From One to Many Users and Contexts: A Classifier for Hand and Arm Gestures

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ABSTRACT
On-body interaction techniques are gaining traction, and opening up new avenues to control interactive systems. At the same time, they reveal potential to increase the accessibility of systems like touch based smartphones and other mobile devices for visually impaired users. However, for this potential to be realised, it is paramount that these techniques can be used in a multitude of contextual settings, and, ideally, do not impose training and calibration procedures. Our approach intends to optimize signal filtering, feature extraction parameters and classifier configurations for each defined gesture. The results show a 98.35% accuracy for the optimized classifier. We proceeded to conduct a validation study (15 participants) in three contexts: seated, standing and walking. Our findings show that, despite the gesture being trained by someone not participating in the study, the average accuracy was 94.67%. We also concluded that, while walking, false positives can impact its usefulness.

Author Keywords
Gesture recognition; surface electromyography; hand and arm gestures; machine learning; user studies.

ACM Classification Keywords
H5.2. Information interfaces and presentation: Input devices and strategies (e.g., mouse, touchscreen).

INTRODUCTION
Input interaction on mobile devices has been traditionally limited to touch and gestures made directly on the touchscreen or a physical keyboard. While this is not an issue for most people, those that have visual or motor impairments, suffer from limited interaction possibilities with these devices. Recent technological advances and research projects in input sensing have opened up new possibilities for using our body as an interaction platform. These solutions may directly use the skin and body as a means of interaction [10, 16, 23] or understand inputs from arm and forearm gestures: WristFlex [8] makes use of pressure sensors to detect pulse gestures; the Intimate Communication Armband developed by Constanza et al. [6] use surface electromyography (sEMG) signals to capture subtle gestures. However, one aspect that has been neglected so far is how it can improve accessibility.

Our aim is to understand how skin and gesture interaction enabling technologies could improve the accessibility of mobile interfaces for users with different levels of visual impairments. The requirements for such a solution comprise technical and social dimensions. For the latter, the solution must be socially acceptable [28] (e.g. no bulky devices that place the user in awkward situations). For the former, the solution should work equally well in different operating contexts (e.g. sitting, standing or walking) and do not require its user to execute complex training procedures. One possible answer is an sEMG based gesture recognizer. The main benefit of relying on a sEMG solution is that, by being based on muscle activation sensing, it requires a single limb. This means users always have a free limb to do other tasks (this might mean a free hand to hold the cane or a mobile phone). Furthermore, both hands can be free, since muscle activation is not dependent on hand or finger gestures. It is also a vision free activity. Moreover, it does not prevent sensing more fine grained activities, like pinching movements as presented in [26].

sEMG technology, similarly to other solutions, implies several variables that must be taken into account, such as what filters to apply to the raw signal, what sampling window size and overlap, and features to be extracted. The quality of gestural recognition also depends on the classifiers used. All these variables affect the reliability and robustness of gesture recognition. By optimizing their configuration we obtain the best classifier accuracy and therefore improve recognition rates. Through a brute-force approach, over five hundred thousand configurations were tested in training six different classifiers. The result is the configuration with highest accuracy for each classifier, which enables us to have a per-gesture classifier feeding of the sEMG stream. For a wrist bend gesture, we obtained a classifier with an accuracy of 98.35% on a ten-fold cross validation of the data. On a user study, this classifier performed reliably across different users and achieved an accuracy of 94.67%.

In the remainder of the paper we review projects using sEMG technology to recognize arm and forearm gestures. This is followed by a description of our methodology and prototype. To validate the prototype, user trials were held and are

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described in the Validation Study section. The last section presents the conclusions and the planned future work.

RELATED WORK

Mobile devices' small size and the lack of tactile feedback of touch devices, limits the interaction space which raises accessibility issues especially for visually impaired users. Possibilities to overcome these limitations include: using the surface as a gestural finger input canvas [9]; voice input [17], widely used by visually impaired, but with limited usefulness due to acoustically unpredictable environments, and privacy issues on public spaces; wearable computing [15, 22]. Bio-sensing devices capturing biological signals for input have also been explored, including: heart rate measured by electrocardiographic signals (ECG) [21], galvanic skin response [20], brain activity through electroencephalographic signals (EEG) [18, 1] and eye tracking [12]. More recent approaches are Skinput [10] and PUB [16], which use bio-acoustics and ultrasonic signals respectively, to locate finger taps on body. However, some of these signals are subconsciously driven or involuntary and therefore cannot be controlled with precision and accuracy, while others require high levels of focus and training.

