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# USER-INDEPENDENT HAND MOTION CLASSIFICATION WITH ELECTROMYOGRAPHY

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## ABSTRACT

*Electromyographic (EMG) processing is an important research area with direct applications to prosthetics, exoskeletons and human-machine interaction. Current state of the art decoding methods require intensive training on a single user before it can be utilized, and have been unable to achieve both user-independence and real-time performance. This paper presents a real-time EMG classification method which generalizes across users without requiring an additional training phase. An EMG-embedded sleeve quickly positions and records from EMG surface electrodes on six forearm muscles. An optimized decision tree classifies signals from these sensors into five distinct movements for any given user using EMG energy synergies between muscles. This method was tested on 10 healthy subjects using leave-one-out validation, resulting in an overall accuracy of $79 \pm 6.6\%$, with sensitivity and specificity averaging 66% and 97.6%, respectively, over all classified motions. The high specificity values demonstrate the ability to generalize across users, presenting opportunities for large-scale studies and broader accessibility to EMG-driven applications.*

## INTRODUCTION

Electromyography (EMG) has been studied extensively in the past three decades due to its ability to non-invasively measure muscle activation. These signals have been used to decode intended joint motions with direct applications to prosthetics [1], exoskeletons [2], robot teleoperation [3–7] and even new methods for human-machine interfaces [8]. Despite rapid advances in these applications over the last decade, EMG signal processing contains many challenges. Among these challenges are signal changes with respect to muscle (motor unit) density, EMG sensor placement, age, fatigue, joint orientation and different muscle synergies across users [9]. These challenges have so far contributed to user-dependent state of the art decoding methods, limiting both their accessibility to the general population and the ability for researchers to perform large-scale studies on these applications.

In order for EMG-based applications to be more broadly accessible and researchers to perform larger studies, the applications must be generalizable and appealing to the entire population. Intense training phases and large learning curves for achieving optimal decoding are often overwhelming and restrictive for users whom prefer simpler, more user-friendly designs [10]. Pre-trained classifiers have been mentioned as a solution to reduce the learning curve for users using these applications [1]. Despite the well-documented inter-user variability that has prevented decoders from performing well across users [1, 11, 12], Ajiboye et al. [9] suggest that a sparse set of muscle synergies are user independent and form a low-level basis for muscle control. Their results imply that EMG signals can be used to decode basic non-precision movements with a user-independent classifier.

Many previous works have explored hand motion classifications with varied potential for user-independent performance. Hand motion decoding algorithms commonly use user-specific neural networks [13] or support vector machines (SVM) [11] to train a classifier. In [11], the authors use support vector machines to classify opening and closing of fingers. Although this method achieved session independence (i.e. a single user can use the classifier over multiple sessions without re-training), the authors were unable to achieve user independence. Despite the popularity of neural networks and SVM in the current field, [14] demonstrates the use of Random Forests to map EMG signals to discrete tasks. The results suggest this decision tree-type classifier is more well-suited than the commonly used SVM for multi-class problems, such as hand motion classification.

A few works have addressed inter-user variability through real-time neural network training algorithms [15, 16]. However, the intensive training phase requires complex interactions from the user, and there is no upper bound on the number of times this training will need to be refined as the user continues to use the model. An attempt to remove this intensive training phase was presented in [12] by adapting new models in real time to a set of pre-trained SVM models. The results of the study are promising but inconsistent. Each pre-trained model was developed from only a single user, where the potential for over-fitting to user-dependent synergies reduces the probability that the SVM separates the data along the sparse criteria that may be well-suited for a general population, as suggested in [9]. The authors in [1] also explore the idea of training on one user and testing on another using SVM to classify different grasps, but were unable to obtain consistent results.

Hand motion classification was also considered in [17], where the root mean square of EMG signals were classified with Twin SVM. It is unclear whether the robust performance could be extended across users, but the method suffers from limited real time application. The root mean square input is calculated over the entire motion and the SVM is trained on only one sample per consecutive motion.

