Study of Wrist Pulse Signals Using a Bi-Modal Gaussian Model

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***Abstract*—Wrist pulse signals contain important information about the health of a person and hence diagnosis based on pulse signals has assumed great importance. In this paper we demonstrate the efficacy of a two term Gaussian model to extract information from pulse signals. Results have been obtained by conducting experiments on several subjects to record wrist pulse signals for the cases of before exercise and after exercise. Parameters have been extracted from the recorded signals using the model and a paired t-test is performed, which shows that the parameters are significantly different between the two groups. Further, a recursive cluster elimination based support vector machine is used to perform classification between the groups. An average classification accuracy of 99.46% is obtained, along with top classifiers. It is thus shown that the parameters of the Gaussian model show changes across groups and hence the model is effective in distinguishing the changes taking place due to the two different recording conditions. The study has potential applications in healthcare.**

***Index Terms*—Wrist pulse signal, Gaussian model, Support vector machine**

I. Introduction

Arterial palpation of the heart beat is termed as a pulse pressure signal. Contraction of the heart results in oxygenated blood flow from left ventricle to aorta, and the heart produces a pulse waveform at that time. Due to compliance of arteries blood continues its flow to the other parts of body after blood is ejected into aorta. The velocity of the pulse pressure waveform depends on the compliance of arteries. Pulse wave travels away from the heart during systolic period and it reflects back towards heart during diastolic period. The pulse wave thus is a combination of forward wave and reflected wave [1]. A person's pulse can be observed at any place that permits an artery to be compressed against a bone. Wrist (radial artery) is widely used to observe the pulse signal. The wrist pulse has been recognized as one of the most fundamental signals of life, containing vital health information since any pathological change in the cardiovascular system is reflected in the wrist pulse as. In view of this, pulse diagnosis has gained importance in recent times.

Usually the pulse examination is done by a physician using his fingertips. The diagnosis requires long periods of practice by individual physician [2] and are subjective in nature.

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Hence there is a need to record wrist pulse signals using sensors and then analyze using the power of digital signal processing techniques.

Pressure wave generated by the heart propagates throughout the arterial system. The morphology of wrist pulse waveform is altered by its continuous interaction with the non-uniform arterial system. Arterial walls are expanded by these waves as they travel along. The expansions are palpable as the wrist pulse. A multi period trend is observable in a typical pulse signal. The main component of the pulse signal is constituted by the systolic wave with higher amplitude. The diastolic wave has lower amplitude and is accompanied by a delay. The systolic wave contains information regarding the heart, whereas information on the reflection sites and the periphery of the arterial system is provided by the secondary wave [3]. It has been observed that the secondary wave plays a major role in determining the shape of the wrist pulse signal [1].

The systolic and diastolic waveforms are somewhat bell-shaped, and hence a Gaussian model has been used to fit the recorded pulse signals [4]. The features obtained from the model will be useful in the classification of the wrist pulse signals recorded under various experimental conditions. Though there are new reliable data-driven techniques which are shown to work in the case of electroencephalogram [5] [6] and functional magnetic resonance imaging [7] signals, we take a model driven approach in this work since the wrist pulse signal is predominantly bell-shaped.

In this paper, a study has been made by recording wrist pulse signals before and after exercise at 500Hz sampling rate by using a Bi-morph sensor. There is very limited literature on analysis of wrist pulse signals during exercise [8] [9]. The exercise case is considered here as an example of comparing physical activity and inactivity. The results obtained in this work provide a better understanding of cardiovascular system using wrist pulse signals recorded under different experimental conditions.

II. Methods

A. Preprocessing of pulse signals

Wavelet de-noising technique is used to remove noise from the acquired pulse signals. Wavelet methods [10] allow us to find high frequency information during short intervals and low frequency information during long intervals. A proper choice of mother wavelet has to be made to suit the given signal. By using that wavelet function we obtain decomposition of the signals. Normally low frequencies appear in high scales whereas high frequencies appear in low scales. Upon removal

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of those high and low scale detail coefficients we obtain the cleaned signals. Normally wrist pulse signals are contaminated by noise due to movement of hand during recording (low frequency) and due to electronic nonlinearities (high frequency.

