



FACE IMAGE REFLECTANCE HEART RATE EVALUATION USING JADE ALGORITHM

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ABSTRACT

Monitoring heart rates using conventional electrocardiogram equipment requires patients to wear adhesive gel patches or chest straps that can cause skin irritation and discomfort. Commercially available pulse oximetry sensors that attach to the fingertips or earlobes also cause inconvenience for patients and the spring loaded clips can be painful to use. Therefore, a novel robust face-based heart rate monitoring technique is proposed to allow for the evaluation of heart rate variation without physical contact with the patient. Face reflectance is first decomposed from a single image and then heart rate evaluation is conducted from consecutive frames according to the periodic variation of reflectance strength resulting from changes to haemoglobin absorptive across the visible light spectrum. Our proposed method is to measure multiple physiological parameters. This includes vital signs, such as HR and RR, as well as correlates of cardiac autonomic function through HVR. Our data demonstrate that there is a strong correlation between these parameters derived from webcam recordings and standard reference sensors and these data are then delivered as a message to the doctor using GSM network. To achieve a robust evaluation, ensemble empirical mode in JADE Algorithm is used to acquire the primary heart rate signal while reducing the effect of ambient light changes.

1. INTRODUCTION

Now a days a high and growing percent of deaths worldwide are related to cardiovascular disease, including sudden cardiac death, hypertension, hemorrhagic shock and septic shock. Heart rate monitors are simple inexpensive tools that can detect potentially life threatening arrhythmias or heart rhythm malfunctions. Heart rate variability is widely used as an indicator for likelihood of fatal myocardial infarction and liver cancer. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms

to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be model in the form of multidimensional systems. Conventional electrocardiogram (ECG) heart rate monitors require the patient to wear adhesive gel patches or chest straps that can cause skin irritation and discomfort. Commercial pulse oximetry sensors that attach to the fingertips or earlobes are also inconvenient for continuous use and the spring-loaded clips can cause discomfort. Recently increased attention has focused on touchless heart rate monitoring which does not require physical contact. Heart rates can be evaluated using consecutive visual images of the subject's face by measuring periodic variation of reflectance strength resulting from varying haemoglobin absorptivity across the visible light spectrum as blood volume in blood vessels increases and decreases with every heartbeat. Each colour sensor records a mixture of the original source signals with slightly different weights. Photoplethysmography (PPG) is typically implemented using dedicated light sources (e.g. red and/or infra-red wavelengths) but recent work has shown that pulse measurements can be acquired using digital camcorders/cameras with normal ambient light as the illumination source. In present a novel methodology for non-contact, automated and motion-tolerant cardiac pulse measurements from video images based on blind source separation. Firstly, they describe their approach and apply it to compute heart rate measurements from video images of the human face recorded using a simple webcam. Second, they demonstrate how this method can tolerate motion artifacts and then validate the accuracy of this approach using an FDA-approved finger blood volume pulse (BVP) measurement device. Their experimental results indicate that best performance is obtained by estimating the heart rate directly from the green channel intensity image. However, the success of face-based heart rate evaluation strongly depends on the measurement of facial illumination, which is the most significant factor affecting facial appearance. Both indoor and outdoor ambient lighting conditions are subject to constant change, and direct lighting sources can cast strong shadows that accentuate or diminish certain facial features. In recent years many appearance based algorithms have been proposed to



deal with these problems Belhumeur and Kriegman showed that the set of images of an object in a fixed pose but under varying illumination conditions forms a convex cone in the image space. The illumination cones of human faces can be approximated well by low dimensional linear subspaces. The linear subspaces are typically estimated from training data, requiring multiple images of the object.

2. LITERATURE SURVEY

Face reflectance is first decomposed from a single image and then heart rate evaluation is conducted from consecutive frames according to the periodic variation of reflectance strength resulting from variations in haemoglobin absorptivity across the visible light spectrum. Christo Ananth et al. [3] discussed about an eye blinking sensor. Nowadays heart attack patients are increasing day by day. "Though it is tough to save the heart attack patients, we can increase the statistics of saving the life of patients & the life of others whom they are responsible for. The main design of this project is to track the heart attack of patients who are suffering from any attacks during driving and send them a medical need & thereby to stop the vehicle to ensure that the persons along them are safe from accident. Here, an eye blinking sensor is used to sense the blinking of the eye. spO2 sensor checks the pulse rate of the patient. Both are connected to micro controller. If eye blinking gets stopped then the signal is sent to the controller to make an alarm through the buzzer. If spO2 sensor senses a variation in pulse or low oxygen content in blood, it may result in heart failure and therefore the controller stops the motor of the vehicle. Then Tarang F4 transmitter is used to send the vehicle number & the mobile number of the patient to a nearest medical station within 25 km for medical aid. The pulse rate monitored via LCD. The Tarang F4 receiver receives the signal and passes through controller and the number gets displayed in the LCD screen and an alarm is produced through a buzzer as soon the signal is received.

