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EMOTION RECOGNITION USING SKIN CONDUCTANCE AND SENTIMENT ANALYSIS

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Abstract: The information about what a user is feeling as a reaction to a product is a very important aspect that we humans have concerned ourselves with within the last decade. From response towards advertisements to making an enhanced and personalized user interface, requires a solution pertaining to the field of finding the emotional state of the user. There are numerous methods to realize emotions including speech recognition and facial expressions, but these methods lack ubiquitous availability and can be fabricated otherwise. The other concern with the above methods is the higher level of inaccuracy. Therefore, the use of bio-signals is increasing. In this paper we utilize "Galvanic Skin Response (GSR)" or "Skin Conductance (SC)" or "Electro-dermal Activity (EDA)" to figure out 6 basic emotions. Feeling emotions is directly linked to the arousal of the body, and stimulates the sweat glands on our body, hence above written bio- signals seem to be a perfect fit for realizing emotions. Hence, we use skin conductance and sentiment analysis to find the emotional state of the user as a response to the social media content, making it a better fit for real-world applications.

Keywords: emotion recognition;bio-signals;galvanic skin response;skin conductance;electro-dermal activity;valence;arousal;sentiment analysis

I. INTRODUCTION

Every activity that one performs is highly a reflection of how one is feeling towards the content. These emotions play a crucial role in communications, making decisions, performing simple chores and what not. The certain field where we extend this logic is communication with technologies around us. Human-computer interaction can utilize the non-verbal cues packed into emotions. As early as the 1970s a lot of research has gone into studies for realizing the emotions of users. [2] The task of finding what someone is feeling is a difficult one, and specifically when done using speech recognition. As expressed by Takahashi [3] in his paper, the accuracy for the same is about 60% and around 70% when using facial expressions.

The problems with the above methods are the lack of continuous availability of the signals, the certain error based on how they can be morphed and how they vary extensively as per the user which prove them to be an unreliable source By analyzing emotion inputs, computers could also be taught to adapt their behavior consistent with the emotional state of the human user and, therefore, perform better and smarter communication. Physiological changes agreeing to exciting emotions can be determined by changes of the body surface and/or involuntary nervous system: e.g., galvanic skin response, ECG, EMG, and blood volume pressure [4]. The choice of signal here is galvanic skin response or skin conductance. [5] The paper describes that realizing emotions is not simple and discreet but requires 2 different dimensions for the same.

Figure 1. Emotions on a 2-Dimensional Plane.

Hence, we need 2 dimensions to read emotions, valence – depicting if the content is to be perceived in a positive or a 1 negative way (therefore valence is also called affectivity), whereas arousal – depicts how excited the body is as a response to some external stimulus. Sweaty palms and pounding heart have always been a depiction of higher arousal in the literature dating long back. Theoretically when one is highly aroused the emotions felt very on the valence, i.e. a person when happy or angry has similar arousal levels but different valence codes, and similarly a person excited and calm has similar valence except different arousal. Our body has around 3 million sweat glands. On the lines of other involuntary processes that our bodies go through (for instance body temperature, blood pressure and heart rate) sweat secretion isn't under our full control. Instead, our autonomic nervous system operates it in order to meet behavioral demands (in response to external stimuli like motions, or how a situation is making you feel). In affective science, such processes occur naturally and in conjunction with each other: The heart beats faster, the pulse rises, hands become sweaty. To put it simply: While we are physiologically or psychologically aroused (in fear, extreme joy or under stress), we start to sweat, and hence the skin conductance varies. Sentiment analysis can be used to find the tone of the language by mere natural language processing, providing the valence associated with each content.

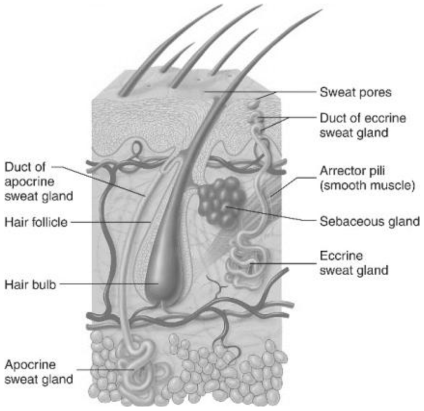

Figure 2. Emotions on a 2-Dimensional Plane.

II. EXISTING MODELS

This esteemed paper [6] in the IEEE Signal Processing Magazine dates back to 2001 where the authors explained the importance of effective methods of signal processing to achieve faster results without any loss. The paper mentions that there are 2 channels described in communication, one is the message itself described by the content and other is the evident feature about the sender himself. The latter is also very hard to figure out and one of the key features here is Emotional State of humans. [7] In this paper, the authors lay out over 4000 words with scores of how they affect to be emotions have been the base of study for a large number of researches. However, the key research here was limited to perceived characteristics of speech, and therefore lack availability at all time, and can be forged easily. Another research paper [8] suggests a new method of emotion and stress recognition using physiological signals pertaining to human body like EEG (Electroencephalography) – This is the monitoring of electrical activity level of the brain. The focus was to perform analysis on signals to improve on the previously present emotion recognition systems.The characteristics extracted from various signals are mentioned below.

