Mood Detection and Memory Performance Evaluation with Body Sensors

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***Abstract*—This paper provides the design of a system employing an Android application connected to body sensors, which is capable of assessing the mood and memory performance of humans. The mood detection is based on the heart rate, its variability, as well as on the captured brain waves. The memory performance is evaluated based on specific brain waves observed as well. Experiments were conducted to assess the main features of the system. The mood experiment has been successful at raising the mood levels of the majority of participants when being shown stimuli composed of images and sounds. Negative or neutral mood levels could be explained by participants having other thoughts or emotions during the experiment, and by the attenuation and dampening of the body sensors' signals. The ability of participants to reach a particular mood (relaxed, engaged, and sad) more quickly in response to a conducive stimulus is related to a person's physical characteristics; for example, younger participants reach a particular mood more quickly than older participants. The memory experiment has been successful at raising the memory levels of the majority of participants when being asked to perform a modified Sternberg memory task. Results show a positive memory activity for the majority of participants, even in the presence of signal attenuation in the body sensors.**

***Keywords-Mood Detection*; *Body Sensors*; *Heart Rate Variability*; *Android Application*; *Brain Waves*.**

I. INTRODUCTION

Mood detectors can identify trends pointing to a person's mood. They can be found in modern computers, laptops, smartphones, tablets, sensors such as skin sensors, electroencephalography sensors, and voice recognition sensors. Thanks to existing technology, they can be carried everywhere and accessed anytime. Furthermore, these devices feature lower costs, high speed, low power consumption, and many other benefits for the subject, clinician or researcher.

Mood detectors can be integrated in our daily lives, such as when driving a car. The driver might feel stressed and tired when driving long distances. A car with sensors can understand the driver's emotion and feelings and prevent an accident, which could save many lives. Sensors could nest in the steering wheel and door handles to pick up electric signals from the skin. A camera mounted on the windshield could analyze facial expressions. When the driver is stressed, the car's sensors could soften the light and music, or broaden the headlight beams to compensate for the loss of vision [1].

The importance of mood detection has been increasingly recognized because it could prevent mood disorders from affecting us and harming us in our daily lives. Mood disorders include depression and bipolar disorders. Anyone can be affected from mood disorders: children, teenagers, adults, and the elderly. Stressful events in our lives can result in transitory depression, or any of several mood disorders. Symptoms include being sad, anxious, hopeless, helpless, and having low self-esteem. These symptoms can be overcome with the knowledge of one's current mood by using the above-mentioned devices and taking the right actions, such as a psychiatric consultation and/or the commencement of medication.

A. Application Features

Mood detection is a growing and rapidly developing field. Many existing devices can approximate one's current mood. Devices such as wrist sensors can provide information on stress levels when worn. They can communicate this information via the internet. For example, a sensor worn on a child's wrist might detect that the child is stressed. The stress signal is communicated via the internet and the parent can see on his/her smartphone that the child is stressed, thereby enabling the parent to take action to reduce that stress level [2].

In recent years, many applications for smartphones and tablets capable of telling a person's mood have been released. Samsung has developed a smartphone that can tell one's mood based on how the phone is used. For example, it monitors the speed at which the user is typing some text, and how much the device shakes [3]. The ”mood detection

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and memory evaluation" Android application combines many of the features from the applications mentioned below:

• The system requires Bluetooth Low Energy in order to work.

• Mood is measured using brain and heart sensors, so it is very accurate.

• Mood data and user data is sent to the Web on a Dropbox Web Server, which is safe and secure.

• Mood data can be compared between users.

• Mood data for each user can be graphed, so it is easy for the user to compare his/her mood on a daily basis.

The paper is organized as follows: section 2 briefly discusses the system's features such as mood and memory performance algorithms and the valence/arousal model. Section 3 discusses the experimental work. Finally, Section 4 concludes on the paper work and speculates on the future of this growing field.

