QUANTIFICATION OF EMOTIONAL FEATURES OF PHOTOPLETHYSOMOGRAPHIC
WAVEFORMS USING BOX-COUNTING METHOD OF FRACTAL DIMENSION

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ABSTRACT

The paper proposes the appliance of box-counting method belongs to fractal dimension in detecting features of Photoplethysmographic signals recorded from different subjects in different sessions of emotional and non emotional state. The objective is to analyze and detect the features and differences in these two types of signals and use that component as a command input in emotional quantification system. However, the study found out that all the nine subjects have higher fractal dimension (FD) values in emotional state than their non emotional state FD values. Hence, the changes in emotional level hold relevant information about the physiological state and can reflects in the PPG signal waveform which is detected using the box-count fractal dimension algorithm.

Keywords – Photoplethysomography, Fractal Dimension, Box-counting, Pulse Oximeter, Singular Value Decomposition.

1. INTRODUCTION

Analysis of photoplethysomographic signal (PPG) and feature extraction has become an important area of research. The ability to extract feature components in one’s PPG waveform forms new challenges in recent studies of photoplethysmography. Previous studies have use systolic values (peaks) or diastolic values (troughs) in the PPG signal to represent variability in the finger pulse waveform [4].

The PPG signal is the representation of the changes in the arterial and venous blood volume at the peripheral body sites where blood vessels are close to the skin such as the ear lobe, finger and toe. From various studies, PPG recording have used photoplethysomogram peaks to detect changes in signal when there is postural change [9].

Most of the studies and analysis on PPG were made to gain some information on physiological state. Several methods have been used for the analysis like FFT spectral analysis and decomposition technique such as principal component analysis (PCA) due to its ability in identifying patterns in data, and expressing the
data in such a way as to highlight their similarities and differences.

The changes in the PPG waveform can be detected using fractal dimension. This can be used as a feature extraction technique to detect changes in the PPG signal. A patterns fractal dimension describes how completely the pattern fills the space in which it resides [3].

Varieties of algorithms are available for computing and estimating the fractal dimension. Some of these algorithms operate on the signal in the time domain while others operate on the phase space domain [1-6].

It is believed in some studies that algorithms that operate in the time domain are faster than those that operate in the space domain [1]. In this study, we have used the box-counting method of fractal dimension estimation. This method is employed to deal with the signal in the time domain by considering the signal waveform as a geometric object [6].

The aim of this study is to detect whether there is significant fluctuation in the PPG signal features of a person in an emotional state from non emotional state. The motive behind the research is to study the possibility of using this feature as a command input in implementing an emotional quantification system.

The experiment aims at estimating the fractal dimension of both the emotional and non emotional signal and the possibility of using this feature as a command input to implement the system.

The current study has proposed a moving average filter as lowpass filtering procedure to acquire a refined PPG pulse waveform before PPG analysis can be conducted [5]. This is also because results from previous studies have shown that lowpass filtered signal produced a variability spectrum which was nearly identical to that of the pulse waveform average value [4].

The rest of the paper is organized into three sections. Section 2 discusses the methodology used to conduct the experiments. Whereas, section 3 and 4 comprises of the discussion, experimental results and conclusion respectively.

### 2. METHODS

#### DATA SET

The experiment in this study was carried out using two pulse oximeters. The ear pulse oximeter which is attached to the air lobe of the subject and the finger pulse oximeter attached to the index finger. The led light in the ear pulse oximeter is used to determine the emotional and the non emotional state and the signal is sampled at 2.75 Hz using the dolphin medical model 210 re-usable finger clip [8].

PPG waveforms were recorded from the 9 subjects in 2 sessions with 3 trials per session during the experiment. To minimize motion artifact, the subjects were told to keep their fingers still. The subjects comprise of both male and female gender from different race. 10 signals were captured in each trial at the interval of 10 minutes. The first 3 trials are for the non emotional PPG signals capture. And the remaining 3 trails are for emotional PPG signals recording for each subject whom were made to go up and down the staircase for a couple of times in order to increase their level of emotion. There is about 45 minutes or more of intervals between the time of recording the emotional and the non emotional signals. However, each subject has 2 sessions of 3 trials and 60 signals each; in total of 30 signal each per session. The sum total of the signals captured from the 9 subjects results to 540 signal samples.
The signals recorded from each trail were decomposed using SVD in Matlab R2009a statistics toolbox and the average of first 5 singular values for each session is calculated for each subject and the total mean value for the 2 states compared.

