Automatic Expression Detection using Muse Brainsensing Headband

Swadhin Pradhan
UTEID: sp38229, CS, The University of Texas at Austin, USA

***Abstract*—This project proposes a system for automatically detecting different facial expressions of a user using EEG and accelerometer data recorded in a headband like *Muse*. We observe that different channels of EEG combined with accelerometer data exhibits specific patterns which can help to identify a specific set of facial expressions. These expression set may help to tag user generated content, e.g. comments on a forum or messages on a messenger (like Whatsapp), with actual emotions of users. Our key observation is that different sensors available on smartphones and different wearables like brainwave sensing headbands could be used to capture a wide spectrum of user reactions or emotions. Especially actual physiological signatures (EEG) captured by Muse [14], which gives more detailed information about the user, can be critical in this regard. We can map these EEG, accelerometer and other sensor data captured to infer the current emotional states of user's mind. To achieve this, we have built a DTW based pattern matching algorithm which benefits from the low-rank structure of sensing data. Through experiments, we have shown that our system achieves reasonable accuracy for detecting expressions based on six expression vocabulary.**

I. Introduction

Wearable technology [24] represents the fastest growing segment in the global computing markets [15] and the next big thing in the technology industry. Recent research highlight that global wearable technology market is expected to cross 130 million units globally by 2018 [15]. As the next big wave, wearable technology will significantly influence the Internet of Things (IoT) and users interaction with the world. While the Google Glass, Samsung Galaxy Gear watch, Fitbit, Jawbone and pebble watch are among the popular synonymous for wearable computing, the consumer market is also filled with many fashionable wearables which records different physical data. So, more than ever, these wearables are becoming part of everyday life.

These wearables in tandem with the smartphones can capture different physiological and activity centric data with some surrounding information using a set of embedded sensors. These information help to infer the activity, the context or even the mental state of user. For example, Muse [14] brain-sensing headband records he EEG of the brain using four channels, which is a good indicator of mental activity. Moreover, it can also capture different facial expressions which can work as a good proxy of emotional states. So, with these EEG and sensor data based emotion recognition, the computer can actually take a look inside the users and can be more context sensitive. As we know that emotion is a psycho-physiological process triggered by perception of a situation and is often associated with mood, temperament, personality and motivation, this can be the first step to make computer more empathic to the user and can open up different aspects of affective computing [3].

However, the time series EEG data collected via Muse headband or any other brain sensing device vary across users and time even for a given expression. There is always a time shift or stretching in the data due to synchronization error and noise. To counter this, we have to employ DTW approach (which is discussed later) to get a robust pattern matching algorithm. We also have tried using traditional supervised machine learning algorithm like SVM to find the pattern for a given expression. The accuracy of classification vary across different expressions. In this project, we have considered six expressions: blink, jaw clench. twitch, yawn, laugh, and wink.

The main goals of this project may be summarized as follows.

- We observe the low rank structure in raw sensor data, which can help in detecting patterns of user emotions with less resource and more speed. Moreover, we are also trying to find an efficient way to detect patterns associated with particular emotions, both on personal and aggregated ways.
- We identify an opportunity to automatically detect facial expressions users via EEG signals detected and accelerometer data by Muse headband.

The rest of the report is organized as follows. Section II describes different concepts and information necessary to understand expression detection mechanism described in this project. Section III presents the different modules of our system for emotion recognition. Section IV shows the experimental setup and evaluation of the algorithm based on wearable traces generated based on different gestures. We conclude in Section VIII.

II. Background

In this section, we describe some of the important concepts, tool or dataset used in this project.

Electroencephalography (EEG) : Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 2040 minutes, as recorded from multiple electrodes

TABLE I
DIFFERENT FREQUENCY BANDS OF EEG

Band	Range	Significance
Delta	< 4	Shows in Sleepy Moments
Theta	4 - 7	Shows in Sleepy and Tired Moments
Alpha	8 - 15	Shows in Relaxed Mood
Beta	16 - 31	Shows in active calm/ stressed / intense moments
Gamma	32+	Displays during cross-modal sensory processing like short term memory

placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals.

