Analysis of Wrist Pulse Signals Using Spatial Features in Time Domain

D. Rangaprakash and D. Narayana Dutt

***Abstract*—Wrist pulse signal contains more important information about the health status of a person and pulse signal diagnosis has been employed in oriental medicine since very long time. In this paper we have used signal processing techniques to extract information from wrist pulse signals. For this purpose we have acquired radial artery pulse signals at wrist position noninvasively for different cases of interest. The wrist pulse waveforms have been analyzed using spatial features. Results have been obtained for the case of wrist pulse signals recorded for several subjects before exercise and after exercise. It is shown that the spatial features show statistically significant changes for the two cases and hence they are effective in distinguishing the changes taking place due to exercise. Support vector machine classifier is used to classify between the groups, and a high classification accuracy of 99.71% is achieved. Thus this paper demonstrates the utility of the spatial features in studying wrist pulse signals obtained under various recording conditions. The ability of the model to distinguish changes occurring under two different recording conditions can be potentially used for healthcare applications.**

***Index Terms*—Wrist pulse signal, Spatial features, Support vector machine**

I. Introduction

Pulse pressure is arterial palpation of heart beat. When heart contracts oxygenated blood flow occurs from left ventricle to aorta. At that time a pulse waveform is produced by the heart. After blood is ejected into aorta, blood continues its flow to the other parts of body because of compliance of arteries. The velocity of pulse pressure waveform depends on the compliance of arteries. During systolic period the pulse wave travels away from the heart and during diastolic period the pulse wave reflects back towards heart. Hence the pulse wave is a combination of forward wave and reflected wave [1]. The person's pulse can be felt at any place that allows an artery to be compressed against a bone, such as at wrist (Radial artery). The wrist pulse has been recognized as the most fundamental signal of life, containing vital information of health because any pathological changes of a person's body condition are reflected in the wrist pulse. In order to detect the pathological changes in the body, pulse diagnosis is gaining importance in recent times.

D. Rangaprakash was with the Indian Institute of Science, Bangalore-560012, India. He is now with the Department of Electrical and Computer Engg, Auburn University, Auburn, AL 36849 USA (corresponding author-phone: +1-334-246-0604; e-mail: abhi88iisc@gmail.com).

D. Narayana Dutt is with the Indian Institute of Science, Bangalore-560012, India (phone: +91-9632243086; e-mail: dndutt@ ece.iisc.ernet.in).

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Normally palm of physicians supports the wrist of patient and pulse examination is done using fingertips. Without the benefit of any physical recording and analysis, the diagnosis requires a long period of study and practice by individual physician [2]. Hence there is a need to use the power of digital signal processing to make a computerized analysis of pulse signals.

A heart beat generates pressure wave which propagate throughout the arterial system. The shapes of wrist pulse waveforms are altered by their continuous interaction with the non-uniform arterial system. These waves expand the arterial walls as they travel along and the expansions are palpable as the wrist pulse. A typical pulse signal has a multi period trend. Systolic wave with higher amplitude constitutes the main component of the pulse signal. The diastolic wave has lower amplitude accompanied by a phase shift. The information regarding heart is contained in the systolic wave whereas the secondary wave provides information on the reflection sites and the periphery of the arterial system [3]. The wrist pulse typically has two maxima and three minima in one cycle. The magnitudes and time indices of these extrema points and various combinations of differences between these times are termed as spatial features of the pulse wave. The spatial features will be useful in the understanding and classification of the wrist pulse signals recorded before exercise and after exercise. There is very limited literature on analysis of wrist pulse signals in case of exercise [4], hence this work attempts to contribute towards understanding the behavior of the cardiovascular system during physical activity using wrist pulse signals. The next section on methods discusses preprocessing of the pulse signals, feature extraction and classification. This is followed by results, discussion and conclusion.

II. Methods

A. Preprocessing of wrist pulse signals

We have used wavelet de-noising technique for removal of noise from recorded pulse signals.. Wavelet methods [5] allow us to find low frequency information during long intervals and high frequency information during short intervals. By using a properly chosen mother wavelet function we obtain decomposition of the signals. Usually high frequencies appear in low scales whereas low frequencies appear in high scales. Upon removal of these low and high scale detail coefficients we can obtain cleaned signals. Usually wrist pulse signals are contaminated by noise due to electronic nonlinearities (high frequency) and due to movement of hand during recording (low frequency).

Segmentation of single period pulse waveform is useful in further analysis. The aim is to segment the complete wrist pulse time series into single period waves [6]. An amplitude threshold is chosen manually by inspection. A simple peak detection algorithm is employed to find the peak of the pulse signal which crosses the threshold. We next find the local minimum which occurs before this peak. We search points in the reverse direction from peak until a positive derivative is reached, and that point is chosen as the pulse's starting point. One cycle is taken as the signal from the starting point of the current pulse to the starting point of the next pulse.

B. *Feature extraction and classification*

The magnitudes and time indices of the two maxima and three minima points of a single period pulse wave, and various combinations of differences between these times are together termed as spatial features of the pulse wave (original and derived). Such spatial features are obtained for both before exercise and after exercise. Totally seventeen spatial features are compared and classified.

