Fuzzy Entropy Based Motion Artifact Detection and Pulse Rate Estimation For Fingertip Photoplethysmography

Neeraj Paradkar[1] and Shubhajit Roy Chowdhury[2]

Abstract— **The paper presents a fingertip photoplethysmography (PPG) based technique to estimate the pulse rate of the subject. The PPG signal obtained from a pulse oximeter is used for the analysis. The input samples are corrupted with motion artifacts due to minor motion of the subjects. Entropy measure of the input samples is used to detect the motion artifacts and estimate the pulse rate. A three step methodology is adapted to identify and classify signal peaks as true systolic peaks or artifact. CapnoBase database and CSL Benchmark database are used to analyze the technique and pulse rate estimation was performed with positive predictive value and sensitivity figures of 99.84% and 99.32% respectively for CapnoBase and 98.83% and 98.84% for CSL database respectively.**

I. INTRODUCTION

Photoplethysmography (PPG) is a technique to monitor the dynamics of blood flow in the body using light radiation. The PPG data signal is typically recorded by using a device which contains an illuminating component (typically LED) and a photo sensor (typically a photodiode). The data is recorded by placing these two circuit components on either side of a finger or ear lobe. The incident light radiation undergoes attenuation along its way as it transmits through skin, blood tissue and other blood parameters, bone and so on. This attenuation is a function of essentially the nature and quantity of blood parameters; such as hemoglobin, glucose etc. and the wavelength of incident radiation.

The most significant constituents absorbing the radiation are skin, bone, muscle, tissue bed, venous blood and pulsatile arterial blood. The absorption signature for all the parameters except for pulsatile arterial blood can be modeled as constant with respect to time. However the time varying absorption of pulsatile arterial blood provides the PPG signal its peculiar form. Conventional practice to determine the pulse rate of a subject is monitoring the R-R interval of his or her ECG signal [1]. However as the periodic nature of the PPG waveform originates from the pulsatile arterial blood, the pulse-to-pulse interval (PPI) of the PPG signal is highly correlated to the R-R interval of the ECG signal [2], [3]. In other words, the pulse rate can be estimated from the PPI. PPG has been an area of active research and finds its use in estimation of blood parameters such as peripheral blood oxygen saturation, hemoglobin, glucose etc [4] due to its non invasive nature. A qualitative analysis of the PPG signal can be used to diagnose possible heart ailments [5].

Some specific applications require continuous measurement of vital signals over a long time viz. diagnosis of arrhythmia. The ease of acquisition and inexpensive cost makes PPG data suitable for vitals monitoring in real time using a wearable sensor. Pulse oximeter is also a typical such wearable sensor used to estimate the blood oxygen saturation of the subject non-invasively. These oximeters use LEDs of different specific wavelengths in order to estimate the absorption characteristic of oxygenated and deoxygenated blood. However the placement of a wearable sensor, typically a fingertip makes the data acquisition susceptible to corruption due to motion induced artifacts.

The artifacts are developed as a result of relative motion between skin and the sensor. Hand movements also result in sudden and unpredictable changes in the instantaneous values of the PPG signals referred to as artifacts. These artifacts can lead to inaccurate estimation of vital blood parameters viz. blood oxygen saturation in case of oximeters and subsequently incorrect diagnosis of diseases. In such a case it is imperative to segment out the motion artifacts from a PPG signal before going for diagnostic methods. Three types of artifacts are found in the database viz.

- Absence of PPG signal
- PPG signal getting clipped
- Motion induced artifact.

A lot of attention has been given to motion artifact segmentation and various techniques have been developed. Techniques have been reported to detect artifacts with prior information about the movement of the subject using accelerometer [6]. Techniques discussed in [7], [8], [9] do not require any prior information about movement of the subject. Time frequency domain methods also have been applied to the corrupted PPG data [10]. However it is still an active area for research in order to increase the accuracy for the same.A

II. ALGORITHM DETAILS

The artifact segmentation and pulse rate estimation is done in three steps; (a) identify all the possible peaks in the signal and make a rough estimate of the pulse rate. (b) calculate the entropy for the entire signal. (c) compare the entropy of all the peaks obtained from steps (a) and then classify them as valid pulse or artifact.

