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Implementation of Denoising Algorithms for Heart-Rate Estimation From Ambulatory Optical PPG

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Abstract : Wearable technology forms a fashion in today's Emerging Embedded technology. Measuring clinical Parameters like Heart rate, Oxygen Saturation level using Smart Watches, Smart glasses from Photo – Plethysmogram (PPG) has become a new research topic in industry as well as academia in the area of Signal Processing and Embedded Environment. Extracting reasonable PPG signals to derive accurate Clinical parameters has become a challenging task as the design includes a low power consuming hardware with low power consuming Denoising Algorithms. This leads in developing efficient PPG extraction hardware designs and efficient Denoising Algorithms to obtain Clinical Parameters accurately most of the time which includes even when subject is running at 15km/hour. Efficient denoising techniques like Sparse Resolution based Spectral Subtraction, Adaptive Noise Cancellation and Intelligent algorithm for HR Estimation are discussed here.

Keywords : Photo Plethysmogram (PPG); Heart Rate (HR); Fine Resolution Spectrum Estimation; Adaptive Noise Cancellation (ANC).

1. INTRODUCTION

HR monitoring has become a vital factor for exercisers to control their training load. Photo Plethysmogram (PPG) has become a popular method for HR monitoring. Sensors required to extract PPG are very compact, simple and number of sensors to extract the signal are less. This has led in developing embedded devices to monitor the health status of patients more effectively. Recently, this trend has increased to effectively monitor the HR of wearer even when the subject is exercising, running at a speed of 12km/hr. This has led to research in effective signal processing techniques to extract the PPG signals under heavy motion.

There is no a unique technique which can de-noise PPG signal to extract parameters like Heart – rate under all working conditions. The choice of the algorithm depends on number of factors such as duration of system operation, number of signal and noise sources, and accuracy of obtaining desired clinical parameters in various working environments. This leads for motivation of development of more efficient denoising and Heart rate extraction algorithms. Few of them existing are Kalman Filters, Independent Component Analysis with block interleaving [2], Adaptive Filters [3], [7], [12], [9], Kalman Smoothers [5], Singular Spectrum Analysis [14], and Wavelets. Frequency domain approaches like Spectral Subtraction are more accurate in denoising while Adaptive Noise Cancellation (ANC) is relatively simple. So, the choice of the algorithm depends up on the end product, HR estimation accuracy, error tolerance, execution time. Further, Fine Spectrum Estimation combined Spectral Subtraction denoising approach provides a better denoising but ends up having higher execution time and more power consumption. Here, in this paper from the perspective of accuracy of HR Estimation, Fine Spectrum Estimation combined Spectral subtraction are

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introduced. Heart rate estimation curves are plotted with data collected from one of the industry standard considered as ‘Ground truth’ which is ‘Mio Alpha’ and the corresponding PPG signals are acquired using Optical Unit (LED, Photo detector and signal conditioning circuit), then post processing is done using denoising and HR Estimation Algorithms.

Literature Survey

The following table lists the existent/ available denoising methods in the field of Signal Processing for denoising.

Table 1

Block diagram indicating various denoising techniques

	No additional sensors required	*No a priori User input required*	*Automatic Artifact removal*	*Can operate online*	*Can operate on single channels*	*Can operate in the nonlinear domain*
Adaptive filter	No	No	Yes	Yes	Yes	Yes
Weiner filter	Yes	No	Yes	No	Yes	Yes
Kalman filter	Yes	No	Yes	Yes	Yes	Yes
Particle filter	Yes	No	Yes	Yes	Yes	Yes
Independent Component analysis	Yes	Yes	No	Yes	No	Yes
Canonical correlation analysis	Yes	Yes	No	No	No	Yes
Single Channel ICA	Yes	Yes	No	No	Yes	Yes
Dynamical Embedding ICA	Yes	Yes	No	No	Yes	Yes
Dynamical Embedding SSA	Yes	Yes	Yes	No	Yes	No
Morphological Component analysis	Yes	No	Yes	No	Yes	No
Wavelet ICA	Yes	Yes	No	No	Yes	Yes
Empirical Mode decomposition	Yes	Yes	No	No	Yes	Yes

The techniques listed in the above table are the algorithms examined in this paper are among the most commonly implemented in the biomedical signal processing field.