Scalp EEG activity shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning (e.g., waking and the various sleep stages). These oscillations represent synchronized activity over a network of neurons. So, the EEG is typically described in terms of (1) rhythmic activity and (2) transients. The rhythmic activity is divided into bands by frequency as shown in Table I. To some degree, these frequency bands are a matter of nomenclature (i.e., any rhythmic activity between 815 Hz can be described as "alpha"), but these designations arose because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance.

For measuring EEG, in general, the 10-20 system (as shown in Fig. 1) is used. The 1020 system or International 1020 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment. This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total frontback or rightleft distance of the skull.

Muse Brain-sensing Headband : Muse headband is a tool that measures brain signals much like a heart rate monitor senses your heartbeat. Muse has 7 finely calibrated sensors 2 on the forehead, 2 behind the ears plus 3 reference sensors detect and measure the activity of your brain, as illustrated in Fig. 2. So, this headband with 7 EEG sensors capable of reading 4 channels of data (two on the forehead and two at the top of the ears, illustrated in Fig. 1) records EEG data at a sampling rate of 220 Hz with 2uV (RMS) noise. Moreover, there is also an on-board 3-axis accelerometer which enables motion input for games and for quantifying head movements.

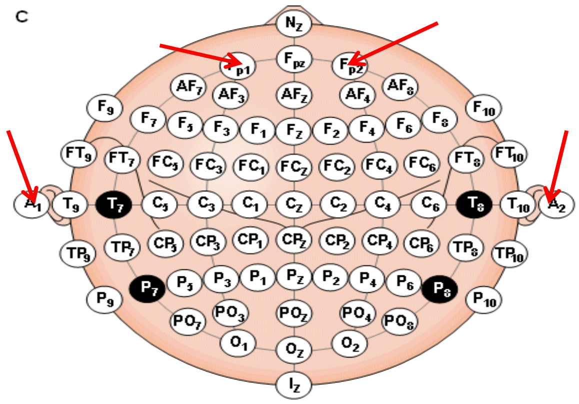

Fig. 1. EEG 10-20 Measurement System. Red arrows signify four points of data collection of EEG sensors of Muse headband.

It communicates data to the computer or smartphone over bluetooth and also has 5 LEDs which display various states of operation.

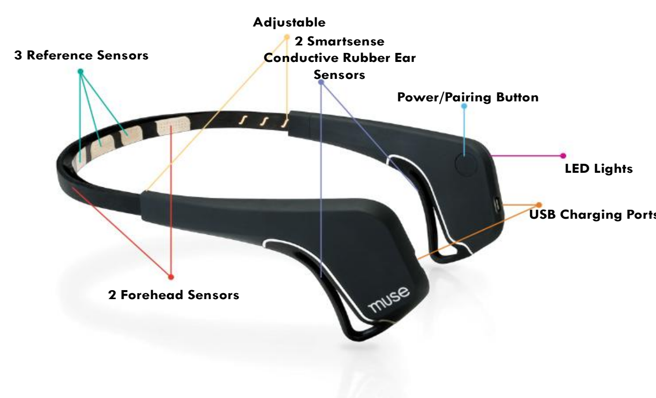

Fig. 2. Muse Brain-Sensing Headband

DEAP Dataset : This is a multi-modal dataset [11] for the analysis of human affective states. The electroencephalogram (EEG) and peripheral physiological signals of 32 participants were recorded as each watched 40 one-minute long excerpts of music videos using the setup shown in Fig. 3. For 22 of the 32 participants, frontal face video was also recorded. A novel method for stimuli selection was used, utilizing retrieval by affective tags from the last.fm website, video highlight detection and an online assessment tool. The data was sampled at the rate of 128 Hz with 40 different EEG and facial movement channels.

Dynamic Time Warping (DTW) : In time series analysis, dynamic time warping (DTW) is an algorithm based on levenshtein distance for measuring similarity between two temporal sequences which may vary in time or speed. For instance, similarities in walking patterns could be detected using DTW, even if one person was walking faster than the other, or if there were accelerations and decelerations during

Fig. 3. DEAP Dataset recording setup

the course of an observation. In general, DTW is a method that calculates an optimal match between two given sequences (e.g. time series) with certain restrictions. The sequences are ”warped” non-linearly in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension. This sequence alignment method is often used in time series classification. Although DTW measures a distance-like quantity between two given sequences, it doesn’t guarantee the triangle inequality to hold. The general technique is shown in action in the following Fig. 4.