**PREPROCESSING USING MOVING AVERAGE FILTER AS LOWPASS FILTER AND FEATURE EXTRACTION**

All the signals captured from the 9 subjects were pre-processed by means of lowpass filtering. A three point moving average filter was implemented non-recursively. The signal processing procedures were implemented in Matlab.

The advantage of using the moving average filter is that it reduces random noise [12]. The 3 point moving average filter can be expressed as [12].

\[
y(n) = \frac{1}{3} x(n) + \frac{1}{3} x(n-1) + \frac{1}{3} x(n-2)
\]  

From the above equation (1), the average is taken from the current and two previous inputs i.e. to compute the current output y(n), two previous inputs x(n-1) and x(n-2) are needed [12].

The preprocessed signal was used as an input to the box-count fractal dimension algorithm which estimates the fractal dimension of each signal. Finally, the fractal dimension values for each subject were calculated to get the mean value of each state.

3. **RESULTS AND DISCUSSION**

The differences between singular values of emotional and non emotional or relaxed state have been identified as well as the fractal dimension values. We have observed that the changes in emotional level holds a lot of information about ones state and can reflects in the PPG signal waveform which is identified in the fractal dimension. Hence, when one is emotional the fractal dimension value is higher than in non emotional state.

The purpose is to identify features and differences that could be used in emotional quantification system. We use the fact that the PPG signal reflects the arterial and venous blood volume changes at the peripheral sites where the blood vessels are close to the skin like the finger [4]. We employ the box-counting algorithm to compute the fractal dimension which holds important information about the PPG. The fractal dimension value shows the dynamic nature of the PPG signal which reflects the changes in the blood volume in the index finger [4]. Furthermore, we have observed that most of the subjects pulse rate increases when they become emotional and decreases when they are relaxed or non emotional [2].

We discovered that all the nine fractal dimension values are higher when emotional than in the non emotional state. The average singular value for the emotional data is 1.2480 which is higher than the non emotional average singular values of 0.9330. Table 1 shows the age and the average singular values for each subject for the emotional and the non emotional data.
Table 1. The average of first 5 singular values of Emotional and Non Emotional PPG signals for each of the 9 subjects

Consequently, all the nine subjects have higher fractal dimension value in emotional state than the non emotional state. In other words, the average fractal dimension is higher when emotional than non emotional. Table 2 shows the age and the total average fractal dimension value of emotional as 1.03661 and that of non emotional as 0.667231 with a difference of 0.369379.

Table 2. The average fractal values of Emotional and Non emotional PPG signals for each of the 9 subjects

However, we have observed that the emotional PPG signal is composed of waveforms that are more instantaneous than that of non emotional. Hence, the emotional waveforms have higher frequency than that of non emotional. Further examination of Fig.1. (a), (b) and, Fig.2. (c) and (d) also shows that the filtered signal produced variability that is very identical to that of the unfiltered signal.
We perform a t-test to assess whether the average of the emotional and the non emotional data are statistically different from each other. This analysis is appropriate in order to identify the difference between the two states which is achieved by calculating the difference between the average relative to the spread or variability of their fractal dimension values.

\[
t = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{\text{var}_T}{n_T} + \frac{\text{var}_C}{n_C}}}
\]

(2)

We use Matlab version R2009a statistics toolbox to perform a t-test of the null hypothesis that the emotional and the non emotional fractal dimension values are independent random samples from normal distribution with equal means and equal but unknown variances, against the alternative that means are not equal. We found a significant difference as measured by emotional/non emotional level (\(t = 8.35, \text{df} = 8, p < 0.05\))
4. CONCLUSION

Our adoption of fractal dimension as a technique for feature detection is as a result to its ability to detect changes when applied on waveforms. This method also enables us to identify the differences from the signals recorded in the emotional and the non emotional state. Biomedical research has successfully applied this method in effort to extract features from various bio signals for analysis.

We observe that the emotional PPG signals from all the subjects’ shows un identical waveforms compared to their non emotional signals which results to the difference in the fractal dimension value. This is found to be higher in the emotional state and lower in the non emotional state. This can serve as a reliable command input in implementing emotional quantification system and other biomedical applications which is our future focus.

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REFERENCES