II. Background

This section discusses essential background information of the work. Please note that this application is not standalone code, but is connected to body sensors communicating with it via Bluetooth Low Energy.

A. Mood and Memory Performance Algorithms

This section discusses the procedure for measuring different emotions and memory performance in real time through the use of mood and memory performance algorithms. This section also shows a pseudocode implementation of the mood and memory performance algorithms.

The recognition of different emotions and memory performance is achieved as follows:

• First, we record the resting heart rate of the participants. Any significant rise in this heart rate (when the participant is seated and relaxed) is explained by strong emotions, such as excitement, happiness, anger, and arousal [4].

• Second, we record the heart rate variability of the participant. We calculate it by using the formulas described in the next subsections. The heart rate variability is a useful feature in mood classification, since a bigger heart rate variability is an indicator of good health and a lower heart rate variability is an indicator of bad health, stress, and heart diseases.

• Third, we process the EEG data of the brain using the procedures described in the next subsection. The processed data consists of the EEG average band powers (alpha, beta, gamma, and theta). Using relations and formulas discussed in the next subsections, we obtain the arousal and valence information and we use this information along with the 2D valence/arousal model to recognize different emotions in real-time. Furthermore, memory performance evaluation follows almost the same procedure except that we look at the band powers, especially the alpha band power to evaluate retention in a short-term memory task.

1) Android Pseudocode Implementation

The pseudocode implementation of the relaxation mood (how to find the relaxation level of an individual given some parameters such as heart rate) is shown as all other mood and memory performance algorithms follow a similar implementation.

Referring to Algorithm 1, RelaxHR% measures how relaxed a person is from heart rate. A value close to 0% indicates that a person is not relaxed, and a value close to 100% indicates that a person is very relaxed. RelaxSDNN% measures how relaxed a person is from heart rate variability (ageSDNN is the ideal SDNN a person should have given his/her age). RelaxEEG% measures how relaxed a person is from EEG. Together, these values are used to find the relaxation level.

B. Data Processing

The procedure for data processing to obtain mood and memory performance levels works as follows: first, the DC offset and slow drift of the raw signal is removed. The best way to do this is with a high-pass filter with a cut-off frequency greater than 0.16Hz. The data segment is then multiplied by a tapered window function which smoothly forces the two ends of the data segment to match exactly. Step changes and start-finish differences will put fake responses into Fast Fourier Transform (FFT) data since the algorithms assume an infinitely repeating copy of the segment of data. The FFT algorithm is then executed. The FFT algorithm returns a complex set of values at each frequency increment. The magnitude of these complex numbers is squared by multiplying each complex number by its complex conjugate. Power is proportional to the square of the magnitude, so now we have the power per frequency interval. The powers are added up for each element of the frequency range of interest, so now we have the average EEG band powers.

C. Resting Heart Rate

The resting heart rate is the heart pumping the lowest amount of blood. If a person is sitting or lying, and is calm, relaxed and in good health, his/her resting heart rate should range between 60 and 100 beats per minute. A heart rate lower than 60 could be explained by a medical condition, taking drugs such as beta blockers, or being physically active and very athletic. Active people often have lower resting heart

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Algorithm 1 Relaxation Mood Algorithm

```
Input: heart rate, heart rate variability (SDNN), valence, and
  arousal.
Output: relaxation level
  if (HR/HRrest*100)<100 then
    RelaxHR% = 100
  else
    if ((1-((HR / HRrest)-1))<0.0) then
      RelaxHR% = 0
    else
      RelaxHR% = ((1 - ((HR / HRRest) - 1)) * 100)
    end if
  end if
  if (age>=0&&age<=49) then
    ageSDNN = 50
  else
    ageSDNN = 40
  end if
  if (SDNN/ageSDNN*100)>100 then
    RelaxSDNN% = 100
  else
    RelaxSDNN% = ((SDNN/ageSDNN)*100)
  end if
  if (valence>0) then
    if (arousal>0.4&& arousal<=1) then
      RelaxEEG% = 100
    else if (arousal>1) then
      if ((1-(arousal-1))<0) then
        RelaxEEG% = 0
      else
        RelaxEEG% = ((1 - (arousal - 1)) * 100)
      end if
    else
      RelaxEEG% = (arousal/0.4)*100
    end if
  else
    RelaxEEG% = 0
  end if
  RL = RelaxHR%/4 + RelaxSDNN%/4 + RelaxEEG%/2
  return RL
```