Table I. Features extracted from various signals

Signal	Extracted features
Respiration	Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum minus Minimum value, Mean of derivative and calculating the power 5 frequency band of 0.25 to 2.75Hz.
Skin Conductance	Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum response, Mean of derivative, energy response and proportion of negative samples in the derivative vs. all samples.
Photo plethysmograph	Mean, variance, Standard deviation, Kurtosis, Skewness, Mean of trough variability, Variance of trough variability, Mean of peak variability, Variance of peak variability, Mean of amplitude variability, Variance of amplitude variability, Mean value variability, Variance of mean value variability, Mean of baseline variability, Variance of baseline variability
Heart Rate Variability	Mean, variance, Standard deviation, Maximum value, Minimum value, Low power frequency of 0.05-0.15Hz, Proportion low power frequency vs. all power frequency, fractal dimension by Higuchi's algorithm

The paper included analysis using the steps of preprocessing, normalization, feature extraction using various discrete transforms, and then classification of the signals. This paper lays down the basis of how the bio-signals can be analyzed and have been used ever since. [9] This paper focuses on 2 signals specifically for emotion recognition called –

- Electromyography (EMG) – perfect for finding valence values
- Galvanic Skin Response – high classification rate for arousal values

The focus of this paper was to develop a real-time mechanism for reading emotions, therefore perfect forindustrial purposes. The architecture laid by it has been this used heavily in games and other systems. The key structure mentioned here was the building of a simple Bayesian network with probabilities of previously existing data. The issues faced here 2 were finding "Baseline Problem" for the Bayesian network, frequency and time interval to operate on, and the magnitude of emotions. The architecture suggested here follows a fairly modern approach to identify emotions in real time and were implemented using ActiveX.

Table II. The layers in the architecture proposed in [9]

Layer	Functions
Sync Layer	This initiates the parameters and provides a model (setting up the environment) to synchronize layers for data procurement.
Sensors	The sensors calculate the values for EMG using Muscle sensors and GSR values using Arduino Kits passing small currents through the fingertips.
Calibration Layer	Calibration layer or as one suggests the categorization layer generates reference point of both the signals and normalize to get better results.
Bayesian Network Layer	Finally a Bayesian network layer Layer that classifies or map the signals to the corresponding emotions.

[10] In this paper the setup used is very minimal and is only limited to finding accuracy of classifications when we use GSR and heart rate separately. For both signals the use of fast Fourier transform was made to calculate wavelet coefficients which was later classified using a Support Vector Machine, according to which they both gave accuracy rates of over 85%, and hence a symbol to the future usage prospective. Multiple algorithms have been utilized to favor faster and more accurate results. Another research [11] in this decade published how the use of a stochastic optimization technique like Genetic algorithm (GA) or Particle Swarm Optimization (PSO) can result in much more accurate results faster. A lot of research (still ongoing) is building on hybrids of the above 2 algorithms to find results faster and with reliability.

Another review in 2011 [12] focused on extracting features from more varied signals. The major points put forward suggested the methods of processing similar bio-signals in regard to achieve the classification.

The literature has correlated emotions and stress for over 2 decades now. The research in [13] explains the usage of EDA in finding the stress levels of the users. Skin Conductance sensors are good solution to detect the same due to –

- Low power usage
- Multiple Nodes
- No harm to the human body

The usage has been widely accepted in polygraph machines, medical purposes and much more. It is quite inevitable to not think about the difference it can make to the real-world everyday applications via interaction through user interface.

III. Proposed System

We proposed a model where the test users were provided with the video content from the internet. Links to the videos have been added to the reference section.

The sentiment analysis is performed for each video's content. Whereas the user wearing the hardware (a GSR sensor) reacts to the video, which is further analyzed using cvxEDA to extract features and classify into bands. Then we use the combination of both valence and arousal to predict an emotion.

One crucial module would be the one that is required to find the arousal values related to a stimulus. The arousal values describe us the calming or exciting extent of the action. For the purpose of the same we require a hardware built using Arduino Uno coupled with sensors that can calculate the skin resistance by passing a small amount of current to the body. Strong emotions lead to inducement of sympathetic nervous system that further increases the sweat released by the sweat glands. This release can be expressed in terms of conductance. Higher the sweat, more will be the conductance of the body. Whereas lower the sweat, lesser will be the conductance of the body. Hence the arousal values can be found perfectly using a Skin Conductance Sensor.