Recognition of gestures using sEMG sensors

Sensing muscle activation [25] also suffers from the aforementioned problems. As Phinyomark et al. state, *Electromyography (EMG) signals have the properties of nonstationary, nonlinear, complexity, and large variation* [24]. However, despite the difficulty in analyzing such signals, sEMG technology has the advantages of being relatively inexpensive and non-intrusive as it makes use of surface electrodes placed on the skin to capture the electrical voltage activity of skeletal muscles. Muscle Computer Interaction (MCI) is already used in a variety of areas from entertainment, industry, to medicine. Examples range from controlling limb prostheses [11], robots [3], diagnosing muscle and nerve diseases [30] to playing games [32]. Our contribution is similar to what Kratzet al. [14] did with accelerometers and gyroscopes, in order to remove the necessity of per-user training of the recognizer, a limitation seen in other works such as [26, 27, 4]. Simultaneously, we achieve better accuracy levels using less hardware. Moreover, we assessed the classifier's performance in three different contexts.

Pattern and Features Extraction

To recognize gestures from sEMG signals there are two important steps: 1) capturing the signal's features; 2) using classifiers to find patterns or using statistical criterion [31]. Phinyomark et al. [24] studied a set of 19 different features. Based on Euclidian distance and standard deviation they concluded that the combined Root Mean Square (RMS), Willinson Amplitude (WAMP) and Waveform length (WL) features are a good set for gestural classification. In their approach, Kim et al. [13] used a different set of features: statistical data such as maximum, minimum and variance values, combined with fundamental frequency ($F0$) and Fourier Variance of the spectrum, and also gestural particular features such as zero-crosses. In their study, Saponas et al. [25] used RMS, Phase Coherence and Frequency Energy features.

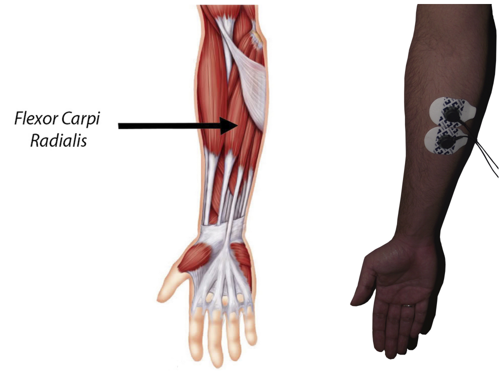

Figure 1. Forearm muscles and sEMG electrodes placement.

Classifiers

Classifiers are an approach used to find patterns and classify, in this particular case, gestures based on the features collected from the signal waveform. The results and performance of these classifiers depend greatly on the characteristics of the data to be classified. There are several types of classifiers: linear (e.g. Naive Bayes), tree based (e.g. Random Tree, Random Forest), rule based (e.g. Decision Table, M5 Rules), function based (e.g. MLP, SVM) amongst others.

Kim et al. [13] uses two simple yet fast classifiers combined in a decision level tree: the K-Nearest Neighbor (K-NN) and the Bayes classifier. Saponas et al. [25] decided for a Support Vector Machine (SVM) algorithm stating that it has a good performance as well. These are examples of supervised classifiers, similar to what we employ in our approach.

BUILDING A sEMG BASED GESTURE RECOGNIZER

Our goal is to build a system that encompasses subtle and non-intrusive technology that allows on-body interaction on mobile contexts. We opted to use sEMG sensors to accomplish these objectives. To enable subtle gestures, sensor's electrodes are placed on the arm's Wrist Flexors Muscle, more specifically on the Flexor Carpi Radialis muscle (Figure 1). This setup gathers signals resulting from forearm and hand gestures with minimal hardware usage as only one sensor is needed. In this section we detail our approach for the development of the sEMG based gesture recognizer.

EMG Hardware

We have used a *Shimmer2r* EMG mounted with a MSP 430 microcontroller (8mHz, 16Bit), with a frequency range of 5Hz to 322Hz and a maximum signal range of 4.4mV. Three electrodes (positive, negative and ground) are used to capture the sEMG data. Communication with the mobile device where the classification takes place is made through Bluetooth-RN42, with maximum range of 10m.

EMG data filtering

The sEMG signal is often contaminated with various noise components which misleads the interpretation of the muscle's activity. To increase the signal's quality, the solution is to eliminate the maximum noise possible without affecting too much the frequency of the muscle's activity signal. This means applying filters in the low and high end frequencies of the signal. An analysis by De Luca et al. [7] established that a Butterworth filter with a corner frequency of 20Hz is recommended for a general use of sEMG signals in order to eliminate the noise artifacts. Although consistent with some works, values differ in several other studies. Merletti [19] suggests a High-pass corner frequency cut of 5Hz while Winter et al. [29] refers 10Hz as the ideal value. As there is not a consensus for these parameters, we opted to test several filters (High-pass, Low-pass, Band-stop) and frequency cut values (1Hz-5Hz and 20Hz for HP, 6Hz for LP and 49-52Hz and 59-62Hz for BS).