The most closely related work to this paper is presented in [10]. A simple classifier distinguishes commands based on the activation levels of the flexor and extensor carpi-radialis. These commands are used for higher level grasping functions where the commands provide transitions between grasping states. Due to the simplicity of the classifier, it could be implemented in real time and applied across users with the only required calibration being an initial maximum voluntary contraction (MVC) measurement to determine appropriate levels of contraction for each state. Although the method showed good results, the classifier considers each muscle activation independently, making it difficult to extend to motion classification with only two opposing muscles considered.

This paper presents a novel user-independent classifier consisting of an optimized decision tree to classify a discrete set of hand and wrist movements in real time on users without requiring a training phase. Rather than considering muscle activations independently to classify commands as in [10], synergies from multiple muscles are used to classify activation into a discrete set of common movements. The classifier model is made to be simplistic and robust to inter-user variability by capturing the sparse set of synergies common across the general population. Six forearm muscles are identified as having consistent synergies across users for a set of five common hand motions: grasping, wrist extension, wrist flexion, index finger pointing, and pronation. A skeleton decision tree is created using biological principles of muscle activations for each motion, and the thresholds on each tree node are optimized based on a training database. By training on multiple users, the classifier is robust to inter-user variability, and can perform decoding in real time on previously unseen users with only a quick calibration needed to record MVC measurements on the muscles.

## METHODS

Initially, the set of muscles to be recorded was decided. This selection was based on anatomical figures and information on the role of individual muscles to hand motions [18]. In a preliminary experiment, EMG signals were recorded from a small set of subjects $A = \{a_1, \ldots, a_M\}, M = 4$, and closely examined for the different hand motions. After pre-processing the raw data and examining the nature of the signals, reliable muscles and motions were selected as a basis for the EMG-based classifier. These observations were used to construct the skeleton decision tree for the classifier, and decision-based parameters were optimized using a cost function via regularized gradient descent on a training database $B = \{b_1, \ldots, b_N\}, N = 10$, $A \cap B = \emptyset$.

### EMG Preprocessing

Before any type of decoding or analysis takes place, the raw EMG data undergoes a pre-processing stage that is commonly used in the field of electromyography, in order to compute the *linear envelope* of the signal [19]. The linear envelope performs full-wave rectification of the raw signals and then passes them through a low pass filter (2nd order Butterworth, cut-off frequency of 8 Hz). This process allows the data to be more easily interpreted, as well as makes the beginning and ending of each motion more identifiable. After the linear envelope, the EMG signals for each muscle are normalized with respect to each muscle's MVC level [18].

### Decision Tree Skeleton

After analyzing the EMG data in $A$ collected from several forearm muscles during various hand motions, five unique motions were chosen to be the focus for the classifier: wrist extension, wrist flexion, grasping, pronation and index finger extension. The selection of the discrete motions is based on the fact that they are very common across every-day life tasks, and therefore can be useful for future users, e.g. hand amputees.

The forearm muscles demonstrating the most promise for accurate and robust ability to generalize were narrowed down to six: the Extensor Digitorum (ED), Extensor Carpi Ulnaris (ECU), Flexor Carpi Radialis (FCR), Flexor Carpi Ulnaris (FCU) and the Pronator Teres (PT). The muscle signals were consistent between subjects and noticeably significant during their expected biological function, providing support for their anatomical placement and reliability in the classifier. Table 1 shows the muscles chosen and their known involvement in hand motions based on research in kinesiology and biology [18].

A wearable sleeve with six wireless EMG electrodes (Trigno

Table 1. SELECTED MUSCLES AND PRIMARY FUNCTIONS [18].

| Muscle | Primary Function |
|---|---|
| Extensor Digitorum | Wrist\Finger Extension |
| Extensor Carpi Ulnaris | Wrist Extension, Ulnar Deviation |
| Flexor Carpi Ulnaris | Wrist Flexion\Abduction, Ulnar Deviation |
| Flexor Carpi Radialis | Wrist Flexion, Radial Deviation |
| Pronator Teres | Forearm Pronation |
| Flexor Digitorum Superficialis | Wrist\Finger Flexion |


Figure 1. The sleeve that was developed allows for fast and precise placement of six wireless EMG electrodes on the subject's forearm.