It is useful to perform the segmentation of single period pulse waveform from a sampled time series for further analysis. Here the task is to segment the wrist pulse from multi period sample series into single period waveforms [11]. To do this, first an amplitude threshold is chosen by visual inspection. Then we find the peak of pulse waveform which crosses the threshold by using a simple peak detection algorithm. Next we find the valley point (local minima) which occurs before the peak obtained earlier. So we search the points in the reverse direction from peak point until a positive derivative occurs. That point is chosen as the starting point of the pulse, and one cycle is taken as the signal from the starting point of the current pulse to the starting point of the subsequent pulse.

B. Gaussian model

A pulse signal can be considered as the superposition of systolic and diastolic waves [4]. Since the two waves are bell-shaped, we can express the single period wrist pulse signal by a bi-modal (two term) Gaussian function

$$f(x|A_1,\tau_1,\sigma_1,A_2,\tau_2,\sigma_2) = A_1 * \exp\left(-\frac{x-\tau_1}{\sigma_1}\right)^2 + A_2 * \exp\left(-\frac{x-\tau_2}{\sigma_2}\right)^2$$

Here the single period wrist pulse signal has been considered as a superimposition of systolic and diastolic waves. It can be seen from the above equation that six coefficients are required in the above Gaussian model: the amplitude, mean and variance of the fitted waveform of the primary wave and the amplitude, mean and variance of the fitted waveform of the secondary wave. These coefficients are obtained by using nonlinear least square formulation to fit the Gaussian model to the recorded wrist pulse signal. This data fitting algorithm is solved in the least square sense. Subsequently, the ratio of amplitudes, the ratio of means, the ratio of variances and the length of the pulse signal are calculated as additional features. Totally eleven parameters are obtained per subject for all the subjects, during both before exercise and after exercise conditions.

C. Statistical analysis and classification

It is interesting to see if the parameters show statistically significant differences across groups. Statistical significance is essential to make inferences from the numbers. A paired t-test is performed between the groups using all the features of all the subjects.

Mean squared error is a widely used measure to assess the quality of the estimated parameters. However, sometimes it is more useful to see if these model parameters have distinguishing capabilities between groups. A Recursive Cluster Elimination based Support Vector Machine (RCE-SVM) is used to perform classification between the groups [12]. This is an effective classifier which divides the data into training and testing sets and performs the classification over many iterations. In this study, 600 iterations are used. Moreover, RCE-SVM uses the top classifying features to iteratively reduce the number of features used for classification and in the end gives the classification accuracies obtained for various numbers of top-classifiers. It will also give those top classifiers which are responsible for giving the highest classification accuracy. Average classification accuracy across all iterations is obtained and the top classifying features are obtained.

III. RESULTS AND DISCUSSIONS

Signals are captured using USB 6009 NI-DAQ (Data Acquisition System). A bi-morph sensor is connected to the DAQ and it is in turn connected to the personal computer. Lab view software is used for acquiring signals onto the computer. Signals are acquired at a sampling frequency of 500Hz by using a bi-morph sensor. Wavelet de-noising is performed and clean signals are obtained.

Figure 3.1 shows an illustration of wavelet de-noising. The noisy pulse is shown in Fig.3.1(a) and the cleaner pulse signal after wavelet de-noising is shown in Fig.3.1(b). It may be observed from the figures that wavelet de-noising has removed the noise considerably.

