition systems face various challenges that highly affect the user acceptance. They include the detection accuracy and classification performance, as well as the system generalization and robustness [21]. System accuracy and performance are influenced by the noisy nature of EMG data that is caused by body interior sources like cross talk effect in which the signals produced by the contraction of neighbor muscles interfere with the readings of the intended muscles. EMG signals are also prone to variations over time for plenty of reasons like electrode shift, emotional, involuntary movements and muscular fatigue. Motor tasks with different imposed force or unintended limb orientation changes also contribute in the non-stationarity of the generated signals [20], [22], [23]. As reported in [20], [24], the time separating training and testing negatively affects the performance of movement recognition systems for the same subject.

The user independent systems, having different participants for both training and testing purposes, impose extra burden as change of physiological features like the age, height, weight, and behavioral characteristics like exercise routine would minimize the system ability to generalize across users [22]. In [25], the high inter-subject variability necessitates long and frequent user-specific training which affects user acceptability. In [26], the authors performed a comparison between the measured muscular activities of amputees and able-bodied subjects when controlling myoelectric device in order to overcome the long and frequent user calibration. Their results confirmed the generalization challenge facing various users in general and amputee in specific.

There is also the issue of small dataset size related to EMG based prediction that is extensively reviewed and studied in [27], confirming the need for bigger datasets to overcome the overfitting problem facing, particularly, deep model generation.

This paper addresses and analyzes the effect of various levels of user involvement in the calibration process on system's performance. Its main contribution is to pave the way for a limited resource-consumption and minimized user-calibration time solution to the gesture classification while preserving reasonable accuracy results. Traditional ML techniques are used due to their low utilization of hardware resources and their comparable results to deep learning solutions which is proved from the related work presented in Section II. The experiments are conducted to measure the impact of changing the number of samples needed from the user in the calibration process in an attempt to reduce this value in order to minimize user-calibration time. Two ML techniques are involved in these experiments. They reach the conclusion that the user-specific features, which can highly improve EMG-classification performance, can be learned from 2%-3% of the training sample space.

The rest of this paper is organized as follows; the next section presents the extensive research work that aims to tackle these issues and increase the EMG based movement classification systems' usability while preserving high accuracy results. Section III describes the used system in this study. Then the results of this analysis are shown and discussed in Section IV while the last Section provides a conclusion reached by this study.

II. Related Work

In order to increase user acceptance for prosthetic devices or gesture based remote controlling systems, multiple researches attempt to increase performance and minimize user calibration. Unfortunately as reported in [28], [29], the performance of deep learning is highly dependent on the data set size available for training. The larger dataset, the higher the performance would be. But the publicly available EMG gestures datasets suffer from the size issue placing restrictions on the use of deep learning solutions as reported [27]. Moreover collecting massive amount of data from the system's end user would form an obstacle to system usability due to time, efforts and frequency requirements of the (re)calibration process [30], [31]. In [30], they state the need for a study that deals with the issues related to prolonged and repetitive recalibration sessions. So investigating the effect of minimizing user calibration, features or dataset size while maintaining high performance using different traditional or deep learning solutions, gets increasing priority.

In [32], the authors analysed working with dataset with variable force levels using traditional classification method (KNN). They proposed an iterative feature extraction method to be used for identifying six grip activities with different force levels; low, medium, and high. The success rates accomplished were relatively comparable as the classification results were 97.78 % for Low, 93.33 % moderate and 92.96 % for high force level. The work with various force levels was also presented in [23] but this time with deep networking solution, where the authors achieved average accuracy of around 91% using LSTM-based neural network across all amputees subjects and force levels confirming a comparable results between deep and traditional solutions when working with different force levels of EMG signals.

