Fuzzy Entropy based Detection of Tachycardia and Estimation of Pulse Rate through Fingertip Photoplethysmography

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***Abstract*—The paper presents a fingertip photoplethysmography (PPG) based technique to detect and diagnose the occurrence of tachycardia and estimate the pulse rate of the subject. The PPG is the study of blood flow and is non invasive. A portable system has been developed to obtain the PPG signal and it is analyzed to carry out the diagnosis. The developed system is inexpensive and easy to use and the data is recorded using the index finger of the subject. The fuzzy entropy of the samples has been used to diagnose possible tachycardia. The pulse rate has been calculated using entropy measure of fuzziness of the detected PPG samples. The proposed system along with CapnoBase database is used analyze the technique and pulse rate estimation was done with an accuracy of 99.39%. The diagnosis for tachycardia has been done with 100% accuracy with respect to the population of 53 people being studied.**

***Index Terms*—tachycardia, photoplethysmography, fuzzy entropy**

I. Introduction

The heart of an adult human being generally beats at around 60 to 100 beats per minute (BPM). Tachycardia is an abnormality which leads to heart beating at over 100 times per minute. The condition may occur when the upper or lower or both chambers of the heart beat at a significantly higher rate. Such an increase in the rate decreases the efficiency of blood flow of the heart throughout the whole body including the heart itself. This may lead to oxygen-starving of various organs and of the heart muscles and increases the risk of stroke, sudden cardiac arrest. This abnormality can be diagnosed by accurately measuring the pulse rate. The pulse rate of an individual can be obtained by identifying the QRS complex of the electrocardiograph (ECG) signals [1], [2] or by identifying the peaks of a typical photoplethysmograph signal.

Photoplethysmography (PPG) is a technique to monitor the dynamics of blood flow in the body. Light radiation having wavelength in red or infrared region is passed through a certain portion of the body viz. fingertip, toe tip, earlobe etc. A part of this incident radiation is reflected back from the surface of the skin itself; a certain portion of the transmitted radiation is then absorbed by various components of the blood viz. water, oxy- and deoxyhemoglobin along with a number of other proteins and glucose etc. wherein each such component absorbs radiation specific to its own chemical properties. Other components such as skin, bone, tissue bed etc. also absorb radiation. Remaining portion of the radiation is transmitted to the other end is sensed through a photo sensor.

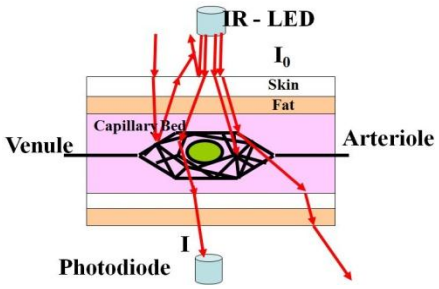

Figure 1. Transmission PPG

This technique is referred to as transmission PPG as shown in Fig. 1. Another variation of this technique is where the radiation reflected from the surface of the fingertip or earlobe is sensed by the photosensor and it is referred to as reflection PPG.

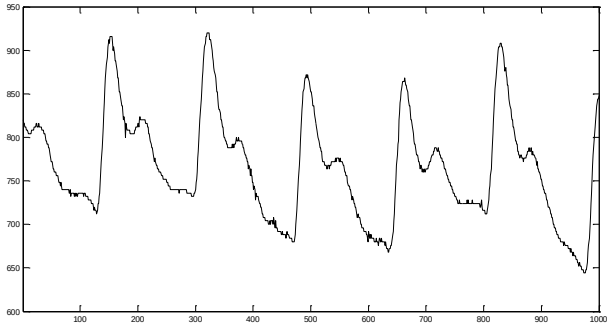

Figure 2. PPG signal obtained by PPG device

Absorption due to blood can be attributed to two main components namely venous blood and pulsatile arterial blood. The absorption of the radiation by the skin, bone, muscle, venous blood and tissue bed can be modeled as a

Manuscript received December 24, 2013; revised February 8, 2014.

doi: 10.12720/jomb.4.1.19-23

constant with respect to time, however that attributed to the pulsatile arterial blood is a function of the systolic and diastolic cycles of the heart and in turn gives the PPG signal its characteristic form (Fig. 2). Typically the light radiation is emitted through a light emitting diode (LED) and the photosensor is often a photodiode, which in essence converts the varying absorption pattern of the blood into an electrical quantity.

In this work, a portable system has been developed to obtain the PPG signal and a new technique has been introduced to obtain the pulse rate from the given PPG signal using its entropy measure of fuzziness. The PPG signal obtained can be modeled as a fuzzy signal as. The entropy measure of such a fuzzy signal is a quantitative measure of the deviation of the signal from its mean. This will enhance the local peaks of the PPG signal and suppress the remaining small peaks in the signal which in turn will result in identifying heart rate and pulse interval.

