DISEASE CLASSIFICATION USING PHOTOPLETHYSMOGRAPHY

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Abstract: ***The yellow substance called bilirubin found in blood which in excess causes neonatal jaundice. In infants this condition is called hyperbilirubinemia. This paper proposes a system to identify the bilirubin in content using photoplethysmography (PPG). Bilirubin absorbs more light than haemoglobin. Therefore PPG can be used for bilirubin monitoring using light absorbance around 480nm.***

Keywords— Bilirubin, noninvasive, absorption, pulse oximeter, haemoglobin

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I. INTRODUCTION

Jaundice is the yellow discoloration of the skin due to excess bilirubin. Bilirubin is a chemical byproduct of recycling old red blood cells. In new born this condition is called hyperbilirubinemia. An estimated 84% of newborns develop this condition .A moderate level of bilirubin is normal in healthy newborns. Higher levels of bilirubin may cause serious conditions like brain damage in newborn infants. Accurate medical tests to assess this condition require a blood draw or the use of a specialized measuring device, making them impractical outside of medical settings. So it is quite important for continuous monitoring of bilirubin is required in medical filed.

II. METHODOLOGY

Plethysmograph is an instrument used to identify the blood volume or blood flow in the body. Plethysmography is the volumetric measurement of an organ, resulting from fluctuations in the amount of blood. In photoplethysmography light is passes through the skin and depending upon the amount of blood the light signal is reflected .Based on this reflected signal a photoplethysmogram is created. Pulse oximeter is the instrument used in clinics generates the photoplethysmogram. The same waveform can be used to identify the amount of bilirubin by monitoring the amplitude variations of the waveform.

The photoplethysmogram contains both AC and Dc components. The AC component is refers the changes in the blood volume with each heartbeat. The DC component represents respiration, sympathetic nervous system activity, and thermoregulation . The point where the systolic phase starts with a valley and marked as pulse wave begin (PWB) and ends with the pulse wave systolic peak (PWSP). The pulse wave end (PWE) is marked by another valley at the end of the diastolic phase (Figure1). The systolic phase (also called "rise time" in a PPG) varies only in a narrow range inversely proportional to the heart rate compared to the pulse wave duration (PWD). The narrowing of a single PWD is covered mainly by reduction of the diastolic phase.

