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Adaptive Signal Processing Algorithm for Remote Detection of Heart Rate (HR) Using Ultra-Wideband Waveforms based on Principal Component Analysis

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Abstract–Ultra-Wideband (UWB) technology provides a convenient approach for remote biomedical sensing and vital signs monitoring in humans. In this paper, a specific algorithm is proposed to improve the ability of Heart Rate (HR) detection. Unlike previous methods for remote HR detection, the proposed method provides an adaptive filter based on respiration and heart rate parameters obtained from UWB waveforms. The algorithm is capable of detecting heart rate by changing the adaptive filter parameters accordingly. The proposed method is employed on real life data collected by UWB transceiver. According to experiments, it is concluded that the proposed technique is able to handle remote detection of different heart rates accurately.

I. INTRODUCTION

Ultra-wideband (UWB) waveforms are in the range of microwave and are used at very low energy levels for short range high-bandwidth communications. For this technology, transmitted information spread over large bandwidth h (in the range of gigahertz).

The use of UWB signals has been suggested for several medical applications because of the high spatial resolution provided by ultra-wideband signals.

Some advantages of UWB waveforms are the large bandwidth, convenient material penetration which leads to good coverage and the capability of performing through wall monitoring, the extremely low power-spectral density, very low electromagnetic interference, and the adverse impacts of UWB signals on the human body may be trivial.

For an UWB antenna setup, the motion of a human body can cause significant changes to the UWB waveforms. In particular, the expansion of the thorax creates an observable change in the UWB waveforms, which is exploited to estimate the respiration rate. Furthermore, the contraction of the heart creates weak changes in UWB signals.

In order to detect these low changes, various techniques have been reported in the literature [1]–[6]. Some studies have been focused more on the technology of hardware, for instance designing specific circuit and antenna to obtain more accurate estimation for HR [4], and some of them concentrated on signal processing algorithm [5],[6]. In [4], a UWB receiver is opened by a time discriminator at the moment of the input of a signal reflected from an object at a certain distance to discard interfering pulses. The given radar consists of fast-acting electronic switches, and the receiver is shut during the rest time. As reported in [6], a bandpass filter with fixed cutoff frequency edges was used to filter a part of input data and estimate the frequency of heart rates.

The normal heart rate for adults is in the range of 60-100 beats per min (bpm) and the normal respiration rate for adults is in the range of 12-20 breaths per min [7]. The given ranges can vary as smaller individuals and children have faster heart and respiration rates than adults.

In some cardiac arrhythmia, the heart rates can significantly change. Ventricular Tachycardia (VT) is a potentially life-threatening cardiac arrhythmia which originates in the ventricles. During VT, the heart rates can increase over 200 beats per min. The heart rates can also decrease below 60 beats per min during bradycardia.

Therefore, the frequency of heart rates can vary from below 1 *Hz* up to over 4 *Hz*. Thus finding an accurate estimation for the number of heart rates which makes weak changes on UWB signals in the presence of various noises at the given wide frequency range is difficult.

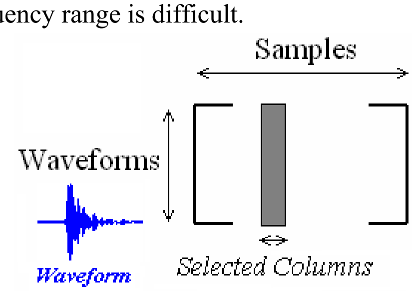

Fig.1. Input matrix; each row including samples of a received UWB waveform

Changes in the heart rate can influence on the respiration rate. It should be considered that both heart rate and respiration rate are influenced by each other. The frequency of breathing can increase above 1 *Hz*, even in emergency cases, the breathing frequency can increase over 2 *Hz*. Therefore, a fixed bandpass filter, for instance with the fixed cutoff frequency edges 1-2 *Hz*, can not discriminate frequency components of heart rates from frequency components of breathing as the frequency of breathing placed in the mentioned range. Whereas the range of the heart movement is very small in comparison with the motion of the thorax during respiration, and less energy is reflected by the heart, the components correspond to the heart motion are very weak. Thus a strong breathing peak causes to fail the detection of the heart rate accurately. The proposed algorithm can deal with this problem.