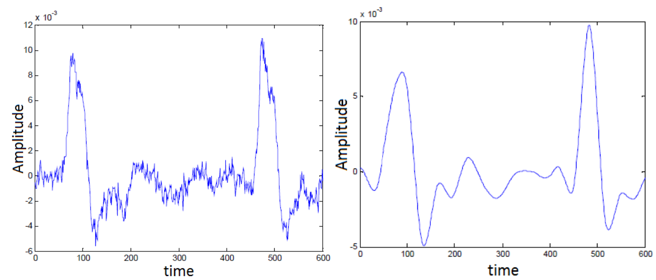

Figure 3.1. (a) noisy pulse, (b) pulse after wavelet de-noising

Figure 3.2 (a) and (b) shows recorded pulse signal and its Gaussian model fit for both before and after exercise conditions.

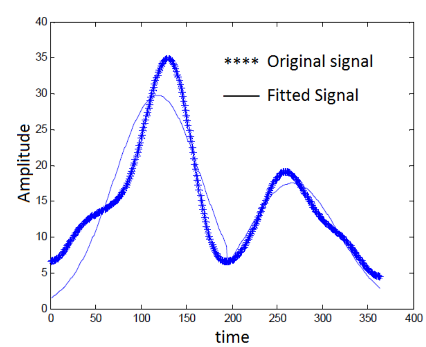

Figure 3.2(a) Original and fitted pulse waveform for before exercise case

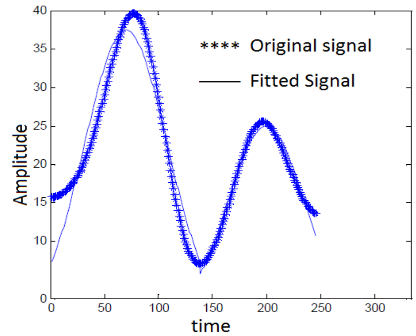

Figure 3.2(b) Original and fitted pulse waveform for after exercise case

Figure 3.3 shows the bar graphs of mean Gaussian model parameters. Blue color represents before exercise and red color represents after exercise case. The parameter values are normalized to enable viewing in a single figure. Table 3.1 shows the look up table of Gaussian parameters for Fig.3.3. A stands for amplitude, M for mean, Sig for variance, L for length of pulse, '1' for systolic (primary) pressure wave and '2' for diastolic (secondary) pressure wave.

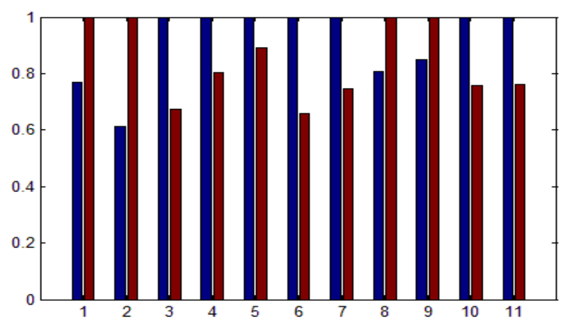
Figure 3.3. Bar graphs of the mean Gaussian parameters before exercise (blue) and after exercise (red)

Table 3.1. Look up table of Gaussian parameters for bar graph

1	A1	7	L
2	A2	8	A2/A1
3	M1	9	M2/M1
4	M2	10	Sig2/Sig1
5	Sig1	11	Mean Squared Error
6	Sig2		

A wrist pulse signal is typically comprised of primary wave and secondary wave. The primary wave is the forward-traveling wave (away from the heart), and is a consequence of heart's systolic cycle. The secondary wave is the reflected wave, and is a consequence of the heart's diastolic cycle. We can observe from Fig.3.3 that both amplitudes (A1 and A2) of the Gaussian modeled signal are less for before exercise case compared to after exercise case, indicative of higher blood pressure after exercise. The ratio of secondary and primary waves' amplitudes is also less before exercise, implying that the secondary wave is relatively stronger after exercise, indicative of a stronger body response. The average signal length after exercise is less than that of signals before exercise by almost 35%. This suggests that pulses are shorter in duration after exercise due to higher heart rate. This also means that there is more rapid heart rate after exercise, along with higher blood pressure.