The hand gestures identification for the sake of stroke rehabilitation is applied in [5] for six hand gestures. Time and frequency features of 20 subjects are provided to the classification phase. KNN has shown better accuracy 98% over Artificial Neural Networks (ANN) and Support Vector Machines (SVM). They also tried to reconstruct identified gesture from EMG-based generated joint trajectories and compare it to the generate movement by a VICON camera tracking system producing a correlation of 0.91. Proving the approximate accuracy produced by traditional methods and neural networks using muscular generated signals.

The work for minimizing the user calibration time and studying the impact of user-independence EMG based classification systems take place in [33]. The authors investigate the feasibility of zero retraining and achieving the rotation and hand independence. The experiments include twenty participants with all rotations and both hands utilization are allowed for eight distinctive gestures; rest, flex, extend, abduct, open, close, thumb, and ok. They find that the accuracy notably decreases under these generalizations except for wrest extension gesture which is found to be consistent among all gestures.

The authors in [25] propose LSTM-CNN model for hand gesture classification in order to check the possibility of creating user independent solution and reduce the need for system recalibration for new users. They start by recognizing seventeen gestures' classes from 40 subjects in a user-dependent way and the model reaches accuracy of 81.96%. But when building the user-independent model, they use gesture signals from only four hand movements in the training process. Their model accuracy drops to 77% for unseen users. They use GradCAM analysis in an attempt of getting a shallower design in order to reduce the high training time and memory consumption that are required when deep learning model is used.

In [34], the objective is to minimize the volume of data needed to train a deep neural model. They used the learned Dilated Efficient CapsNet with a decrease of 20% of the training EMG signals per repetition in the transient phase. They maintain an accuracy of 80%.

As demonstrated from the shown recent related work that the problems related user acceptance for EMG based classification and their prosthetic devices massively depends on user calibration time which is needed for reaching reasonable performance results. Different solution approaches are considered including the use of deep learning techniques or reducing the need for user involvement using previously collected samples from other users. The deep learning techniques face the issue of small EMG dataset size and high required computational and storage resources. Some researches reached the conclusion that the results of deep learning and traditional machine learning are comparable either for user dependent or independent solution. So in this paper, the incremental minimization of user calibration is analyzed using traditional classification methods; KNN and SVM.

III. Methodology

As shown in the previous section, one of the main challenges facing the EMG based hand activity recognition system is the lack of inter and intra-user generalization which causes the need for extensive calibration that consumes user's time and negatively affects user experience. The accuracy of the recognition system is found to be dropping when the movement activity samples used in the training process are gathered from subjects other than the final user whose samples are used in the testing or validation processes. This user generalization issue limits the user acceptability which is highly depending on accuracy and calibration time [25]. So in this paper we investigate the effect of incremental involvement of the final user's samples in the training process on the overall model accuracy results. The results are analyzed using ANOVA test in Section IV. The next paragraph describes the used system in order to view the influence of incremental user samples in the training process.

The hand gesture recognition system used in this study utilizes the traditional recognition methods. It is composed of various components as shown in Fig. 1.

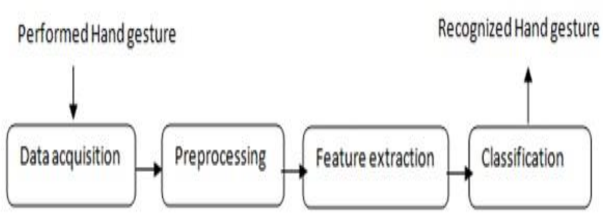

Fig. 1. EMG hand gesture recognition system.