Because of its excellent performance, HHT has been widely applied in signal processing and other related fields. An IMF represents a generally simple oscillatory mode as a counterpart to the simple harmonic function. By definition, an IMF is any function with the same number of extreme and zero crossings, with its envelopes being symmetric with respect to zero. The definition of an IMF guarantees a well behaved Hilbert transform of the IMF. An IMF is defined as a function that satisfies the following requirements:

- In the whole data set, the number of extreme and the number of zero-crossings must either be equal or differ at most by one.
- At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The horizontal and vertical axes respectively denote the time and amplitude. Therefore, an IMF represents a simple oscillatory mode as a counterpart to the simple harmonic

function, but it is much more general: instead of constant amplitude and frequency in a simple harmonic component, an IMF can have variable amplitude and frequency along the time axis. The procedure of extracting an IMF is called sifting and consists of the following steps:

1. Identify all the local extreme in the test data.
2. Connect all the local maxima by a cubic spline line as the upper envelope.
3. Repeat the procedure for the local minima to produce the lower envelope.

The upper and lower envelopes should cover all the data between them, the difference between the data and their mean m_1 is the first component h_1 as defined by,

$$h_1 = x(t) - m_1.$$

Theoretically the decomposed h_1 could be an IMF since h_1 satisfies all the requirements. However, original data usually contains significant variations and is thus insufficient to form the basic IMF after only a single iteration. During the process, a new extreme could be produced or shifted since upper and lower envelopes are formed by connecting all the local extreme by a cubic spline line.

$$h_{11} = h_1 - m_{11}.$$

$$h_{1k} = h_{1(k-1)} - m_{1k}.$$

$$c_1 = h_{1k}.$$

3. PROPOSED NOVEL METHOD USING JADE ALGORITHM

In our proposed method we use JADE Algorithm to measure the three physiological parameters such as RR, HR and HVR. The parameters are then delivered as a message to the doctor through GSM network. Photoplethysmography (PPG) is an optical method to measure cardiac-synchronous blood volume change in body extremities such as the face. The goal of a camera-based vital sign monitoring system is to estimate the PPG waveform which is proportional to these small change.

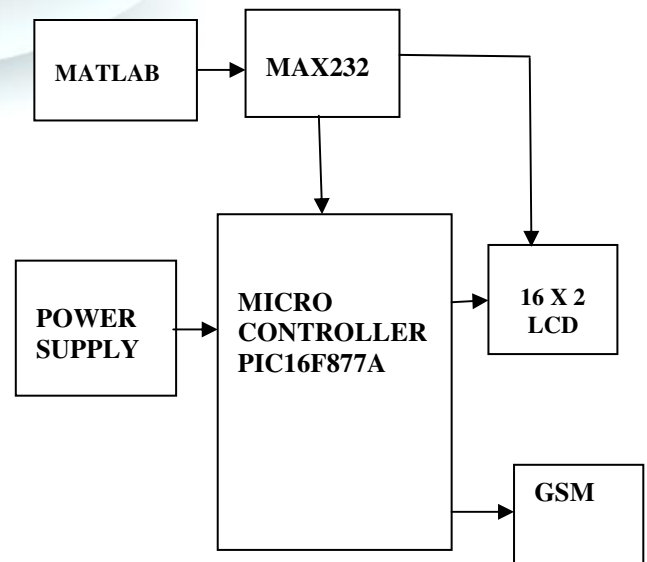


Fig.1 Block diagram of heart rate evaluation system

3.1 Face reflectance based heart rate evaluation

Thus in our project we are going to measure the multiple physiological factors such as HR, HVR, RR by using the face reflectance of the patient.