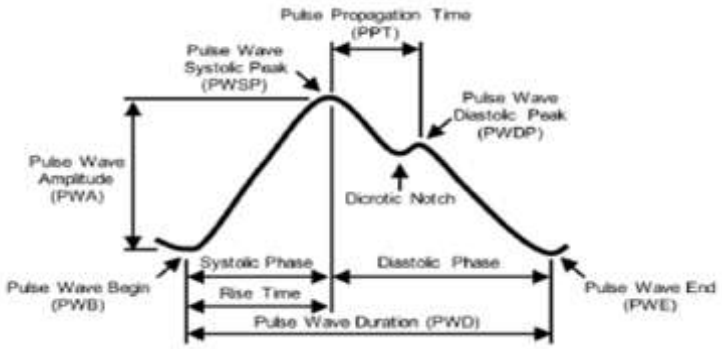


Figure1:PPG Waveform

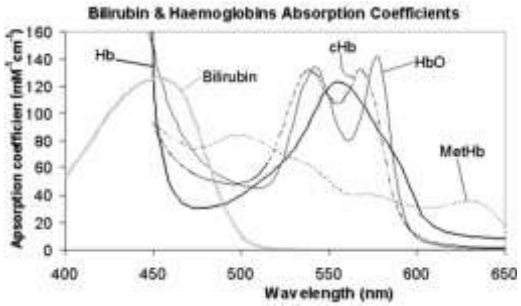


Figure 2: Absorption spectra for Haemoglobin and bilirubin

Pulse oximeter principle is based on measuring the absorbance of light passed through fingertip or reflected from/within tissue. With these configurations light passes through several layers of tissue and blood, and encounters several light absorbing and scattering substances. Pulse oximeter assumes that there are only 2 major absorbers of red and near infrared light in blood. Apart from haemoglobin , bilirubin is also a strong absorber of light (as shown in figure 1). Hyperbilirubinemia is the condition where the bilirubin concentration above 86µM (5mg/dL). Pulse oximeter wave forms are prone to motion artifacts and these make the photoplethysmogram useless. The amplitude and frequency of these artifact change during data collection depending on the environment. Specifically, motion and noise artifacts are the most common causes of false alarms, loss of signal, and inaccurate measurement in clinical monitoring .A simple real-time PPG analysis with pulse waveform segmentation and artifact detection is used to remove artifacts.

III. System Design

A. Pulse oximeter circuit

The commercially available pulse oximeter (used in clinics) cannot save the waveform .It require an additional circuitry to save the waveform. So an Arduino based pulse oximeter was designed to collect and save waveform from patients. .Here the actual saturation probe (the ones used in the pulse oximeter).This saturation probe from Nellcor with DB7 connector was used in the circuit. The waveforms from the circuit were read and stored using Processing software.

B. Motion artifact removal

The real-time PPG algorithm performs pattern recognition by analyzing the PWF. For development, validation, and referencing of the PWF analysis [24]. To assess the performance of the algorithm records were manually annotated and then a beat-to-beat comparison was performed of the pulse waveform segmentation and artifact detection. Pulse waveform analysis (shown in Figure 3 and 4) uses 6 stages and 3 decision list to identify the artifacts and the actual pulse waves. First the higher amplitude artifacts are clipped before proceeding to further processing. The top and bottom clipping thresholds are determined based on the recording or signal techniques. The second stage consists of low pass filter whose cut off frequency was set to 15 Hz in order to remove higher artifact frequencies. The third stage consists of a high pass filter set to 0.01 Hz, in order to suppress the DC part of the waveform .In the fourth stage the potential valleys and peaks of the waveform are identified by using a moving average filter with a span size of 75 % of the last valid PWD. Each time a complete pulse wave (called N-1 pulse wave) is recorded, the fifth stage with the second decision list checks absolute and relative pulse wave characteristics. In addition, the sixth stage compares relative changes (Check 11 to 13) of the last complete pulse wave (N-1) with the previous pulse wave (N-2). After the PWF analysis, in a post-processing stage various beat-to-beat metrics like PWA, PWD, rise time and pulse rate are calculated based on the detected pulse waves.

C. Support Vector Machine Classification

Based on the signal parameters from the pulse waveform algorithm are then passed through an support vector machine(SVM) classifier to identify the decrease in amplitude due to the bilirubin content in blood. A single input prediction type SVM classifier is used. Support Vector Machines (SVMs) are very popular and powerful in pattern learning because of supporting high dimensional data and, at the same time, providing good generalization properties. SVMs are used in pattern recognition and data mining applications

