Online and Offline Anger Detection via Electromyography Analysis

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***Abstract*— Emotional states involving anger, hostility, anxiety and stress have been associated with an increased risk of cardiovascular disease. Online emotion recognition has achieved little attention in the literature in comparison to offline approaches. We present both online and offline methods to identify anger based on EMG data. In the offline method, the Hilbert-Huang transform is used to extract energy features from different time-frequency blocks. This approach achieves an overall classification accuracy of 87.5%. We also develop a novel online method combining machine learning with the tracking of a single parameter for anger detection. Here, band energy is calculated within time windows, and is continuously adjusted based on classified peak amplitudes. Although this technique has a lower classification accuracy than the offline method, it is quite promising as it is well-suited for wearable monitoring and long-term stress management.**

I. Introduction

Cardiovascular disease (CVD) is one of the leading causes of death in the United States. While smoking, high cholesterol levels and diabetes have typically been associated with an increased risk of developing CVD, other psychosocial factors such as anger, hostility, anxiety, stress and social conflict also contribute to elevate CVD risk [1]. Although directly quantifying a person's exact stress level remains challenging, a number of physiological signals including Galvanic skin response (GSR), electroencephalography (EEG), respiration, blood volume pulse (BVP) and the electromyogram (EMG) have been analyzed in studies involving anger and stress identification. In a survey describing sensors and computational techniques for stress classification, Sharma and Gedeon [2] point out how neurofeedback training has been used to help manage stress through gaming. They provide an example where EEG signals measure stress and continually provide feedback to a player so that the person having a lower stress level finally wins. Similar low power, wearable biofeedback monitors utilizing different signals could have far reaching consequences in managing negative emotions and stress, ultimately lowering disease risk. In this research we present two methods to identify anger using EMG data.

Several studies have already investigated the use of EMG signals in emotion or affective state classification. Rad *et al.* [3] conducted an experiment in which signals were recorded from three pairs of electrodes attached to muscles on participants foreheads while they listened to pleasant and irritating music. EMG and EEG signals were separated through filtering and their Shannon entropies were calculated. The authors reported that although statistically significant differences could be observed between the irritated and pleasant states and the baseline, no significant difference was noticeable in the features between the pleasant and irritated states [3]. Qiu *et al.* [4] recorded EMG signals from 408 subjects viewing different video clips. They applied multi-level wavelet decomposition and extracted the mean, median, standard deviation etc. at different levels. Thereafter, correlation analysis and an improved Tabu search were used to select the best features for classification into six emotional states consisting of surprise, joy, disgust, grief, anger and fear. They achieved a true positive rate of 82.65% and a false positive rate of 45.83% in identifying anger. Tan *et al.* [5] conducted a study comprising of 43 subjects who viewed sets of images while EMG from two facial muscles associated with smiling and frowning were recorded. The pictures were meant to elicit five emotional states ranging from low valence and low arousal to high valence and high arousal. After bandpass filtering and noise cancellation, the Hilbert spectrums of the EMG signals were obtained from which instantaneous mean frequency (IMNF) values were derived. Statistical analysis in [5] showed that the IMNFs from the frowning muscle (*corrugator supercilii*) during low valence and high arousal were different to that of all other affective states. IMNFs from the other muscle (*zygomaticus major*) during low valence and low arousal were significantly different to three of the other states. In a similar experiment, Tan *et al.* [6] recorded EMG from the same facial muscles from 108 participants. Again, Hilbert spectrums were obtained and 32-dimensional feature vectors were extracted from the data for subsequent Support Vector Machine (SVM) classification. The features included standard deviation, maximum value, fuzzy entropy, central frequency etc. In [6], classification accuracy ranged from 75.69-90.65% for the five emotional states and was shown to depend on the length of the time window being considered. Anger is considered to be an emotion with negative valence and high arousal and the mean classification accuracy for this particular state in [6] was between 80.69-87.92%.