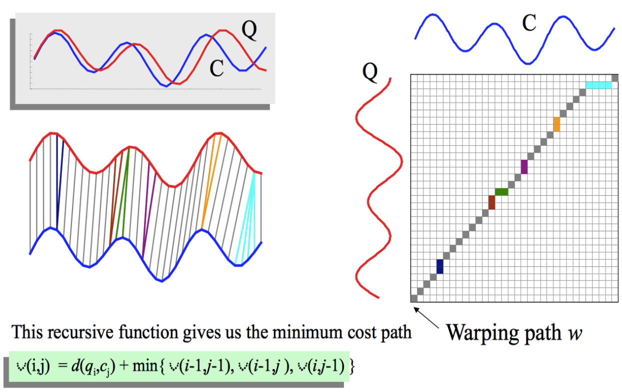

Fig. 4. Dynamic Time Warping Technique Shown in two signals: Q and C

Averaging Sequences using DBA : Averaging is the problem of finding an average sequence for a set of sequences. The average sequence is the sequence that minimizes the sum of the squares to the set of objects. NLAAF[10] is the exact method for two sequences. For more than two sequences, the problem is related to the one of the Multiple alignment and requires heuristics. DBA[19] is currently the reference method to average a set of sequences consistently with DTW. DBA stands for Dtw Barycenter Averaging. It consists in a heuristic strategy, designed as a global averaging method. DBA is an averaging method which consists in iteratively refining an initially (potentially arbitrary) average sequence, in order to minimize its squared distance (DTW) to averaged sequences.

Paul Ekman Emotion Model : For more than 40 years, Paul Ekman has supported the view that emotions are discrete, measurable, and physiologically distinct. Ekman’s most influential work revolved around the finding that certain emotions appeared to be universally recognized, even in cultures that were preliterate and could not have learned associations for facial expressions through media. Another classic study found that when participants contorted their facial muscles into distinct facial expressions (e.g. disgust), they reported subjective and physiological experiences that matched the distinct facial expressions. His research findings led him to classify six emotions as basic: anger, disgust, fear, happiness, sadness and surprise, which are called macro expressions as illustrated in Fig. 5.

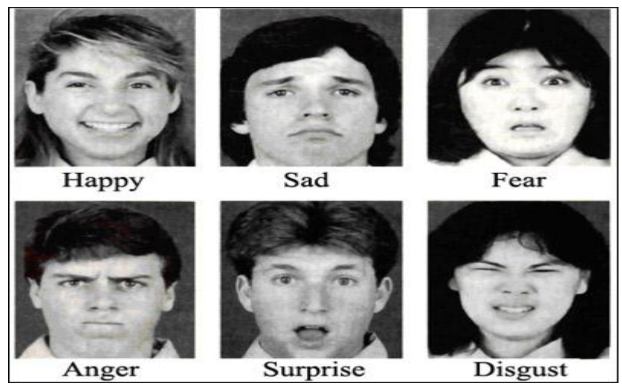

Fig. 5. Six Basic Emotions according to Paul Ekman

III. System Overview

This section presents the data analyzing module for the DEAP dataset [11]. This section also presents the initial framework for implementing the system and it also presents a few challenges faced by the system.

A. DEAP Dataset Analyzer

We investigate the genres of 40 music videos used in the experiment and classify the music videos into melody or rock categories based on the tags (provided in the meta-data of DEAP dataset) and content. We also tried to calculate the rank of the dataset for a given video (i.e. the matrix dimension 32 (no of persons) by 8064 (no of samples)) and the rank after doing shifting or stretching or DTW on that dataset. This study will help in revealing the underlying structure in the dataset if there is any rank reduction after this operation. For example, if rank reduces drastically after shifting the data then it means underlying asynchrony in this time-series data is the main reason behind the apparent high rank structure of dataset. Moreover, we have tried to find the structure in DEAP dataset because it is relatively large dataset having proper statistical significance.

B. Modules of Expression Detection System

This sub-section briefly describes the four main modules of *EmoSense* : 1) Sensor Data Recording Module, 2) Feature Extraction Module, 3) Data Processing Module, 4) Pattern Recognition Module.