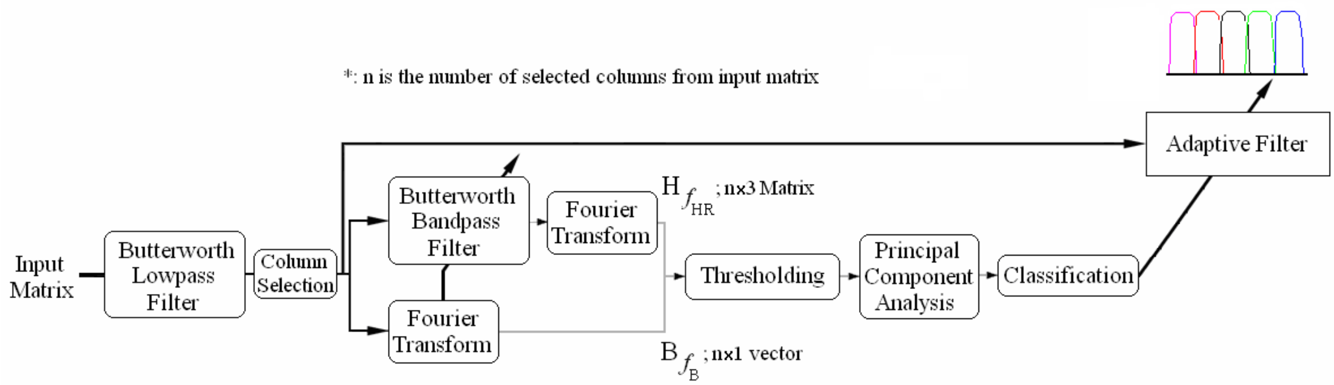

Fig.2. Block diagram of adaptive signal processing algorithm

In the following section, the adaptive signal processing algorithm is explained. In section III, the proposed algorithm is tested using real life data acquired by UWB antenna and the results are provided. Section IV concludes the paper.

II. PROPOSED ALGORITHM

For remote detection of heart rate, a large number of UWB waveforms with intervals on the order of milliseconds are sent out by a UWB antenna toward a person.

Each received UWB waveform is then preserved in a matrix named *input matrix* and its samples are consecutively placed in a row of the given matrix. As shown in Fig. 1, the number of rows in the input matrix equals the total number of received UWB waveforms.

The general block diagram of the proposed algorithm is illustrated in Fig. 2 to show processing steps.

As mentioned in previous section, the frequency of breathing and heart rate frequency for the human in the worst conditions is less than 4.1 *Hz*.

The presence of noise corrupts the received signals, and makes the feature extraction and classification less accurate. Therefore, denoising procedure is necessary. For first processing step, a Butterworth lowpass filter of order 6 with the cutoff frequency of 4.1 *Hz* is used.

Afterwards, some columns of the input matrix are selected. Selection of columns is based on the energy of their elements. In fact, a column with maximum energy is most likely to include motion information.

For next step, Fourier transform is implemented on every selected column to determine breathing frequency (f_B) related to the given column. To do this, the frequency corresponds to the largest peak of frequency spectrum is calculated. Furthermore, a Butterworth bandpass filter with the cutoff frequency edges of 1-4.1 *Hz* is used and Fourier transform is then performed to determine probable values for the frequency of the heart rate (f_{HR}).

As mentioned in the previous section, it is possible that the frequency of breathing increases over 1 *Hz*, so that frequency components of breathing can be placed in the range of the Butterworth bandpass filter (which possesses the cutoff frequency edges of 1-4.1 *Hz*). Therefore, determination of the heart rate frequency (f_{HR}) will be very difficult. To deal with this problem, the low frequency edge of the Butterworth bandpass filter can be changed according to the estimated values for the breathing frequency. Consequently, the low frequency edge is increased as f_B becomes more than 1 *Hz*.

Up to this stage, two categories of information have been obtained. A vector $n \times 1$ (B_{f_B}) consists of estimated values for breathing frequency from each selected column, and a matrix $n \times 3$ ($H_{f_{HR}}$) which includes probable values for the frequency of the heart rate (f_{HR}) from every selected column. In fact, the frequencies correspond to three large peaks of frequency spectrum for each selected column construct a row in the heart rate matrix ($H_{f_{HR}}$). The parameter n is the number of selected columns from the input matrix.

When vector B_{f_B} and $H_{f_{HR}}$ formed, a matrix $2 \times 3n$ (X) is constructed for which the first row includes estimated values for the breathing frequency from B_{f_B} and the second row consists of probable values for the heart rate frequency from $H_{f_{HR}}$. In fact, each estimated value for f_B related to each selected column is assigned to three estimated values for the frequency of the heart rate for the given selected column.

Before generation of features, thresholding phase is done. Therefore, a thresholding scheme is applied to remove the outliers that are not appropriate for training and classification. As the possible frequency range for breathing and the heart rate are certain, it is possible to define acceptable range for estimated values related to f_B and f_{HR}.

