MUSE: A Portable Cost-efficient Lie Detector

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***Abstract*— The recent advanced in the low-cost, small-scale EEG scanners open the doors for many innovations in the domains of disease detection, social sciences, cyber security, and much more. In this paper, we investigate the possibility of using EEG signals as an indication of deception or lies. Further, we exploit one of the new EEG scanners, MUSE, to investigate its ability to provide what is needed to detect potential lies. Our experiments showed great success for the MUSE in providing what is needed for a moderate-quality lie detector, with very low-cost and complexity. Integrating machine-learning techniques into the presented results would provide a much more accurate detection opening the door for a vast number of potential applications.**

Keywords—muse; deception; EEG; lie; detection.

I. Introduction

Communication is far more than an exchange of words. Facial expressions, hand gestures, posture, eye contact, style of speech, and even silence constantly send messages about attitudes, emotions, and relationships. Of particular interest here are a person's emotional state and degree of trustworthiness during face-to-face discussions, with emphasis on interviews and negotiations.

Deception is a common aspect of human social interaction. According to studies reported in [1, 2], people lie in 14% of emails, during 27% of face-to-face interactions, in 37% of phone calls, and on average twice a day. False displays of emotions can have an effect on the way decisions are made, and therefore can have major consequences. For example, a judge's decision during a parole hearing depends heavily on the convict's level of remorse. The convict tries to be persuasive, and the judge attempts to distinguish real and fabricated remorse ("crocodile tears")[3]. More scenarios include assessments of people during negotiations, so as to steer discussions toward a desired goal. In many situations, deception takes on many forms that are much subtler than outright lying, such as withholding information that could be exploited by the other partner.

Deducing and giving information, in its simplest form always, involves communication. Since the early 40s scientists have been working to develop a complete identifiable model of the communication process and system. Though communications models are not capable fully capturing all key elements of information deduction, they offer some useful theories and frameworks. To begin with, they both identify the key components in a communication encounter (e.g., sender, message, medium, receiver). Then, they arrange these components in the framework of a dynamic process in which they all interact with each other. Finally, the trans-active model in particular emphasizes the centrality of "fields of experience" that both source and receiver bring to the encounter and that surround the overarching process. In deducing information, cultural factors such as different facial expressions and hand gestures having different meaning across countries and differences in backgrounds are critical to understanding how to connect and translate the intended and received message.

Recently there has been an increase in the production of low cost EEG headband devices, although not as accurate as professional medical EEG devices these low cost devices can be used in enhancement of research in multiple fields.

The purpose of this paper is to explore the possibility of using THE MUSE headset in order to develop a high performing machine learning dependent lie detector.

We study different frequency bands scanned by the muse to determine which has the most significance during truth and lie states. Finally we will conclude which signals will be used for the future work in the machine learning stage.

The remainder of this paper is organized as follows:

The first section is a brief introduction; the second section explores lie detection research till date. The third section presents the muse and the efforts and contribution it has in research. The fourth section introduces the methodology and the experimental procedure used. Finally sections five and six discuss the obtained results and the conclusions.

II. Related Work

Due to the importance of lie detection in several fields there already exists methods for detection. Methods are categorized into physiological or behavioral. The most common physiological method is the "polygraph" which monitors heart rate and electro dermal response, in order to do that it must be connected to the subject's body. This means that co operation of the subject is required and since the subject knows he is under polygraph testing and what measurements are made he can take precautions to overcome the test. Some of the behavioral methods can be found in [8,9,10,11,12,13].

Zhang et al. [8] Tried to automatically measure several prior identified Deceit Indicators based upon reliable facial expressions through computer vision analysis of image sequences in real time. Reliable expressions are expressions said by the psychology community to be impossible for a significant percentage of the population to convincingly simulate, without feeling a true inner felt emotion. Their experiments suffered from slow feature extraction phase which prevented the system from being real time. All the experiments are performed on static data.

Shan Lu et al. [9] presented Blob analysis, a method for analyzing the movement of the head and hands based on the identification of skin color. Blob analysis extracts hand and face regions using the color distribution from an image sequence. After extracting the hand and face regions from an image sequence, the system computes elliptical "blobs" identifying candidates for the face and hands. The presented work suffers from lack of comprehensive data set for establishing deceptive and truthful behavior. Better performance could be achieved if the system included the combination of multiple cues for a more robust behavioral model.

A similar Blob analysis work has been introduced by Tsechpenakis et. al. In [10] but they used hierarchical Hidden Markov Model to explore behavioral state identification in the detection of deception mainly involving the detection of agitated and over-controlled behaviors. The main advantage of using Hidden Markov Models is that they allow the observation of behavioral changes over time, and is robust to gesture variations. Again they lack a comprehensive data set also their work could be enhanced by extending the visual cues, including torso and shoulders position, and relative positions between the blobs.