rates because their heart muscle is in better condition and does not need to work as hard to maintain a steady beat [5].

D. Heart Rate Variability

Heart rate variability (HRV) is the degree of fluctuation in the length of intervals between heart beats. A bigger regularity of heart beats lowers HRV and vice versa. Regularity of heart beats is derived from a quantity of numbers equal to the time elapsed between successive heart beats. These are named R-R intervals and are measured in milliseconds (ms) [6].

HRV can be assessed in two ways: as **Time Domain Analysis**, or in the frequency domain, as **Power Spectral Density Analysis**. We will concentrate on **Time Domain Analysis** because it is more simple and straightforward.

Time domain measures are the simplest to calculate and include the mean normal-to-normal (NN) intervals during the entire recording and statistical measures of the variance between NN intervals. The most important time domain measures are the SDNN (HRV), and the RMS-SD.

- The SDNN is the standard deviation of the NN intervals, which is the square root of their variance. A variance is mathematically equivalent to the total power of spectral analysis, so it reflects all cyclic components of the variability in recorded series of NN intervals. It is inappropriate to compare SDNN values derived from the NN recordings of different lengths. A recording can last a short period of time, such as five minutes, or it can last a full 24-hour day. SDNN is measured in milliseconds [6].
- The RMS-SD is the square root of the mean squared differences of successive NN intervals. This measure estimates high-frequency variations in heart rate in short-term NN recordings that reflect an estimate of parasympathetic regulation of the heart. RMS-SD is measured in milliseconds [6].

Formulas to calculate these time domain measures are given:

Let N be the total number of heart beats. Let MRR be the mean of RR (or NN) intervals. It is calculated as follows:

$$MRR = \bar{I} = \frac{1}{N-1}\sum_{n=2}^{N} I(n) \tag{1}$$

In this formula, I(n) is the value in milliseconds of the nth NN interval. The SDNN can be expressed as:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=2}^{N}[I(n)-\bar{I}]^2} \tag{2}$$

Finally, the RMS-SD can be expressed as:

$$RMSSD = \sqrt{\frac{1}{N-2}\sum_{n=3}^{N}[I(n)-I(n-1)]^2} \tag{3}$$

E. Valence/Arousal Model

The 2D Valence/Arousal model is used to characterize emotions such as: happy, sad, relaxed, and angry. Emotions are characterized based on their valence and arousal values. For example, happiness is characterized by a positive valence and high arousal, anger is characterized by negative valence and high arousal, relaxation is characterized by positive valence and low arousal, and sadness is characterized by negative valence and low arousal [7].

High arousal (excitation) is characterized by a high alpha power and a low beta power (a high alpha activity and a low beta activity). The ratio of the beta to the alpha power characterizes the arousal level of a person ($Arousal = beta/alpha$). The arousal level of a person is measured using the frontal electrodes of the Emotiv Insight brain sensor. This relationship holds because beta brainwaves are associated with an alert or excited state, while alpha brain waves are associated with a relaxed state [7].

To determine the valence level, we compare the activation levels of the two cortical hemispheres. Left frontal inactivation is an indicator of a withdrawal response, which is often linked to a negative emotion. On the other hand, right frontal inactivation may be associated with an approach response, or positive emotion [7].