It means the process of evaluation on estimated values for the frequency of the heart rate or breathing frequency is performed in this stage.

Estimated values for the frequency of the heart rate and breathing frequency are shown in Fig. 3.

Principal component analysis or PCA is a transform domain technique for feature extraction. PCA is an unsupervised learning method which provides an optimal representation (in the least mean square error sense) of the input in a lower-dimensional domain.

PCA is applied to the matrix X to obtain the eigenvectors of the covariance matrix (Σ_X).

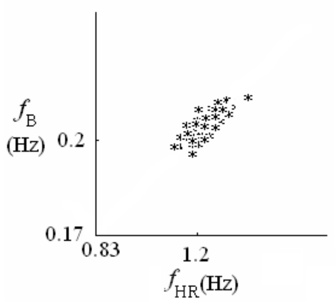

Fig.3. Estimated values for the frequency of the heart rate and breathing frequency from selected columns of *input matrix*

The covariance matrix is formulated as follows:

$$\Sigma_X = E[X.X^T] \tag{1}$$

Where *X* is a matrix $2 \times 3n$ including estimated values for the frequency of the heart rate and breathing frequency from selected columns of the input matrix. The eigenvectors of the covariance matrix Σ_X are denoted as *A*. Therefore, the matrix *X* is transformed to new space as the following:

$$Y = A^T.X \tag{2}$$

The classification is then performed in the transformed space.

As normal heart rate ranges for people can be different, to determine the heart rate, definition of classes should exactly be done. Therefore, it is required to consider individual maximum heart rates. The parameter of maximum heart rate has a great influence on the process of class definition.

Different formulas are used to estimate individual maximum heart rates according to age, but maximum heart rates vary significantly between persons. As mentioned in [8], the most decent formula for HR_{Max} is as follows:

$$HR_{Max} = 205.8 - (0.685 \times age) \tag{3}$$

To clarify the process of class definition, it is assumed that the definition of classes for a 40 years old person is of interest. According to equation (3), the HR_{Max} is ~178 bpm or the maximum frequency of heart rates is ~3 *Hz*.

The bandwidth of the adaptive filter is chosen based on the variance of the estimated values for the heart rate. It means that if the variance of the estimated values for the heart rate be larger, the bandwidth of the adaptive filter should be narrower.

For this example, the bandwidth of the adaptive filter is considered as 0.5 *Hz*, so that six status are assumed for the adjustment of the parameters of the adaptive filter for the given person (i.e. for the frequency range of 3 *Hz*, based on the bandwidth of 0.5, six status $[3 \div 0.5 = 6]$ are considered). The center frequencies at different status are 0.5, 1, 1.5, 2, 2.5 and 3 *Hz*. It is required that the center frequency of the first adaptive filter be selected appropriately as the first adaptive filter should not include the frequency of breathing.

As each status for the adaptive bandpass filter corresponds to a class, six classes are defined.

According to the position of the features (f_B and f_{HR}) in the transformed space, a class is selected and the parameters of the adaptive filter is then adjusted correspond to a selected class. In other words, it is possible that the transformed space is categorized into separate areas based on acceptable variations in heart and respiration rate for an adult (or child or infant). The generated features are placed in different areas at the transformed space. The prototype of the features related to an area (i.e. a class) is then calculated. Class selection is performed based on the distance between the features and prototypes (the Euclidean distance is used).

The frequency of breathing is used to reach more accurate estimation of the heart rate. According to the medical information of a patient, it is possible to estimate the process of variations f_{HR} based on variations f_B. Therefore, the process of variations f_{HR} is evaluated better.

As shown in Fig. 2, an adaptive filter is utilized to filter selected columns from the input matrix, and determine an accurate estimation for the heart rate, even if the heart rate changes.

Consequently, the adaptive bandpass filter based on estimated frequency of the heart rate and breathing frequency can be adjusted.

III. RESULTS

To show the efficiency of the proposed algorithm, real life data collected by UWB antenna is used. The transmitter and receiver antennas are PulsOn 210, from Time Domain Incorporation. For PulsOn 210 system, the bandwidth of radiated waveforms is 3.2 GHz.

Experiments are presented in two status. First, the proposed algorithm is tested on collected data in the situation that heart rate is approximately stable. Secondly, the algorithm is employed on dataset in which heart rate changes.

In each experiment, 75% of collected data is used for training phase and 25% is used for testing phase.

A. Stable Heart Rate

The proposed algorithm is tested on 4 dataset from 4 different experiments. Each dataset includes 20-second length of waveforms collected by UWB antenna. The measured heart rates and estimated heart rate are presented in Table I.

