Pattern Recognition of sEMG signals for Emulation of Human Limb Movements

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***Abstract*—In the recent years the use of assistive technology in the fields of rehabilitation (rehab), prosthesis and industrial domains have increased many fold. Electromyogram based pattern recognition control is at the forefront of this Human-Machine Interface technology. Primarily these systems focus on using EMG signals generated in the musculoskeletal system as input to a pattern recognition based classification system which is then linked with an external armature in order to control it according to the intention of the user. In this work a system for control of forearm and wrist movement of a robotic actuator an EMG based system is proposed. A simulation of the robotic actuator is controlled using EMG signal classification output. Additionally a new feature set has been proposed. It has been tested across multiple data-sets and the results are at par with other feature sets frequently used in literature. Finally the classifier performance using an ensemble subspace of KNN classifier is found to be 99.9% across data-sets for the proposed feature set and it is better than some of the current standard classification schemes. The simulation of the entire robotic simulation has been performed and attached as an external multimedia.**

***Index Terms*—EMG, Machine Learning, Exoskeleton, Robotic arm, Feature Extraction**

I. Introduction

A. Motivation for Simulation Approach

The principal challenge in realizing the human robot interface (HRI) technology for an orthotic exoskeleton is the design of a control mechanism driven by the user intention. In the recent literature, a surface EMG signal driven Pattern recognition based control has gained considerable traction. In the pattern recognition (PR) based control, the statistical features are computed to characterize the EMG signals. These computed features are then fed as inputs to a classification framework which learns the movements corresponding to the input sEMG signals and identifies the intended motion of the user. These decisions become the inputs to a control mechanism of the exoskeleton in order to perform the intended motion. The development of the physical system requires the construction of an exoskeleton which is expensive and time consuming.

A simulation of the robotic system is a viable alternative to test and evaluate the PR based framework before the actual deployment. The simulations of the movements can be used for training purposes prior to the exoskeleton rehabilitation process. Further a simulation can be gamified which will help alleviate the stress that is often associated with extended periods of rehabilitation post a traumatic event. The gamified simulation while distracting the patient can help to collect other valuable data about specific muscle groups through extended measurement sessions. An interaction with virtual the robot can provide visual cues in form of a game or a level gauge to help in the rehabilitation process. For patients in places where rehab robots might not be accessible, a simulation based system can initially support them. A simulation can also prove helpful in testing the various test cases in the system. For instance in-case of a wearable robotic arm it is important to limit the motion to the extent possible by the human arm. If this constraint is failed during transition from one limb position to another then it can cause injury. This is useful in design and testing of the overall system as it would be viable to simulate the system before building the robotic hand manifold. Thus a simulation is tractable as a precursor to the actual implementation. In this work WEBOTS software [1] has been used to validate the functioning of the entire system.

B. Review of Simulation Approaches

In [2], a 3D simulation of the human forearm is developed by the authors which is actuated using sEMG signal classification outputs and is capable of mimicking 10 classes of hand motion. Another application of sEMG controlled interface is demonstrated in [3] where a virtual menu is controlled using jaw contraction signals. In [4], the authors proposed a hybrid sEMG and motion tracking framework that enabled users to manipulate objects in a virtual reality interfaced using a VR headset. This hybrid framework enables an immersive experience for the user. In recent years a gamified approach to rehabilitation has gained traction. One such example is [5], wherein the authors developed a game which used movements similar to those in rehabilitation therapies to control and navigate a game.