- *Sensor Data Recording Module* This module continuously records different sensor data from different sources and sends it to central server. For example, Muse headband (shown in Fig. 2) sends raw eeg data over bluetooth at about sampling rate 220Hz and a service running in android smartphone (shown in Fig. 6) also sends the sensor data at highest possible sampling rate [1]. This module will then pass these raw sensor data to the feature extraction module running in the server.

Fig. 6. Android App to record data from different embedded sensors

- *Feature Extraction Module* This module initially removes noise from the data using butterworth filter and extract features from the data-stream. For EEG data available from four channels, we have taken 100 mili-second window interval to extract different statistical features (e.g. mean, standard deviation, kurtosis) of the data stream. We have also extracted alpha, beta, and delta values [8] applying standard DSP filtering methods on EEG data.
- *Data Processing Module* Next, we try to process the data to reduce the high rank structure using dynamic time warping [7]. We perform temporal shifts and uniform stretch/compress on the data to get the low rank structure of the data using this module. This data processing module initially builds the expression template library using DBA (as discussed earlier) and after building the library uses quantization to extract the pattern. We have used 32 quantization level from the recorded EEG data.
- *Pattern Recognition Module* We use the processed data to find different patterns corresponding to different expression using pattern recognition module. We initially create a training set of based on different expressions or patterns corresponding to emotions. Then, we try to find the closest match of a given pattern to a set of pattern database using DTW [7]. Different application like *Facebook Messenger* can call this module via APIs to annotate the messages with expressions.

Fig. 7 shows the expression detection system employed by this project. Sensor data recording and feature extraction module are not shown in the figure. Initially, we build the expression template library using DBA as shown in Fig. 7. Next, while detecting the expression, we employ data processing module to do quantization and pattern recognition module to calculate the smallest distance using DTW, as shown in Fig. 7.

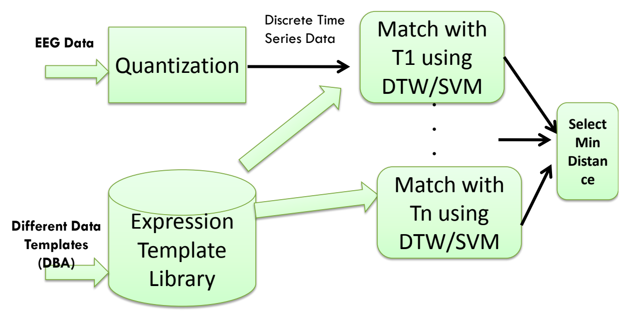

Fig. 7. Expression Detection System

IV. Evaluation Setup and Results

This section describes the results and evaluation setup employed in this project.

A. DEAP Dataset Analysis

As discussed earlier, we have analyzed the DEAP dataset for validating our hypothesis, which is there is structure in this kind of EEG data. We claim that if we find rank reduction after doing shift or stretching or DTW then the data contains some structure. However, all 40 channels or all 40 videos do not show same kind of rank reduction. Especially EEG channels of FP1, A1, PO3, A2, facial muscle movement do show more rank reduction. After selecting those channels, when we look into different music genres, the rank reductions are different. Specifically, rock music in general shows more rank reduction than music melodies as illustrated in Fig. 8 and Fig. 9. It signifies that rock music actually elicits similar kind of EEG responses from the users comparing to low decibel rhythmic music.

[1]However, in this project, we did not use the smartphone sensor data in conjunction with the Muse headband. In principle, this data can be used to reduce false positives or false negatives.

