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3D Characterization and Trend Analysis of Scents from EEG Recordings of Repeated Scent Exposure

Brendan Fu-Long Sieow*, Wee Ser, IEEE Senior Member, Melvin Weiyuan Ho, May Oo Lwin, Kenneth Kwok

***Abstract*—Scent plays an important role in influencing the brain and has been commonly used in psychological research. Much of such research has been conducted without the use of electroencephalography (EEG) to measure the response of the human brain to scent stimulus. Recent studies have involved the use of EEG to perform comparative studies on how different scents can affect brain activity. However, little has been done to analyze the trend of brain activity when a subject is repeatedly exposed to the same scent. This paper discusses the use of 4 features - Entropy Difference, Entropy Ratio, Entropy Time and Root Mean Square (RMS) to perform trend analysis of EEG signals in a repeated scent-exposure setting. The results show that different types of scents cause the brain to be stimulated at different degrees for each repeated exposure, giving rise to different trend patterns. It is also observed that the 4 features give similar trends for the same scent. This similarity allows us to combine the 4 features by forming a feature vector and plotting them in 3 dimensional (3D) space, using 3 repeated scent exposures as the axes. The region of space where the feature vector lies is represented by an ellipsoid, which can be used to characterize a particular scent. Unlike previous work, which did not characterize scent from EEG recordings, this paper investigates the different trends of scent after its repeated exposure to the human subject and by using the 3D representation to characterize the scent.**

I. Introduction

Scents have always played an important role in influencing the psychological aspect of the human brain, be it cognitive processes, emotion or perception to behaviour [1]. Many psychological studies have been conducted to investigate the effect of scent on the human body. There have been psychological studies done on how scent can affect a person's learning and memory [2] as well as a person's performance in carrying out a complex task [3]. Furthermore, by knowing the effect of stimulations at the different instances of repeated scent exposure, a corresponding clinical procedure can be used to deliver the optimal amount of scent exposures to enhance the cognitive function and brain performance (e.g. learning, memory and mental performance) for a given scent. Looking at current research in the field of EEG and scent, there have been studies that investigate the brain response between different types of odors by using features such as Fractal Spectra and Fast Fourier Transform spectra analysis [4-5]. Other feature extraction methods such as the fundamental Shannon's Entropy [6] and its derivatives have become more popular due to their effectiveness. Other entropy based feature extraction methods such as the proposed Entropy Difference and Entropy Ratio have also been reported in the literature [7]. On the other hand, statistical features such as Root Mean Square (RMS) can also be used as a feature. Besides simply looking at a single scent exposure, there have been experiments that look into repeated scent exposures such as the study of the effect of induced olfactory sensitivity to androstenone under a repeated exposure condition [8]. To the best of our knowledge, a comparative study and trend analysis of repeated scent exposure has not been reported in literature. Also, there has not been published work on the 3 dimensional (3D) representation of scent.

This paper proposes to use 4 features, Entropy Difference, Entropy Ratio, Entropy Time and RMS to represent the brain signal pattern when the human subject is subjected to 3 repeated scent exposures. The resultant feature vector is then plotted in a 3D space using the 3 repeated scent exposures as the axes.

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Brendan Fu-Long Sieow is with Nanyang Technological University, Singapore (corresponding author to provide phone: +65 91552829; e-mail: bfsieow1@e.ntu.edu.sg).

Wee Ser, is with Nanyang Technological University, Singapore (email : ewser@ntu.edu.sg)

Melvin Weiyuan Ho, is with Nanyang Technological University, Singapore (email : mwho1@e.ntu.edu.sg)

May Oo Lwin, is with Nanyang Technological University, Singapore (email: tmaylwin@ntu.edu.sg)

Kenneth Kwok, is with DSO National Laboratories, Singapore (email: kenkwok@dso.org.sg

II. EEG Signal Acquisition

A. Experimental Set-up

The experimental set-up and the procedures of the experiment are discussed in this section. The Eucalyptus and Ylang Ylang scents chosen for this study were classified to be an arousing scent and calming scent respectively. 0.5ml of each scent in the form of aromatherapy oil was micro-pipetted onto a tissue and placed into a fully air-pumped Ziploc® bag. This was done 10mins before the EEG recording for each subject to ensure the freshness of the scent. The scent was delivered to the nose of each subject using a modified medical oxygen mask, connected to the Ziploc® bag. During each recording, the Ziploc® bag was compressed to pump the scented air out. Subjects were told to breathe normally when exposed to the scent.

