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RESEARCH ARTICLE

BEAT CLASSIFICATION OF AN ECG SIGNAL USING PHOTOPLETHYSMOGRAPHY AND NEURAL NETWORK

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ABSTRACT

This paper presents a simple method to indirectly estimate the range of certain important electrocardiogram (ECG) parameters using photoplethysmography (PPG). The proposed method, termed as PhotoECG, extracts a set of time and frequency domain features from fingertip PPG signal. A feature selection algorithm utilizing the concept of Maximal Information Coefficient (MIC) is presented to rank the PPG features according to their relevance to create training models for different ECG parameters. The proposed method yields above 90% accuracy in estimating ECG parameters on a benchmark hospital dataset having clean PPG signal. The same method results an average of 80% accuracy on noisy PPG signal captured by iPhone, indicating its feasibility to create phone applications for preventive ECG monitoring at home.

An abnormal respiratory rate is often the earliest sign of critical illness. A reliable estimate of respiratory rate is vital in the application of remote tele-monitoring systems, which may facilitate early supported discharge from hospital or prompt recognition of physiological deterioration in high-risk patient groups. Traditional approaches use analysis of respiratory sinus arrhythmia from the electrocardiogram (ECG), but this phenomenon is predominantly limited to the young and healthy. Analysis of the photoplethysmogram (PPG) waveform offers an alternative means of non-invasive respiratory rate monitoring, but further development is required to enable reliable estimates. This review conceptualizes the challenge by discussing the effect of respiration on the PPG waveform and the key physiological mechanisms that underpin the derivation of respiratory rate from the PPG.

INTRODUCTION

Falsely issued alarms in intensive care units (ICUs) disrupt patients' rest, drain hospital resources, and desensitize the hospital staff to potential emergency situations. It has been estimated that 43% of life-threatening electrocardiogram (ECG) alarms issued by bedside monitors are false, with some categories of alarm being as high as 90%. These false arrhythmia alarms are often triggered by noise and other artifacts in the monitored ECG waveform, and can be suppressed in the presence of other data which indicate that there are no critical abnormalities in cardiac function. Such information can come from signals which are related to cardiac function but are measured in a location remote to the heart and are therefore unlikely to exhibit the same types of noise and artifacts as the ECG. Signals with pulsatile waveforms offer the additional benefit of having features indicative of the cardiac cycle, which can be later compared to timing and morphology of features in the ECG waveform. Aboukhalil *et al*. have created an algorithmic framework which consults the arterial blood pressure (ABP) waveform to corroborate critical ECG arrhythmia alarms. If an ECG alarm is triggered, the algorithm checks the signal quality of the simultaneously recorded ABP waveform. If this waveform is of poor quality, the ECG alarm is accepted as true. If the ABP signal is of high quality, the algorithm checks that the features extracted from the blood pressure waveform corroborate the condition which triggered the ECG alarm. The alarm is suppressed if the blood pressure waveform does not exhibit features consistent with a cardiac arrhythmia.

A robust, reliable, and patient-acceptable method of remotely monitoring respiratory rate is essential to the development of tele-monitoring technology. PPG-based estimation of respiration rate is desirable, given that heart rate and oxygen saturation can also be derived from the same probe, but the analysis of respiratory-induced variations in the waveform requires frequency analysis of the PPG baseline, which is often removed in the processing performed by commercial devices. The cardiovascular and respiratory physiology underpinning the PPG signal is complex, and the exact origin of the PPG waveform remains unclear.

It is well-known that the electrocardiogram (ECG) is a non-invasive method that can be used to measure heart rate variability (HRV). Photoplethysmogram (PPG) signals also reflect the cardiac rhythm since the mechanical activity of the heart is coupled to its electrical activity. Photoplethysmography is a non-invasive, safe, and easy-to-use technique that has been developed for experimental use in vascular disease. A useful algorithm for *a*-wave detection in the acceleration plethysmogram (APG, the second derivative of the PPG) is introduced to determine the interval between successive heart beats and heart rate variability. In this study, finger-tip PPG signals were recorded for twenty seconds from 27 healthy subjects measured atrest.

Photoplethysmography is a non-invasive electro-optic method developed by Hertzman, which provides information on the blood volume flowing at a particular test site on the body close to the skin. PPG waveform contains two components; one, attributable to the pulsatile component in the vessels, i.e. the arterial pulse, which is caused by the heartbeat, and gives a rapidly alternating signal (AC component). The second one is due to the blood volume and its change in the skin which gives a steady signal that changes very slowly (DC component).PPG signal consists of not only the heart-beat information but also a respiratory signal.