As mentioned in [3]-[5], the Pulse to Pulse Interval (PPI) of the PPG signal is highly correlated to the R-R peak interval (RRI) of the ECG signal. This signifies that the PPG signal can be used to analyze the pulse rate of an individual as effectively as the ECG signal. Works in [6], [7] have established the PPG as a viable option for the diagnosis of arrhythmias as well.

II. Previous Work

A. Electrocardiogram

The ECG technique monitors the electrical activity of the heart through electrodes attached to the surface of the skin. In conventional clinical practice, differential analysis of the QRS complex of the ECG signal is used for diagnosis of tachycardia. However, since it is necessary to attach some electrodes to the patient's chest in the case of the Holter ECG, it is troublesome to check tachycardia using a Holter ECG. Therefore, development of a heart rate monitor that is simpler and easier to use than the Holter ECG is desirable.

These electrodes are required to be highly sensitive and thus the set up for the ECG measurement is costly.

B. Photoplethysmography as an Alternative

PPG is the study of blood circulation to the body. PPG signals are typically used in devices such as pulse oxymeters to determine the oxygen saturation of the blood and can further be analyzed for the diagnosis of dysfunctions related to heart [8], [9]. The typical PPG device consists of a clip which houses the LED and the photodiode inside it, to be put on the fingertip and the output of the photodiode is then processed and analyzed to determine the necessary parameter. The most significant advantage of using the PPG signal over ECG is the ease of use, lower costs.

Such a heart rate monitor would also be useful for checking the change of a physical condition of an artificial dialysis patient during dialysis and to check the stress condition of a normal person by autonomic analysis of the heart rate variability.

III. Entropy Measure of Fuzziness

First we recall a concept of the entropy measure of fuzziness, introduced by de Luca and Termini in 1977 [10] and also studied for ECG signal processing in [11], [12]. Local measures (in a given point of a set) or global measures (for the whole fuzzy set) can also be distinguished. An entropy measure of fuzziness H is a mapping from the set of all fuzzy subsets of a base set X into the nonnegative real numbers, i.e.

$$H: Fz(X) \to [0, \infty) \tag{1}$$

The entropy measure of fuzziness has the following properties:

- The entropy measure of fuzziness $H(A) = 0$ for any crisp set A if $A(x) = 0$ or $A(x) = 1$, for all x.
- $H(A)$ reaches maximum if $A: X \to \{1\}$.
- If A^* is any sharpened version of A, i.e. if $A(x) \leq 0.5$ then $A^*(x) \leq A(x)$ and if $A(x) \geq 0.5$ then $A^*(x) \geq A(x)$ and $H(A^*) \leq H(A)$.
- The symmetry property i.e. $H(A) = H(A^c)$ where $(A^c) = 1 - A(x)$ is required for convenience.

A wide class of entropy fuzziness measure can be obtained assuming a measure v for space X. Such a class can be expressed by means of the formula:

$$H(A) = F_1 \int_x h(A(x))\, dv \tag{2}$$

where $A: X \to [0,1]$ is any v-measurable function, $dv = dx$ or $dv = p(x)dx$ where $p(x)$ is the probability distribution function, $h: [0,1] \to R_+$ is an increasing function in the interval [0,½] and a decreasing function in the interval [½,1] for $h(0) = h(1) = 0$, $F_1 : R_+ \to R_+$ is an increasing function for $F_1(z) = 0$ if and only if $z = 0$.

C. Entropy Measure of Fuzziness for PPG Signal

Let us consider the original, 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 $x(n)$ and also the $2k+1$ windows of the original samples: $x(n-k)\cdots\cdots x(n)\cdots\cdots x(n+k)$ centered at $x(n)$.

The idea of the construction of a fuzzy signal denoted $X(n, k)$ from the original signal is based on two assumptions:

- It is assumed that the constant signal contains no fuzzy uncertainty. The fuzzy value $X(n, k)$ which represents the respective fuzzy number of the nth sample is reduced to real number $x(n)$. The measure of fuzziness will take the value of zero and this means that the information conveyed by such a signal is maximal.
- The fuzziness of the variable signal $X(n, k)$ is higher if the dynamics of the changes of the original signal is on the increase.