The subjects used in this study were 9 healthy, randomly selected right-handed male college students (ages ranging from 20 to 25 years) who had normal nasal anatomy. The EEG brain waves were recorded using the 16 channel g.USBamp. The 4 chosen electrodes positions (F3, C3, P3 and P4) used for this recording were placed on the scalp of the subjects according to the international 10-20 standard. F3 and C3 are located in the left and right frontal region of the scalp respectively. P3 and C4 are correspondingly situated in the left and right temporal region of the scalp. FPz and Cz were chosen as the ground and reference. The subjects were made to look at a drawn cross 2m away from their seated position and told not to move during the recordings to reduce artifacts resulting from eyeball movement and voluntarily skeletal muscle contraction. Additionally, the electrode impedance was minimized by applying ECI Electro-Gel, so that all electrode impedances were below 3kΩ. The room temperature was maintained at 23˚C and humidity set at 80% throughout the whole experiment.

B. Experimental Procedures

A baseline recording of EEG waves was conducted for each subject for 12s without any odor stimulus. This was then followed by recording EEG waves of each subject for 240s where a scent stimulus was repeatedly introduced at the 0s, 80s and 160s mark in the recording, as seen in Figure 1. Each of the 3 repeated scent exposure lasted for 20s. Following each 20s stimulus, there was a 60s non-scent exposure stimulation period. This 3 time repeated scent exposure routine was done for the 2 different scents used and presented in random order for every subject. A 5mins break was given after each scent recording to minimize the effect of the previous scent on the subject. This would allow the brain to return to its original state, before the excitation of the next scent. The sampling frequency used was 256Hz. A band pass filter of 0.5 to 30Hz was used to digitally filter the data (Alpha and Beta waves) and the AC noise problem was addressed by introducing a notch filter of 58Hz. The raw data was collected and then processed using MATLAB software.

III. PROPOSED REPEATED EXPOSURE TREND ANALYSIS AND 3D REPRESENTATION OF SCENT

After completing the recording of EEG signals from the subjects, the time samples of the 3 times scent exposure were extracted. A median filter was applied to the raw data. Feature extraction was done using Entropy Difference, Entropy Ratio, Entropy Time and RMS to perform a trend analysis after repeated exposure to a particular scent. For each sample, a weighted summation of the 4 features was done to combine them into 1 feature vector, represented in a 3D space, defined by the 3 times exposures. Scent characterization was done by plotting an ellipsoid to represent the region in space where the feature vectors belonging to each sample were found for each scent.

A. Entropy-based Feature Extraction Method

For each scent's EEG recording data, the 3, 20s segments were extracted, coinciding with the repeated scent exposure at the 0s, 80s and 160s mark. For processing, data within the 4-24s, 84-104s and 164-184s time frames were used. The starting time of each chosen segment was 4s after a subject was exposed to the scent with the intention of extracting a period where the subject's brain had started to respond to the scent. The whole 12s base line recording data was also processed. A median filter, a sliding-window spatial filter was applied to all raw data extracted. A 1 x 3 window was chosen and the center value in the window was replaced by the median of all the values in the window.

Each 20s period was divided into 5, 4s time segments and a Short Time Fourier Transform (STFT) was done on each of the 4s, which was represented by 1024 data points. The non-exposure 12s period was divided into 3, 4s time segments and a STFT was done on each segment as well.

The absolute $\boldsymbol{y}$ values for each of the 4s were normalized.

$$\boldsymbol{y_i} = \frac{\boldsymbol{y_j}}{\sum_{j=1}^{5} \boldsymbol{y_j}} \qquad (1)$$

Where $\boldsymbol{y_j}$ and $\boldsymbol{y_i}$ is the amplitude from STFT and the normalized amplitude respectively.