High alpha activity is an indication of low brain activity, and vice versa. Thus, an increase in alpha activity together with a decrease in beta activity may be associated with cortical inactivation. The frontal electrodes of the Emotiv Insight brain sensor, AF3 and AF4, are the most used positions for looking at this activity, as the frontal lobe plays a crucial role in emotion regulation and conscious experience.

We estimate the valence value in a person by computing and comparing the alpha power α and beta power β in channels AF3 and AF4, like so:

$$valence = \frac{\alpha_{AF4}}{\beta_{AF4}} - \frac{\alpha_{AF3}}{\beta_{AF3}} \tag{4}$$

III. Experimental Study

The experiment is performed to assess how effective is the system at finding the mood and memory performance levels of each participant. It presents part of the results obtained from performing the experiment and a discussion based on these results.

A. The System

The system is composed of the following components:

- External sensors, such as the Texas Instrument Sensor Tag, the Polar H7 heart rate sensor, and the Emotiv Insight brain sensor.
- The Cloud, where the Dropbox Core Api is used to store the users' data and access it anytime needed.

B. Subjects

Sixteen subjects (ages 22-80, 12 males and 4 females) performed the experiment, which consisted in evaluating their mood and memory performance levels while their heart and brain data was recorded. Informed consent was obtained from each subject prior to the study. Ethical approval was obtained from the Research Ethics Board Office of McGill University. The reference number is: 306-0116.

C. Stimulus

Both pictures and music were used to be the stimulus to elicit emotion. To represent good moods such as relaxation, happiness, engagement and arousal, pictures displaying beautiful nature scenery, people jumping out of joy, beautiful birds, plants, and animals, were selected. To represent bad moods such as sadness, anger, and stress, pictures displaying angry and wild animals, people crying, and children all alone sleeping in the streets, were selected. Three to four music pieces were chosen to represent each mood. Each lasted 30 seconds. For example, annoying alarm clock sounds were chosen to represent stress, bomb siren sounds were selected to represent anger, ”Don't Worry be Happy” by Bobby McFerrin was selected to represent relaxation, ”Chariots of Fire” theme song was selected to represent arousal, the theme song from the movie ”Pirates of the Caribbean” was chosen to represent engagement, ”Happy” by Pharrell Williams was selected to represent happiness, and ”Very Sad Violin” classical music was chosen to represent sadness.

This procedure achieved stimulation by increasing and decreasing the neural activity of the brain. The cerebral cortex became synchronized at any given moment. The limbic system's cingulate gyrus, which connected actions with emotional responses, became synchronized. This synchronization happened mostly in brain parts responsible of processing sights, sounds, and emotions.

D. Testing Procedure

The experiment took a total time of 45 minutes. Data was recorded using a tablet (Samsung Galaxy Tab 4). The participant was instructed to sit and not to move his/her head for the entire duration of the experiment. The Polar H7 heart rate sensor was placed on the participant's bare chest and the Emotiv Insight brain sensor was placed on the participant's head. The data was stored on a Dropbox account. For added security, the data in the Dropbox account was encrypted using Boxcryptor. Boxcryptor features a fast and easy Dropbox encryption, a state-of-the art AES-256 encryption standard, and top security for all private and business needs. The application was launched and the participant was prompted to create an account. Creating an account requires him/her

