

Facial Expression Recognition through Pattern Analysis of Facial Muscle Movements Utilizing Electromyogram Sensors

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Abstract

Emotion recognition is one of the important highlights of human emotional intelligence and has long been studied to be incorporated with machine intelligence argued to make machines even more intelligent. This paper aims to contribute to this field of study by enabling machines to recognize emotion from facial Electromyogram (EMG) signals. This includes a compilation of the groups attempt to recognize basic facial expressions namely happy, angry, and sad through the use of EMG signals from facial muscles. The group extracted features from the three EMG signals from the face of two human subjects, a male and a female, and analyzed these features to serve as feature templates. Using a minimum-distance classifier, recognition rates exceeded the target accuracy – 85 percent - reaching 94.44 percent for both the male and female subjects.

Key Words – Affective Computing, Electromyogram, Minimum-Distance Classifier, Pattern Recognition

1. Introduction

Affective computing is computing that relates to, arises from, or deliberately influences emotions. It focuses on creating personal computational systems endowed with the ability to sense, recognize and understand human emotions, together with the skills to respond in an intelligent, sensitive, and respectful manner toward the user and his/her emotions [1]. The success of computer emotion recognition will further raise the level of man-machine interactions, making it more effective and consequently, more advantageous to humans.

Facial muscle movements correspond to a certain facial expression. Since facial expressions are the most visual

representation of a person's emotional state, it must not be disregarded if computers are to recognize emotions accurately. Thus, for computers to recognize emotions, it must be able to monitor facial muscle movements.

2. Design Considerations

Emotion, as people understand it, is expressed in the mind (cognitive emotion) and in action (physical emotion). The group only intended to explore the physical aspect of emotion so the group observed the patterns of physical activity whenever one expressed an emotion. After meticulous scrutiny, it was concluded that facial muscles such as the masseter, corrugator supercilli, and levator labii superioris were the ones most blatant in terms of contraction for the intended emotions to be recognized.

The corrugator muscle is one of the most important expressive muscles. Some suggest that this is the muscle of grief and suffering while the masseter is one of the most powerful muscles and is associated with angry and aggressive states [2].

2.1 Data Acquisition System

The group's device for instrumentation is separated into two parts. The first part is an instrumentation circuit primarily composed of 3 instrumentation amplifiers and 3 pairs of EMG electrodes and the second part is basically a signal conditioning circuit composed of a multiplexer, high-pass filter, amplifier and a low-pass filter.

The group used Nicolet EMG Surface Electrodes as the sensors to detect facial muscle movements. The AD620 was used as the instrumentation amplifier to provide the

necessary rejections for common interferences present in the electrodes.

The signal conditioning circuit is basically comprised of devices that will properly make the signal suitable for further processing and interpretation. An analog multiplexer (CD4051) was utilized to alternately switch the 3 EMG signals from the instrumentation circuit for further processing in the signal conditioning circuit. The parallel port (DB-25) was used to control the analog multiplexer to determine which EMG signal input is to be processed first using MATLAB 6.5.

2.2 Software

The entire software consists of three parts: Initialization, System Training, and Pattern Recognition.

Before the EMG signals can be acquired, the analog input and parallel port device objects must first be initialized. Initialization of the analog input object involves setting the sample rate, sampling triggers and the acquisition duration while the parallel port object initialization implicates setting the parallel port lines as outputs for control of the analog multiplexer. For the sampling rate, a 5 kHz sampling rate was used for acquiring the EMG signals. For the sample triggers, a 0.5 second trigger delay time was necessary to eliminate the in-between signal disruptions caused by the switching of the analog multiplexer. And for the data acquisition duration, a 0.25 second acquisition time for each signal proved to be enough for signal analysis and feature extraction.

The second part of software is the system training. The objective of this part of the software is to create a template vector for each of the three classes happy, angry, and sad. System training consists of three functions: the template function, the feature differentiation function, and the feature selection function.

The template function consists of the acquiring of data from the EMG sensors and the algorithms used to compute for the features of the EMG signals. Figure 2.1 shows the block diagram of the template function.

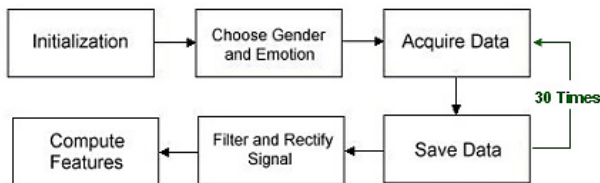


Figure 2.1 Block Diagram of the Template Function

Initialization is first executed, followed by the choosing of the gender and emotion. Once the emotion has been chosen, the subject then portrays that emotion, acquires

data, and then saves the data. This is done thirty times per emotion. Once all the data has been saved, the function then filters all the signals, rectifies them, and then computes for its features. The features include the mean, standard deviation, root mean square (RMS), and the power density spectrum (PDS) of the EMG signal for each muscle, thus producing a total number of 12 features. Figure 2.2 shows the output of the template function. Three emotion vectors are created containing the 12 features.