Meservy et al. In [11] collect videos of interactions and divide them into meaningful segments. Then, analyzes the segmented videos to find the positions of the head and hands in each frame. Using elliptical blobs to approximate the location and size of the head and hands, the system calculates the center point, axes' lengths, and angle of major axis for every blob. It calculates additional features from the basic features extracted from each blob. The system calculates these features for each frame in the video clip. It must then classify them using an alternating decision (AD) tree, a neural network, and a support-vector machine (SVM). The most important limitations to the proposed work is the high quality video requirement. Another problem with the proposed work is that it's trained only on short responses to a single question.

Michael et al. [12] proposed a data-driven, unobtrusive and covert method for automatic deception detection in interrogation interviews from visual cues only. Using skin blob analysis together with Active Shape Modeling, they continuously track and analyze the motion of the hands and head as a subject is responding to interview questions, as well as their facial micro expressions, thus extracting motion profiles. The proposed system as presented has the limitation that training data must first be collected for a test subject so that the model can be trained. The presented work could be further enhanced by augmenting temporal dimension to the model.

Bhaskaran et al. In [13] developed a deceit detection framework around eye movement changes. A dynamic Bayesian model of eye movements is trained during a normal course of conversation for each subject, to represent normal behavior. The remaining conversation is broken into sequences and each sequence is tested against the parameters of the model of normal behavior. At the critical points in the interrogations, the deviations from normalcy are observed and used to deduce verity/deceit. Again they lack a comprehensive data set.

J.G.Proudfoot et al.[15].In this research extends extant work by looking at how users of deception detection systems alter their behavior in response to the presence of guilty knowledge, relevant stimuli, and system knowledge. An analysis of data collected during two laboratory experiments reveals that guilty knowledge, relevant stimuli, and system knowledge all lead to increased use of countermeasures, they address three different areas address include: (1) the impact of guilty knowledge, (2) the impact of relevant stimuli being presented during the interaction and (3) the impact of increasing a user's knowledge about the system.

Meijer et al.[16]They focus on the paradigms that have been most frequently used in deception and detection of deception research. They discuss the potential use of brain imaging techniques for the detection of deception. Contrary to what has been advocated by many researchers as well as practitioners, but unfortunately P300 and fMRI is by no means a solution to the problems associated with the polygraph test. As of its lacking of proper controls and being unstandardized, its outcome is often contaminated by prior information available to the examiner. None of these criticisms can be resolved by replacing polygraph recordings with fMRI measures.

Timothy J. Luke et al. [17] From a police point of view they experiment the accuracy of The Strategic Use of Evidence (SUE) approach is a framework for planning and executing suspect interviews with the aim of facilitating judgments of truth and deception.

III. MUSE: THE BRAIN SENSING HEADBAND

Muse: the brain-sensing headband is an electroencephalography (EEG) technology. EEG is a well-established, non-invasive, harmless method of recording the electrical activity of groups of brain cells [18]. Muse has only 4 electrode poles to measure brain waves of four parts—F7, F8 and the back of ears as reference.

Muse is an open platform: anyone can record raw data with Muse and anyone can build their own Muse application. EEG data can be recorded with MuseLab, MusePlayer, or via the third-party mobile application MuseMonitor . The library for building native muse applications, data includes:

- Absolute and relative power for delta, theta, alpha, beta, and gamma, for each channel.
- FFTs for each channel.
- Proper fit indicator for each channel.
- Blink event.
- Jaw clench event.

A. Muse Research History

In [19], the Muse headband, was used to detect cold-induced pain using self-calibrating protocols.

In [20] [it is shown that using the Muse headband it is possible to measure concentration and relaxation.

In [21] A team of McMaster and industry researchers is using the Muse to explore what happens to our thinking processes as we age, for example, or how women and men process thoughts differently.

A Massachusetts General Hospital team [22] explores the use of Muse in stress management.
One study at the Mayo Clinic [23] is investigating the effects of meditation on breast cancer patients undergoing surgery. Also at the University of Victoria and New York University, researchers are using the device to conduct pedagogical neuroscience research by investigating whether educational outcomes can be improved by better understanding students' brain activity.