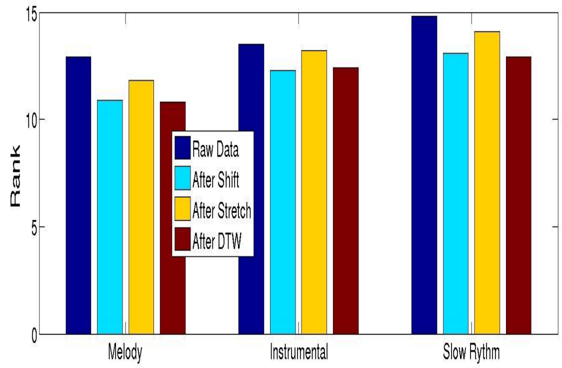

Fig. 8. Analyzing DEAP Data : Rank Reduction in Melody Music Data

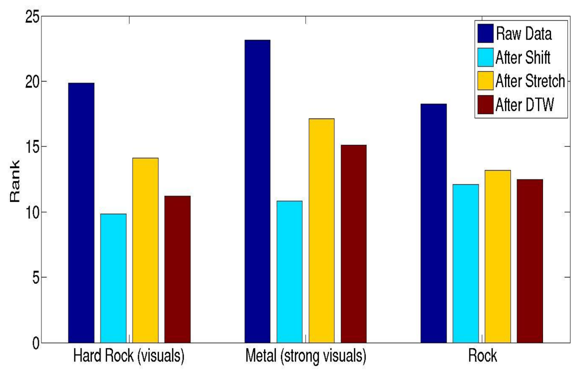

Fig. 9. Analyzing DEAP Data : Rank Reduction in Rock Music Data

B. Experimental Setup

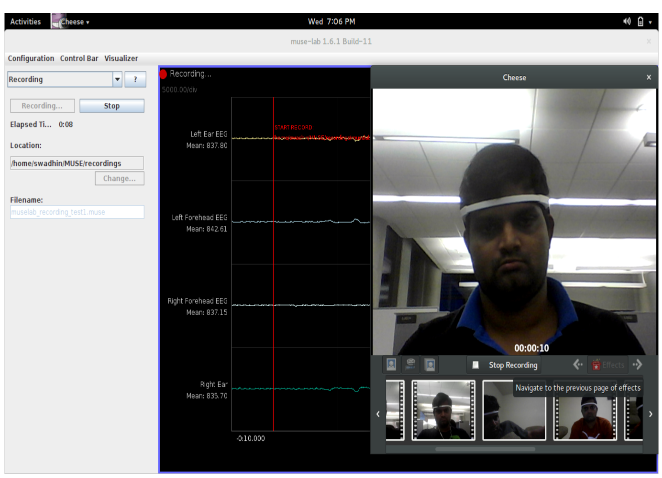

Fig. 10. Data Recording Setup Snapshot

We have connected Muse with a laptop using muse-io tool over bluetooth. Muse has four EEG channels using seven sensor on the hardware following the 10-20 system [8]. We record the EEG data of only one user in OSC format using MuseLab provided in muse sdk [14], while watching videos. User, wearing *Muse*, is asked to watch any of their favorite videos on laptop, while we record the videos via webcam of their face using *Cheese* for ground-truth. A sample recording process is shown in Fig. 10. We manually find the moments of their different facial expressions and extract the corresponding data from EEG data to investigate any pattern. Fig. 13 shows a sample EEG traces recorded using visual representation of MuseLab. We have also instructed the user to do the six expressions multiple times. For each expression, we have collected 30 samples across different channels and used DBA to get average patterns.