The choice of which algorithm to employ depends on a number of different factors.Long term patient monitoring is often required to evaluate a patient’s well-being and is commonly performed in an out-patient domain. This requires that the systems implemented are capable of operating for prolonged periods, without the overhead of frequent changing or charging of batteries. If significant power is consumed by on-board processing, battery life will reduce and this may excessive changing or charging of the batteries, thus, disrupting the desired recordings. It is also possible to perform long-term recordings and to implement the Artifact removal on a PC offline. In these situations, the computational load of the algorithm becomes less problematic, but the results are no longer reported in real time. The availability of reference signals should also be taken into account when designing or selecting an algorithm. The number and quality of recording sensors also has an impact on the choice of Artifact removal technique employed. It is a requirement in most Blind source separation (BSS) algorithms that there be as many measurement sensors as underlying sources. This will increase the complexity of the system when implemented real time. Therefore, algorithms utilized in these environments are required to be capable of separating sources with no redundant sensors which is a challenging task.

2. DENOISING ALGORITHMS

Fine Spectrum Resolution Based Spectrum Subtraction

Fine Spectrum resolution based SST approach integrates spectral subtraction technique and compressed sensing approach in Joint Spectrum Estimation to enhance the efficiency of estimation of HR [6], [11]. This can be explained with the flow chart considered below. Fine Spectrum Resolution SST is an approach which forms an Observation matrix by combining PPG and Accelerometer signals to obtain a Signal Noise model and hence estimating Sparse solution Vector consisting of fewer frequency points for the corresponding Observation matrix. The Obtained Sparse Vector is then de noised using Simple Spectral Subtraction and further HR is estimated. Fine Spectrum resolution methods believe in obtaining compressed/sparse solutions using Optimization methods. There are various types of Fine Spectrum resolution algorithms which are based on the principle of problem of optimization as follows [6], [11].

$$\widehat{X} = \min \|(Y - \varnothing X)\|_2^2 + a g(x) \tag{1}$$

The above Optimization problem is minimum l2 norm optimization. Hence, squared of the error between actual measurement Y and estimated measurement vector is minimized. For the above Optimization problem from equation 1, proper ‘Ø’ matrix should be chosen for perfect sparse representation of real valued signal ‘*y*’ which is based on minimizing the coherence between ‘sensing’ matrix and ‘sparse matrix’. For convenience, if the ‘*y*’ signal is represented by the measured PPG signal values multiplied by shifted impulse function at those particular instants, Sparse matrix can be chosen on DFT basis since there is minimum coherence between DFT matrix and sensing matrix which is a combination of impulses. Regularized MFOCUSS Algorithm [13] solves the problem of Optimization to obtain minimum norm 2 solution of estimate X.

Sparse matrix is chosen as DFT basis

$$\varnothing = e^{j\frac{2\pi mn}{N}} \quad m = 0, 1, \ldots M-1, n = 0, 1 \ldots N-1 \tag{2}$$

Where M is the number of measurements, N is NFFT points considered. Solution of equation 1 gives Spectrum coefficients ‘X_k’; $k = 1,2\ldots N$.

Since the Spectrum coefficients consists of spectrum coefficients corresponding to ‘N’ NFFT values, actual frequency bins need to be calculated for one to one mapping between maximum power in current time window and its corresponding frequency.

The whole frequency band [0, *fs*] is divided into ‘N’ frequency bins as follows :

$$f = \frac{(Nf - 1) fs}{N} \tag{3}$$

Where $Nf \in \{1,2,\ldots.N\}$.

Obtained Spectrum coefficients are Band – Pass filtered where the location indexes $N_f \in L_{Ø}$ satisfying non zero values where $L_{Ø}$ is given by [1]

$$L_{Ø} = \left[\frac{0.4}{fs}N + 1 - \Delta_{f1}, \frac{5}{fs}N + 1\,\Delta f_2\right] \cup \left[N - \frac{5}{fs}N + 1 - \Delta_{f2}, N - \frac{0.4}{fs}N + 1\,\Delta f_1\right]$$

Where Δ_{f1} and Δ_{f2} are width of transition band of practical Band Pass filter.