It is necessary to see if the spatial features show statistically significant difference across groups. A paired t-test is performed between before exercise and after exercise groups using all the features of all the subjects. Resulting p-values are used to see if the parameters are statistically significant or not.

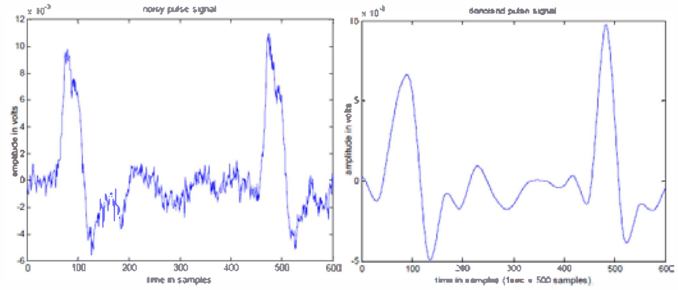
It is important to see if the spatial features can distinguish between the groups. A Recursive Cluster Elimination based Support Vector Machine (RCE-SVM) is used to classify between the groups [7]. This classifier divides the data into training and testing sets and does classification over many iterations. In this work six hundred iterations are used. Moreover RCE-SVM iteratively reduces the number of features used in classification and gives classification accuracies for various reducing number of top-classifiers. It also gives those top-classifiers which are responsible for giving highest accuracy. Average accuracy across all iterations is obtained and the highest accuracy across clusters are obtained along with the corresponding top classifying features.

III. RESULTS AND DISCUSSIONS

A. *Preprocessing of wrist pulse signals*

USB 6009 NI-DAQ (Data Acquisition System) has been used to acquire pulse signals. A bi-morph sensor is connected to the DAQ which in turn is connected to the Personal Computer (PC). Lab view software is used in accordance with USB to acquire signals onto the PC. Signals are acquired at 500Hz sampling rate by placing the bi-morph sensor at a position where the pulse is efficiently sensed on the wrist.

Figure 3.1 shows an example of wavelet de-noising. Fig.3.1(a) shows the noisy pulse signal and Fig 3.1(b) shows the signal after wavelet denoising. It is clear from the figures that noise has been considerably removed by wavelet denoising.



(a) (b)

Figure 3.1 (a) noisy pulse, (b) pulse after wavelet denoising

B. *Spatial features analysis*

A typical wrist pulse signal has two peaks and three extrema in general as shown in Figure 3.2. We have marked the various spatial parameters of interest in the figure.

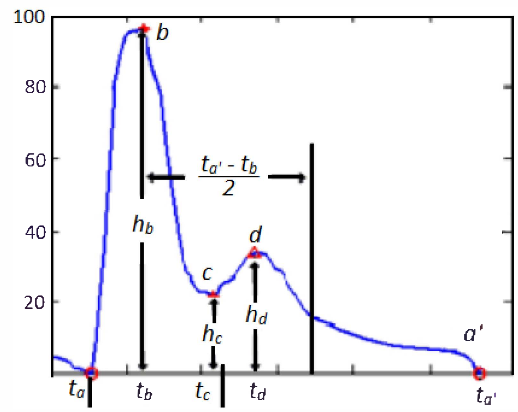


Figure 3.2. Wrist pulse wave with various extrema

We can see from Fig.3.2 that the first peak (h_b) of pulse is related to the blood ejaculation by heart contraction; the second (h_d) peak reflects the artery recovery and peripheral vessels' reflected wave. t_i is the time at which h_i occurs. t_c is the starting point of the diastole, T is the signal length. These spatial features can be used to derive more features are shown below. Here t_{ab} is same as t_a-t_b

t_{ba}/T = time of ascent part of primary wave ÷ period

t_{cb}/T = time of descent part of primary wave ÷ period

t_{dc}/T = time of ascent part of secondary wave ÷ period

$t_{a'd}/T$ = time of descent part of secondary wave ÷ period

$t_{a'b}/t_{ba}$ = time of descent part of pulse wave ÷ time of ascent part of pulse wave

h_c/h_b = amplitude of dicrotic notch at c ÷ amplitude of primary peak

h_d/h_b = amplitude of secondary peak ÷ amplitude of primary peak

Figure 3.3 shows bar graphs of averaged spatial features. Blue represents before exercise and red represents after exercise case. The values are normalized. Table 3.1 shows the look up table of spatial features for Fig.3.3.