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to enter a username, a password, his/her height, his/her weight, and his/her sex. The participant was prompted to take a picture of himself/herself. The air temperature, the air humidity, and the air pressure were recorded using the Texas Instrument Bluetooth Low Energy Sensor Tag. The participant was asked if he/she was relaxed or not and if not, he/she was given a short period of time (2 minutes) to relax. When relaxed, the participant's resting heart rate was recorded. Then, for each stimulus composed of pictures and sounds (each representing a particular mood such as relaxed, engaged, stressed, happy, angry, aroused, and sad) which was displayed on a laptop screen, the data was recorded on a tablet before evoking the stimulus, the stimulus was evoked, and the data was recorded on a tablet after evoking the stimulus. At the end of each stimulus, there was a relaxation period of 1 minute. The first part of the experiment took 35 minutes. In the second part of the experiment, the subject was first given a 1-minute resting period. The memory test was given immediately afterward, and the test subject's memory performance level was recorded. For the memory test, the participant was shown three sets of 4-6 letters displayed on a laptop screen. After being shown each set of letters, the participant was given a brief moment (2-5 seconds) to memorize the set of letters. The participant was then shown a letter which may or may not be part of the set of letters previously shown to him/her. The participant was asked to state whether or not this letter belongs to the set of letters. There were three sets of letters and three probes in the memory experiment. EEG data was recorded twice per set of letters: before showing the set of letters to the participant and just after showing the set of letters to the participant while he/she was busy memorizing them. The second part of the experiment took 10 minutes.

E. Results

Results were gathered from the participants' brain and heart data under the following environmental conditions: the temperature ranged from 60.28 deg/F to 67.57 deg/F, the humidity ranged from 32.25 %rH to 48.18 %rH, and the pressure ranged from 999.70 nPA to 1032.32 nPA. All participants confirmed that they were relaxed at the beginning of the experiment. All participants remained seated and did not move their heads for the entire duration of the experiment. Results for this paper contain relaxation data graphs such as the relaxation level recorded before evoking the stimulus and the relaxation level recorded after evoking the stimulus for each participant, the age, height (in meters), and weight (in kilograms) of each participant versus the difference in the relaxation level recorded after evoking the stimulus and the relaxation level recorded before evoking the stimulus. Mood and memory performance levels are in percent. A mood level of 0% suggests that the participant is not feeling at all in that particular mood, and a mood level of 100% suggests that the participant is feeling very strongly in that particular mood. A memory performance level close to 100% may be associated with strong memory activity, whereas a very low memory performance level, approaching 0%, may be associated with no memory activity.

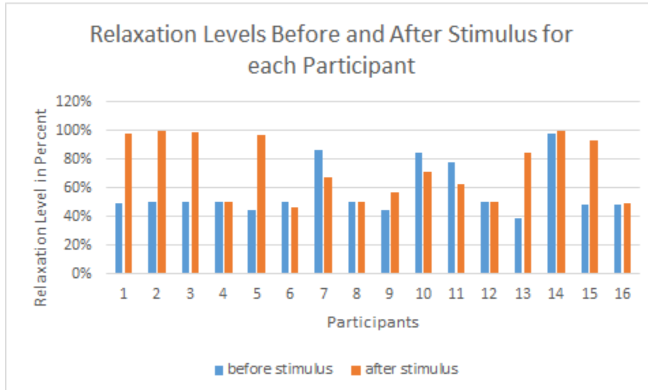

Fig. 1. Relaxation Level before and after Evoking Stimuli for each Participant

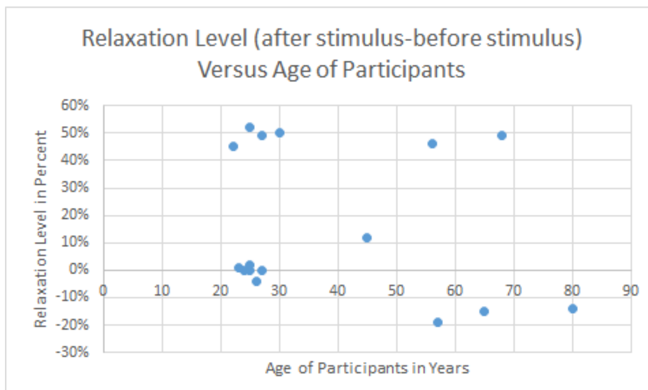

Fig. 2. Relaxation Level (after Evoking Stimuli - before Evoking Stimuli) for each Participant versus their Age