$$\Delta_{f1} = \frac{0.4}{fs}N - 1; \quad (5)$$

$$\Delta_{f2} = \frac{2}{fs}N;$$

3. HEART RATE ESTIMATION ALGORITHM

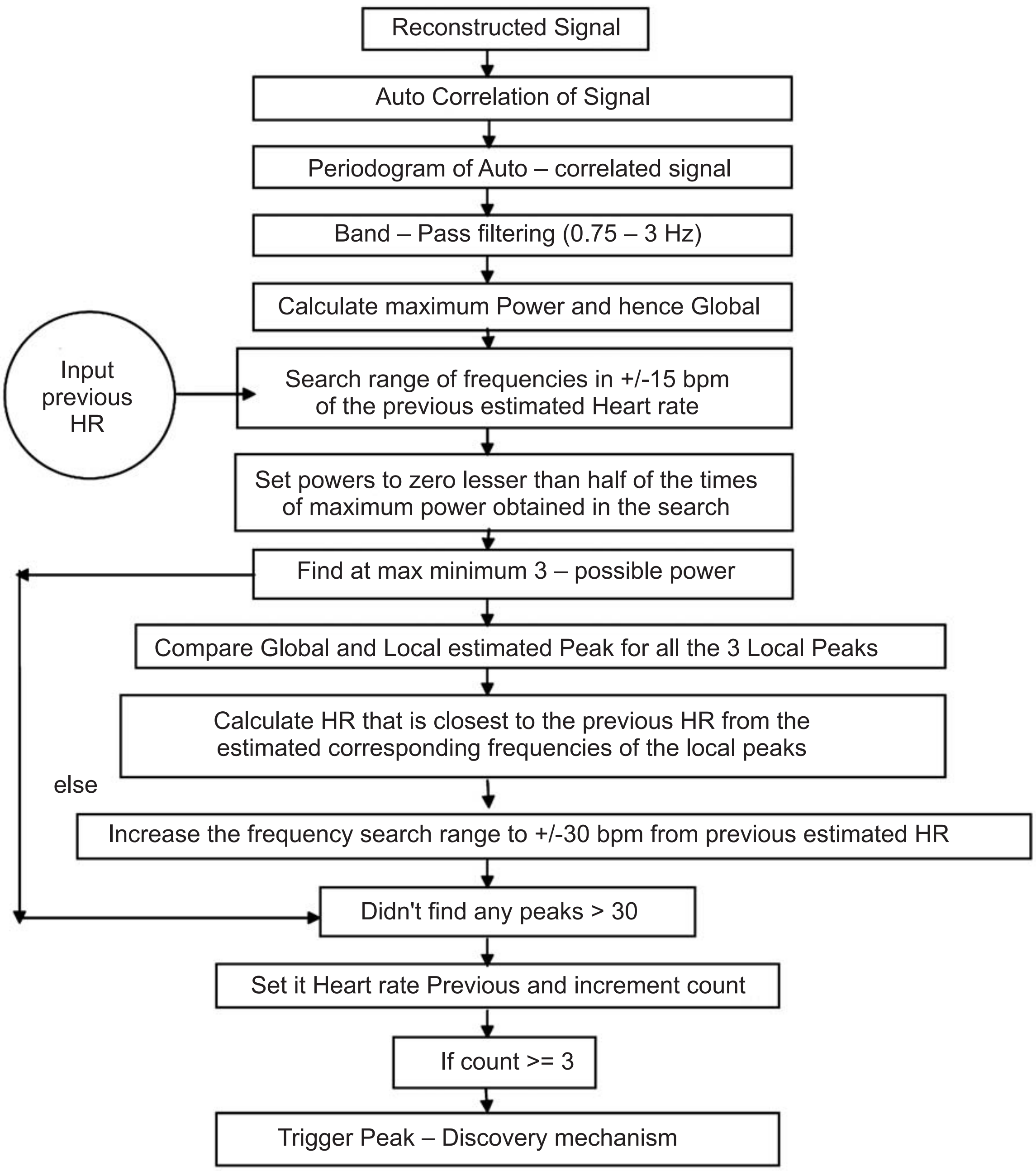

Figure 1: Flow chart of HR Estimation Algorithm

Figure 1, depicts an Intelligent HR frequency selection approach. The approach is based on fact that HR values in two successive time windows are close if successive time windows overlap largely [6]. Initially, wearers are required to minimize the hand motions to estimate HR correctly in first few window slots.

The aim is to estimate a peak in the PPG spectrum with the knowledge of HR values estimated in previous time windows. Initially, the region of search will be +/- 15 bpm of previous estimated HR is set and if at max 3 power peaks are found, the minimum distance between current estimated frequencies and previous HR frequency is calculated and hence most probable HR is estimated. If not able to find at least one peak in above range, +/-30 bpm of previous estimated HR is set and frequency corresponding to maximum power peak is calculated. If not able to find any peak in +/-30 bpm range of previous HR frequency, current HR is set to previous HR and variable 'count' is incremented. If count is greater or equal to 3, Peak discovery procedure is called.