Wireless, Delsys Inc) was developed to allow for easy and precise placement of the electrodes across subjects. The sleeve is shown in Fig. 1. The processed EMG signals are fed into a classifying decision tree that is based off of signal amplitude thresholds and relationships. As one can see in Fig. 2, certain muscles must be showing activation levels beyond a certain threshold value $\theta_k$, while other decision criteria involve relating the amplitudes between muscles. These decision criteria evolved from the observations of the EMG data across subjects in $A$, in which generalizable patterns of EMG for each hand motion were sought out.

### Optimization

The original threshold values $\theta_0$ were obtained through observing EMG patterns, as mentioned above; although, since these threshold values vary slightly between subjects, regularized gradient descent optimization with a nonlinear conjugate gradient [20] was used to find the optimal threshold values $\hat{\theta}$. The optimization algorithm finds the set of parameters $\theta$ which minimizes a given cost function $J$. In the case of the decision tree, the parameters to optimize are each $\theta_k$ in Fig. 2, and the cost function to minimize should be a representation of the desired performance of the decision tree classifier.

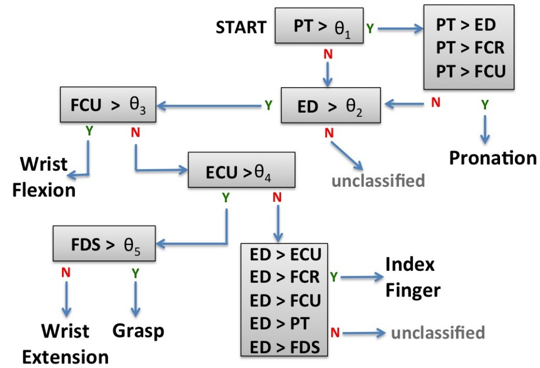


Figure 2. Skeleton decision tree classifier using variable thresholds.

To obtain a robust, user-independent classifier, the decision tree should favor primarily very high specificity, and secondarily high sensitivity, where specificity is a measurement specifying the likelihood of not predicting a given motion if the user is not performing that motion, and sensitivity is a measurement specifying the likelihood of predicting a given motion when the user is actually performing that motion [21]. This can be achieved by defining a penalty function $\phi$:

$$\phi(\theta, X, Y) = M - tp + fp - 0.5tn + 0.5fn \tag{1}$$

where $X$ is the input vector of EMG amplitudes for all 6 muscles, $Y$ is the manually classified output, $M$ is the total number of samples used in the optimization, $tp$ is the number of true positives, $fp$ the number of false positives, $tn$ the number of true negatives, $fn$ the number of false negatives formally defined by:

$$\begin{aligned} tp(\theta,X,Y) &= \textstyle\sum_i[\psi(\theta,X_i) = Y_i \wedge Y_i \notin \emptyset] \\ fp(\theta,X,Y) &= \textstyle\sum_i[\psi(\theta,X_i) \neg Y_i \wedge \psi(\theta,X_i) \notin \emptyset] \\ tn(\theta,X,Y) &= \textstyle\sum_i[\psi(\theta,X_i) = Y_i \wedge Y_i \in \emptyset] \\ fn(\theta,X,Y) &= \textstyle\sum_i[\psi(\theta,X_i) \neg Y_i \wedge \psi(\theta,X_i) \in \emptyset] \end{aligned} \tag{2}$$

respectively, where $\psi(\theta, X_i)$ is the output of the decision tree classifier on sample $X_i$ with thresholds $\theta$ and $\emptyset$ represents unclassified motion.