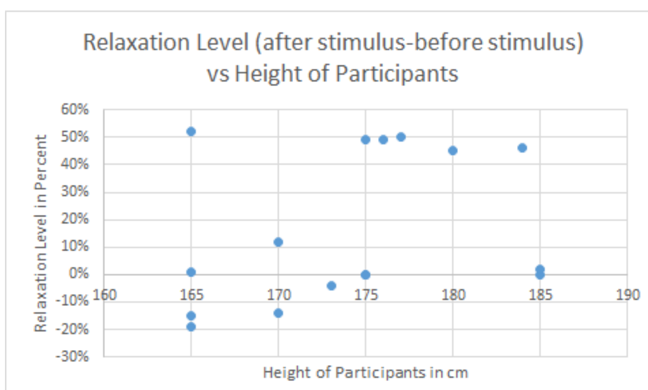

Fig. 3. Relaxation Level (after Evoking Stimuli - before Evoking Stimuli) for Each Participant versus their Height

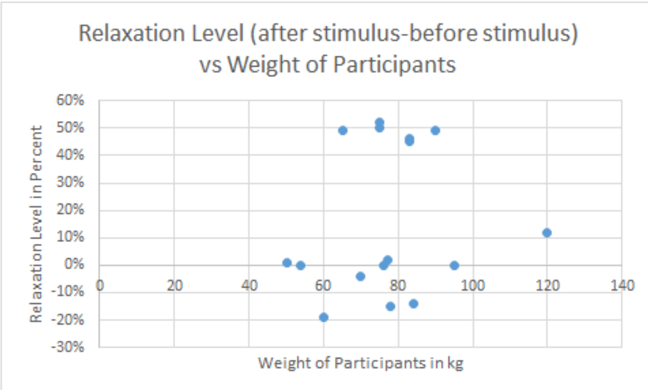

Fig. 4. Relaxation Level (after Evoking Stimuli - before Evoking Stimuli) for each Participant versus their Weight