Existing System

A complete ECG cycle contains five major points (P, Q, R, Sand T) and few time interval parameters (PR, QRS, QT) for checking heart condition. A prolonged PR interval indicates a possibility of first stage heart block. A prolonged QT-interval, caused due to effects of certain drugs is a risk factor of ventricular tachy-arrhythmias. RR interval indicates the heart rate. Thus, rather than measuring accurate values, an estimation of the range of PR, QRS or QT interval can indicate the heart condition of a person for initial screening purpose and alert generation at home. Both ECG and PPG are directly synchronized with human cardiac cycle. The peak to peak interval of PPG is known to be highly correlated with the RR interval, indicating the possibility of deriving other ECG parameters from PPG. In this paper we propose an approach to predict the range of PR,QRS and QT intervals along with actual value of RR interval parameter of a person from PPG. Although the method does not claim to compete with the accurate ECG machines, it introduces a simple initial screening system (possibly a phone application) for household ECG monitoring.

Blood Pressure (BP) is considered to be a strong indicator of an Individual‘s wellbeing and one of the most important physiological parameters that reflect the functional status of the cardiovascular system of human beings. Therefore, the measurement of BP is helpful for a physician to understand and diagnose the integrity function of the cardiovascular system. The various indirect methods of measuring BP such as Riva- Rocci‘s, oscillometric, ultrasound, and tonometry method, etc. Different noninvasive methods utilizing occlusive air cuffs are frequently used by physicians and nurses in hospitals as well as by laypersons in home care. Such a simple measurement reveals the systolic and diastolic pressure in a specific instant of time. Traditional cuff based methods using Korotkoff sounds or oscillometric methods do not measure BP continuously. These methods require inflation and following deflation of the cuff, which is time consuming and prevents continuous measurement. Furthermore, for reliable measurements, the interval between measurements should be at least 2 min. Therefore, changes in BP, which are in the range of seconds to minutes, cannot be detected.

A reliable continuous non-invasive blood pressure measurement is highly desirable. While the possibility of using Pulse Transit Time (PTT) and Pulse Wave Velocity (PWV) were shown to have co-relation with arterial blood pressure (BP) and have been reported to be suitable for indirect BP measurement. Arterial blood pressure (BP) was estimated from Electrocardiography (ECG) and PPG waveform. PTT is a time interval between an R-wave of electrocardiography (ECG) and a photoplethysmography (PPG) signal. This method does not require an air cuff and only a minimal inconvenience of attaching electrodes and LED/photo detector sensors on a subject.PTT computed between the ECG R-wave and the maximum first derivative PPG was strongly correlated with systolic blood pressure (SBP) (R=0.734) compared with other PTT values, and the diastolic time proved to be appropriate for estimation diastolic blood pressure (DBP) (R = 0.731). Our proposed method can be used for continuous BP monitoring for the purpose of personal healthcare.

Disadvantages

- It might not be feasible for all to have a day to day clinical ECG diagnosis.
- There may be cases where some of these points are either wrongly detected or not detected at all, for some cycles, producing wrong values of the feature.

Proposed System

The process can be implemented by employing the following statistical feature for the feature extraction from the ECG signal.

Standard Deviation: The standard deviation (SD) measures the amount of variation or dispersion from the average. A low standard deviation indicates that the data points tend to be very close to the mean (also called expected value); a high standard deviation indicates that the data points are spread out over a large range of values.

Energy: Energy is a property of objects, transferable among them via fundamental interaction, which can be converted in form but not created nor destroyed.

Entropy: Entropy is the average amount of information contained in each message received. Here, message stands for an event, sample or character drawn from a distribution or data stream. Entropy thus characterizes our uncertainty about our source of information.

Mean: In probability, mean and expected value are used synonymously to refer to one measure of the central tendency either of a probability distribution or of the random variable characterized by that distribution.

Median: The median is the numerical value separating the higher half of a data sample, a population, or a probability distribution, from the lower half. The median of a finite list of numbers can be found by arranging all the observations from lowest value to highest value and picking the middle one.

Mode: The mode is the value that appears most often in a set of data. The mode of a discrete distribution is the value *x* at which its probability mass function takes its maximum value (Most frequent value in a data set).

Skewness: Skewness is a measure of the asymmetry of the probability of a real-valued random variables about its mean.μ is the mean, σ is the standard deviation, and E is the expectation operator.

Phase: Phase in sinusoidal functions or in waves has two different, but closely related meanings. One is the initial angle of a sinusoidal function at its origin and is sometimes called phase offset or phase difference. Another usage is the fraction of the wave cycle which has elapsed relative to the origin.