It includes the data acquisition process performed by [26] which first collects the EMG signals from two differential electrodes using as a programming kernel, the National Instruments (NI) Labview. The electrodes are placed on the forearm surface by elastic bands with an additional reference electrode is put in the middle, in order to record information about the muscle activation. Then the preprocessing phase is applied on the captured signals to cleanse, remove noise and unwanted signals, performs segmentation and normalization. So it uses an 8th-order bandpass IIR filter with lower frequency 15 Hz and higher frequency 500 Hz. Then the feature extraction takes place for each trial. It extracts twelve AutoRegression (AR) [35] coefficients as three coefficients are generated per trial segment. AR features are the coefficients of a statistical model that is generated to predict new values of data given the old ones. A K-th order autoregression AR(k), is the model that uses K past points of the time series in order to guess the new point to come with K coefficients to give weights for each previous point and determine its participation in calculating the next value according to its distance from it according to the following equation.

$$X_t = \sum_{j=1}^{k} \varphi_j X_{t-j} + \omega_t \quad (1)$$

Then at the classification phase, one-versus-all SVM classification model with Gaussian radial based kernel is trained using the previously extracted features. The one-versus-all SVM classifier [28,29] is generated by combining the decision from various binary classifiers that separate one class from all other classes. The binary version is utilized to calculate the separation hyperplane with transformed Hilbert space vectors. The decision function is computed as

$$D(x)=\sum_{i=1}^{p} \alpha_i y_i K(x_i, x) - b \quad (2)$$

Where xi are the training samples input vectors and yi are the samples output which have different sign for the two classes. The Gaussian Radial basis function is formulated as:

$$K(x_i, x) = e^{-\|x_i - x\|^2/2\sigma} \quad (3)$$

To confirm the results, another classifier, KNN, is used. It is a supervised machine learning algorithm. It categorizes the item according to the most common class of its K nearest neighbours. It relies on a distance metric to determine the item's neighbours. In this paper we use Euclidean distance.

The trained model is then used to distinguish the testing features. The use of the traditional feature extraction and classification methods like AutoRegression and SVM and KNN is beneficial for achieving the simplicity and saving the time required for the training process [32] specially with the small size of the dataset that could cause overfitting and reduce accuracy when deep neural networks are used [33].

The next section describes the experiments conducted to study the effect of decreasing user provided samples in the calibration process in order to achieve acceptable performance and increase the user acceptance.

IV. Experiments and Results

Two experiments are conducted with the two classifiers, SVM and KNN. One uses complete user dependence condition while the other uses the partial dependence. The dataset is collected by [26] from five normal and healthy subjects of age 20-22. They are asked to perform six different movements for thirty trials. The measured time is 6 sec.

The movements are Spherical, Tip, Palmar, Lateral, Cylindrical, and Hook. Spherical movement is recognized when holding spherical objects while Cylindrical movement is recognized when holding cylindrical objects. Tip movement is recognized when holding small objects while thin and flat objects grasps are recognized as Lateral. Grasping with palm facing the object is called palmar movement and Hook movement for supporting a heavy load. No previous instructions about speed or force are given to subjects.

The dataset is partitioned using 10 folds, nine folds contributes in building the training model while the last fold is used for testing the unseen samples. The average Correct Classification Rate (CCR) for various movements using SVM is shown in Table I. The results show that the average accuracy across various users is around 97% with average 99% for tip and lateral movements as the most identified movements.

TABLE I. CCR FOR VARIOUS MOVEMENTS WHEN SVM BASED USER DEPENDENT CLASSIFICATION IS APPLIED

Subject / Move	1	2	3	4	5	average
Cyl.	0.97	0.97	0.93	1	1	0.97
hook	1	0.93	0.93	0.93	1	0.96
tip	0.97	1	1	1	1	0.99
palm	1	0.97	0.93	0.97	1	0.97
Sph.	0.93	0.93	0.97	0.93	1	0.95
Lateral	0.97	1	1	0.97	1	0.99
average	0.97	0.97	0.96	0.97	1	0.97

While using KNN classification with K=3, The average Correct Classification Rate (CCR) for various movements, as shown in Table II, The results show that the average accuracy across various users is around 92% with average 93% for tip and lateral movements as the most identified movements.