Zong and Chetouani [7] applied the Hilbert-Huang transform to four different physiological signals recorded from subjects listening to different types of music. The signals included EMG, skin conductance, respiration and the electrocardiogram. The maximum, IMNF, weighted IMNF and rms values were calculated for each Intrinsic Mode Function (IMF) along with a few other statistical measures. The authors used SVMs for classification and reported a maximum accuracy of 76% [7]. Zheng *et al.* [8] recorded EMG signals from the shoulder muscles of 10 subjects while they viewed video clips eliciting disgust, fear, sadness, anger, surprise and happiness. After filtering and wavelet-based noise removal,

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four features were investigated to distinguish between positive and negative emotions. The features included the sum of squares, sum of the absolute values, standard deviation and absolute sum of the first differences. Nearest neighbor classification yielded a maximum accuracy of 70.85% in categorizing negative and positive emotions and 68.58% accuracy in further classifying the negative emotions into stressful and non-stressful categories [8]. Cheng and Liu [9] used EMG data recorded from a single subject while listening to different types of music to identify joy, anger, sadness and pleasure. They applied a six-level wavelet decomposition and extracted the maximum and minimum coefficients at each level. These features were used to train both a neural network and a template matching classifier. They obtained a higher accuracy of 75% overall, and 83.33% for anger alone with the neural network [9]. Gouizi *et al.* [10] used EMG recordings from five subjects to classify fear, sadness and disgust. They too applied six-level decomposition and extracted the maximum and minimum values at each stage. This was supplemented by additional features including the rms value, mean energy and integral. SVMs were used for classification and they reported maximum overall accuracy values ranging from 45.45-81.82% for the different participants [10].

Much of the work cited here utilizes EMG data to simultaneously distinguish a range of emotional states using machine learning. Moreover, most methods are offline and seek to classify the entire signal duration corresponding to a particular emotion. We focus solely on anger identification and propose two methods - one similar to the conventional feature extraction and classification approach, and another technique based on continual parameter tracking more suited to a low power, wearable device.

II. Methodology

A. Data

We selected the Eight-Emotion Sentics Data described in [11]. The dataset was made available by the MIT Affective Computing Group and provides four physiological measurements acquired from a subject during eight emotional states over a period of 20 days. The signals include BVP, EMG, respiration and skin conductance. Here, we only use the EMG signal recorded from the *masseter* (jaw) muscle at a 20 Hz sampling frequency. In the original experiment, the subject viewed images to express no emotion, anger, hate, grief, platonic love, romantic love, joy and reverence. Each emotion has approximately 100 s of data every day.

On day six, the EMG signal is very noisy and quite unlike that of other days. Furthermore, on day seven, the EMG peak values are several times larger than on the remaining days. These two days were discarded from our analysis.

B. Method 1: Feature Extraction and Classification

Two separate methods were evaluated for detecting anger. In the first approach, we classified energy features extracted from different instantaneous frequency bands in separate time intervals using the Hilbert-Huang transform. Using [12], 100 s EMG segments were first decomposed into constituent

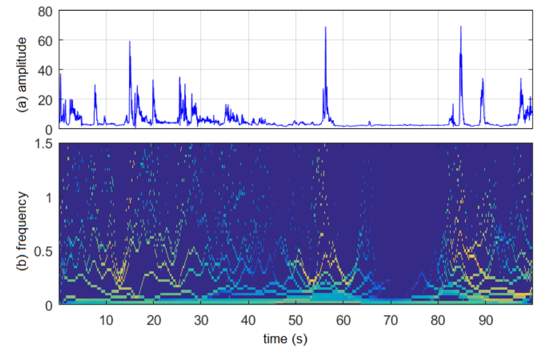

Fig. 1: **An EMG signal and its Hilbert spectrum**. (a) The raw EMG signal. (b) The Hilbert spectrum depicting the amplitudes associated with instantaneous frequency. Only the frequency range from 0-1.5 Hz has been shown for clarity.

IMFs. Each segment $x(t)$ can then be expressed as a sum of n IMFs $c_i(t)$ and a residue $r(t)$.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{1}$$

The Hilbert transform of each IMF $c_{ih}(t)$ is then utilized to obtain an amplitude $A(t)$ and phase $\phi(t)$ as follows.

$$A(t) = \sqrt{c_i^2(t) + c_{ih}^2(t)} \tag{2}$$

$$\phi(t) = \tan^{-1}\left[\frac{c_{ih}(t)}{c_i(t)}\right] \tag{3}$$

The derivative of $\phi(t)$ yields instantaneous frequencies. The resulting Hilbert spectrum indicates different frequency component amplitudes appearing at specific time instances. An example EMG signal spectrum is shown in Fig. 1. We divide each 100 s segment into blocks of 10 s intervals and calculate the energy in each 1 Hz band up to 10 Hz resulting in a 100-dimensional feature vector for each emotion.

A Mann-Whitney U test was used to select the best features for distinguishing anger. The test identifies samples that are distributed with different medians and we chose features at $p = 0.01\%$ significance. The feature distribution projected onto a 2D space using Principal Component Analysis (PCA) is shown in Fig. 2. We evaluated a Naive Bayes classifier with Leave-One-Out cross validation using Weka [13]. This classifier separates data by calculating a posterior probability using a simplifying independent features assumption.