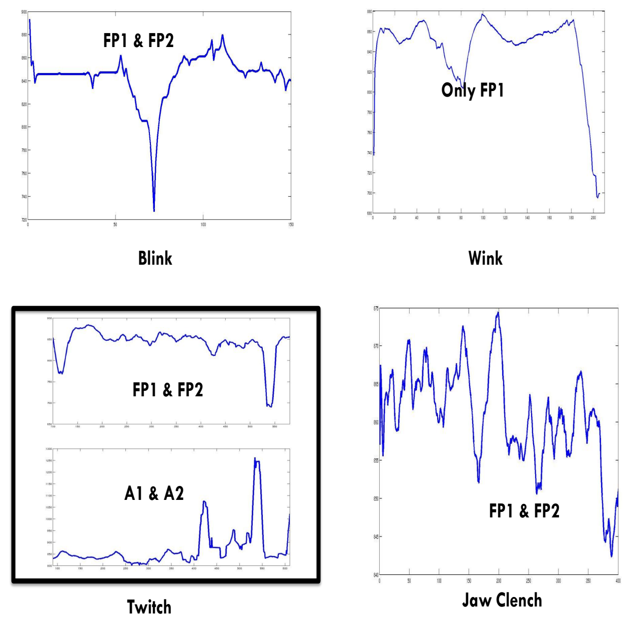

Fig. 11. EEG pattern corresponding to different expressions

C. Experimental Results

Initially, we have identified 'blink' as a good facial expression easily detected by the Muse EEG headband. We are observing a wave like pattern only on first and fourth channel of EEG, if user blinks (as shown in Fig. 11). If the head is still and the there is no facial skin/muscle movement, this pattern is pretty consistent among three users. However, we can compensate the head movement using the accelerometer data embedded in Muse. Then, have discovered consistent patterns for other five expressions namely jaw-clenching, yawning, forehead skin twitching, winking, and laughing activity. Jaw-clenching gives a wavy and frequently changing pattern in FP1 and FP2 channels whereas twitching gives frequently changing signature on all four channels, as illustrated in Fig. 11. Yawning gives a wavy pattern on FP1 and A1 channel and for laughing, EEG signature is associated with wavy pattern in accelerometer reading, as illustrated in Fig. 12. We can map these facial expressions to emotional states like yawning or frequent blinking may indicate tiredness or boredom of a particular user.