3.1.1 Heart rate

Is the speed of the heartbeat measured by the number of contractions of the heart per minute (bpm). The heart rate can vary according to the body's physical needs, including the need to absorb oxygen and excrete carbon dioxide. A normal resting heart rate for adults ranges from 60 to 100 beats a minute. Generally, a lower heart rate at rest implies more efficient heart function and better cardiovascular fitness. For example, a well-trained athlete might have a normal resting heart rate closer to 40 beats a minute. To measure your heart rate, simply check your pulse. Place your index and third fingers on your neck to the side of your windpipe. To check your pulse at your wrist, place two fingers between the bone and the tendon over your radial artery which is located on the thumb side of your wrist. When you feel your pulse, count the number of beats in 15 seconds. Multiply this number by 4 to calculate your beats a minute. Keep in mind that many factors can influence heart rate, including Activity level, Fitness level, Air temperature, Body position (standing up or lying down, for example), Emotions, Body size, Medications. Although there's a wide range of normal, an unusually high or low heart rate may indicate an underlying problem. Consult your doctor if your resting heart rate is consistently above 100 beats a minute (tachycardia) or if you're not a trained athlete and your resting heart rate is below 60 beats a minute (bradycardia) especially if you have other signs or symptoms, such as fainting, dizziness or shortness of breath.

3.1.2 Heart rate

Is the physiological phenomenon of variation in the time interval between heart beats. It is measured by the variation in the beat-to-beat interval. Variation in the beat-to-beat interval is a physiological phenomenon. The SA node receives several different inputs and the instantaneous heart rate or RR interval and its variation are the results of these inputs.