C. Method 2: Band Energy Tracking

The second method, more suited to a wearable device, continuously tracks energy in the 0-0.1 Hz frequency band in overlapping windows and flags anger whenever a threshold is exceeded. First, the signals are filtered with a 1 Hz lowpass FIR filter. Large EMG amplitudes often accompany anger expression. The converse however, is not necessarily true and high signal peaks are observed during hate, joy and romantic love, albeit infrequently. Unaccounted for, these peaks will cause a large number of False Positives (FPs) to be generated.

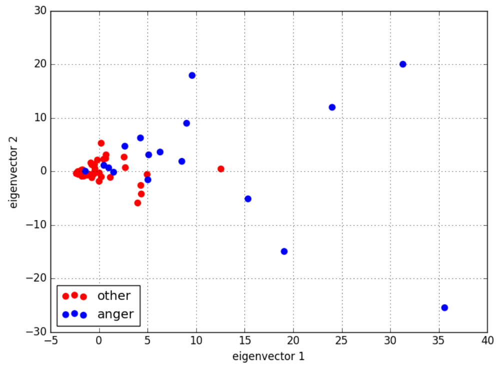

Fig. 2: **EMG feature distribution**. High dimensional features extracted from 100 s EMG intervals projected onto a 2D plane using PCA for visualization.

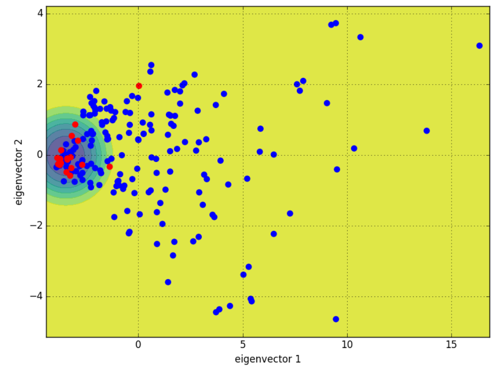

Fig. 3: **Feature distribution for EMG data peaks**. 19-dimensional feature vectors projected onto a 2D plane using PCA. The blue dots correspond to negative valence peaks and the red dots otherwise. Decision surface contours of the GNB classifier are also shown.

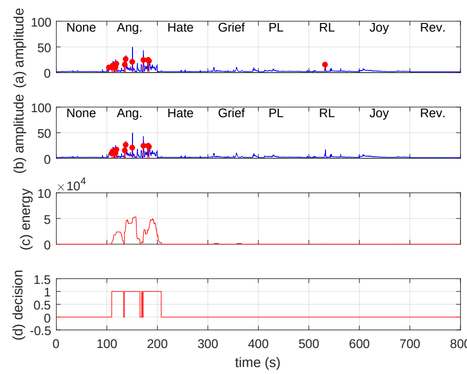

Fig. 4: **EMG peak classification, energy tracking and anger detection.** (a) The EMG signal (solid blue line) with detected peaks (red dots). Some emotional states have been abbreviated (Ang - anger, PL - platonic love, RL - romantic love and Rev - reverence). (b) The EMG signal with peaks classified into the negative valence class. (c) Tracked 0 - 0.1 Hz band energy. (d) Final detection result.

Generally, other relatively high amplitudes accompany peaks during negative valence (anger, hate and grief) and are indicative of sustained jaw clenching. In contrast, peaks observed during joy and love (positive valence) tend to be isolated. Peaks rarely accompany reverence or the expression of no emotion. We seek to classify these peaks first and adaptively increase or decrease window length based on it.

A constantly updating histogram is maintained for each day. We flag a peak as a value greater than 10 above the 97.5th percentile if no other peaks have been observed in the previous 2 s. When a peak is detected, six features including the mean, median, standard deviation, maximum, sum of squares and number of peaks are each extracted from the previous 10 s, 20 s and 30 s intervals. After incorporating the peak amplitude into these measures, a 19-dimensional feature vector characterizes each peak.

Despite the objective of solely identifying anger, incurring FPs during hate or grief is of less impact than doing so during joy or love. We can also allow for some misses during anger as long as the FP rate during joy and love is minimal. If a peak during joy or love is incorrectly classified as belonging to the negative valence class, the window within which we track energy will increase and most likely cause future samples for a considerable period of time to be mistakenly identified with anger. Certain peaks had to be manually discarded during the training phase. PCA was applied to the 19 extracted features and the first two principal component scores were fed into a Gaussian Naive Bayes (GNB) classifier. This model was trained using Python's Scikit-learn library. The feature distribution and the contours of the classifier's decision surface are shown in Fig. 3.