A. Preprocessing

No preprocessing is required for the Capnobase recordings. However one of the samples from CSL database con-

[1]N. Paradkar is persuing M.S. in E.C.E. with the Center of VLSI and Embedded Systems Technology, International Institute of Information Technology, Hyderabad, India neeraj.paradkar@research.iiit.ac.in

[2]S. R. Chowdhury is faculty at the Center of VLSI and Embedded Systems Technology, International Institute of Information Technology, Hyderabad, India src.vlsi@iiit.ac.in

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

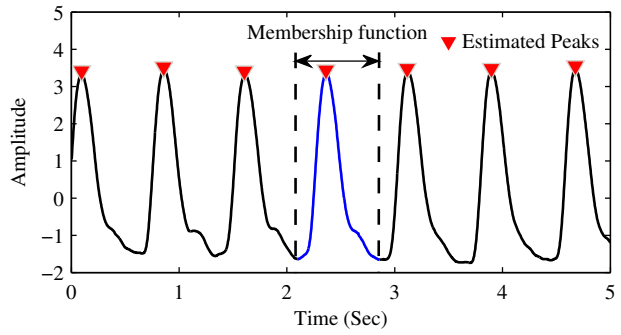

Fig. 1. Membership function obtained from input PPG signal

tained lot of quantization noise and thus had to be band pass filtered before further processing. The cut off frequencies were 1 Hz and 10 Hz respectively.

B. Peak Identification

First all the peaks present in the input PPG signal are identified in order to make a rough estimate of the pulse rate. The maximum pulse rate is restricted to 160 beats per minute. Capnobase recordings are sampled at 300 Hz and CSL at 125 Hz. Thus the peaks which are spaced not less than 110 samples from each other are found for Capnobase and and 30 samples in case of CSL. Once all the peaks are obtained in this fashion, an appropriate window of the original signal representing one complete pulse is selected around a peak for the entropy calculation.

C. Entropy Calculation

The entire PPG signal is divided in windows as discussed and one such window is used as the membership function for entropy calculation as shown in Fig. 1 (signal between dashed lines). Entropy is calculated for each wondow using the selected membership function. The length of each window is adjusted to make it same as the membership function and then it is normalized before calculating the entropy for that window.

D. Classification

The peaks obtained from first step would contain both true systolic peaks and those arising from motion induced artifact, if present. The entropy value for all the peaks are considered and then a decision is made to classify the peaks as true pulses or artifacts. Two thresholds are set in order to distinguish between true pulses and artifacts.

III. Entropy Measure of Fuzziness

The concept of the entropy measure of fuzziness was introduced by de Luca and Termini in [11]. The fuzzy entropy is applied to ECG signals in [12], [13]. An entropy measure of fuzziness H is a mapping from the set of all fuzzy subsets of a base set X into the non negative reals, i.e.

$$H : Fz(X) \rightarrow [O, \infty). \tag{1}$$

Algorithm 1 Peaks identification

loop
if $\frac{d}{dn}(PPG(n)) = 0$ && $\frac{d^2}{dn^2}(PPG(n))$
* $peak\_dist = PPG(n) - peaks(i)$
if $peak\_dist \geq min_{Threshold}$
* $peaks(i) \leftarrow PPG(n)$
* $n++$
endif
endif
endloop

Algorithm 2 Entropy calculation

* $mem\_f = PPG(x_1 : x_2)$
* $win = (x_2 - x_1 - 1)/2$
loop
for $i = n - win : n + win$
* $h = (A^{\lambda}_{n,k}(x(n)))^2 \cdot \triangle PPG(i)$
endfor
* $H(n) = \sum h^2$
endloop

A. Entropy measurement of fuzziness of PPG signal

Let us Consider a uniformly sampled discrete signal with period T in the time interval from 0 to t. The value of the n^{th} sample of this signal is denoted as $x(n)$.