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

$$x(n-k) \cdots\cdots x(n) \cdots\cdots x(n+k) \tag{3}$$

Let us sort these $(2k+1)$ values starting with minimal value i.e. $x_{min}(n) = x_1(n)$ and $x_{max}(n) = x_{(2k+1)}(n)$. Also we get

$$x_{(1)}(n) \leq x_{(2)}(n) \cdots\cdots \leq x_{(2k+1)}(n) \quad (4)$$

Therefore the median of the set would be

$$x_{(M)}(n) = x_{(k+1)}(n) \quad (5)$$

Having the median and the set of samples mentioned above, we will construct the membership function for each point n in the following way. First let us assume that $A_{n,k}(X_{min}(n,k)) = 0$, $A_{n,k}(X_{max}(n,k)) = 0$, $A_{n,k}(X_M(n,k)) = 1$. The membership function is given by:

$$A_{n,k}(x) = \begin{cases} \frac{p}{k}, & x \leq x_M \\ \frac{2k+1-p}{k}, & x > x_M \end{cases} \quad (6)$$

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

We can also create a parameterized version of our membership function that possesses the ability to discriminate between certain levels of membership, i.e.

$$A^{\lambda}_{n,k} = A_{n,k}(x) \cdot I\left(A_{n,k}(x) - \lambda\right) \quad (7)$$

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

$$I(x) = \begin{cases} 1, & x \geq 0 \\ 0, & otherwise \end{cases} \quad (8)$$

It should be noted that the above-mentioned parameterized version differs from the version encountered in literature i.e.

$$H\left(A_{n,k,\lambda}\right) = \int_X h_{\lambda}\left(A_{n,k}(x)\right) dv \quad (9)$$

where

$$h(x) = \begin{cases} h(x), & x \in (\lambda, 1-\lambda) \\ 0, & x \geq otherwise \end{cases} \quad (10)$$

Using the above given formulas, we can write a formula for the entropy measure of nth sample in the form of the sum of respective rectangles:

$$H\left(A^{\lambda}_{n,k,\lambda}\right) = F \cdot \left(\sum_{i=1}^{2k} h(A^{\lambda}_{n,k}(x_{(i)}(n))) \cdot \Delta\, x_{(i)}(n)\right) \quad (11)$$

where

$$\Delta\, x_{(i)}(n) = x_{(i+1)}(n) - x_{(i)}(n) \quad (12)$$

IV. Methodology

A. PPG Device

The fingertip PPG is obtained through a clip as montioned before using infrared radiation of 970nm and the transmitted radiation is sensed through a photodiode. The obtained signal is weak and contaminated with noise such as baseline wander and higher freaquency noise predominantly resulting from power supply fluctuations and typically has 50Hz frequecny. The signal needs to be amplified before filtering and the necessary amplification is provided by instrumentation amplifier. The amplified signal is then applied to a low pass filter which removes the higher frequency powerline interference. This is signal is then sampled and quantized using an analog to digital converter (ADC) and then is analyzed to estimate the heart pulse and to detect the possibility of tachycardia using Matlab. A typical PPG signal obtained is shown in Fig. 2.

B. Signal Processing

1) Filtering

The filtering carried out before digitization does not remove the noise completely and the ADC may add quantization errors.

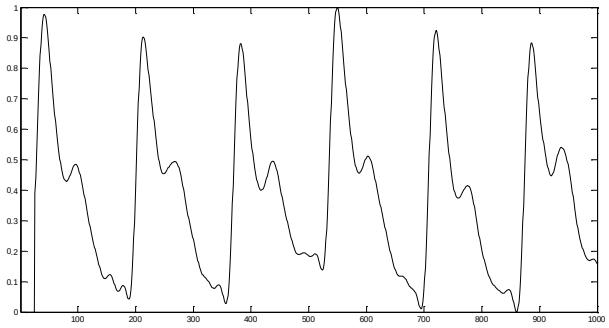

Figure 3. Same PPG signal after bandpass filtering and normalizatiom

The signal is first passed through a bandpass filter which removes the low frequency baseline wander, minute powerline interference which may still be present and produces a smooth waveform, Fig. 3.

2) Calculation of fuzzy entropy

The sampling frequency for the PPG data samples obtained from the database is 300Hz. Fuzzy entropy for the signal is calculated using the technique discussed previously. The window size factor, k is selected as 10 which means we consider 21 samples for calculation of entropy corresponding to the center sample. The theshold is set as $\lambda = 0.8 * \max(A_{n,k}(x))$. The functions h and F are defined as $h(x) = x^2$ and $F(x) = x^2$. Fig. 4 shows the actual entropy measure obtained for each signal sample.

3) Pulse rate estimation

We analyze one minute windows of the filtered signal to estimate the pulse rate. We calculate the fuzzy entropy for every sample of the signal as discussed earlier. The entropy measure for each sample enables us to precisely locate the point corresponding to a heart beat. We then use window based threholding to remove incorrect peaks from being detected. The window length is set to 1000 samples to ensure that local artifacts do not affect the entire signal.