One day is held out for testing and the signal peaks classifier is trained with data from the remaining days. The process is subsequently repeated for all other days. During testing, a starting window length of 10 s is initialized. Whenever a peak appears and it is classified as being associated with negative valence, the window size is increased to 30 s and is gradually allowed to return to 10 s at a rate of one sample with each incoming value. In contrast, a positive valence peak causes window length to drop to 1 s and is then allowed to increase at a rate five times slower. This minimizes the contribution of the high amplitude peak to the band energy.

Finally, a threshold is applied to the band energy to detect anger. As EMG amplitude ranges change from day to day, the threshold is selected to be a constant multiplied by the median signal value of the first 100 s during that day (this period occurs while the subject is expressing no emotion). After exploring a range of values, a suitable constant was selected from the Receiver Operating Characteristic (ROC) curve. The result of detecting anger by energy thresholding for a particular test day is shown in Fig. 4.

III. Results and Discussion

Sensitivity, specificity and accuracy were calculated for Method 1 described above. Sensitivity measures the percentage of correctly classified features vectors corresponding to anger. Specificity measures the same quantity but for all other emotions. Accuracy measures the overall percentage of correctly classified feature vectors. The proposed method achieves a sensitivity of 83.3%, a specificity of 88.1% and an overall accuracy of 87.5%. Most of the literature reviewed here reported similar accuracy values in the 75-90% range. Note that some of them (e.g. [5], [6]) actually attempt to capture facial expressions via EMG for emotion recognition rather than relying on purely physiological sensing.

Method 2 does not perform as well as expected. Even a slight jaw tightening within a moderate time period results in a high accrued energy over a predetermined window. Secondly, although the peak classifier is able to successfully distinguish initial EMG peaks that occur during anger, hate and grief from those that accompany other positive emotions, secondary peaks are often misclassified. This again results in a window length increase entailing prolonged FP generation. Furthermore, EMG amplitude values during anger do not constantly remain high but occasionally drop close to the baseline. The subject in the experiment later admitted that expressing the same emotion continually over a few minutes “often got boring” [14] and it is likely that not all the images being viewed caused equivalent jaw clenching.

The classical machine learning approach seems to achieve comparatively high accuracy in identifying anger as it has a longer signal segment to work with and needs to output just a single label for the entire 100 s duration as a whole. The band energy tracking technique only measures a single parameter and has to continuously identify anger based a threshold. On certain days, the subject’s EMG response for emotions such as romantic love and hate appear very similar to that of anger. An emotion such as hate could well involve the expression of anger and as such be accompanied by similar clenching of the subject’s teeth. It is also possible that the electrodes record some facial expression bioelectric activity such as smiling or frowning [11].

It is acceptable to perform emotion recognition and anger detection with wearables once every few minutes in certain applications (e.g. monitoring a patient with post-traumatic stress disorder throughout the day). Therefore, we proposed an extension to the online approach. Instead of identifying anger every sample, each 100 s interval was classified based on energy exceeding a threshold (a different optimal threshold) at least once. The result for the same test day is shown in Fig. 5. With this method, sensitivity increased to 83.33% and specificity was 85.71% for the entire dataset.

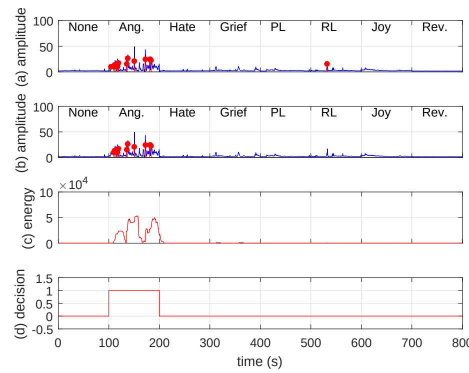

Fig. 5: **Performance of the combined approach for the same test day.** Sub-panels (a), (b), (c) and (d) have the same definitions as in Fig. 4

IV. Conclusion

Offline methods for emotion classification are more common in the literature compared to online ones. The offline method we presented in this paper has a reasonably high classification accuracy while the online method is a preliminary approach, which we plan to extend to achieve desired performance. This second approach however, is more suited to a wearable monitor and combines the tracking of a single parameter with machine learning for detection. In future, we plan to supplement this analysis with other physiological signals and features to improve performance.

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