Contributions: In this work, a surface EMG driven Pattern Recognition based control for moving the virtual robotic arm is proposed. In this work, a feature set is proposed that is a combination of features that are observed to perform well in

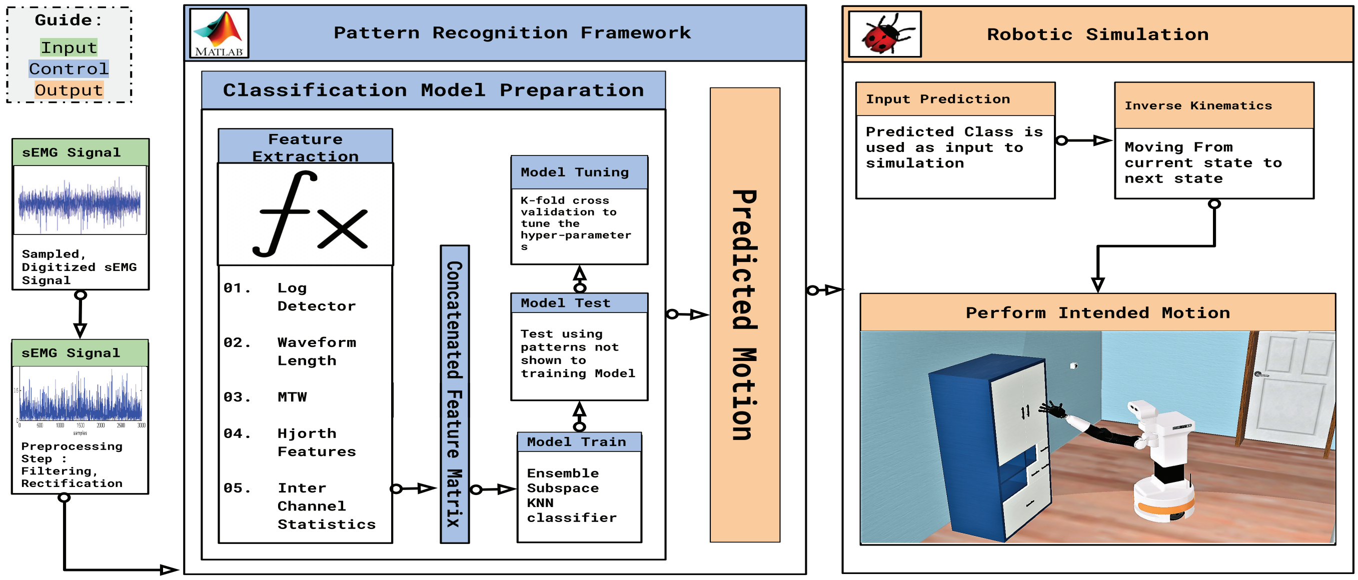

Fig. 1: Proposed System Model

sEMG signal classification. This new feature set is analyzed against the current state of art features used in sEMG signal classification. Finally, a few virtual robotic arm movements driven by the classifier decisions are demonstrated.

II. Methodology

A. Overview

As shown in Fig. 1, initially, in the PR framework, a sEMG signal is converted into a feature vector based on prior design. This feature vector is fed to a trained model which classifies it into one of the known categories, . Thus, the PR framework gives a joint prediction for both the forearm and wrist movements and are given as inputs to the simulator. Subsequently this estimated information is used to actuate the robotic manifold, hence moving it as per the user's intention.

B. Pattern Recognition Stage

The data-set consists of surface EMG signals for each of N_T trials repeated for N_C categories of movements from N_S subjects. Hence the data-set contains a total of P = $\{N_S$ x N_C x $N_T\}$ patterns. Here each class corresponds to a distinct motion performed by the subject. The EMG data collected is of the form

$$\mathbf{S}_i = \{\mathbf{s}_{i,1}, \mathbf{s}_{i,2} \ldots, \mathbf{s}_{i,N_{Ch}}\} : \qquad i = 1, 2, \ldots, P \tag{1}$$

Here N_{Ch} represents the number of distinct electrode locations used during EMG data collection and

$$\mathbf{s}_{i,j} = \{s_{i,j}(k)\}_{k=1}^{M_T} \tag{2}$$

is the EMG signal of the j-th channel of length M_T, where M_T is the number values in one trial given by $M_T = t_T \rho$, where ρ is the sampling rate and t_T is the trial duration.