Figure 2.2 Feature Vectors for Happy, Angry, and Sad

The next function is the feature differentiation. The role of this function is to establish a relationship between the three emotions by comparing the features of one emotion to the others. This is done by computing for the difference of all twelve features between emotions. For example, for the emotions happy and sad, all of the features of happy are subtracted to the corresponding features of sad, mean minus mean, standard deviation minus standard deviation, rms minus rms, and pds minus pds. This is also done for the emotions happy and angry, and the emotions angry and sad. Figure 2.3 displays the output of the feature differentiation function. Three new vectors are generated: one is for the relationship between happy and sad, another is for happy and angry, and another is for angry and sad.

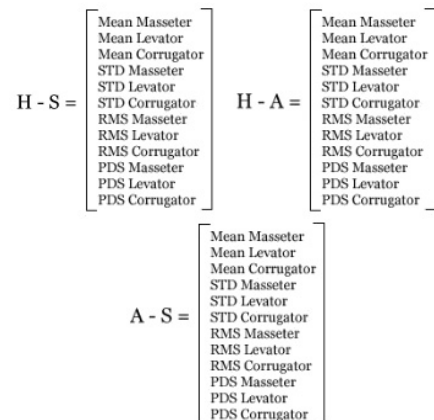


Figure 2.3 Output of Feature Differentiation Function

Finally, a feature selection program that looks for the most distinguishable features out of the twelve resulting from the feature differentiation program is executed. This is done by selecting the feature that has the greatest difference compared to the others. One feature is selected for the relationship of happy-sad, another for happy-angry, and another for angry-sad, resulting in a total of three features. This will serve as the features to be used for the emotion template vectors. Figure 2.4 shows the output of the feature selection program. The three emotion template vectors are generated, with each vector containing the features that were selected by the feature selection function. Feature 1 represents the maximum difference value between happy and sad. Feature 2 represents the maximum difference value between happy and angry. And feature 3 represents the maximum difference value between angry and sad.

$$\begin{aligned} \text{Happy Template Vector} &= \begin{bmatrix} \text{Feature 1} \\ \text{Feature 2} \\ \text{Feature 3} \end{bmatrix} & \text{Angry Template Vector} &= \begin{bmatrix} \text{Feature 1} \\ \text{Feature 2} \\ \text{Feature 3} \end{bmatrix} \\ \text{Sad Template Vector} &= \begin{bmatrix} \text{Feature 1} \\ \text{Feature 2} \\ \text{Feature 3} \end{bmatrix} \end{aligned}$$

Figure 2.4 Emotion Template Vectors

The last part of the software is the pattern recognition. The objective of this part is for the computer to successfully recognize the emotion being portrayed by the subject. It consists of two parts, the construction of the input vector, and the minimum-distance classifier.

In generating an input vector, initialization, choosing of gender, acquiring of data, and the computing of features is again executed. Once the feature computations are completed, an input vector is generated based on the features that were selected earlier in the feature selection program. Figure 2.5 shows the block diagram of the construction of the input vector.

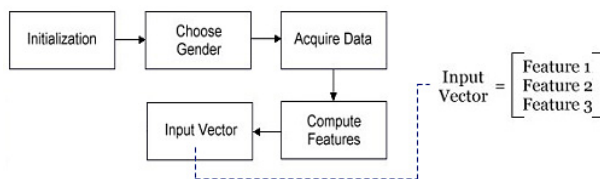


Figure 2.5 Construction of the Input Vector

Finally, a minimum-distance classifier is used for the classification process of the emotions. The function computes for the distance of the input from the happy template, the angry template, and the sad template. The class or emotion which has the least distance value to the input is selected.

3. Experiments and Analysis of Results

Presented in this part are the summary and analyses of the data collected in the prototype experimentation, in the duration of the data gathering phase, and in the facial expression recognition phase of the research.

3.1 Data Gathering and Pattern Recognition

Thirty samples from the different facial muscles were acquired to provide as templates for the pattern classifier. Only three figures showing the graphs of the EMG signals and Power Density Spectrum from the three muscles are shown here per emotion for a human subject. Although the group utilized 3 male and 3 female subjects for its complete data analysis, only the data of a single subject will be shown, and will serve only as a sample, to minimize the abundant data gathered for this research.

“Happy”, “Sad” and “Angry” for this research corresponds to the subject smiling, frowning and expressing an angry look respectively. The group felt the need to let the subjects express their usual facial expressions when they experience the said emotions since a closer resemblance to the natural facial expression is more desirable.