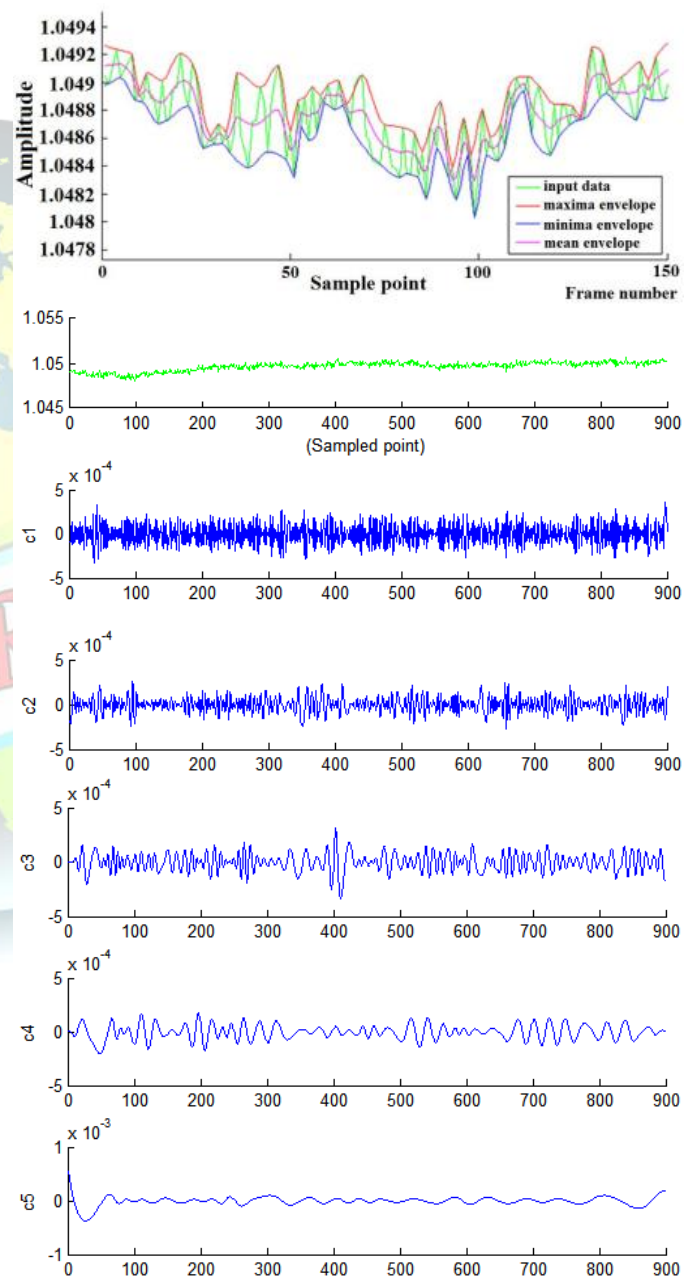
3.1.3 Respiration rate

Is the number of breaths per minute or, more formally, the number of movements indicative of inspiration and expiration per unit time. In practice, the respiratory rate is usually determined by counting the number of times the chest rises or falls per minute. The typical respiratory rate for a healthy adult at rest is 12–20 breaths per minute. Average resting respiratory rates by age are: birth to 6 weeks: 30–60 breaths per minute, 6 months: 25–40 breaths per minute, 3 years: 20–30 breaths per minute, 6 years: 18–25 breaths per minute, 10 years: 17–23 breaths per minute, Adults: 12–18 breaths per minute.

Elderly ≥ 65 years old: 12–28 breaths per minute, Elderly ≥ 80 years old: 10–30 breaths per minute.

4. IMAGE SENSOR BASED HEART RATE EVALUATION

The face reflectance is used for heart rate evaluation since, as blood volume in the blood vessels in the face expands with every heartbeat. The reflectance strength shown by the face will vary with haemoglobin absorptive across the visible light spectrum.



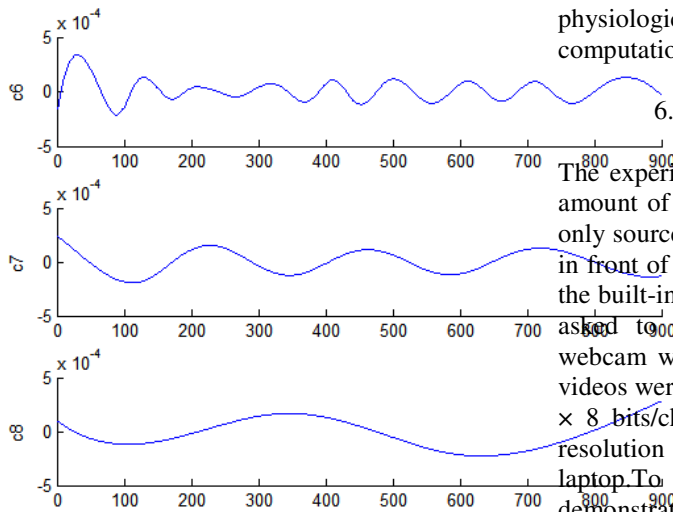


Fig.2 Graphical Representation of HR,HVR,RR Evaluation

5. LOGICAL JADE ALGORITHM

When working with images in Matlab, there are many things to keep in mind such as loading an image, using the right format, saving the data as different data types, how to Display an image, conversion between different image formats, etc. The following image formats are supported by Matlab:

- BMP,HDF,JPEG,PCX,TIFF,XWB

Most images you find on the Internet are JPEG-images which is the name for one of the most widely used compression standards for images. JADE stands for Joint Approximate Diagonalization of Eigenmatrices and is a matlab implementation of ICA. It is freely available online and is an implementation by the original author of the algorithm. It works by inputting the original signals as matlab row vectors. It then analyzes the recordings and outputs the so called M matrix which one can matrix multiply with to extract the original sources. The option of monitoring a patient's physiological signals via a remote, noncontact means has promise for improving access to and enhancing the delivery of primary healthcare. Currently, proposed solutions for noncontact measurement of vital signs, such as heart rate (HR) and respiratory rate (RR), include laser Doppler, microwave Doppler radar, and thermal imaging. Noncontact assessment of HR variability (HRV), an index of cardiac autonomic activity, presents a greater challenge and few attempts have been made. Despite these impressive advancements. Photo plethysmography (PPG) is a low-cost and noninvasive means of sensing the cardiovascular blood volume pulse (BVP) through variations in transmitted or reflected light. Although PPG is typically implemented using dedicated light sources (e.g., red and/or infrared wavelengths). Color versions of one or more of the figures in this paper are available online at with normal ambient light as the illumination source. However, the study lacked rigorous physiological and mathematical models amenable to computation; it relied instead on manual segmentation and heuristic interpretation of raw images with minimal validation of performance characteristics. In this letter, we extend this methodology to quantify multiple

physiological parameters. Specifically, we extract the BVP for computation of HR, RR, as well as HRV.