Magnitude: The relative size of an object.

Kurtosis: Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. For univariate data Y_1, $Y_{2,}Y_N$, the formula for kurtosis is kurtosis=$\sum Ni=1(Yi-\bar{Y})\ 4(N-1)\ s4$ where $\bar{Y}$ is the mean, $\boldsymbol{s}$ is the standard deviation, and N is the number of data points. Frequency: Frequency is the number of occurrences of a repeating event per unit time.

$$f = \frac{n}{t}$$

Where n is number of times an event occurred and t is the time. The obtained statistical parameters were then classified using kNN classifier for the retrieval of the similar audio signal. Rpeak, Qpeak, RR interval of ECG signal.

Advantages

- The system have scaled and offset the PPG waveform input to resemble physiologic range for blood pressure measurements (in mmHg) in order to take advantage of the existing low-pass filter.
- The sudden decrease in pulse amplitude causes several missed pulse detections when the PPG algorithm is used to mark the onset of each PPG pulse, yielding long intervals between detected beats.

System Architecture

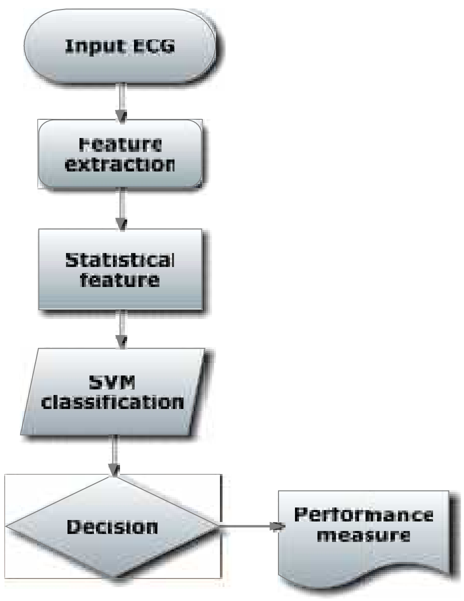

Fig. 1 System Architecture

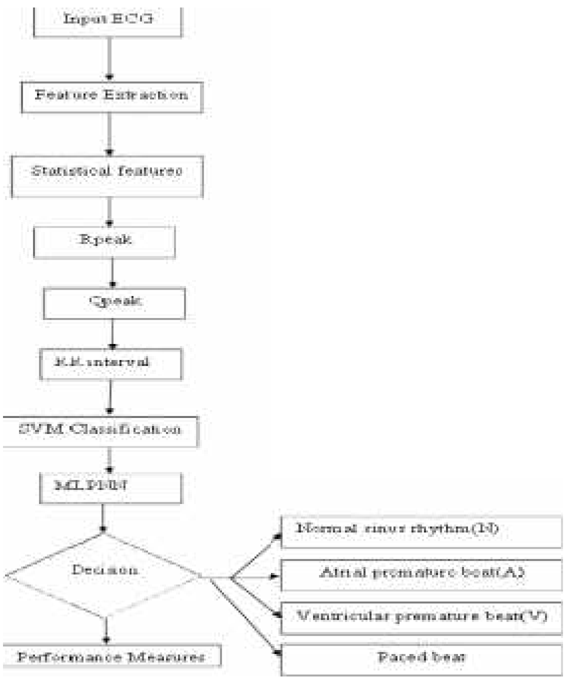

Fig. 2 Program flow for ECG beat Classification

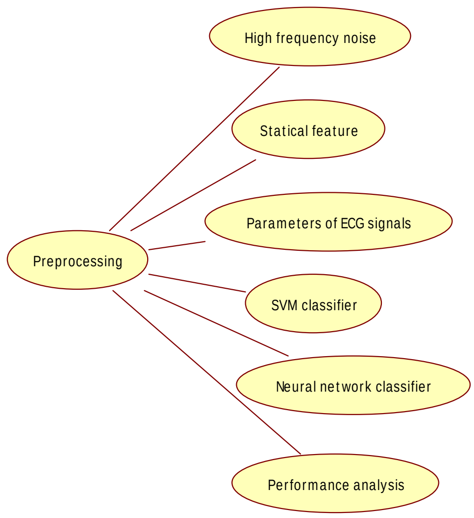

Fig. 3 Case Diagram

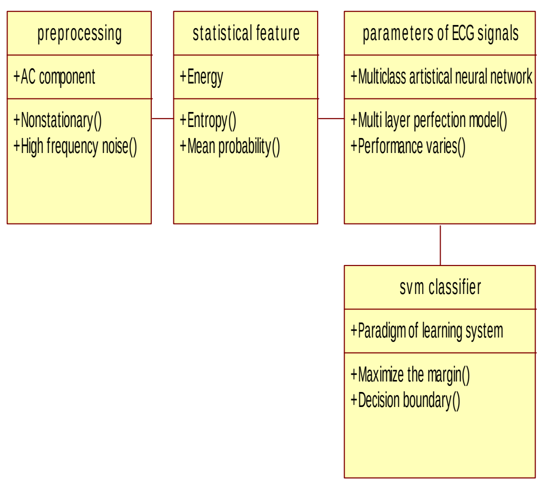

Fig. 4 Class Diagram

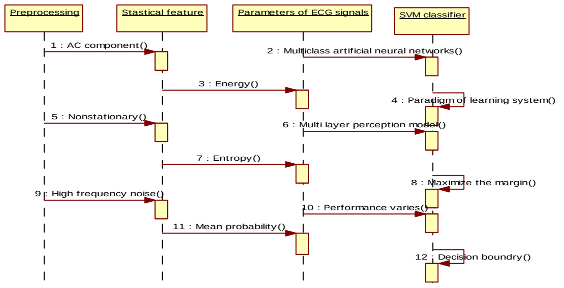

Fig. 5 Sequence Diagram

The different modules used in ECG beat classification are as:

- Preprocessing
- Statistical features
- Parameters of ECG signal
- SVM classifier
- Radial basis Neural network classifier
- Performance

Preprocessing

PPG signal generally contains a large but slowly varying DC part along with the AC component. Moreover, PPG signals are largely non-stationary. So, a frame processing approach is taken to extract the stationary part out of it. PPG signal is segmented into fixed length small non-overlapping windows (5-10 second). Samples corresponding to each window are passed through a 4th order band pass Butterworth filter (cut-off frequency0.25 Hz and 20 Hz) to remove the DC and high frequency noise components. The samples are further passed through a moving average filter for smoothing and to remove high frequency noise. Thus the PPG samples are prepared to feature extraction.

Statistical features

Energy: Energy is a property of objects, transferable among them via fundamental interaction, which can be converted in form but not created nor destroyed.

Entropy: Entropy is the average amount of information contained in each message received. Here, message stands for an event, sample or character drawn from a distribution or data stream. Entropy thus characterizes our uncertainty about our source of information.

Mean: In probability, mean and expected value are used synonymously to refer to one measure of the central tendency either of a probability distribution or of the random variable characterized by that distribution.