Figure 1 : Muse headband

IV. METHODOLOGY

In the proposed Deception Test , EEG (Electroencephalogram) waves were used as Detection tool to differentiate between Truth state and Lie state of Volunteered participants .
EEG Signals were Collected using Muse Headband dry electrodes which record data from 4 Channels(AF7,AF8,TP9 ,TP10) , In our Experiment we will use Data collected from Frontal Lobe in regions of F7 and F8 which mirror others behavior and place personal value .
For this Experiment there were 15 Participants (4 Females and 11 Males) between 20-25 years old who for the Lie test by wearing Muse Headband which is connected with Bluetooth of Mobile Phone in order to receive EEG raw data stream and record it in real time.
The Deception Test was Divided to 3 Phases: Data Acquisition, Data Filtering and Processing, Results Analytics**.**

A. Expermintal Procedure

a) First phase: Data Acquisition:

Each Volunteer was asked to answer Questions on 3 stages : Truth Questions , Lie Questions , Baseline state questions were being selected based on GKT (Guilty Knowledge Test) Style then explain the number or color of given cards.
In Truth Stage volunteers will have to answer the correct facts in 1 Min Questions for example:
1 – What is your Name?
2 – What is your Nationality?
3 – What is your Age?
4 – What is your Job?
5 – What is your Religion ?
After Questions they were given 10 Cards and asked to give its color or number correctly.
In Lie Stage volunteers will have to create Wrong answers in 1 Min Questions which are:
1 – What is Sky Color?
2 – How Many Sisters Do you have?
3 – Are You Afraid from snakes?
4 – Have you ever lie before?
5- Do you love money?
6– Have you ever Steal before?
After Questions they were given 10 Cards and asked to give its color or number incorrectly.
In Baseline Stage volunteers were asked to be silent for 1 Min without answering any Questions

b) Second Phase: Data Filtering and Processing

After EEG Real Time Recording , Raw Data from AF7 and AF8 will be Categorized using FFT (Fast Fourier Transform) to 5 Frequency Bands : Delta (0.2-3) Hz Theta (3-8) Hz Alpha(8-12) Hz Beta (12-27) Hz Gamma(27 - Up) Hz
Each of frequency Bands indicates a mental state: Delta detects full sleepiness, Theta detects deep relaxation, Alpha detects relaxation, Beta detects Attention, Gamma detects highest mental activity.
Every Volunteer have 3 EEG Data files (Truth, Lie, Baseline) with 60 records per each file, Each File contains the amplitude of Delta, Theta, Alpha ,Beta, Gamma measured in µV (Micro Volts) , EEG recorded signals from AF7 and AF8 during Deception Test for the 3 stages illustrated in the figures Below.