To construct a fuzzy signal from the crisp signal, let us consider a symmetric window consisting of $2k+1$ original samples for each sampling point n, i.e. we will consider the following set of samples:

$$x(n-k), x(n-k+1), \cdots x(n) \cdots x(n+k-1), x(n+k). \tag{2}$$

Next, this window of $2k+1$ samples is sorted starting from the minimal value, i.e. $X_{min}(n) = x_{(1)}(n)$ and ending with the maximal value i.e. $X_{max}(n) = X_{(2k+1)}(n)$. So, the following relations are true:

$$x_{(1)}(n) \leq x_{(2)}(n) \cdots \leq x_{(2k+1)}(n). \tag{3}$$

Therefore the median of the set would be

$$x_{(M)}(n) = x_{(k+1)}(n). \tag{4}$$

The membership function for each point n is constructed in the following way. First let us assume that $A_{n,k}(x_{min}(n,k)) = 0$, $A_{n,k}(x_{max}(n,k)) = 0$ and $A_{n,k}(x_M(n,k)) = 1$ and then an upper semi continuous step-wise membership function is built according to the formula:

$$A_{n,k}(x) = \begin{cases} \frac{r}{k} & x \leq x_M(n) \\ \frac{2k+1-r}{k} & x > x_M(n) \end{cases} \tag{5}$$

where r is the number of $x_{(i)} < x$.

Algorithm 3 Classification

* $Th_{low} = \Gamma_1$
* $Th_{high} = \Gamma_2$
loop
* $p \leftarrow peaks(i)$
if $H(p) \geq \Gamma_1$ & $H(p) \leq \Gamma_2$
* $true\_peak \leftarrow peaks(i)$
else
* $art \leftarrow peaks(i)$
endif
* $i++$
endloop

A parametrized version of our membership function can be created to discriminate between certain levels of membership, i.e.

$$A^{\lambda}_{n,k}(x) = A_{n,k}(x) \cdot I(A_{n,k}(x) - \lambda), \tag{6}$$

where $I(A_{n,k}(x) - \lambda)$stands for Heaviside pseudo function,

$$I(x) = \begin{cases} 1 & x \geq 0 \\ 0 & otherwise \end{cases} \tag{7}$$

Using the above given formulas, the entropy measure of n^{th} sample is calculated in the form of the sum of respective rectangles:

$$H(A^{\lambda}_{n,k,\lambda}) = F(\sum_{i=1}^{2k} h(A^{\lambda}_{n,k}(x_{(i)}(n)) \cdot \triangle x_{(i)}(n)). \tag{8}$$

where

$$\triangle x_{(i)}(n) = x_{(i+1)}(n) - x_{(i)}(n). \tag{9}$$

B. Modified Entropy Measure

The above technique works very well when the input PPG signal is free of any motion artifacts. However the technique suffers from certain shortcomings. The shape of the membership function is fixed whereas the characteristic shape of the PPG signal is unique to an individual and is difficult to be modeled. As a result, the entropy values resulting from one PPG signal are considerably different from one individual to other. As a consequence, it is difficult to select a threshold which would distinguish a true pulse and an artifact for a general case.

This limitation is addressed by selecting a part of original PPG signal itself as a membership function instead of a fixed triangular one. We calculate mean of the peak-to-peak distance of the peaks obtained in first step and using that information, select a membership function representing a complete systolic interval. The interval is selected from a region of the original PPG signal where the deviation of the peak-to-peak value compared to the mean distance is minimum and has a length of $2k + 1$. For every sample of the input PPG data, a window of length same as that of the membership function i.e. $2k + 1$ is then considered to calculate the entropy with k samples on each side of the point in consideration.

The entropy measure is now calculated as

$$H(A^{\lambda}_{n,k,\lambda}) = F(\sum_{i=1}^{2k} h(A^{\lambda}_{n,k}(x(n)) \cdot \triangle x_i(n)). \tag{10}$$

where $A^{\lambda}_{n,k}(x(n))$ is the membership function obtained from the signal itself i.e.

$$A^{\lambda}_{n,k}(x(n)) = ppg(n_1 : n_2) \tag{11}$$

and

$$\triangle x_i(n) = x_{i+1}(n) - x_i(n). \tag{12}$$

The value of λ is is set to 0, n_1 and n_2 are the start and end points of the membership function from Fig. 1.

