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Recognition of facial movements and hand gestures using surface Electromyogram(sEMG) for HCI based applications

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Abstract

This research reports the recognition of facial movements during unvoiced speech and the identification of hand gestures using surface Electromyogram (sEMG). The paper proposes two different methods for identifying facial movements and hand gestures, which can be useful for providing simple commands and control to computer, an important application of HCI. Experimental results demonstrate that the features of sEMG recordings are suitable for characterising the muscle activation during unvoiced speech and subtle gestures. The scatter plots from the two methods demonstrate the separation of data for each corresponding vowel and each hand gesture. The results indicate that there is small inter-experimental variation but there are large inter-subject variations. This inter-subject variation may be attributable to anatomical differences and different speed and style of speaking for the different subjects. The proposed system provides better results when is trained and tested by individual user. The possible applications of this research include giving simple commands to computer for disabled, developing prosthetic hands, use of classifying sEMG for HCI based systems.

1. Introduction

With the increase in need of more robust applications in computer - human interaction, research and development of new techniques that enhance the flexibility and reliability for the user are important. Human-computer interaction requires the design, and implementation of interactive computing systems for human use. Research on new methods of computer control has focused on various types of body functions like speech, hand gestures, bioelectrical activity, facial expressions, etc. This research paper examines the use of the bio-signals like Electromyogram (sEMG) in

applications of HCI. In this paper, the authors present two methods - one for identification of unvoiced vowels during speech and other for identification of subtle hand gestures. Both these methods use recorded surface Electromyogram (sEMG) as the input signal to the system.

Surface Electromyogram (sEMG) is a surface recording of the underlying muscle activity. The strength of sEMG is a good measure of the strength of contraction of the muscle, and can be related to the movement and posture of the corresponding part of the body. SEMG reflects functional state of muscle fibres[1]. This muscle activity recorded using sEMG can be useful as a input signal to the system which can control the devices such as keyboard, mouse of a computer. Such systems utilise a natural ability of the human user, and therefore have the potential for making computer control effortless and natural.

In recent years, significant progress has been made in gesture recognition technology. Identification of gestures from hand, face(speech), body is an effective modality in multimodal human-machine interaction. The use of hand gestures and speech recognition systems provides an attractive alternative to cumbersome interface devices for human-computer interaction (HCI). The identification of speech by evaluating lip movements can be achieved using visual sensing, or tracking the movement and shape using mechanical sensors [4], or by relating the movement and shape to facial muscle activity [2, 3]. Each of these techniques has strengths and limitations. This research reports identification of silent vowel-based verbal commands without the need to sense the voice sound output of the speaker using sEMG.

The paper also reports the recognition of subtle hand gestures using muscle activity from forearm. Human hand gestures are basically a mean of non-verbal interaction among people. These gestures can be simple actions of pointing at objects and can be more complex actions that express our feelings and communicate with others [14]. A novel appli-

cation for dynamic computer control using gesture recognition based on EMG has been reported in [15]. A lot of progress has been done on evaluating these gestures for controlling machines, developing prosthetic hands for disabled and for applications in HCI. The important applications of gesture recognition are manipulative like controlling machines and communicative like sign language recognition.

This research paper examines and reports the results on the use of surface Electromyogram in identifying the unvoiced speech and hand gestures for applications in controlling the computers. In this paper, the authors have demonstrated the use of multi-channel surface electromyogram (sEMG) for applications in HCI in two methods - one method is to identify the unspoken vowel based on the normalized integral values of facial EMG during the utterance, and this construction had been tested with English speakers and in other method, the authors report using fractal properties of the sEMG signal from different recordings as features to study the model of sEMG for identification of different hand gestures.

2. Theory

The aim of this research is to identify the facial muscle activity during speech and also to identify subtle hand gestures using the recorded sEMG for giving simple commands and control to the computer. For this work, the first step is to determine the role of facial muscles and hand muscles in production of simple control. In order to identify the muscle activity for the corresponding speech and gesture, the study on sEMG is performed.