1) Preprocessing: Preprocessing of the raw EMG data is necessary for reduction of noise and improving classification performance. The raw EMG signals during the data-set creation were filtered to remove line interference and digitized using a 12 bit ADC. In this work, rectification is used as the primary preprocessing step [6], [7]. Following this, the data is segmented using non-overlapping sliding windows of length W = 200ms [8] containing L samples per window.

$$L = \rho \frac{W}{1000} \tag{3}$$

$$\mathbf{x}_n = [s_{i,j}(k)^T, s_{i,j}(k+1), \ldots, s_{i,j}(k+L-1)]^T \tag{4}$$

Here $\mathbf{x}_n$ denotes the n^{th} sliding window and k denotes the starting index at the n^{th} sliding window. The total number of sliding windows containing L samples each is $\lfloor \frac{P}{L} \rceil$. Further from each segment features are extracted using the relevant algorithms, described in the next section.

2) Feature Extraction: Feature extraction is done apriori to classification in order to extract meaningful information from the raw EMG signal to make it suitable for input to a classifier. Moreover feature extraction also provides a compact representation of time series for computation purposes.

In this work, the following features are proposed for improved classification.

- Hjorth Features are extracted as described in [9] consisting of mobility, activity and complexity. The Hjorth activity α describes the variability in the shapes of Motor unit action potential (MUAP) [10] The Hjorth-Mobility γ represents the true firing statistics of MUAP and is a function of the standard deviation and the Hjorth activity. The Hjorth Complexity δ is a function of the Hjorth

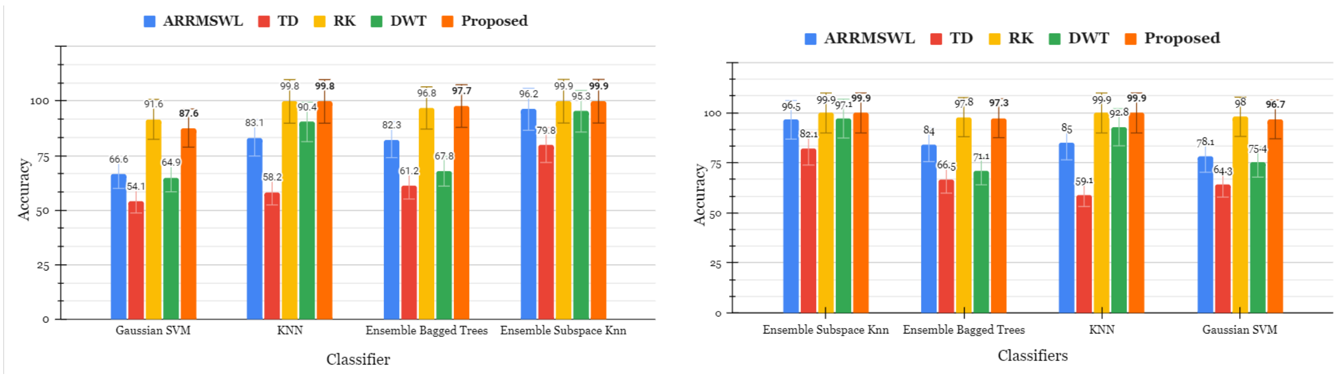

Fig. 2: Classification accuracies for data-set 1 for movements of (left) forearm (right) wrist

Mobility θ. It represents the change in frequency of an EMG signal relating to the MUAP waveform.

- Log Detector provides a measure of the muscle contraction force. [11]. It depends on the logarithm of the magnitude of the Fourier transform of the EMG signal.
- Multiple Trapezoidal Window is used to interpret the change in EMG signal energy over a duration by using windowing functions. The energy of a segment of the signal is used as a feature. As per [12] trapezoidal windowing function $f_{i,j}(.)$ is multiplied with the signal and the energy is computed.
- Inter Channel Statistics are used to interpret the correlation between the various EMG channels of the EMG signals [8].
- The final feature used in this set is the wavelength feature from [11].