Parameters of ECG signal

For a particular ECG parameter, we have included those PPG features in its redefined feature set, where the corresponding MIC value is higher than 0.5. Multiclass Artificial neural Network (ANN) and Multiclass Support Vector Machine (SVM). Both ANN and SVM are very powerful and popular approach in machine learning. ANN mainly follows a multi-layer Perception Model (MLP). SVM in the other hand is a learning mechanism, based on the principle of structural risk minimization from learning theory. It is hard to prefer a particular classifier out of these two, as their performance varies from problem to problem.

SVM classifier

The SVM classifiers perform better than their ANN counterparts in most of the cases.SVM is a new paradigm of learning system. The technique of SVM is a powerful, widely used technique for solving supervised classification problems due to its generalization ability. In essence, SVM classifiers maximize the margin between training data and the decision boundary (optimal separating hyperplane), which can be formulated as a quadratic optimization problem in a feature space. The subset of patterns those are closest to the decision boundary are called as support vectors.

Radial basis neural network classifier

This work, the ECG classification is performed using sparsely connected radial basis neural network (RBNN). Unlike the fully-connected RBNN architecture, this type of structure reduces the computational cost and increases the classification accuracy. Only prominent features are necessary to a certain class of ECG during classification task.

RBNN networks have the disadvantage of requiring good coverage of the input space by radial basis functions. RBF centers are determined with reference to the distribution of the input data, as a result, representational resources may be wasted on areas of the input space that are irrelevant to the learning task. Therefore, in this work, sparsely connected RBF is used to effectively classifying the signals.

Performance

Firstly, the overall performance was tested with the10 dimensional PPG features, bypassing the feature selection phase. Secondly, selected features were used for performance analysis. Both ANN and SVM were used for performance comparison in both the cases. For ANN we used a single hidden layer with 7 nodes. It was observed that, the performance did not have a significant effect in increasing the number of hidden layers and number of nodes per hidden layer. For SVM we used Radial basis function (RBF) as the kernel. In both the cases the class decision is made based on maximum occurrence in an aggregated data of 30 seconds to ignore the instantaneous fluctuation of some of the ECG parameters. The accuracy mentioned here is also the average accuracy obtained by combining all the test subjects.