Next, we attempt to classify six different facial expressions

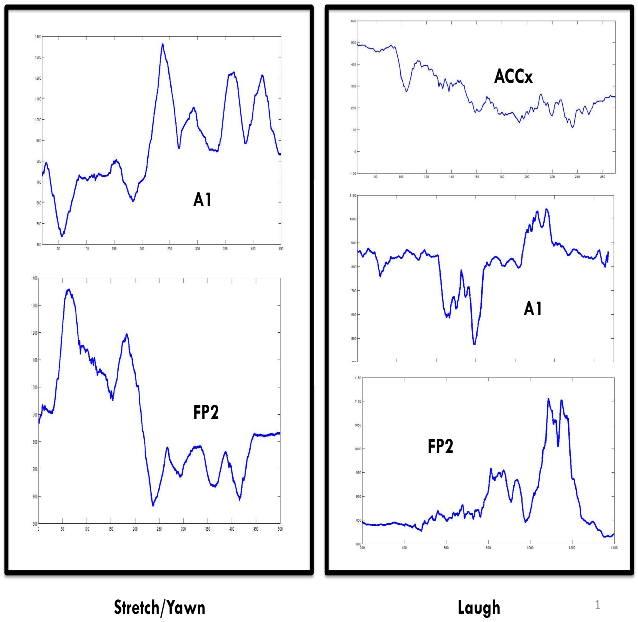

Fig. 12. EEG pattern corresponding to different expressions

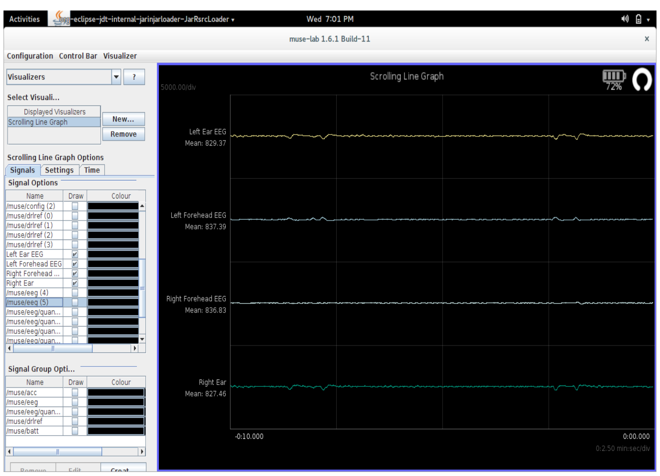

Fig. 13. Muse Recorded EEG in Real Time

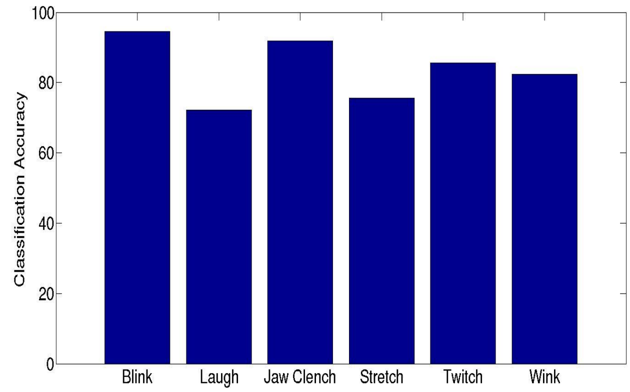

Fig. 14. SVM Classification Accuracy for Different Facial Expressions

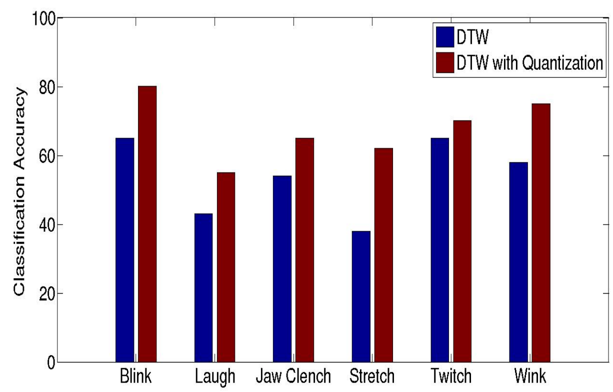

Fig. 15. Dynamic Time Warping based Classification Accuracy for Different Facial Expressions

using Fig. 7 system using SVM and DTW based method. For SVM we have selected five statistical feature (mean, standard deviation, max, min, skewness) for each channel and train the model with 20 samples and test with 10 samples. As illustrated in Fig. 14, classification accuracy ranges from 65% to 85% for training and testing each expression separately. Thereafter, we tried to use DBA on 20 samples to get an average template corresponding to a particular expression and tried to match on the other 20 samples using DTW. As shown in Fig. 15, the classification accuracy in DTW merely hovers around the rang 35% to 65% as DTW is not that robust against noise. So, to counter this, we employ quantization in the data and experience improved accuracy results. Fig. 15 illustrates that we get around 25% to 35% accuracy improvement from the non-quantized data. Thereafter, we attempted to classify different expression classes simultaneously using SVM and DTW. As shown in Fig. 16, the accuracy for multiple classes decreases drastically with the increase of number of classes. However, SVM and DTW with quantization performs similarly in detecting expressions of user.

V. EmoSense: A Possible Application

In this section, we want to propose an interesting application using facial expression detection. According to Ekman[9], each expression is associated with corresponding emotion. For example, anger can be associated with jaw clench and twitch, happiness can be associated with laugh etc. If our system work accurately to infer expressions then we can also infer the corresponding emotion. As shown in Fig. 17, our expression detection API can tag messages in *WhatsApp* with appropriate emoticons (e.g. a smiley when user is happy). It will be like location check-in (which is authenticated by GPS) but for emotions. Users can tag their Whatsapp messages or Facebook posts with these emotions which is authenticated by this application.

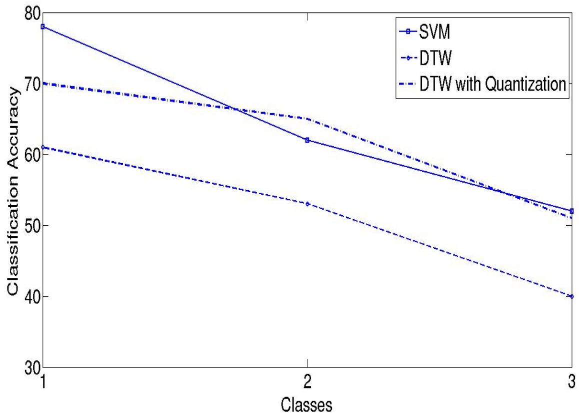

Fig. 16. Dynamic Time Warping and SVM based Classification Accuracy for multiple classes

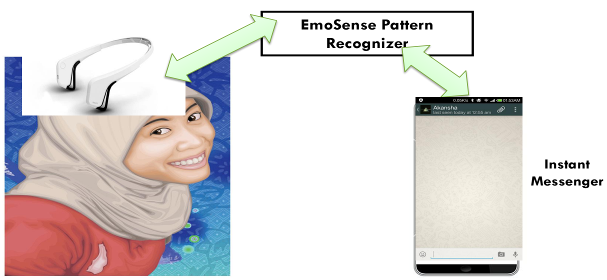

Fig. 17. EmoSense : An emotion detection system

VI. Future Works

We have a lot of work to do before we realize our vision. We have just only managed to observe different signatures with respect to different facial activities using Muse EEG data. However, we need to do the following things to create a real working prototype of *EmoSense* like system :