Additionally four other feature sets commonly used in the literature are also implemented for comparison purposes. They include the feature set developed by [13] denoted RK feature set. The second feature set is based on Discrete wavelet transform technique [14] denoted as DWF. The third feature set [15] is based on RMS (root mean square) of EMG signal, AR coefficients and Waveform length denoted as ARW. Lastly the time domain feature set [8] denoted as TD consisting of mean, variance, skewness and kurtosis of the EMG signal. A final feature matrix $\mathbf{F_n}$ of the form

$$\begin{aligned} F &= [F_1^T, F_2^T, \cdots, F_n^T]^T \\ F_n &= [\mathbf{f}_{n,1}, \mathbf{f}_{n,2}, \ldots, \mathbf{f}_{n,N_{Ch}}] \quad n = 1, 2, \ldots \frac{P}{L} \end{aligned} \tag{5}$$

where F_n denotes the n^{th} row of the feature matrix.

3) Classification: In the experiments, different classifiers as listed below are implemented and a comparative analysis is carried out to identify the optimal framework. The classifiers are (1) the ensemble of subspace KNNs [16], (2) the KNN (K nearest neighbour classifier) [16], (3) the SVM with a Gaussian Kernel [17], and (4) the Bagged Trees Classifier [18]. The performance of each classifier is compared using classification accuracy, F1 score, Kappa Coefficient and the multi-class area under the ROC curve. For the forearm and wrist movements a hierarchical classification scheme has been used where the EMG signal features from forearm and wrist movements are used to train two different models. The results of the two models are then combined to yield the overall prediction.

C. Robot Movement Simulation

The PR framework writes the classification result to a command-file. This file is periodically checked by the robot's actuator command program which then updates the robot's position based on this new result. The positions corresponding to the EMG signals are coded accordingly in the webots software which are invoked as per the result in the command-file. Hence, the success of the simulation mainly depends on the accuracy of the result delivered by the PR framework; since the virtual robotic arm moves according to this command and a single classification error can lead to a wrong final robotic position.

The robot model used is the TIAGO-titanium robot which contains a model capable of mimicking entire range of motion of the human forearm. The robot used for simulation of forearm and wrist movements in the data-set is PAL Robotics, TIAGo Titanium robot. It is a two-wheeled human-like robot with a torso, a head and one articulated arm finished by a hand as an end-effector. The end effector is capable of performing most of the wrist movements of a healthy human and is attached to a forearm and shoulder that can mimic a human elbow and shoulder joint motions. The forearm part has 7 DOF and the attached wrist end effector has 19 DOF. The simulation of the robot has been done in Python in the weBOTS software and it connects with the PR framework in matlab.

III. Implementation and Results

A. Datasets

The first data set of interest [19] consists of combined forearm and wrist movements from 11 subjects 9 male and 2 female out of which 9 have been considered in this work. This data set contains a total of 40 classes and 7 channels. The second data-set consists of the wrist and finger movements with 10 classes [20] from 2 electrodes. Similarly, the third dataset has the similar categories with 15 classes collected over