IV. RESULTS AND DISCUSSION

The first step used to identify all potential systolic peaks and possible motion artifact induced peaks performed highly accurately. The number of peaks missed by the algorithm is very small although improvements can be made to make it more robust in order to identify all possible peaks. The function h is defined as $h(n) = n^2$ and similarly, H is defined as $H(n) = n^2$. The length of the membership function $2k + 1$ varies from signal to signal as it represents the length of one full systolic cycle.

The algorithm was calibrated and tested using the Capnobase database [14] and the CSL Benchmark dataset [9]. Capnobase consists of 42 recordings which include 23 recordings free from any sort of artifact and remaining 19 contain artifacts. CSL dataset consists of 2 recording and both contain artifacts. The entropy values for the artifact free recordings strongly exhibit a regular pattern with very few corrections shown by 2 recordings. The recordings containing artifact manifest a similar uniform pattern for regions containing true systolic peaks; however the entropy values are significantly different for the peaks corresponding to artifacts. The entropy values close to 1 indicate a high degree of similarity between the signal window being considered and the membership function. It also follows that values differing significantly from 1 suggest that the signal window has low degree of similarity with the membership function. Very high entropy values arise due to a very large gradient of the input PPG signal at the concerned point. The gradient of a healthy PPG data follows a specific pattern, very high gradient values thus can be attributed to artifact induced corruption in data. The classification is carried out using two thresholds; a lower bound (Γ_1) to eliminate data samples bearing very low degree of similarity and a higher bound (Γ_2) to remove data samples with very high gradient. Γ_1 is assigned value of $0.3 \cdot mean(entropy\_peaks)$ and Γ_2 is assigned $1.5 \cdot mean(entropy\_peaks)$.

The performance of the algorithm for identifying true pulses is observed using the positive predictive value (PPV) and sensitivity (Se) parameters defined as follows:

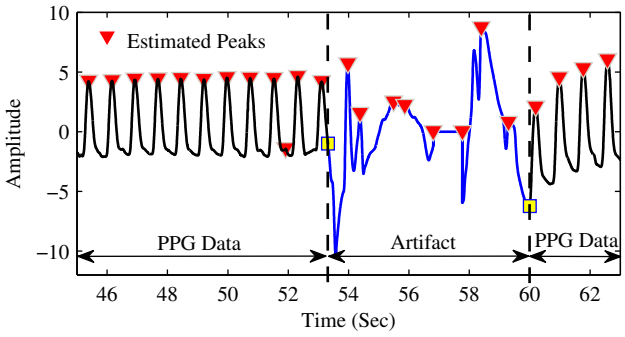

Fig. 2. PPG signal corrupted by motion artifact

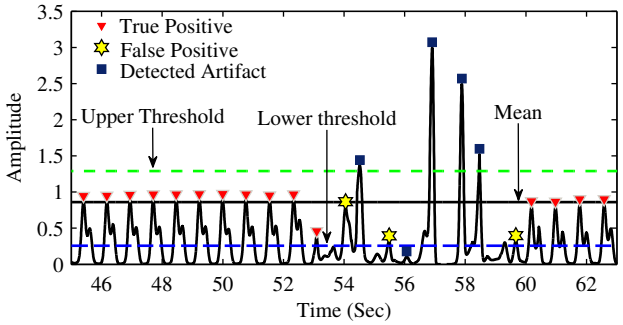

Fig. 3. Entropy value of the corrupted signal in Fig. 2

$$Sensitivity = \frac{tp}{tp + fn} \tag{13}$$

$$Positive\ Predictive\ Value = \frac{tp}{tp + fp} \tag{14}$$

The calculated PPV and Se figures for the algorithm are for Capnobase and CSL database are as discussed in Table I and in Table II respectively. The performance of the algorithm was predictably better when applied on PPG data void of any artifacts. PPG signal corrupted by artifact and the corresponding entropy values for the same signal as shown in Fig. 2 and Fig. 3 respectively.