2.1. Surface Electromyogram (sEMG)

Surface Electromyogram (sEMG) is the non-invasive recording of the muscle activity. It can be recorded from the surface using electrodes that are stuck to the skin and located close to the muscle to be studied. Surface electromyogram (sEMG) is a gross indicator of the muscle activity and is used to identify force of muscle contraction, associated movement and posture. SEMG is a complex non-stationary signal. The strength of sEMG is a good measure of the strength of contraction of the muscle, and it can be related to the movement and posture of the corresponding part of the body [1].

2.2. Face movement and muscles related to speech

The facial musculature is a three dimensional assembly of small, pseudo-independently controlled muscular lips performing a variety of complex orofacial functions such as speech, mastication, swallowing and mediation of motion

[6]. When using facial SEMG to determine the shape of lips and mouth, there is the issue of the proper choice of muscles and the corresponding location of the electrodes, and also the difficulty of cross talk due to the overlap between the different muscles. Chan et al.[2] demonstrated the presence of speech information in facial myoelectric signals using an SEMG based system. Kumar et al.[3] have demonstrated the use of SEMG to identify unspoken sounds under controlled conditions. Root Mean Square (RMS) of SEMG is related to the number of active muscle fibers and the rate of activation, and is a good measure of the strength of the muscle activation. Applying integral RMS of SEMG is useful in overcoming the issues of cross talk and the temporal difference between the activation of the different muscles that may be close to one set of electrodes. With the variation in speed and pronunciation of speaking, and the length of each sound, it is difficult to determine an appropriate window in time domain for best signal analysis. When the properties of the signal are time varying, identifying suitable features for classification will be less robust. Since it is impractical to consider the entire facial muscles and record their electrical activity, only the following four facial muscles have been selected in this study: *Zygomaticus Major*, *Depressor anguli oris*, *Masseter* and *Mentalis* [5] as shown in Fig.1.

Figure 1. Location of different facial muscles
[Source:[6]]

2.3. Use of Fractal properties on sEMG for hand gesture identification

Many natural objects exhibit the property that as one views the object at greater manifestations, more and more similar structures are revealed. Fractals exhibit this self-similar property[13]. The source of sEMG is a set of similar action potentials originating from different locations in the muscles. Because of the self - similarity of the action potentials that are the source of the sEMG recordings over a range of scales, SEMG is expected to have fractals properties.

Fractal dimension (FD) is a measure of the fractal properties of any structure. Biosignals such as sEMG are a result of the summation of identical motor units that travel through tissues and undergo spectral and magnitude compression. Anmuth et al.[9] determined that fractal dimension was linearly related to the activation of the muscle measured as a fraction of maximum voluntary contraction. They also observed a linear relationship between the fractal dimension and the flexion-extension speeds and load. Hu et al.[10] distinguished two different patterns of hand movements from forearm using fractal dimensions of sEMG signals.

Fractal dimension is a measure of the source properties and hence the authors propose to use it as a measure of the overall muscle properties. The fractal dimension is estimated by measuring the change in the length of the curve with the change in the measurement scale. An obvious application of these properties of sEMG is the identification of small changes in muscle activity in the presence of multiple active muscles. This paper reports experiments conducted to use the features - Fractal dimension (FD) and Maximum Fractal Length (MFL) of sEMG recorded from the forearm to identify simple hand and wrist gestures. For this experiment, four following different muscles from forearm which are responsible for wrist and finger gestures [11] were considered : *Brachioradialis Flexor Carpi radialis (FCR)*, *Flexor Carpi Ulnaris (FCU)*, *Flexor digitorum superficialis (FDS)*.

3. SEMG Recording and Experiments

Experiments were conducted to evaluate the use of sEMG in HCI applications by identifying unvoiced vowel from facial muscle activity and by identifying subtle hand gestures from forearm muscle activity. The experiments were approved by the Human Experiments Ethics Committee of the University.