TABLE II. CCR RESULTS WHEN APPLYING KNN WITH K =3 AND EUCLIDEAN DISTANCE METHOD

Subject / Move	1	2	3	4	5	average
Cyl.	0.9	0.9	0.93	0.93	0.93	0.92
hook	0.9	0.93	0.9	0.9	0.9	0.91
tip	0.93	0.93	0.93	0.9	0.93	0.93
palm	0.9	0.9	0.93	0.9	0.9	0.91
Sph.	0.9	0.9	0.93	0.93	0.9	0.91
Lateral	0.93	0.93	0.93	0.93	0.93	0.93
average	0.91	0.92	0.93	0.92	0.92	0.92

The second experiment performed tends to measure the effect of user samples contribution in building the training model. Using SVM as the classifier, the involvement of the first 10 user samples influences the classification accuracy as presented in Table III. The results show huge increase in the average accuracy. The performance enhancement could reach around 62.6% on average, when more than one sample from the user is involved in the training process and building the model. This sample represents around 1% of the training sample space. It achieves an accuracy result that equals to 89.6% on average.

The results of involving the user samples in building KNN model, as shown in Table IV, lead to the same conclusion. A great increase of accuracy of 50.9% on average is reached, as the number of user's involved samples is more than 2. Two samples represent around 2% of the training sample space. The KNN model achieves an accuracy result equals to 78.2%.

The effect of 27 of user samples contribution in building the training model is summarized in Fig. 2. It shows that the effect of user involvement decreases after three or more samples. Furthermore, the performance does not witness much difference after the involvement of the tenth sample and the sixteenth sample in case of SVM, and KNN respectively. The involvement of those samples lead to an accuracy of 98%, and 88% on average in case of SVM, and KNN respectively.

TABLE III. SVM BASED USER PARTIAL PARTICIPATION CCR ACCURACY RESULTS

Subject / No.Samples	1	2	3	4	5
1	0.22	0.21	0.41	0.27	0.24
2	0.88	0.86	0.94	0.93	0.87
3	0.89	0.89	0.95	0.94	0.88
4	0.9	0.89	0.97	0.95	0.89
5	0.92	0.92	0.97	0.95	0.91
6	0.93	0.92	0.97	0.96	0.92
7	0.96	0.95	0.99	0.99	0.94
8	0.96	0.95	0.98	0.98	0.93
9	0.98	0.97	1	0.99	0.94
10	0.98	0.98	1	1	0.96

TABLE IV. KNN, K=3 USER SAMPLES PARTICIPATION CCR ACCURACY RESULTS

No.Samples / Subject	1	2	3	4	5
1	0.18	0.19	0.28	0.01	0.32
2	0.26	0.21	0.32	0.04	0.35
3	0.79	0.79	0.77	0.76	0.80
4	0.81	0.80	0.77	0.76	0.81
5	0.79	0.78	0.77	0.75	0.81
6	0.79	0.78	0.77	0.76	0.80
7	0.81	0.81	0.77	0.76	0.81
8	0.83	0.80	0.81	0.77	0.83
9	0.82	0.82	0.81	0.79	0.83
10	0.83	0.83	0.81	0.81	0.85

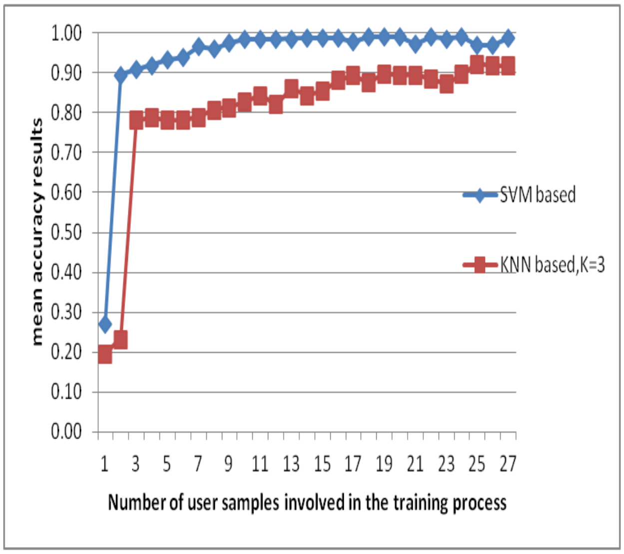

Fig. 2. The effect of involvement of user samples in building the training model.