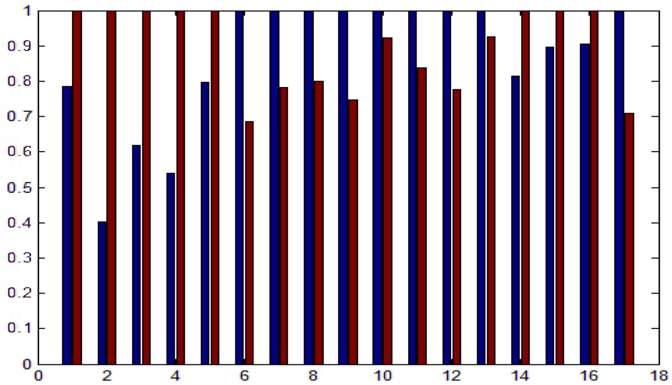


Figure 3.3. Bar graphs of averaged spatial features before exercise (blue) and after exercise (red)

Table 3.1. Look up table of spatial features for the bar graph

1	h_b (percussion peak)	10	t_{cb} (p-wave descent time)
2	h_c (incisure point)	11	t_{dc} (s-wave ascent time)
3	h_d (peak of dicrotic wave)	12	$t_{a'b}$ (pulse descent time)
4	h_c/h_b	13	t_{ba}/T
5	h_d/h_b	14	t_{cb}/T
6	t_b (primary wave peak time)	15	t_{dc}/T
7	t_c (start of diastole)	16	$t_{a'b}/t_{ba}$
8	t_d (secondary wave peak time)	17	T - t_c (diastole time)
9	T (length of pulse)		

From Fig.3.3, the ratio of primary wave time of ascent to the signal length is less after exercise. However, before exercise, the ratio of primary wave time of descent to length, the ratio of secondary wave time of ascent to length and the ratio of total time of descent to length have lower values. This could imply that the reflected waves are relatively quicker than the forward waves after exercise. That would mean that the body is responding relatively quicker than the heart after exercise. These inferences could be useful while trying to understand more complex biological phenomena.

C. SVM classification

A paired t-test is performed using the spatial features of all the subjects. A p-value of $9.1 * 10^{-4}$ is obtained (threshold=0.001), showing that these spatial features are statistically significant between before exercise and after exercise cases.

RCE-SVM classification is carried out using all the seventeen spatial features of all the subjects. 17 clusters are chosen initially, with a decrease of 0.2, meaning the second iteration will have $10 - 0.2 * 10 = 8$ clusters, with decimal values being rounded off. In the same way, number of clusters is decreased until only two clusters remain; and this is performed recursively for six hundred iterations. Average classification accuracy is obtained across clusters, along with the highest classification accuracy. Fig.3.4 shows average classification accuracies obtained for all clusters.

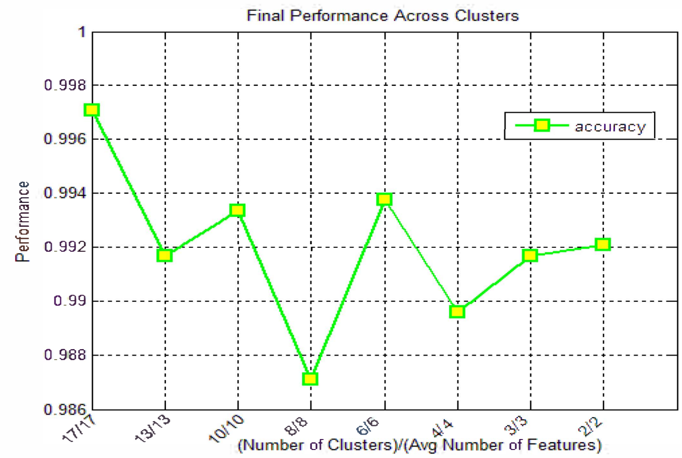


Figure 3.4. Average classification accuracy across clusters

Maximum classification accuracy obtained is 99.71%, using all seventeen features. This clearly shows that all spatial features have a high distinguishing ability. A high accuracy of 99.38% is obtained using six top classifiers. These 6 top classifiers are h_c (incisure point), h_d (peak of dicrotic wave), h_d/h_b, t_{cb}, t_{ba}/T and T-t_c (diastole time).

These results demonstrate that the spatial features used to analyze wrist pulse signals contain useful information, which are statistically significant between groups and have high distinguishing ability resulting in high classification accuracy.

IV. CONCLUSION

The wrist pulse signal of a person contains significant and important information about the condition of the cardiovascular system. Extracting this information through digital signal processing techniques is important for computerized pulse diagnosis. In this study we have analyzed the wrist pulse signals recorded before and after exercise by extracting useful spatial features from the signals. It has been shown that the spatial features are very effective in detecting the changes in signals obtained under the two recording conditions. The spatial parameters have been used as features for further statistical study. The parameters are found to be statistically significant (p-value=0.00091) with high classification accuracy of 99.71% which clearly demonstrates the efficacy of the parameters. Further work is needed for studying the potential of these parameters in detecting abnormality condition in the cardiovascular system.

Processing of wrist pulse signals has a lot of potential for various healthcare applications. However, it appears that not many studies have been made on wrist pulse signals and this study is an attempt in the direction. This study is important since it attempts to address the issue for signals recorded under one experimental set up and illustrate the efficacy of spatial features for the purpose. While the paper demonstrates the feasibility of the use of spatial features for wrist pulse signals for one experimental condition, there is a need for applying these results for various healthcare applications. This can be accomplished only by recording wrist pulse signals from patients in hospitals and then comparing it with signals from normal subjects. Efforts are being made in this direction.

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