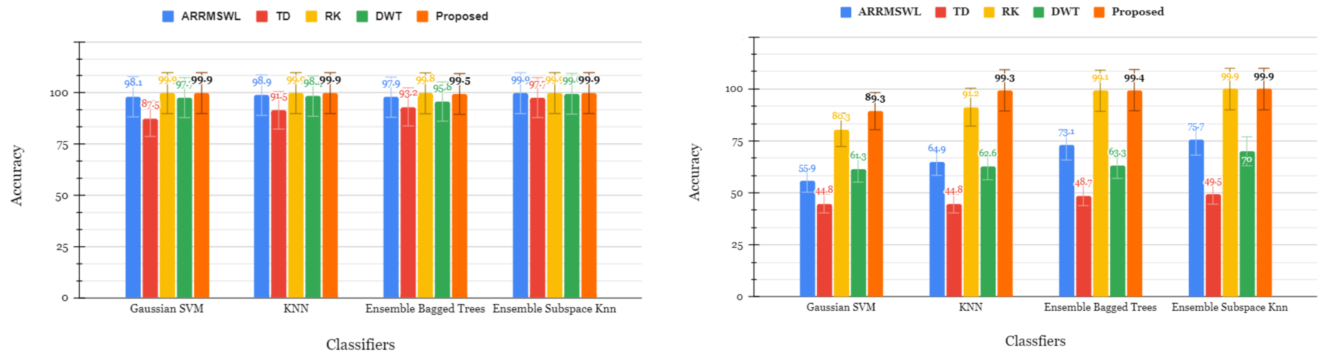

Fig. 3: Classification accuracies for data-sets (left) two and (right) three

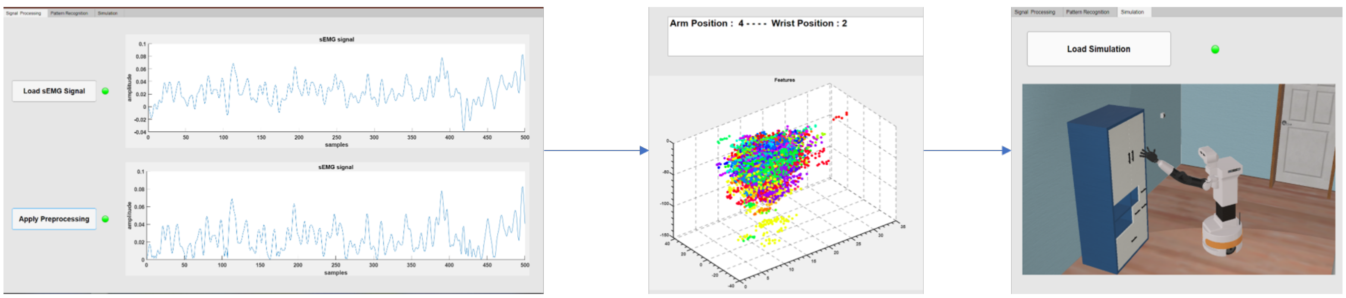

Fig. 4: A demonstration of the proposed simulation driven by an EMG signal

Fig. 5: Robot in three simulation scenarios (left) Living Room, (mid) Kitchen and (right) Factory floor

8 channels. The subjects in all the data sets were able bodied and had no neurological/ musculoskeletal diseases. However, the current approach may be applied to transradial prothesis as well.

B. Classification Results

In this section the performance metrics for the classification and feature sets are outlined. The feature matrix **F** is split into training and testing set with uniform representation of classes in both the sets.Firstly all classifier accuracies are calculated using a 5 fold cross validation scheme. In Fig. 2 and 3 the comparison of the various feature sets v/s classifier is illustrated. From this it can be inferred that the proposed feature set gives comparable performance with the current state of the art feature set (RK) across classifiers. From Fig. 3 it can bee seen that across data-sets the proposed feature set is giving good performance. The highest cross-validation accuracy for the proposed feature set for data-set 1,2 and 3 is obtained to be 99.9%. The ensemble subspace of KNN classifier is used for the system model since it provides high values of the performance metrics mentioned previously across data-sets and also compared to other classifiers provides high accuracies.

In this work an end to end system to decode the intention of the user from the sEMG signal is proposed with emphasis on simulation of the motion with a robotic simulation software.

C. Webots Experiments and observations

In order to demonstrate the simulation which would solve modern day prosthesis related real-world problems, three environments have been chosen. In the first environment a living room setup is made. Patient's having limb disabilities might find it difficult to perform daily activities hence one such situation wherein the robot manifold is reaching to open a cabinet is simulated. In the second environment a kitchen scenario is made where the robot aims to pick up an apple from the table. This proposed system model can be extended beyond rehabilitation purposes and one such scenario of industrial automation has also been modelled. Aforementioned scenarios can be referred in Fig. 5

IV. Conclusion

In this paper, an end-to-end system is proposed which detects the intention of the user and mimics the intended position in a robotic simulator. We have showed that our classification model with the new proposed feature set gives performance comparable to other feature sets commonly used in EMG signal classification. The system model presented is promising for practical deployments in prosthesis, rehab and industrial purposes as well as being computationally tractable.

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