Extracting data features

The sEMG features used in our approach were based on the Phinyomark et al. [24] study. Therefore we used the following features: WL (Equation 1), RMS (Equation 2) and WAMP (Equation 3). As the authors state, WAMP registers the number of times the signal's amplitude change surpasses a predefined threshold, which is used to reduce background noise. The suitable value for the threshold is between 10 and 100mV so we decided also to test the suggested range of values for the threshold with increments of 1mV.

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{1}$$

$$RMS = \sqrt{(1/N) \sum_{i=1}^{N} x_i^2} \tag{2}$$

$$\begin{gathered} WAMP = \sum_{i=1}^{N-1} f\left(|x_i - x_{i+1}|\right) \\ f\left(x\right) = \begin{cases} 1, & if x \geq threshold \\ 0, & otherwise \end{cases} \end{gathered} \tag{3}$$

The sample frequency was set to 512Hz. The sampling window size (from 400 to 1200 samples, increments of 100) and overlap (from 25% to 95%, increments of 1%) were also tested in order to obtain the optimized values.

Classifiers' training process

We opted to train several supervised classifiers. Besides Bayes based algorithms and SVM classifiers referenced in other projects, we decided to analyze others, not necessarily faster but possibly more accurate. Therefore we considered a total of six classifiers: 1) Naive Bayes; 2) Bayes Net; 3) SVM; 4) J48; 5) Random Tree; and 6) Random Forest. The classifiers were trained using Weka, a data mining toolkit, API version 3.6 [5]. Accuracy was computed using 10-fold cross-validation.

To train the classifiers, we recruited an healthy male subject of 26 years, with 171cm height and 65Kgs of weight. We asked the subject to perform 60 repetitions of wrist flexion intercalated with 60 pauses while in a sitting position. These two muscle movements (flexion and relaxation) were classified by a human supervisor while observing the subject. The mobile application used to record the gestures automatically saved the sEMG raw data and its classification to a file.

Optimized configuration

Classifiers were trained on a desktop computer, due to the performance requirements of the followed brute force approach. The following steps were applied: 1) The collected data is processed with one of the possible filters and cut-off frequencies. 2) Data is sampled with one possible combination of window size and overlap. 3) Features for each sampled window are computed. 4) Features are converted from numeric to nominal, through a 10 interval unsupervised attribute discretization filter. 5) The accuracy computed over a 10-fold cross-validation, together with the parameter values of the tested configuration are recorded. The process was repeated for every combination of parameter values.

In total 517,563 combinations were used for training. The best configuration achieved the following accuracy: 91.74% for Naive Bayes, 94.21% for Bayes Net and 98.35% for the other four classifiers. This configuration corresponds to a second order Butterworth filter with High-pass corner frequency of 20Hz, with a sampling window size of 1000 samples and 30% overlap, with the WAMP threshold set to 23mV.

VALIDATION STUDY

We conducted a user study to assess if the trained classifier: 1) shows a practical accuracy of the same order of the theoretical one; 2) generalizes to other users; and 3) generalizes to other contexts (standing and walking). Given that our configuration produced four classifiers with the same accuracy, we selected one from that group to use in the study: Random Forest.

Setup and procedure

The hardware used in this study was the Shimmer2r sensor and a Samsung Galaxy SII smartphone. An Android application was installed in the smartphone to receive the data stream from the sensor, apply the elicited configuration and classify the signal.

In order to validate our sEMG recognition prototype, we recruited 15 individuals and interviewed them on age and body characteristics. Each participant was instructed on the gesture to perform (flexion of the wrist) and was able to freely try the recognizer to get acquainted with its operation. Afterwards, participants had to perform 3 tasks, in a randomly assigned order. In each task the participant was asked to execute 15 repetitions of the gesture. The tasks differ by the participant's position: 1) sitting; 2) standing-up still; and 3) walking.

Participants

The participant group was composed of 8 males and 7 females, with ages ranging from 23 to 57 years old (average 30). Height ranged from 152cm to 195cm (average 169.5cm). Average weight was 71.2Kg and ranged from 48Kg to 97Kg. All participants were able to perform the gesture without difficulties. No participant had severe visual impairments. Albeit accessibility is the main concern of this work, in this study we wanted to demonstrate that the trained classifier can be generalized among users and usage contexts, without specific accessibility design concerns.

Data analysis

Across the total of 675 collected gestures, the average accuracy of the recognizer was 94.67% ($Min = 82.22\%, Max = 97.78\%, SD = 5\%$). We also registered 107 false positives, where we considered false positives the occasions when the classifier identified a wrist flexion when the participant was relaxing the wrist, or when after a true positive the classifier did not change classification to a relaxed state.