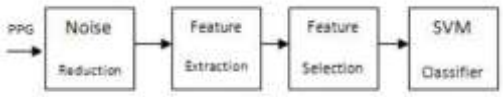


Figure 3: System Design

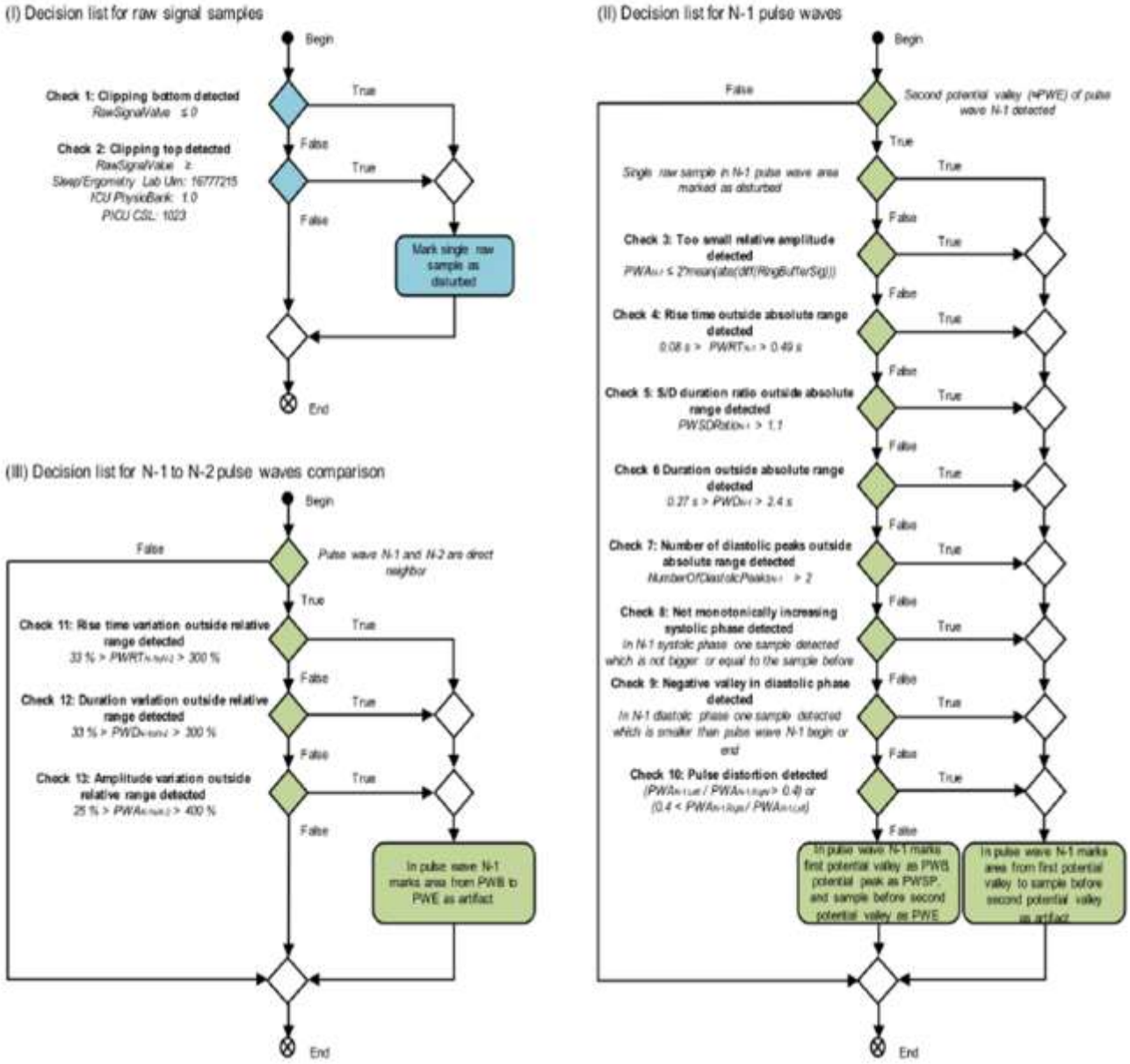
Figure 4: Pulse Oximeter Circuit

IV. Results And Analysis

For this study photoplethysmogram of full term babies of 2 -3 days old were considered. By comparing the photoplethysmogram of the healthy infant and the hyperbilirubinemia infant, it was shown that the amplitude of the photoplethysmogram was reduced in hyperbilirubinemia infants. The SVM classifier was trained using the photoplethysmogram of a healthy infant.

V. Conclusion And Future Scope

In this paper, a new method based on support vector machines for feature selection of photo -plethysmogram signals is proposed. Experimental results show that feature selection greatly improves the quality of classification. Future scope is to design the classifier to include more parameters so as to increase the performance efficiency of the system.



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