Peak detection by masking [9] is done by applying a standardized amplitude threshold value, $\boldsymbol{thv}$ at 0.00001 for both scents.

$$\boldsymbol{C_p} = \begin{cases} \boldsymbol{y_i - thv} & \boldsymbol{if\ y_i - thv > 0} \\ \boldsymbol{0} & \boldsymbol{if\ y_i - thv \leq 0} \end{cases} \qquad (2)$$

Equation (2) shows that peaks (dominant values), denoted as $\boldsymbol{C_p}$ are retained. $\boldsymbol{thv}$ becomes the new zero level.

The Entropy value, $\boldsymbol{E_i}$ for each sample could then be calculated as

$$\boldsymbol{E_i} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{C_i\, log_2(C_i)} \qquad (3)$$

<u>Entropy Difference, $\boldsymbol{E_D}$</u>

Entropy difference [7] is the difference in the disorderliness across a time frame. The entropy difference is obtained by taking the absolute of the maximum entropy value $\boldsymbol{E_{max}}$ among the 5 entropy values for each exposure time frame subtracted by the minimum entropy value $\boldsymbol{E_{min}}$.

$$\boldsymbol{E_{difference}} = |\, \boldsymbol{E_{max} - E_{min}}| \qquad (4)$$

<u>Entropy Ratio, $\boldsymbol{E_R}$</u>

Entropy Ratio [7] is the ratio of disorderliness across a time frame. It is obtained by taking the ratio of the minimum entropy value $\boldsymbol{E_{min}}$ against maximum entropy $\boldsymbol{E_{max}}$ in each time frame.

$$\boldsymbol{E_{ratio}} = \boldsymbol{E_{min}} / \boldsymbol{E_{max}} \qquad (5)$$

<u>Entropy Time, $\boldsymbol{E_T}$</u>

Entropy Time is entropy calculated directly in the time domain where the extracted and absolute data from the 3 time frames of 4-24s, 84-104s and 164-184s were put through the 1 x 3 median filter. A single entropy value was then calculated to represent the time frame using equation (3).

B. Statistical Feature Extraction

Root Mean Square (RMS), $\boldsymbol{x_{rms}}$

The extracted raw values of time frames 4-24s, 84-104s and 164-184s were also put through the 1 x 3 median filter and a RMS value, $\boldsymbol{x_{rms}}$ can be calculated by using the RMS formula to represent each time frame.

C. 3D Representation of Scent for Characterization

From each feature we have extracted, a feature vector, $\boldsymbol{F_p}$ of length dependent on the number of scent exposures, $\boldsymbol{N}$ can be represented for each subject in the following manner:

$$\boldsymbol{F_p = \{F_{p,1}, F_{p,2}, \dots, F_{p,N}\}} \tag{6}$$

Where $\boldsymbol{p}$ is the feature $\boldsymbol{E_D, E_R, E_T}$ ***or*** $\boldsymbol{x_{rms}}$

Each of the 4 feature vectors was scaled to standardize the feature coefficients. A weighted sum was then performed on the 4 feature vectors. This is represented by:

$$\boldsymbol{Z = \sum_{p=1}^{4} \propto_p F_p = \{Z_1, Z_2, Z_3\}} \tag{7}$$

A different $\boldsymbol{\alpha}$ weighting is assigned to each feature to either increase or decrease its contribution to the combined feature vector $\boldsymbol{Z}$. The $\boldsymbol{\alpha}$ value used for Entropy Difference, Entropy Ratio, Entropy Time and RMS were 1, 5, 0.2 and 2 respectively. The combined feature vector for each subject was then plotted out as a point in a 3D graph with the first, second and third scent exposures as the axes. This was done for both Eucalyptus and Ylang Ylang scents. We can then observe regions in space, where the combined feature vectors of the same scent would be found in the 3D plot.

In order to characterize different scents in space, a 3D shape such as the ellipsoid was proposed to represent the region in space where the combined feature vectors belonging to each sample were found at for each scent. To determine its location, the mean of the 9 combined feature vectors for a single scent was calculated to be the center of the ellipsoid. The general geometrical formula of the ellipsoid used is:

$$\boldsymbol{\sum_{j=1}^{N} \beta_j (Z_j - Z_{j,0}) \leq 1} \tag{8}$$

Where $\boldsymbol{\beta_j}$, $\boldsymbol{Z_j}$ and $\boldsymbol{Z_{j,0}}$ are the weights for each scent exposure, combined feature vector value and mean combined feature vector value respectively.