This type of information cannot be obtained using electrocardiogram (ECG). This shows the value added by the use of wrist pulse signals as a supplement to ECG in order to understand the human body through the cardiovascular system. These observations can be particularly useful when studying pulse signals from experiments of unknown outcome. An example is the study of diseases using pulse signals.

A paired t-test is performed using all the features of all the subjects between both the groups. A p-value of 0.0154 is obtained (threshold=0.05), thus showing that the model parameters are statistically significant between the groups.

RCE-SVM classification is performed using all the eleven Gaussian model parameters. Ten clusters are chosen initially, with a decrease of 0.2, meaning that the second iteration will have 10-0.2*10 (=8) clusters, with decimal values being rounded off. Number of clusters is decreased until two clusters are remaining. This is performed recursively for six hundred iterations, and average classification accuracy is calculated across all clusters. Fig.3.4 shows the average classification accuracies obtained across clusters.

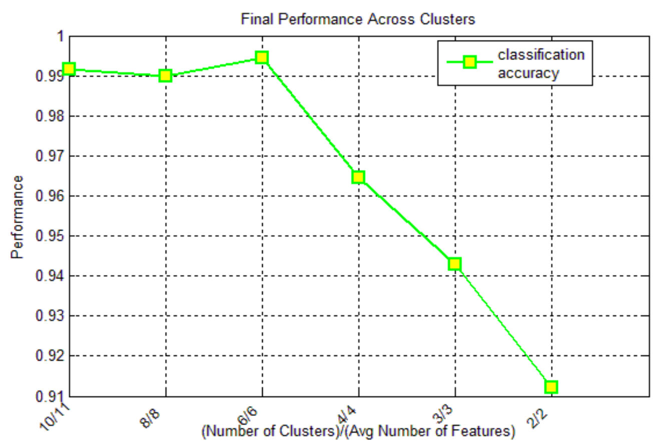

Figure 3.4. Average classification accuracy across clusters

Highest classification accuracy of 99.46% is obtained for 6 clusters with 6 top classifiers. These six top classifiers are found to be A2, M1, A2/A1, M2/M1, sigma2/sigma1 and MSE. We see that all the ratios of model parameters are top classifiers. We can infer from this that the ratios of model's parameters have better distinguishing ability than their absolute values. This appears plausible since parameters like variance and amplitude are expected to vary over time and across subjects, but their ratios can still remain almost the same if the morphology of the signal remains consistent. The classification results corroborate well with this observation.

Fig.3.4 also shows that high classification accuracy (99.17%) is obtained using all the eleven features. This shows that all the model parameters have a high distinguishing ability.

IV. CONCLUSION

The wrist pulse signal contains significant information about the changes in person's cardiovascular system. It is important to extract this information through digital signal processing techniques which in turn will help in developing computerized pulse diagnosis system. Keeping this in mind, we have studied in this paper the efficacy of a bi-modal Gaussian model in analyzing pulse signals recorded under different experimental conditions. This has been illustrated for the case of wrist pulse signals obtained under before exercise and after exercise conditions. The bi-modal Gaussian model has been used to fit the pulse signal. The model parameters and its derivatives have been used as the features for further statistical study. Statistical significance of model parameters (p-value=0.0154) and high classification accuracy (99.46%) clearly demonstrate that the proposed Gaussian model is a good approximation for the wrist pulse signal. These results show that the parameters contain useful information which are statistically significant and have good distinguishing ability resulting in high classification accuracy.

There seems to be not many studies on wrist pulse signals even though there is a lot of potential of using wrist pulse signals for various healthcare applications. The importance of this study is that it attempts to address this issue for signals recorded under one experimental set up and show how a bi-modal Gaussian model is very efficient in distinguishing the signals recorded under two different conditions. While this paper demonstrates the feasibility of bi-modal Gaussian model in distinguishing wrist pulse signals for the cases of before exercise and after exercise, there is a need for applying these results for various healthcare applications. This can be done only after recording wrist pulse signals from normal subjects as well as from patients in hospitals and then analyzing them. Efforts are being made in this direction.

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