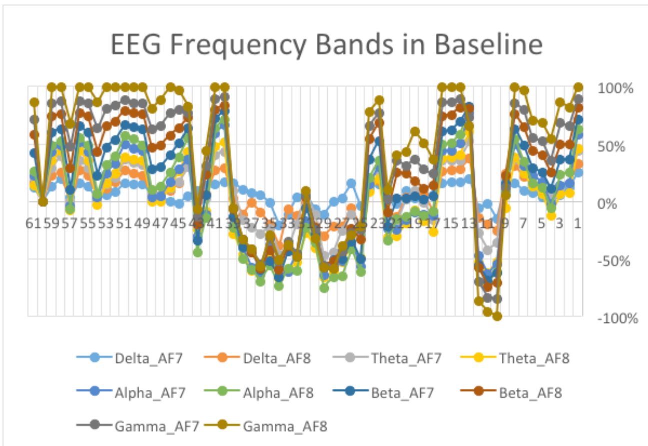

Figure 2:EEG Frequency Bands in Baseline

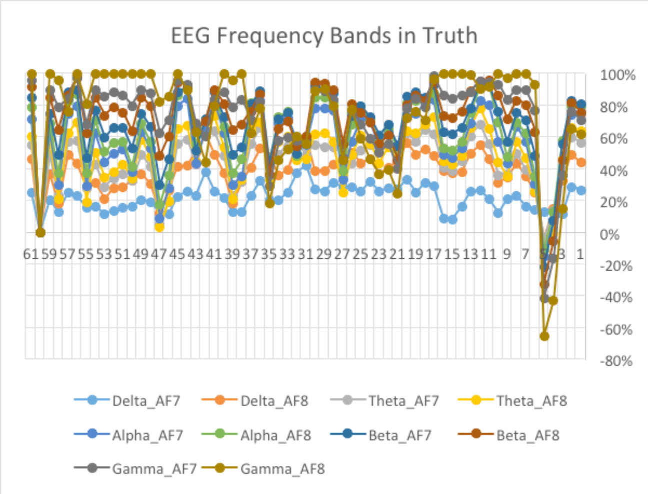

Figure 3: EEG Frequency Bands in Truth state

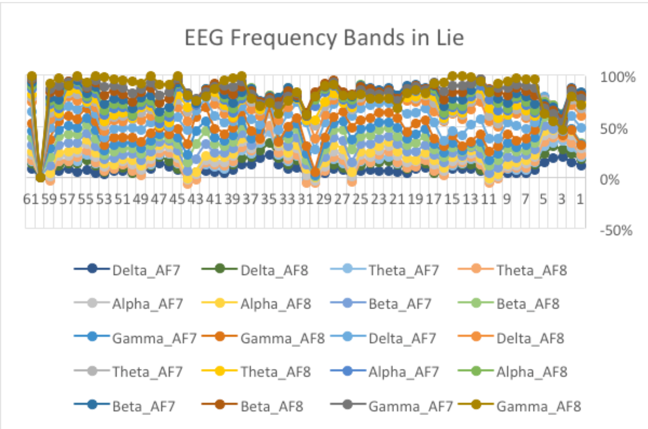

Figure 4: EEG Frequency Bands in Lie state

V. RESULTS

After collecting Data from 15 Volunteers ,we discard 4 of them due to invalid data zero readings from one of two electrodes AF7 and AF8. Data Analysis depends on values of Delta, Theta , Alpha , Beta and Gamma in 3 Files (Truth , Lie, Baseline) of each participant. The Difference between Truth Mental State and Lie Mental State detected by calculating Percentage of increasing and decreasing of Truth vs. Baseline Value and Lie vs. Baseline value for 5 EEG Frequency Bands following the equation Below :

Percentage of (i) Frequency Band in Truth state = [(Value of (i) in Truth - value of (i) in Baseline) value of (i) in Baseline] * 100

Percentage of (i) Frequency Band in Lie state = [(Value of (i) in Lie - value of (i) in Baseline) / value of (i) in Baseline] * 100

The Results of calculations for all experiment participants in 5 EEG Frequency Bands Show that in Theta Frequency Band there is significant difference between Truth and Lie mental states, In Truth mental state Theta wave increased but in Lie mental state it decreased.

Theta in Truth increases due to answering of questions related to facts or beliefs which doesn't require time thinking or more attention, on the opposite side Theta in Lie state decreases due to solving questions which require more attention and less relaxation than truth state.
Theta wave Difference between Truth and Lie mental status of sample from participants in Deception Test is shown in the figures below:

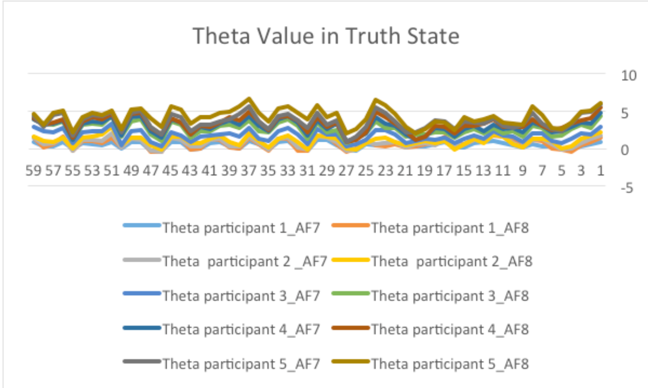

Figure 5: Theta in truth state

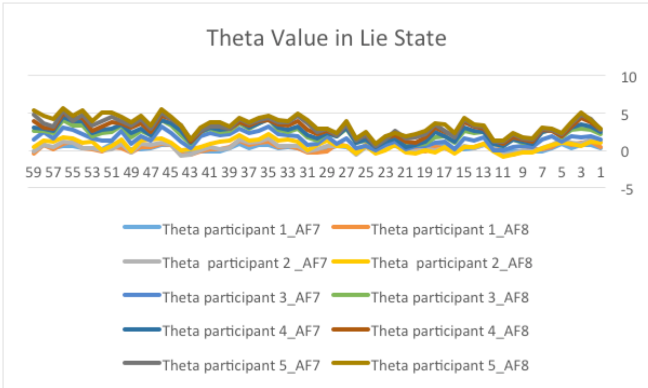

Figure 6: Theta in Lie state

VI. CONCLUSION

In this paper, we illustrated the recent work in the domain of EEG-based deception detection and the suitability of using EEG as a base for lie detection devices. Using experimental studies, we showed that relying on low-cost, small-scale EEG scanners with enough electrodes could be efficient to provide enough raw-data for such device. In these experiments, we used MUSE as our EEG scanner. Experiments showed it's effectiveness and efficiency in achieving the targeted goal. Our future work includes building a comprehensive suit as a mobile application exploiting deep-learning mechanisms among other machine learning techniques for enhanced detection quality.

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