With 3 scent exposures, the ellipsoid formula is expressed as the following:

$$\boldsymbol{\beta_1 (Z_1 - Z_{1,0})^2 + \beta_2 (Z_2 - Z_{2,0})^2 + \beta_3 (Z_3 - Z_{3,0})^2 \leq 1} \tag{9}$$

When all the $\boldsymbol{\beta}$ values in equation (9) are assigned a value of 1, we have simplified the ellipsoid into a sphere to visually characterize the 2 different scents by the formula:

$$\boldsymbol{(Z_1 - Z_{1,0})^2 + (Z_2 - Z_{2,0})^2 + (Z_3 - Z_{3,0})^2 \leq r^2} \tag{10}$$

By plotting out the combined feature vector $\mathbf{Z}$ in the 3D space and using a sphere to represent the region of space belonging to a specific scent, different scents (eg. Eucalyptus and Ylang Ylang) can be characterized by having different visual representations in space. From equation (10), the $\boldsymbol{r}$ value would determine the size of the sphere. To determine the optimal size of each sphere, a visual analysis and adjustments to the $\boldsymbol{r}$ value were performed to allow the maximum number of combined feature vector samples, belonging to the same scent, to be clustered together and fall within the sphere.

IV. Results and Discussions

A. Trend Analysis

A trend analysis for 9 male subjects was done by taking the mean of each feature value and plotting it against the number of scent exposures. We would be able to observe how the brain responded to having 3 times exposure to an individual scent, as well as to make comparisons between calming scent Ylang Ylang and arousing scent Eucalyptus. For an equal comparison, the threshold value of 0.00001 was chosen. As the trend was found to be most significant for the electrode position F3-Cz, we have used this in our results.

Figure 2 showed that different types of scent caused the brain to be stimulated at different degrees for each instance of repeated exposure, giving rise to different trend patterns. The Eucalyptus, which is an arousing scent gave the highest stimulus at the first exposure and subsequently decreased in stimulus for the next 2 repeated exposures. Ylang Ylang, which is a calming scent, had a lower first stimulus compared to Eucalyptus and even lower stimulus for the second exposure. However at the third scent exposure, its stimulus increased and exceeded Eucalyptus. All 4 feature graphs showed a visible difference in the brain's arousal in the presence of scent stimulus and without.

Entropy Difference and Entropy Ratio gave an almost identical trend which suggests that they could be used interchangeably to determine the comparative trends of arousal of the brain by different scents when subjected to 3 times exposure. Entropy Time and RMS which were measured in the time domain also showed similarities in trends. The similar trends by the 4 features show the potential to combine the features together for representing different scents in 3D space for scent characterization.

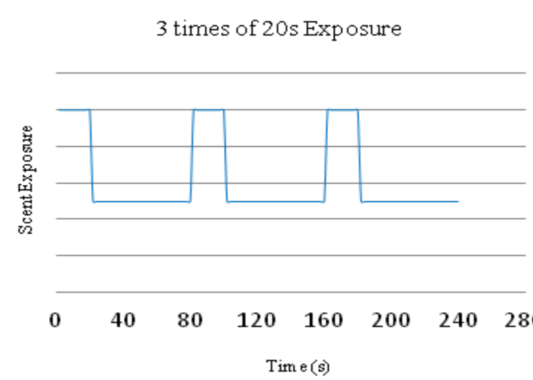

Figure 1: Graph of Scent Exposure vs Time illustrating the 3 times the subject was exposed to the scent stimulus during the EEG recording.