V. CONCLUSIONS

In this paper, an entropy based technique to detect motion artifact and estimate pulse rate of the subject has been established. This technique has been effective to identify the peaks and then detect the artifact and determine the pulse rate of the subject. The entropy measure for the input data samples is a good classification feature for discriminating true pulses from artifact. The selection of correct membership function is essential for a good performance of the algorithm and further improving this selection criteria would enhance the performance.

The discussed approach can be extended for the diagnosis of cardiac diseases related to the pulse rate information of the subject. Diseases like tachycardia, braddycardia and arrythmias can be diagnosed from the PPG data after pulse identification and artifact removal.

TABLE I

ALGORITHM PERFORMANCE BASED ON CAPNOBASE DATABASE

		Annoted Data			PPV (%)
		True Peaks	Artifact	None	
Entropy Based Algorithm	True *Peaks*	27725	100	91	99.84
	Artifact	3	30	-	
	None	42	31	-	
Se(%)		99.32			

TABLE II

ALGORITHM PERFORMANCE BASED ON CSL BENCHMARK DATABASE

Annoted pulses	Correct pulses	Incorrect pulses	Undetected pulses	Se (%)	PPV (%)
15867	15683	186	186	98.84	98.83

REFERENCES

[1] P. De Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 7, pp. 1196–1206, 2004.

[2] M. Bolanos, H. Nazeran, and E. Haltiwanger, "Comparison of heart rate variability signal features derived from electrocardiography and photoplethysmography in healthy individuals," in *Engineering in Medicine and Biology Society, 2006. 28th Annual International Conference of the IEEE*, pp. 4289–4294.

[3] T. Ma and Y. Zhang, "A correlation study on the variabilities in pulse transit time, blood pressure, and heart rate recorded simultaneously from healthy subjects," in *Engineering in Medicine and Biology Society, 2005. 27th Annual International Conference of the*. IEEE, pp. 996–999.

[4] R. Swathi Ramasahayam and S. Roy Chowdhury et.al, "Non invasive estimation of blood glucose using near infra-red spectroscopy and double regression analysis," in *7th IEEE International Conference on Sensing Technology, Wellington, New Zealand*, December 3-5, 2013.

[5] M. Elgendi, "On the analysis of fingertip photoplethysmogram signals," *Current cardiology reviews*, vol. 8, no. 1, p. 14, 2012.

[6] P. Gibbs and H. H. Asada, "Reducing motion artifact in wearable biosensors using mems accelerometers for active noise cancellation," in *American Control Conference, 2005. Proceedings of the*. IEEE, pp. 1581–1586.

[7] R. Yousefi, M. Nourani, and I. Panahi, "Adaptive cancellation of motion artifact in wearable biosensors," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pp. 2004–2008.

[8] W. Karlen, J. Ansermino, G. Dumont *et al.*, "Adaptive pulse segmentation and artifact detection in photoplethysmography for mobile applications." in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society.*, 2012, pp. 3131–3134.

[9] M. Aboy et.al, "An automatic beat detection algorithm for pressure signals," *Biomedical Engineering, IEEE Transactions on*, vol. 52, no. 10, pp. 1662–1670, 2005.

[10] R. Couceiro et.al, "Detection of motion artifacts in photoplethysmographic signals based on time and period domain analysis," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pp. 2603–2606.

[11] A. De Luca and S. Termini, "On the convergence of entropy measures of a fuzzy set," *Kybernetes*, vol. 6, no. 3, pp. 219–227, 1977.

[12] E. Czogala and J. Leski, "Application of entropy and energy measures of fuzziness to processing of ECG signal," *Fuzzy sets and systems*, vol. 97, no. 1, pp. 9–18, 1998.

[13] S. Roy Chowdhury, "Field programmable gate array based fuzzy neural signal processing system for differential diagnosis of QRS complex tachycardia and tachyarrhythmia in noisy ECG signals," *Journal of medical systems*, vol. 36, no. 2, pp. 765–775, 2012.

[14] W. Karlen, M. Turner, E. Cooke, G. Dumont, and J. M. Ansermino, "Capnobase: Signal database and tools to collect, share and annotate respiratory signals," in *Annual Meeting of the Society for Technology in Anesthesia (STA)*, West Palm Beach, 2010.