3.1. Experiment 1

In experiment 1, participants were asked to speak while their sEMGs were recorded. The sEMG recordings from four channels were visually observed, and all recordings with any artefacts - typically due to loose electrodes or movement - were discarded. During these recordings, the participants spoke three selected English vowels (/a/, /i/, /u/). Each vowel was spoken separately such that there was a clear start and end of its utterance. The experiment was repeated ten times. A suitable resting time was granted to the speakers between each experiment. The participants were asked to vary their speaking speed and style to obtain a wide training set.

3.2. Experiment 2

In experiment 2, participants with no history of myo or neuro-pathology were chosen for experiments. The following four different hand gestures were used as protocol to record sEMG from the participants: *Wrist flexion*, *Index and Middle finger Flexion*, *Wrist flexion (towards little finger in horizontal plane)*, *all finger flexion*. Each gesture was repeated during a period of 120 seconds. A suitable resting period of 20 seconds was given during each gesture.

4. Data Analysis

The recorded sEMG data was used for further analysis for identification of corresponding vowel and hand gestures in two different methods.

4.1. Method One: Identification of Unvoiced vowels using sEMG recordings

In method one, the identification of unvoiced vowels using features of sEMG was performed. The first step in this analysis was to identify the temporal location of the muscle activity. Moving root mean square (MRMS) of the recorded signal with a threshold of 1 sigma of the signal was applied for windowing and identifying the start and the end of the active period. A Window size of 20 samples corresponding to 10 ms was used for computing the MRMS.

The start and the end of the muscle activity were also confirmed visually. The next step was to parameterise the SEMG for classification of the data. MRMS values of SEMG between the start and the end of the muscle activity was integrated for each of the channels. This provided a four long vector corresponding to the overall activity of the four channels for each vowel utterance. This data was normalised by computing a ratio of integrated MRMS of each channel with respect to channel number one. This ratio is indicative for the relative strength of contraction of the different muscles and reduces the impact of inter-experimental variations. The outcome of this step was a vector of length three corresponding to each utterance. Fig.2 is an example of the computation of the integral of RMS of SEMG. For computing the integral of RMS of SEMG, Durand's rule [7] was used, because it produces approximations that are more accurate, since these represent a straightforward family of numerical integration techniques. Three dimensional scatter plot between the three normalised integral MRMS values of muscles was performed to determine the separation of data clusters for each corresponding vowel.

Figure 2. Example of the computation of the IRMS of sEMG

4.2. Method Two: Identification of hand gestures using sEMG recordings

In method two, the identification of hand gestures using fractal features of sEMG was performed. As a first step of data analysis, fractal dimension and maximum fractal length for sEMG recordings of hand gestures, were computed. These features were analyzed in relation to the level of muscle activity and its activity pattern with respect to the muscle anatomy. The performance of the feature set for classification against the corresponding hand gestures. At the second instance, the fractal property of recorded sEMG signal was analyzed by determining fractal dimension. Fractal dimension was calculated using the procedure reported by Higuchi [8] for irregular time series. This procedure yields a more accurate estimation of fractal dimension [12].

- Defining the length of the curve, X_k^m , as in (1)

$$L_m(k) = \frac{\left(\sum_{i=1}^{\lfloor \frac{N-m}{k} \rfloor} |X(m+ik) - X(m+(i-1).k)| \right) \cdot \frac{N-1}{\lfloor \frac{N-m}{k} \rfloor \cdot k}}{k} \quad (1)$$

The length of the curve for the time interval k , $\langle L(k) \rangle$ is defined as the average value over k sets of $L_m(k)$. If $\langle L(k) \rangle \propto k^{-D}$, then the curve is fractal with the dimension - D.

From the logarithmic plot, the MFL i.e., the maximum fractal length of the curve at the lower scale which represents the originating data point for the each sEMG signal for the respective hand motions was determined. This MFL represents the level of muscle activity for the particular gestures. The logarithmic plot of the modified sEMG signal for each of the four channels for all hand gestures was plotted. Each individual plot contains the curve for four channels for the each of the hand gesture. An example of this plot

Figure 3. Example of Logarithmic plot of the curve length $\langle L(k) \rangle$ and k for the four channel recorded sEMG signal during Wrist flexion hand gesture

is shown in Fig.3. This gives different pattern of muscle activation for different gestures. The MFL and Fractal dimension for each sEMG Channel was determined from the logarithmic plot and tabulated. The feature set of fractal dimension and maximum fractal length was used for classification. To identify the formation of data clusters for corresponding hand gesture, scatter plot was performed.