- Are these signature of patterns consistent for a number of users or even for a single user ?
- What is the upper bound of patterns one can capture using this kind of noisy system ?
- How to design the *EmoSense* architecture such that it becomes fast, robust, and energy-efficient ?
- How to aggregate different sensor features from different users to get meaningful emotional information ?
- How to incorporate different context information from the sensor data collected from other sources like location to make the emotion detection more robust and faster ?
- Which architecture is good for this kind of system: in-device computation, cloud computation, or device-cloud computation ? If so, how to distribute the work items between device and cloud ?
- How to make this system privacy-aware and preserving ?

VII. Related Work

Image based Facial Expression Detection : In the past years, the literature on automatic facial expression recognition has grown dramatically by applying advanced techniques of image and video processing. Most studies of automatic facial expression recognition focus on six primary facial expressions or a subset of them, namely happiness, sadness, anger, fear, surprise, and disgust. The expression and recognition of these primary facial expressions were found in Ekmans extensive studies[9] to be universal in different cultures. The studies of computer-assisted recognition of facial expressions started in 1990s. Mase[13] explored the technique of optical flow for facial expressions recognition. Lanitis et al.[12] applied a flexible shape and appearance model to recognize person identities, genders and facial expressions. Black and Yacoob[2] used local parameterized models of image motion to track non-rigid facial motion that was fed to a rule-based classifier of facial expressions. Rosenblum et al.[20] used optical flow and a radial basis function network to classify expressions. Otsuka and Ohya[16] used optical flow and a hidden Markov model (HMM) for facial expression recognition. Tian et al[23] explored action unit recognition by using multi-state facial component models and a neural-network-based classifier. Cohen et al.[5] introduced the structure of Bayesian network classifiers and a multi-level HMM classifier to automatically segment an arbitrary long sequence to the corresponding facial expressions. For extensive survey of facial expression analysis using images done in the recent years, readers are referred to the overview papers, including [17], [18] written by Pantic and Rothkrantz in 2000 and 2003.

EEG based Expression and Emotion Detection : Several works have attempted recognition of emotions from EEG signals. In [4], participants are asked to remember an episode in their life that corresponds to positive/excited and one that corresponds to negative/excited emotions. A third emotional state called calm/neutral is elicited by asking the participants to stay calm and relax. For these three classes, a classification accuracy of 63% is reported using the short-time Fourier transform for feature extraction and a linear SVM for classification. In [11], participants watch a series of music videos selected to elicit emotions. The participants then rate the felt emotions in terms of valence, arousal and like/dislike. In performing a binary classification, accuracies of up to 62% are attained based on EEG band-power features and a Gaussian Nave Bayes classifier. Regression results for the same experiment are reported in [21]. In [22], 5 different emotions (joy, anger, sadness, fear, and relaxation) are elicited by using video stimuli in 12 participants. Using a one-vs-all SVM classifier, a classification rate of 41.7% is reported. Besides these works, much research has been done in psychology into ERP analysis and correlations with emotion (e.g. [1], [6]). These works show clear associations between ERP activity and valence/arousal.

However, they mostly have in common that they work with time-locked stimuli (such as pictures), and average the ERP signal over several trials to increase the signal-to-noise ratio. However, all these works do not concentrate upon the facial expression detection cum emotion recognition which we attempt to address.

VIII. Conclusion

In this project, we have attempted to infer the facial expressions of users to augment daily technological interactions of users with another dimension. It can help to mine deeper context in daily activity and can provide intelligence to different daily applications. To achieve this, we use only Muse brain-sensing headband, but it can be extended or used with conjunction with other wearables like smartwatch or fitness bands, which users are already using at scale. For this reason, this kind of system can be readily available for real world adaptation. However, it brings another set of challenges like noise or anomaly in the data and resource constraints to perform the operation. In this project, for a reasonable six emotional templates we have found different patterns in EEG data which can be used to detect facial expressions which can in turn infer emotional context of user.

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