Figure 6: Matlab GUI showing the values of dominant features of PPG signal

Program Outputs

Matlab program is used to extract the features from PPG signal and Beat classification using SVM classifier. Also the Sensitivity, specificity and accuracy of classification is calculated. A Matlab GUI is designed to display the values of dominant features, display waveforms and results of classification. The screenshots of the outputs are as shown in figure below:

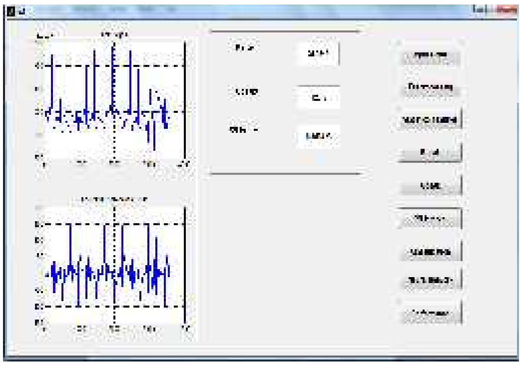

Figure 7 Low pass filtered signal with R-peak, Q peak and RR interval values for Sample 1

Figure 8 Result of Classification for sample1.

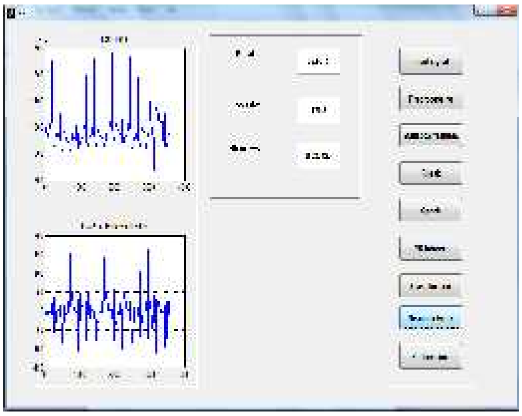

Figure 9 Low pass filtered signal with R peak, Q peak and RR interval values for sample 2.

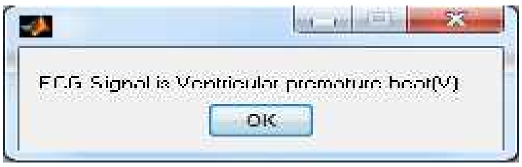

Figure 10 Result of Classification for Sample 2

CONCLUSION

The paper presents an empirical approach to estimate some ECG parameters from PPG. The method is successfully tested on two datasets to justify its suitability for coarse ECG estimation even on noisy PPG data for initial screening. The proposed feature selection algorithm boosts up the overall detection accuracy by selecting the relevant features for classification. Currently, we are at the initial stage of PhotoECG project. The method still needs to be tested on larger and more diverse dataset before actual system deployment. Our future work concentrates in proposing new PPG features relevant to ECG and also to integrate them with other easy-to-measure cardiovascular features to search for better accuracy.

A robust, reliable, and patient-acceptable method of remotely monitoring respiratory rate is essential to the development of tele-monitoring technology. PPG-based estimation of respiration rate is desirable, given that heart rate and oxygen saturation can also be derived from the same probe, but the analysis of respiratory-induced variations in the waveform requires frequency analysis of the PPG baseline, which is often removed in the processing performed by commercial devices. The cardiovascular and respiratory physiology underpinning the PPG signal is complex, and the exact origin of the PPG waveform remains unclear. However, this does not matter if the parameter of interest is respiratory rate. The PPG waveform is likely to provide better estimates of this parameter than ECG-derived estimates using RSA analysis because variations in the PPG waveform are at least in part influenced by the mechanics of respiration and are not solely dependent on an intact autonomic nervous system.

Future Enhancements

The ECG waveforms may differ for same patient to such extent that they are unlike each other and at same time alike for different types of beats. Many algorithms have been developed for the classification and detection of the ECG beat. In order to improve the accuracy of the ECG image feature extraction and classification system, the present research work proposes the use of different feature extraction methods. ECG image feature extraction and classification system, uses five feature extraction methods, namely wavelet decomposition, and probabilistic neural network classification. The objective of this present research work is to achieve the high accuracy and simplest classifiers related to extract the input features. An ECG image is classified by PNN using various feature extraction. The experimental results shows that wavelet decomposition gives a maximum accuracy compared to other feature extraction methods. ECG images classification using artificial neural network based on several feature extraction methods. The main advantage of probabilistic neural network classification is that it is a multi-classifier. It can be successfully validated that the integration of the PNN classifier with the proposed feature reduction method can achieve satisfactory classification accuracy.

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