5. Results and Observations

The results of the experiment was analysed for its inter-experimental and inter-subject variations. This analysis shows that there is very minimal inter-experimental variations but large inter-subject variations. The results also suggest the proposed methods demonstrate that sEMG can be a source of input to interface between human and computer.

5.1. Method One: Identification of Unvoiced vowels using sEMG recordings

The experimental results from the method one, report the performance of individual subject and different subjects in identifying the integral RMS values of the three selected vowels. The linear separation of normalised IRMS values of different vowels was tested using three dimensional plot. Fig.4 shows the three-dimensional plot between the normalized areas of the different muscles for different vowels. In this plot, the different vowels yield clusters, which are clearly separated from each other. It appears evident from the plot that three different class of vowels form clusters that appear to be separate and distinct for each of the vowels. This is a clear indication that the three vowels are easy

to separate using this technique. There is large inter-subject variation when the plot for all subjects are made, this may be due to the different speed and style of speaking between different subjects.

Figure 4. 3-D plot of normalised IRMS values from single subject

5.2. Method Two: Identification of hand gestures using sEMG recordings

In method two, the feature set from the four hand gestures were used to classify the gestures with respect to the muscle activity pattern. The logarithmic plot for the four different hand gestures was performed as shown in Fig.3. Each sEMG from the different channel for a particular hand gesture has a particular pattern with respect to the level of the muscle activity.

The experimental results were analyzed to determine the inter-subject and intra-subject variations. The fractal dimension for different sEMG signal varied between 1.95 and 2. The MFL for each Channel for different hand actions was considered along with fractal dimension for identification of hand actions. The two-dimensional scatter plots between the FD and the MFL of EMG recordings during different hand motions for single subject is shown in Fig.5.

From Fig.5, it is observed that there are different patterns for different EMG channels for a single subject. There are clear clusters formed for each of the gestures and for all the four channels. The relationship for each channel appears to be unique for each hand motion. This is attributable to the variation in the level of muscle activity for different hand actions that is represented by the MFL. The data points from each channel form visually different clusters with distinct separation from other clusters. This demonstrates that the

data points are easily separable when used for further classification. It is observed that pattern for different subjects

Figure 5. Scatter plot of different Channels between FD and MFL of sEMG data recorded from single subject

(inter-subject variation) are very varied. The scatter plot does not demonstrate formation. This is due to the variation in the MFL which varies with the variation in the level of the muscle activity.

6. Discussion and Conclusion

The results indicate that the proposed methods provide better results for recognising silently spoken vowels by measuring the movements of facial muscles and for identifying simple wrist and finger gestures by evaluating the muscle activity from forearm. The separation of data points corresponding to each vowel is high when it is tested for a dedicated user. The separation is poor when the plot is made for all subjects. This shows the large variations between subjects (inter-subject variation) because of different style and speed of speaking. This method has only been tested for limited vowels, because the muscle contraction during the utterance of vowels remains stationary. The promising results obtained in the experiment indicate that this approach based on the facial muscles movement represents a suitable, reliable method for classifying vowels of single user without regard to the speaking speed and style in different times.

This paper also has tested the efficacy of MFL and fractal dimension to identify the pattern of sEMG activity corresponding to each hand gesture. The scatter plot demonstrates the presence of clusters corresponding to each action. The results also demonstrate the inter-subject variations

which may be attributable to the differences in anatomy of different subjects. The results also demonstrate the relative small inter-experimental variations.

Applications of these methods include developing more robust model of sEMG for machine control, unvoiced control for speech-impaired, developing prosthetic hands and identifying muscle activity for applications in Human Computer Interface.

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