This penalty function places a primary emphasis on rewarding correct motion predictions and penalizing incorrect motion predictions, with a secondary emphasis on rewarding correct detections of unclassified motions and penalizing incorrect predictions of unclassified motions. As a result, higher penalties are accrued when the classifier misclassifies motions as other motions rather than unclassified motions. This penalty function is incorporated into the cost function along with a traditional regularizing component to prevent the optimization from overfitting

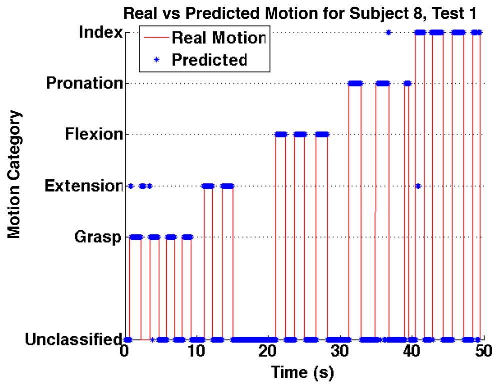


Figure 3. Example classifier output for entire data sequence.

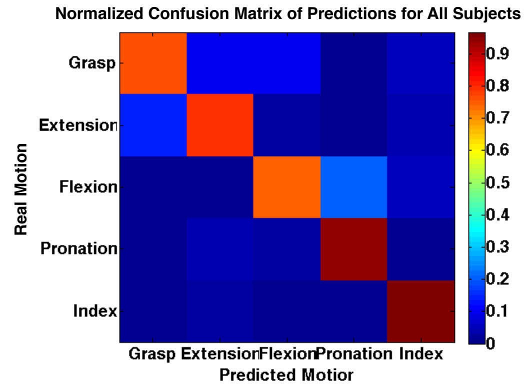


Figure 4. Normalized confusion matrix for all subjects tested with leave-one-out validation.

to the training data, resulting in cost function $J$:

$$\begin{aligned} J(\theta,X,Y) = & \ \frac{1}{M}\phi(\theta,X,Y) + \frac{\lambda}{2M}\sum_k |\theta_k - \theta_{0_k}|^2 \\ \frac{\partial}{\partial\theta_k}J(\theta,X,Y) = & \ \frac{1}{M}\frac{\partial}{\partial\theta_k}\phi(\theta,X,Y) + \frac{\lambda}{M}|\theta_k - \theta_{0_k}| \end{aligned} \quad (3)$$

where $\lambda = 1$ is the regularization parameter and $\frac{\partial}{\partial\theta_k}\phi(\theta,X,Y)$ is estimated by evaluating the finite difference on small perturbations of $\theta_k$. Running nonlinear conjugate gradient descent on $J$ with inputs from training database $B$ results in parameters tuned for a classifier with very high specificity with robustness to generalize to unseen subjects, as desired.

## RESULTS

The proposed method is evaluated on a set $B$ (7 males, 3 females, age $22 \pm 3$, 9 right-handed, 1 left-handed). The subjects were instructed to perform each one of the five aforementioned hand motions for approximately ten seconds each. After the electrode placement, the subjects were asked to go through MVC testing for each muscle, according to directions found in the literature [18]. The collected data were pre-processed as described above and then stored in $B$. To support the user-generalizability sought after in this study, the evaluation was performed using leave-one-out validation. For each $b_i \in B$, the classifier is first trained on the set $\{b_j \in B, j \neq i\}$ to include all subjects except $b_i$. Then the optimized classifier is tested on data from $b_i$ to measure classifier performance and generalizability. An example prediction sequence is shown in Fig. 3.

As shown in Table 2, the accuracy of the classifier with optimized threshold values averages around 79% with a standard deviation of 6.6%. Using $sensitivity = \frac{tp}{fn+tp}$ and $specificity = \frac{tn}{tn+fp}$ as defined in [21], the mean sensitivity and specificity for all motions and subjects is 66% and 97.6%, respectively. It's apparent in the metrics that there is significant variability within motion sensitivity, demonstrating that the classifier predictions for specific motions are far more accurate for some subjects. While variability is high in motion sensitivity, there's much less