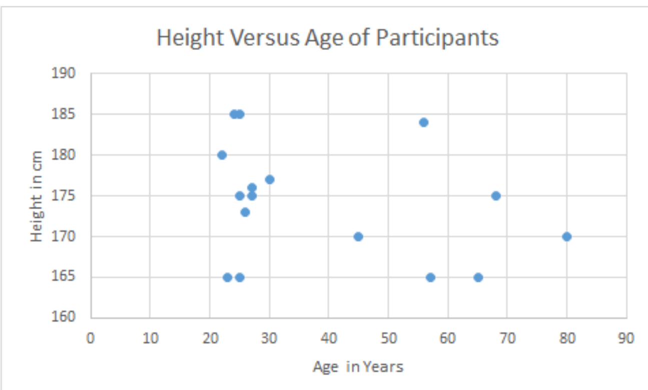

Fig. 5. Height of Participants versus their Age

F. Discussion

The experiment has been successful at raising the relaxation levels of the majority of participants. Referring to Figure 1, about 56% of all participants had a higher relaxation level after the stimulus as compared to before the stimulus. The 44% remaining participants were found to have varying reactions when exposed to such stimulus: some of the 44% may have had other thoughts or emotions during the experiment, and may have been preoccupied with other matters, thereby negating any effect of the relaxation stimulus on them. Another problem potentially accounting for the variation in results is the fact that the brain sensor's EEG data had to travel from the brain cortex to the electrodes of the brain sensor. During its travel, the signal may have been attenuated or dampened as a result of traveling through many brain regions. Thus, the quality of the signal using this method is not optimal, and results in a lower-quality EEG signal. Figure 2 showing the change in relaxation level (the relaxation level after the stimulus minus the relaxation level before the stimulus) was plotted against the age of all participants. The graph reveals that almost all participants had positive or neutral changes in relaxation levels and that most participants with the greatest positive changes in relaxation levels (higher than 40%) are the younger participants, those aged 22 to 30. The older population, those aged 40 to 80, had the most participants with negative changes in relaxation levels (3 participants aged 50-80 versus 1 participant aged 26). The results reveal that the ability of the participants to relax quickly in response to a conducive stimulus is greater for younger individuals than for older ones. The change in relaxation level was plotted against the height of all participants (Figure 3). The results reveal that the tallest individuals (heights ranging from 175 to 185 cm) had the majority of values corresponding to the highest changes (higher than 40%) in relaxation levels (5 individuals with heights ranging from 175 to 185 cm versus 1 individual with a height of 165 cm). The participants with all values corresponding to negative changes in relaxation levels are the shortest individuals (4 individuals with heights ranging from 165 to 175 cm). The results mean that taller participants are better able to relax quickly than shorter participants. The graph (Figure 4) showing the change in relaxation level against the weight of participants reveals that the majority of individuals with the greatest changes in relaxation levels are those with weights ranging from 60-90 kg. The graph also shows that the individuals from the same weight range have all values associated with negative changes in relaxation levels. Therefore, the results stating that participants with a weight range of 60-90 kg are better able to relax quickly than the other participants are inconclusive. According to the last graph (Figure 5), the majority of tall participants (those with height ranging from 175 to 185 cm) are 20 to 30 years old (7 participants with heights ranging from 175 to 185 cm versus 2 participants with the same height range who are 50 to 70 years old). The results mean that in general taller and younger participants are better able to relax quickly than shorter and older participants.

The first, second, and third trial memory performance levels before and after memorizing the set of letters for each participant show that the experiment has been successful at raising the memory performance levels of the participants. Almost all participants had higher memory performance levels after memorizing the set of letters as compared to before memorizing the set of letters which is associated with positive memory activity. The success rates of all trials are 81%. The 19% remaining participants for each trial had memory performance levels lower or equal after memorizing the set of letters as compared to before memorizing the set of letters. An explanation of the variation in results is the fact that the brain sensor's EEG data had to travel from the brain cortex to the electrodes of the brain sensor. During its travel, the signal may have been attenuated or dampened as a result of traveling through many brain regions before reaching the brain sensor's electrodes. It is very likely that the more head hair a participant had, the more attenuated or dampened the signal was when reaching the electrodes of the brain sensor.

IV. Conclusion and Future Work

This paper has presented a system capable of detecting the mood and memory performance of humans. A discussion of the mood and memory performance algorithms, data processing, resting heart rate, heart rate variability, and the valence/arousal model, was given in Section 2. Section 3 described the testing procedure and a discussion on only part of the results of the experiment was formed in order to respect the paper's length.

This application can be a first step in mental health evaluation, and, as we know, it is up to the patient to take the right decisions so that meaningful changes in health and lifestyle can be made.

To increase the accuracy of mood and memory detection in the future, we could use more external sensors such as skin sensors and infrared sensors (infrared camera to measure body temperature), all of which are connected via Bluetooth Low Energy or another protocol to a smartphone, tablet, or other electronic device. Although mood and memory evaluation from heart and brain sensors is accurate, it does not provide enough information on all body activity such as skin (perspiration), arms and legs (motion), and back (posture). The algorithms on mood and memory detection could be more refined and accurate and, when combined with the multiple external sensors, could be used to detect a bigger range of emotions. To evaluate memory, we could use more sophisticated devices such as fMRI (Functional Magnetic Resonance Imaging) and MEG (Magnetoencephalography) to get a better view of brain activity. In order to acquire such devices, experience and funding would be required.

Mood and memory evaluation devices have become very popular with the expansion and improvement of technology. The field of mood detection and memory evaluation can be expected to grow and evolve thanks to researchers and developers who seek to improve quality of life by introducing new devices and systems that help raise awareness of individuals' health and well-being. We hope that our contribution can make difference in many fields of study, especially in computer engineering, biomedicine, mental health and other medical specialties.

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