TABLE I
MEASURED AND ESTIMATED HEART RATES

dataset	Measured Heart Rate (bpm)	Estimated Heart Rate (bpm)
1	72	73
2	73	70.2
3	66	64.9
4	80	79.7

The estimated heart rate related to a male is shown in Fig. 4. The measured heart rate is 80 beats per min and the estimated heart rate is obtained as 79.7 beats per min.

Fig. 5 demonstrates the strong breathing peak in comparison with weak peak related to the HR in frequency domain.

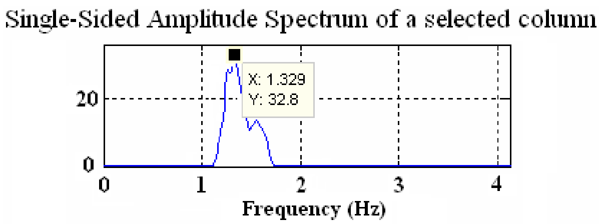

Fig.4. Fourier spectrum of a selected column from input matrix; detected peak shows the frequency of 1.329 *Hz* for heart rate (i.e. 79.7 bpm)

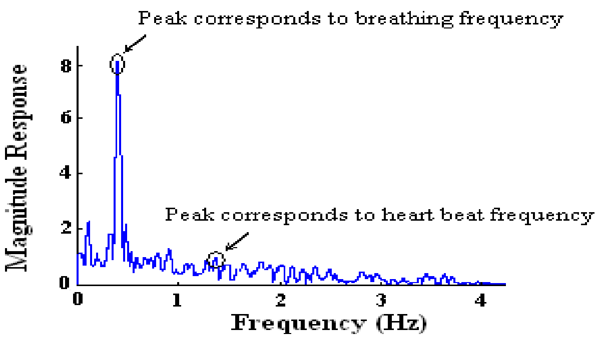

Fig.5. Frequency of heart rate and breathing frequency shown in frequency domain; Breathing peak is too stronger than the peak related to heart rate

For Fig. 5, the frequency of the heart rate has been obtained after all processing steps. Afterwards, the final estimated value for the heart rate has been shown in the Figure.

B. Heart Rate Changes

To simulate the conditions in which the heart rate changes, data is collected in several stages. First, the data from a person has been collected in the normal situation. Then, the person had a light physical exercise and data has been collected. In third stage, data has been collected immediately after a heavy and fast physical exercise. A dataset related to collected data from three given stages is formed and the proposed algorithm is employed on the given dataset.

Every stage has the length of 1 min, and measured heart rates for each stage are 71, 90, and 127, respectively.

TABLE II
MEASURED AND ESTIMATED HEART RATES

Measured Heart Rate (bpm)	Estimated Heart Rate (bpm)
71	67
90	94
127	125

The person is 26 years old. The maximum heart rate is calculated based on equation (3) for this person, so the HR_{Max} is 188 beats per min or 3.13 *Hz*. Whereas the bandwidth of the adaptive filter is considered as 0.6 *Hz*, five classes are defined, and five status are also considered for the adaptive bandpass filter. The center frequencies for each status are 0.5, 1.1, 1.7, 2.3, and 2.9 *Hz* (i.e. center frequencies for the adaptive filter correspond to five classes respectively). Three classes are selected during the experiment; class 2, class 3, and class 4. Thus parameters of adaptive filter change for three status. The estimated values for heart rate based on the given dataset are presented in Table II.

IV. CONCLUSION

In this paper, an adaptive signal processing algorithm to improve the ability of remote heart rate detection was presented. For feature extraction phase, the principal component analysis was used. In classification phase, classes defined according to the variance of estimated values for the frequency of the heart rate, and maximum heart rate based on age.

In previous methods for remote detection of the heart rate, the results have been considered for a person with stable conditions. But it is important that a detection algorithm is capable of detecting variations in heart rate. Furthermore, the breathing frequency should be considered in analysis whereas it can make a problem in detection of heart rates, in particular, for some emergency cases in which respiration rate extremely increases (if the breathing frequency increases significantly, filters with fixed frequency edges will not be useful).

Using the proposed algorithm, it is possible to detect different heart rates and adjust the parameters of the adaptive bandpass filter to reach more accurate estimation for the heart rate. In particular, when detection of the heart rate related to an old person who is a potential case for heart problems or a patient with the experience of a heart disease is of interest, detecting the heart rate is imperative.

The proposed technique was tested on collected dataset including some different heart rates. In order for enhancing the efficiency of the algorithm, it is suggested that the algorithm be tested on more data collected from people with variable heart rate. In particular, the test should be done while the person has an unstable situation, and the heart rate changes significantly, but it can be difficult.

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