Hardware needs: Arduino Board and a GSR Sensor

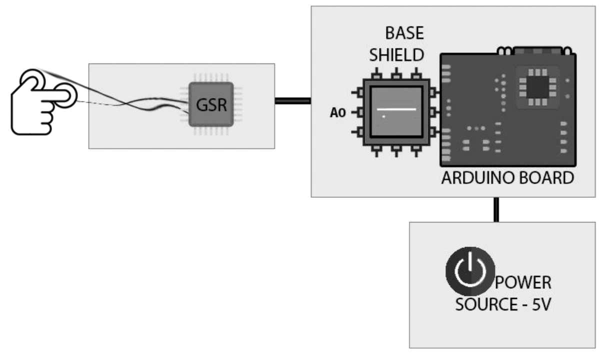

Figure 3. Setup of needed hardware

[14] Proposes a new algorithm for processing galvanic skin response values, which is expressed using 3 components –

- Phasic component – depicts the short-term response to the stimulus
- Tonic component – depicts little variation in the base skin conductance level
- White Gaussian noise

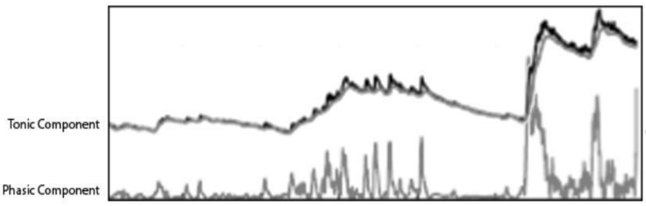

Figure 4. Tonic and Phasic components extracted from galvanic skin response signal

Extracting these features is highly important because –

- baseline skin conductance level varies widely,
- effects of temperature,
- effects of humidity,

extensively affect the measurements. These all contribute to the phasic component of the activity. Hence one must classify the variations on the basis of both components separately. We separate the signals using adaption of convex optimization algorithm for finding multiple features and classify the signals into following bands of arousal levels –

- Very Low
- Low
- Low to Medium
- Medium to High
- High
- Very High

The same algorithm is used in this project to extract features and classify the signal using a Naïve Bayes classifier.

The usage of convex-optimization algorithm for extracting the 2 components had an accuracy of approximately 94%.

IV. Observations

This system was tested on 12 subjects and the analysis was performed using content fromvariations of 12 different write-ups. Each subject was given a slight variation of each write-up to read while his reactions were captured, and then the subject was asked to pick the emotion being felt from the list -

- Relaxed
- Mournful
- Content
- Sad
- Joyous
- Distressed

The 12 write-ups had following general reactions –

Table III. General emotion expressed by content consumers for the write-ups

Write-Up	General Emotion Expressed By Content Consumers
1	Content
2	Mournful
3	Relaxed
4	Mournful
5	Distressed
6	Joyous
7	Sad
8	Content
9	Sad
10	Distressed
11	Joyous
12	Relaxed

The results from the experiment gave the following scatter plot. The plot confirmsthe expected trend of valence and arousal values.

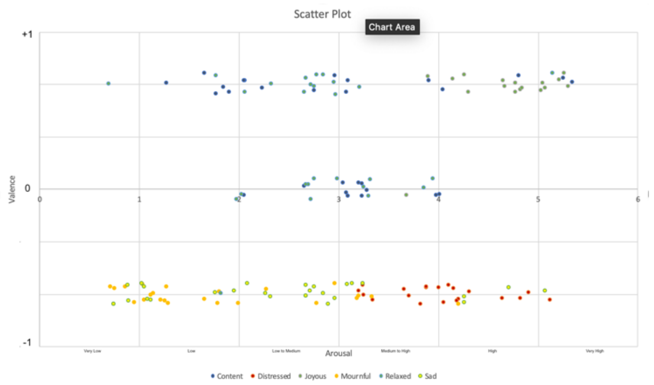

Figure 5. Scatter plot of arousal, valence and user's reaction response to the emotions.

The results from the experiment gave the following scatter plot. The plot confirms the expected trend of valence and arousal values. To take this further, we made predictions using the existing data to classify the emotions that the subject would feel on 2 more write-ups.

V. Comparing Results and Issues

Our observations were then passed through a Support Vector Machine (SVM), and even with the low number of data points, the method was able to predict emotions accurately for 18 out of 24 test cases presented to it.

Meanwhile using only, the knowledge of Skin Conductance with the SVM to build the predictions, the success rate was less than 10 out of 24 cases.

As significant the results may come out to be, this method has some issues. This method requires a significant calibration per user. Drawing the components from the actual signal requires a significant amount of calibration because tonic component varies significantly per user.

Another flaw would be that this method suffers from appropriate timing problem, since the signal to be analyzed as a response to stimuli happens after an arbitrary time and ranges for an arbitrary amount of time. Therefore, the analysis of emotion might not take place, or the emotion may range for a very small time or a very large time making it harder to distinguish from the baseline skin conductance. This can lead to incorrect results.

Another issue is relating to the content where the sentiments analysis provides values with low confidence, falling back on only Skin Conductance to provide results, or in extreme cases swaying the analysis into a wrong direction.

VI. Results and Conclusions

In this paper, we proposed a simple model that delineates the relationship between the two dimensions of emotions – namely arousal and valence using Skin Conductance and Sentiment Analysis respectively. This also provides a confirmation of the method in providing promising results as the data set grows. It is believed that determining user's response to a stimulus is the future of human computer interaction.

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