Peak Discovery

The Smoother algorithm which is a least square is performed on 'K' previously estimated spectral locations of HR values to predict the spectral location of heartbeat in current time window. By default 'K' is set to 10. So, this Algorithm predicts the trend by taking into account previous estimated HR estimates and corresponding time instants and hence HR for current time instant is estimated.

4. SIMULATION RESULTS

Results have been obtained based on output of denoising and Heart rate Extraction algorithms and have been plotted on MATLAB known as 'Heart rate Estimation Curves' versus Ground truth, values being obtained from one of Industry standards 'Mio – Alpha' Smart watch in time synchronization and have been compared , analyzed for different User data sets. Results for a data set acquired are shown below.

Data set 1

A data set was captured with 10 minutes of sedentary, 10 minutes walking and with 10 minutes desk work.

Normalized LMS ; Noise Estimation method: FFT. Sampling Frequency = 200 Hz

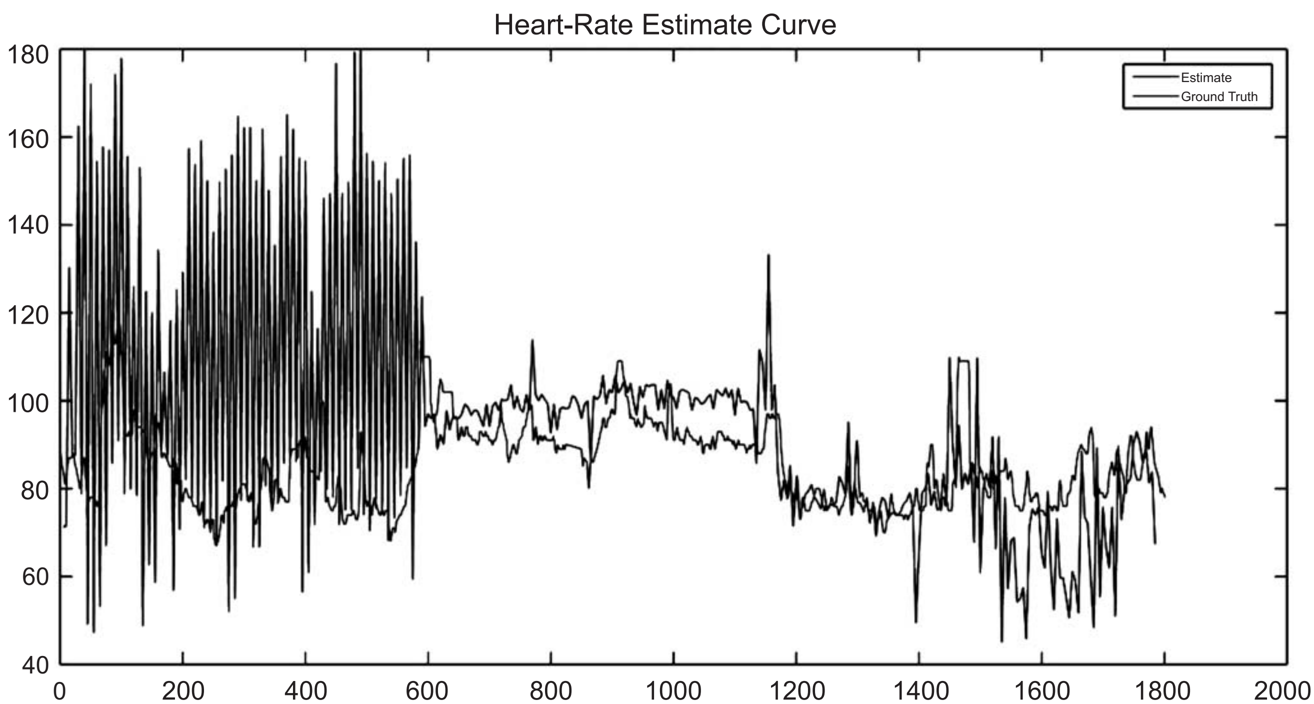

Figure 2: HR estimate plot with spectral subtraction with compressed sensing

Fine Spectrum resolution based Spectral Subtraction; Noise Source: 3 – Axes Accelerometer. Sampling Frequency = 200 Hz down sampled to 25 Hz

From the above HR Estimation plot of NLMS, it has been found that NLMS based Spectral Peak tracking is one of the simple methods for HR Estimation. But, since Spectral peak tracking limits the search in the neighboring frequency bands of previous estimated HR, a wrong HR Estimation will lead to successive wrong HR Estimations. This has been depicted in Figure 2. From the HR Estimation of Fine Spectrum Estimation based spectral subtraction, it has been shown that this method is a reasonable approach. One more interesting feature is the denoising has been carried out at a lower sampling rate of 25 Hz.