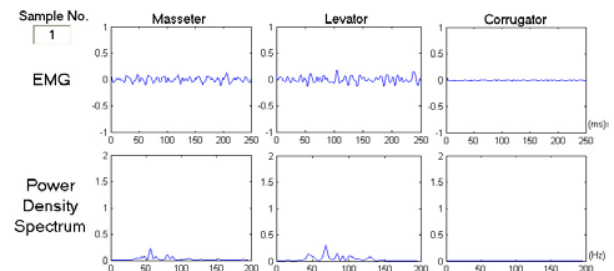


Figure 3.1 Sample EMG signal for a Happy Male

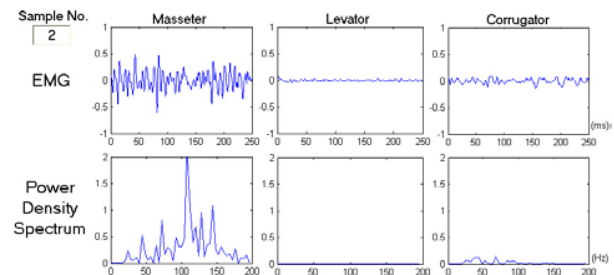


Figure 3.2 Sample EMG signal for an Angry Male

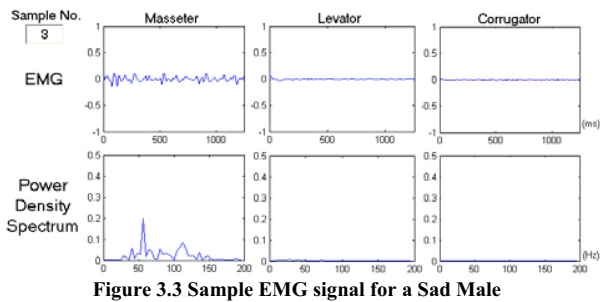


Figure 3.3 Sample EMG signal for a Sad Male

Figure 3.4 shows the 3-dimensional plot for a male subject and will serve as the template to be used for comparison in the facial expression recognition phase. It consists of 3 clusters of data pertaining to a particular emotion. The green +s correspond to happy, the blue Os to sad, and the red Xs to angry.

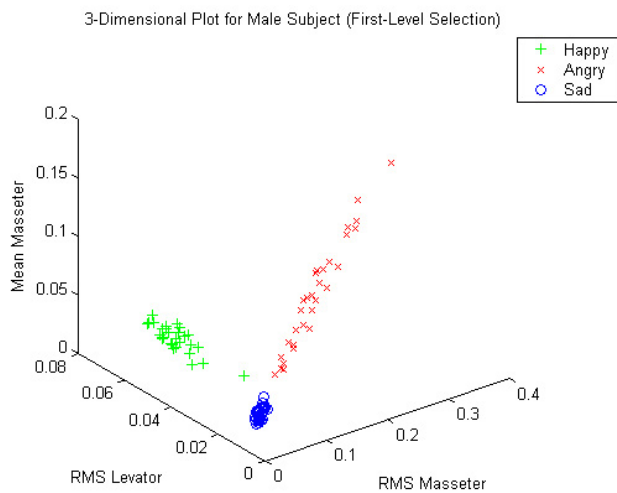


Figure 3.4 3-Dimensional Plot for a Male Subject

For the pattern recognition phase, 90 random inputs were given to a subject. For the male, there were a total of five errors, resulting in a percentage of 94.44%. The accuracy for happy and sad were very high, with percentages of 96.67% and 100% respectively, compared to the angry emotion, which only had a percentage of 86.67%. These may be due to EMG probe placement factors such as electrolytic gel amount and minimal differences in the position of EMG electrodes on the skin since the recognition phase was done in a different day after the data gathering/system training phase. Skin resistance may have also played a factor since it varies daily for a person.

3.2 Pattern Recognition Results of Other Subjects

Additional subjects underwent the same process of data gathering and recognition using the same three facial

muscles. The following shows the results for these subjects.

Table 3.1 Results from Other Subjects

Subject	Accuracy
Male #2	100/100 = 100%
Male #3	76/90 = 84.44%
Female #1	85/90 = 94.44%
Female #2	80/90 = 88.89%
Female #3	85/90 = 94.44%

4. Conclusions

The group was able to establish certain facts that would be useful for the future projects on EMG signal acquisition and processing. The following are conclusions based on the data and results of emotion recognition and EMG electrode application:

1. EMG signals from facial muscles convey information about the emotional state of the human person and the computer can recognize the emotional state provided the emotion conveyed is expressed clearly through facial expression. The target emotions were recognized by using only 3 facial muscles all at a very high accuracy. This proves that emotion recognition is possible through the acquisition of EMG signals from facial muscles.
2. Facial muscles that can be used to gather surface EMG data are only those that lay near the skin surface with considerable flatness and large enough to accommodate two EMG surface electrodes. This is to ensure that the surface electrodes would not lose good contact with the skin when the muscle contracts.
3. Features that best discriminate one emotion from another vary considerably for the different subjects. This strengthens the hypothesis that emotion is person dependent and so are the physiological signals arising from emotional expressions.

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