The classifier's accuracy for each of the 3 tasks was as follows: sitting ($M_1 = 95.11\%, SD = 6.41\%$), standing ($M_2 = 91.56\%, SD = 11.94\%$) and walking ($M_3 = 97.33\%, SD = 4.21\%$). In order to check for any significant differences between them, we began by assessing the normality of the data. The results for all tasks showed that the normality was not verified ($p_1 = 0.002; p_2 = 0.001; p_3 = 0.001$). Following this, we conducted a non-parametric Friedman test between the tasks which revealed that there was not a statistically significant difference in accuracy depending on user's position ($X^2(2) = 2.227, p = 0.328$).

Given that the classifier was trained with data from a male, and Arjunan et al. [2] states there are differences in sEMG signals originating from males or females, we wanted to analyze if the participant's gender had any effect on the accuracy ($M_{male} = 94.29\%, SD = 3.6\%; M_{fem} = 95\%, SD = 6.26\%$). Similarly to the previous results the data was not normal ($p_{male} = 0.019; p_{fem} = 0.011$), thus we conducted a non-parametric Mann-Whitney test. The results show that there is no statistically significant difference between genders ($U = 19.5, p = 0.316$).

Finally, we analyze the occurrence of false positives during each task per person ($M_1 = 0.47, SD = 1.13; M_2 = 1.4, S = 1.92; M_3 = 5.27, SD = 3.93$). Given the non-normality of the data ($p_1 < 0.001; p_2 = 0.001; p_3 = 0.209$), we used the non-parametric Friedman test and found a statistically significant difference between false positives detected in different positions ($X^2(2) = 15.362, p < 0.001$). We proceeded with a Post-Hoc test in order to analyze the different combinations. A Wilcoxon test revealed that the false positives detected on task 3 (walking) in comparison with task 2 (standing) and 1 (sitting) were significantly higher ($Z_{3-2} = -2.906, p_{3-2} = 0.004; Z_{3-1} = -3.066, p_{3-1} = 0.002$). On the other hand, there was no significant difference between tasks 1 and 2 ($Z_{2-1} = -1.691, p_{2-1} = 0.091$).

The same analysis was done comparing gender ($M_{male} = 5.13, SD = 4.32; M_{fem} = 9.43, SD = 4.76$). The data was shown to be normalized ($p_{male} = 0.484; p_{fem} = 0.437$), therefore an unpaired t test was conducted. This study found that the gender does not affect significantly the number of false positives ($t(13) = -1.836, p = 0.089$).

Discussion

Regarding the overall performance of this recognizer, results show that its accuracy on a practical setting is in the same order of the theoretical results, albeit not as good as could be expected. Furthermore, results show that, even though the classifier was trained by someone not participating in the study, it performed accurately when used by the participants in the validation study. This indicates that an sEMG based gesture classifier is capable of generalizing among users, which can be very important for users with impairments.

Moreover, despite the classifier being trained with data collected only in a sitting position, results show that accuracy rates are not affected by the different positions assessed. This is another indication that sEMG based classifiers have the ability to generalize to different contexts of use, which is very relevant for the envisioned mobile usage scenarios.

However, false positives are still a concern. We found that, while walking, the classifier was more prone to recognize a gesture even though the participant was just naturally moving the arm to walk. This happened, on average, more than five times per user during the walking task. We observed that the large majority of these false positives happened right after the participant performed a gesture, with the recognizer not transitioning from the flexion state back to the relaxed state. To trigger this transition we had to ask the participants to briefly stop walking. Only a residual (less than 1%) part of the false positives occurred with the participant's wrist relaxed and the classifier recognizing the execution of a gesture.

CONCLUSION

In this paper we addressed the issue of using minimal technological apparatus, in order to foster social acceptance, for subtle hand and arm gesture recognition. The availability of recognition technology that does not require the use of vision for input, and that is capable to address the requirements for social acceptance (by avoiding the use of speech in public places, the need to perform unsubtle movements, or even having to reach for or hold a device, for example) is bound to increase the accessibility in diverse contexts of use for every person, and in particular for the visually-impaired. In its current state this system is capable of addressing simple scenarios, like being used to subtly and in an easy way turn down a call or accept it.

Furthermore, our approach proves, for a gesture with characteristics similar to what was used, that a classifier can be trained with one person and be used by several other persons without affecting accuracy significantly. Moreover, we could verify that even though training was performed in the seated position, the recognizer worked both in standing and walking contexts.

In the future we plan to address some limitations of this solution and study. We will train classifiers and conduct user studies with more gestures comprising finger, wrist and arm movements. We will focus on measures to avoid false positives to increase the efficacy of the recognizer in all contexts. And even though the sEMG based solution can be fairly easily deployed (e.g. embedding the sensors in an armband), we wish to explore other technical possibilities that are becoming increasingly available, like wearables (e.g. smartwatches or fitness wrist bands). This implies working with different signals (e.g. accelerometer), and looking for other features, in order to evaluate if the proposed approach still holds.

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