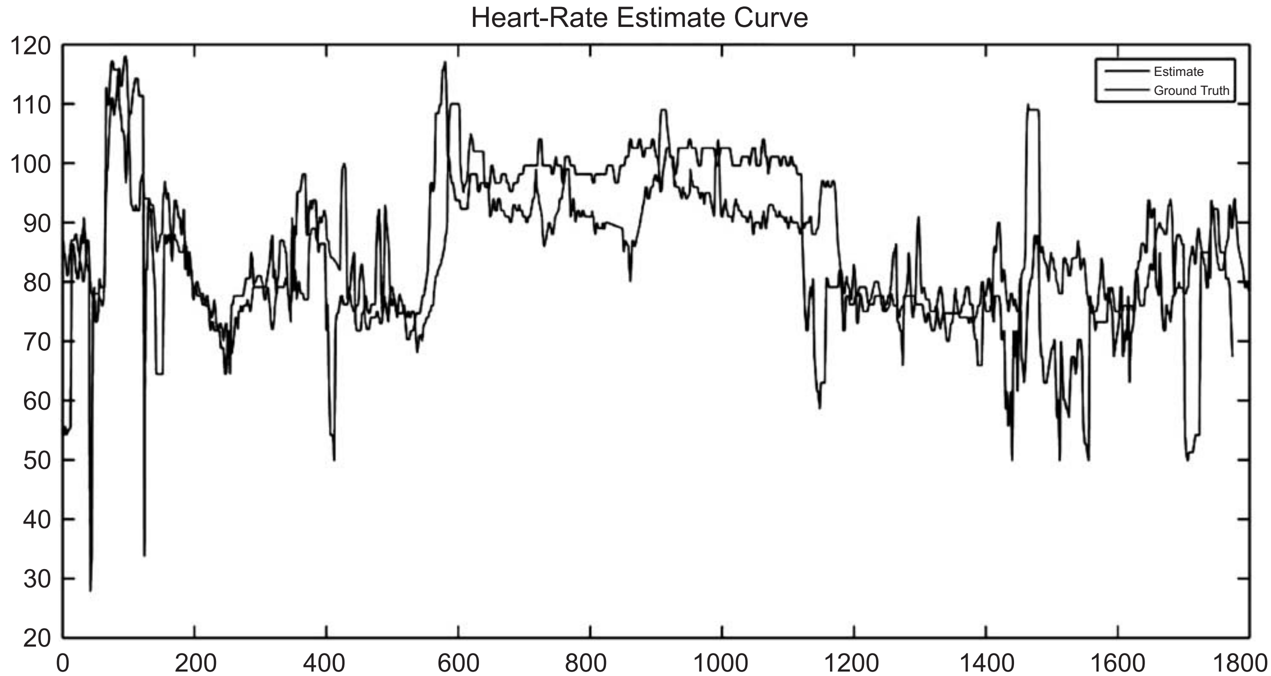

Figure 3: HR estimate plot with Fine Resolution Estimation based spectral subtraction

5. CONCLUSION

Although FFT noise reference based NLMS is a good denoising approach since the method rely's on subtraction of signal components from Input Motion Corrupted PPG signal based on the pre assumption that PPG signal falls in frequency range (0.75 – 5 Hz), this fails for the cases when noise overlaps with PPG signal spectrum and this degrades the accuracy of HR estimation. Using the above HR Algorithm Estimation approach, estimating HR around the previous estimated HR improves the accuracy of HR Estimation rather than searching HR frequency in fixed PPG signal range. This results in HR Estimation Overshoots. But, on the other way, if the initial HR peak is detected is wrong this leads to continuous wrong estimations which can be seen from the Figure 2.

Comparing HR Plots from NLMS and Fine Spectrum Estimation based denoising approach, latter performs better since it's a frequency domain based denoising approach and moreover, Fine Spectrum Estimation results in sparse spectrum for selection of HR frequency. These techniques have advantages over some Non Parametric methods like Periodogram as latter results in 'Spectral Leakage'. At a lower sampling rate, Fine Spectrum Estimation based denoising approach provides high accuracy for HR Estimation.

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