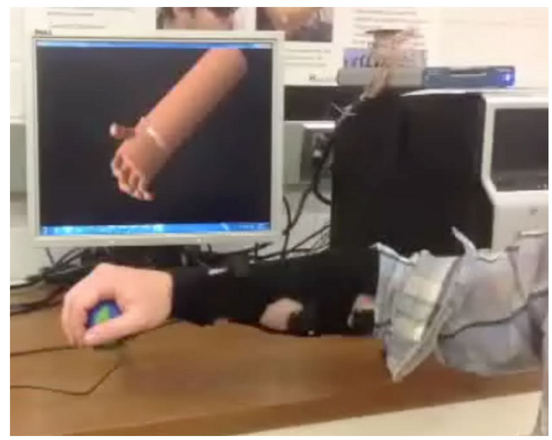

Figure 5. Snapshot of the EMG-based real-time control of the virtual hand.

variability within motion specificity, demonstrating the ability of the classifier to avoid making incorrect motion prediction, as desired. The confusion matrix for all predicted motions is shown in Fig. 4, which demonstrates that grasping is often confused with extension and flexion. This is most likely linked to the tendency of a few subjects to slightly flex or extend the wrist while grasping, but much of this classifier confusion can be avoided by providing visual feedback in real time, as would occur in a real application.

The system was also tested with a real-time control of a simulated hand using the EMG signals and the classifier. The setup is shown in Fig. 5. It is worth mentioning that the performance of the system is far much better when the subject has real-time visual feedback of the classifier's results, suggesting the positive effect of both the high specificity and the cognitive embodiment of the system dynamics. A video of the real-time experiment can be found at http://horc.engineering.asu.edu/HORC/Research_files/EMG.mp4.

Table 2. LEAVE ONE OUT VALIDATION RESULTS

| Subject # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Mean | SD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Overall Accuracy (%) | 79 | 83 | 77 | 82 | 85 | 69 | 80 | 91 | 72 | 73 | 79 | 6.6 |
| Grasp Sensitivity (%) | 73 | 42 | 97 | 77 | 44 | 9 | 29 | 86 | 85 | 92 | 63 | 30.1 |
| Grasp Specificity (%) | 99 | 100 | 99 | 94 | 100 | 100 | 99 | 100 | 94 | 98 | 98 | 2.4 |
| Extension Sensitivity (%) | 94 | 80 | 93 | 36 | 99 | 0 | 36 | 98 | 9 | 90 | 63 | 39.0 |
| Extension Specificity (%) | 93 | 99 | 99 | 100 | 91 | 100 | 100 | 98 | 98 | 100 | 98 | 3.1 |
| Flexion Sensitivity (%) | 78 | 94 | 17 | 43 | 87 | 17 | 85 | 91 | 94 | 23 | 63 | 33.7 |
| Flexion Specificity (%) | 100 | 99 | 100 | 98 | 100 | 100 | 94 | 100 | 97 | 100 | 99 | 1.9 |
| Pronation Sensitivity (%) | 61 | 92 | 86 | 96 | 87 | 89 | 84 | 77 | 36 | 97 | 81 | 18.9 |
| Pronation Specificity (%) | 100 | 100 | 96 | 99 | 100 | 95 | 100 | 100 | 100 | 94 | 98 | 2.3 |
| Index Sensitivity (%) | 79 | 97 | 36 | 74 | 99 | 13 | 65 | 89 | 0 | 46 | 60 | 34.9 |
| Index Specificity (%) | 92 | 89 | 87 | 99 | 95 | 100 | 97 | 98 | 93 | 98 | 95 | 4.4 |

## CONCLUSION

This paper introduced a method for classifying EMG signals from several forearm muscles into five distinct hand motions. The main novelty of the study lies on the fact that the classifier generalizes across subjects, performing accurately without any necessary individualized training phase for a particular subject. The classifier achieves an overall accuracy of $79 \pm 6.6\%$, with sensitivity and specificity averaging 66% and 97.6%, respectively, over all classified motions when testing on subjects that were not included in the training phase of the algorithm. The high specificity and overall accuracy demonstrate the robustness of the algorithm to generalize to a larger population. These results present opportunities for large-scale studies with EMG processing, leading to broader accessibility to EMG driven applications for the general population.

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