Among the moves, as shown in Fig. 3 the hook move is the most distinguished one across all users from the first user sample using the one-versus-all SVM classifier. The other moves give approximately similar accuracy results after the involvement of two samples.

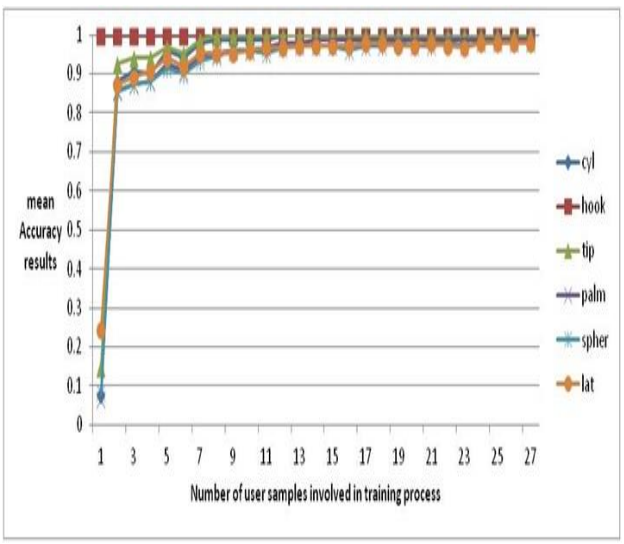

Fig. 3. The effect of involvement of user samples in building the training model with respect to movement.

To confirm that the results' means do not suffer from significant differences, two-way ANOVA test is applied to the partial samples inclusion results. It is proved that in both SVM and KNN based classification, for various subjects, the rejection of the null hypothesis is implied as the value of p is less than 0.05 for partial samples and different users.

V. Discussion

The results of our experiments show the possibility of involving only a small number of user samples, which could represent 2%–3% of the total sample space, in the re-calibration process in order to gain significantly increased performance accuracy. These findings could lead to the minimization of calibration time while maintaining relatively high performance results and thus increasing the user acceptance which is a main challenge in the EMG based gesture classification systems and the industry of EMG based prosthetic devices.

Our results used a small dataset that is publicly available which includes only five normal and healthy subjects with six different movements for thirty trials. So in future work, we intend to confirm our results using larger datasets with various movements for both healthy users and amputees.

VI. Conclusion and Future Work

This paper is concerned with the user independence challenge facing the EMG-based movement recognition system. It reviews the previous research work regarding this obstacle that affects both user accuracy and acceptability. It studies the effect of partial user samples involvement in the calibration process using AutoRegressive features and traditional classification methods like one-versus-all SVM with Gaussian radial based kernel and KNN.

The findings are interesting in that a huge increase of accuracy has occurred as a result of including two to three user samples which represents around 2%-3% of the total training sample space. The increase is estimated to reach 62.6% on average in case of SVM classifier and 50.6% in case of KNN, achieving accuracy results equal to 89.6% on average in case of SVM and 78.2% in case of KNN. The results somehow stabilize after ten samples in case of SVM to reach 98% on average and after sixteen samples in case of KNN to reach 88% on average.

After applying two way ANOVA test to the partial samples inclusion results, either in SVM based classification or KNN based classification, for various subjects, it implies the rejection of the null hypothesis as the value of $p < .05$ for partial samples groups and different users confirming that the results' means do not suffer from significant differences.

The results assured the great influence on system accuracy when involving small number of user samples in the model-building process using traditional classification methods.

As a future work, we intend to confirm our results using larger datasets with various movements for both healthy users and amputees.

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