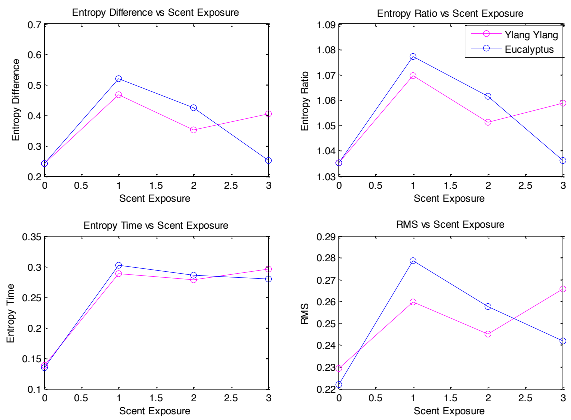

Figure 2: Graph of Feature vs repeated scent exposure for Ylang Ylang (Magenta) and Eucalyptus (Blue) from F3-Cz

B. Results for 3D Representation of Scent for Characterization

By doing a weighted summation on the 4 features and plotting in a 3D graph with the first, second and third scent exposure as the 3D axes, the 2 spheres were developed for Eucalyptus and Ylang Ylang. We propose that the spheres can be used to represent the region in space where a larger proportion of the combined feature vector can be found for a particular scent, in other words, characterizing the scent. It can be suggested that new subjects whose combined feature vector falling within a sphere could then be identified to be exposed repeatedly to that particular scent. The results of the scent characterization are shown in Figure 3. The 2 suggested spheres can be represented with the following formula:

<u>Ylang Ylang</u>

$$(\boldsymbol{Z_1} - \mathbf{2.81})^2 + (\boldsymbol{Z_2} - \mathbf{2.64})^2 + (\boldsymbol{Z_3} - \mathbf{2.75})^2 \leq \mathbf{0.16}^2 \quad (11)$$

<u>Eucalyptus</u>

$$(\boldsymbol{Z_1} - \mathbf{2.91})^2 + (\boldsymbol{Z_2} - \mathbf{2.74})^2 + (\boldsymbol{Z_3} - \mathbf{2.56})^2 \leq \mathbf{0.12}^2 \quad (12)$$

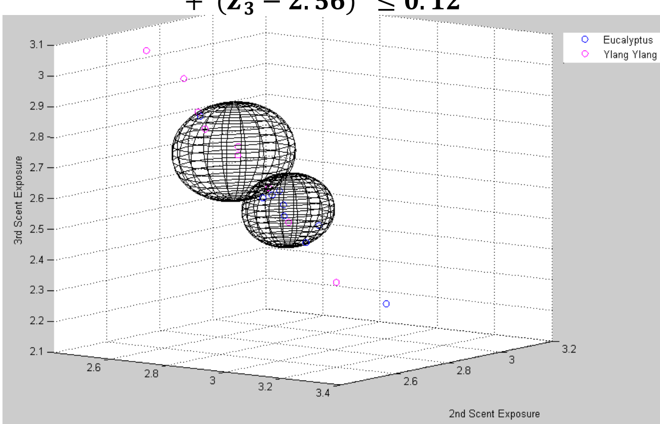

Figure 3: 3D Characterization of Scent for Eucalyptus (Blue) and Ylang Ylang (Magenta)

Eucalyptus combined feature vectors were observed to be closer to each other in space compared to Ylang Ylang. Hence, its feature vectors have a higher probability of falling within its own sphere, resulting in higher characterization accuracy. A smaller sphere can be proposed to encapsulate the region in space for Eucalyptus, for a more accurate scent characterization. However it would be hard for the suggested spheres to achieve full accuracy, as seen in Table 1. Every subject is physiologically different and there is a possibility that a subject might react very differently to certain scents. A larger sample size would be needed to spot outliers.

TABLE I. SCENT CHARACTERIZATION ACCURACY TABLE

Scent	Sample within sphere	Sample within wrong sphere	Sample not within any sphere
Ylang Ylang	5	1	3
Eucalyptus	7	1	1

V. CONCLUSION

This paper proposes to use 4 feature extraction methods, namely Entropy Difference, Entropy Ratio, Entropy Time and RMS to perform a brain signal trend analysis when the human subject is subjected to 3 repeated scent exposure. Despite having a small data size, the 4 chosen features were able to show how the different scents can have different trends. Similar repeated scent exposure trends are observed for the 4 features for a given scent. When the 4 features are combined to form a feature vector, a 3D plot can be obtained using the number of scent exposure as the axes. It can be seen that, feature vectors generated from the same scent tend to cluster around an ellipsoid. Our findings have allowed us to have a better understanding of how our brain responds to repeated exposure of scent.

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