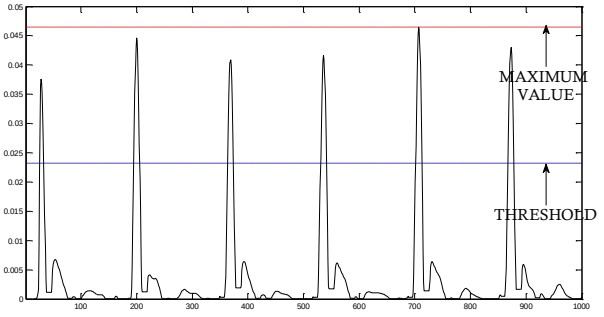

Figure 4. Entropy of bandpass filtered signal

Threshold is set to 50% of maximum value as shown in Fig. 4.

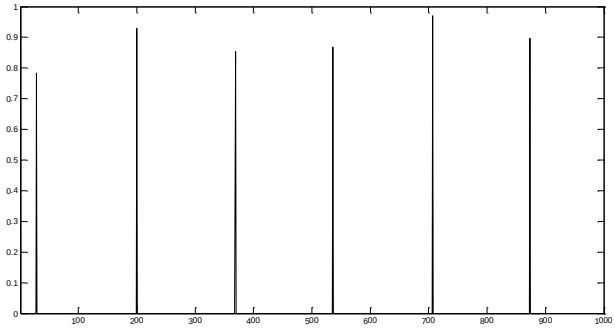

Figure 5. Final entropy after thresholding, threshold set at 50% of maximum value

The local thresholding prevents most of the incorrect peaks from being classified as heart pulses. Finally we obtain the points which represent the heart pulses, Fig. 5.

4) Detection of tachycardia

Once we obtain the number of beats per minute, a decision can be made whether the person is suffering from tachycardia or not. Such diagnosis from ECG signals is discussed in [13]. As mentioned before, if the number of beats per minute is higher than 100, it can be classified as tachycardia. We consider a one minute window of the continuous PPG signal and calculate the number of pulses present in that window. The entropy measure is maximum for the signal points where a pulse occurs. Once we separate these pulses from the remaining signal, we can simply count the number of peaks in the interval to reveal number of pulses.

V. Results

PPG samples were recorded for 15 healthy volunteers. The volunteers are asked to relax for about 2 minutes before recoring their samples. The PPG signal samples are recorded for a duration of one minute with the volunteers at rest to avoid motion atrifacts. The samples were then analyzed and the results are as follows:

- Total number of annoted pulses: 1191
- Total number of pulses detected: 1191
- Total number of undetected pulses: 6
- Total number of wrongly detected pulses: 6

Accuracy = 99.49%.

The samples were also analyzed for tachycardia and bradycardia diagnosis. One case was diagnosed positive.

Additionally, the technique is analyzed using the CapnoBase database [14] and the pulse rate estimated is compared with the results obtained from the corresponding annoted data. The dataset contains 42 PPG signals taken from different individuals. Out of these, 23 signals are free from any motion induced artifacts and remaining 19 contain motion artifacts. All 23 artifact free signals were analyzed along with 15 signals containing artifacts for our test. The results obtained are as follows:

1) For artifact free signals:

- Total number of annoted pulses: 15269
- Total number of pulses detected: 15213
- Total number of undetected pulses: 62
- Total number of wrongly detected pulses: 6

Accuracy = 99.59%.

2) For artifact containing signals:

- Total number of annoted pulses: 10428
- Total number of pulses detected: 10347
- Total number of undetected pulses: 100
- Total number of wrongly detected pulses: 19

Accuracy = 99.04%.

3) Combining 1. and 2.:

- Total number of annoted pulses: 25697
- Total number of pulses detected: 25560
- Total number of undetected pulses: 162
- Total number of wrongly detected pulses: 25

Accuracy = 99.37%

These samples were also tested for possible diagnosis of tachycardia. The results obtained are as follows:

- Total number of diagnosed cases from artifact free signals: 6
- Total number of diagnosed cases from artifact containing signals: 4
- Total number of positive cases: 10.

The results as shown in Table I.

TABLE I. Results for Pulse Detection Using CapnoBase

Input PPG signal	Results			
	Annoted Pulses	Detected Pulses	Undetected Pulses	Incorrect Pulses
Artifacts absent	15269	15213	62	6
Artifacts present	10428	10347	100	19
Overall	25697	25560	162	25

Combining the results obtained from the PPG device and the database, we get:

- Total number of annoted pulses: 27688
- Total number of pulses detected: 27551
- Total number of undetected pulses: 168
- Total number of wrongly detected pulses: 31

Accuracy = 99.39%.

Also, false positive rate is found to be 0.097% and false negative rate is 0.63% for entire data.

VI. Conclusion

In this work, we have designed a system to obtain the fingertip PPG signal. Once the PPG signal is obtained, after subsequent preprocessing we calculated the fuzzy entropy of the given PPG signal in order to accurately identify the heart rate. The results are analyzed for a possibility of tachycardia depending upon the number of heart beats per minute. The technique is found to be very accurate for easy, inexpensive and continuous monitoring of heart rate for a longer duration as compared to conventional ECG monitoring.

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