6. EXPERIMENTAL SET UP

The experiments were conducted indoors and with a varying amount of ambient sunlight entering through windows as the only source of illumination. Participants were seated at a table in front of a laptop at a distance of approximately 0.5 m from the built-in webcam. During the experiment, participants were asked to keep still, breathe spontaneously, and face the webcam while their video was recorded for one minute. All videos were recorded in color (24-bit RGB with three channels \times 8 bits/channel) at 15 frames per second (fps) with pixel resolution of 640×480 and saved in AVI format on the laptop. To the best of our knowledge, this is the first demonstration of a simple, low-cost method for noncontact HRV measurements. The underlying source signal of interest in this study is the BVP that propagates throughout the body. During the cardiac cycle, volumetric changes in the facial blood vessels modify the path length of the incident ambient light such that the subsequent changes in amount of reflected light indicate the timing of cardiovascular events. By recording a video of the facial region with a webcam, the red, green, and blue (RGB) color sensors pick up a mixture of the reflected plethysmographic signal along with other sources of fluctuations in light due to artifacts. Given that hemoglobin absorptivity differs across the visible and near-infrared spectral range, each color sensor records a mixture of the original source signals with slightly different weights.

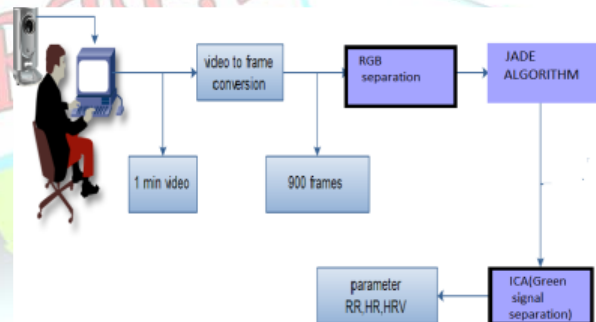


Fig.3 Experimental Setup

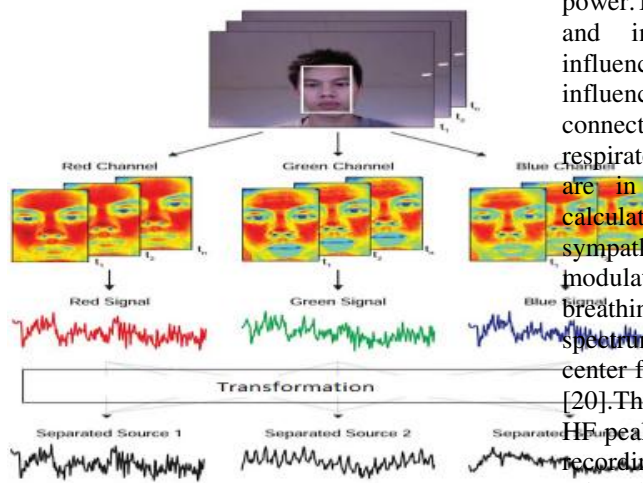


Fig.4 Separation of RGB signal Separation

7. RECOVERY OF BVP FROM WEB RECORDINGS

All the video and physiological recordings were analyzed offline using custom software written in MATLAB. It provides an overview of the stages involved in our approach to recover the BVP from the webcam videos. to automatically identify the coordinates of the face location in the first frame of the video recording, We selected the center 60% width and full height of the box as the region of interest (ROI) for our subsequent calculations. The ROI was then separated into the three RGB channels and spatially averaged over all pixels in the ROI to yield a red, blue, and green measurement point for each frame and form the raw signals $y_1(t)$, $y_2(t)$, and $y_3(t)$, respectively. Each trace was 1 min long. The raw traces were detrended using a procedure based on a smoothness priors approach with the smoothing parameter $\lambda = 10$ (cutoff frequency of 0.89 Hz) and normalized as follows. To perform motion-artifact removal by separating the fluctuations caused predominantly by the BVP from the observed raw signals. Quantification of Physiological Parameters: The separated source signal was smoothed using a five-point moving average filter and band pass filtered (128-point Hamming window, 0.7–4 Hz). To refine the BVP peak fiducial point, the signal was interpolated with a cubic spline function at a sampling frequency of 256 Hz. We developed a custom algorithm to detect the BVP peaks in the interpolated signal and applied it to obtain the interbeat intervals (IBIs). To avoid inclusion of artifacts, such as ectopic beats or motion, the IBIs were filtered using the noncausal of variable threshold algorithm with a tolerance of 30%. HR was calculated from the mean of the IBI time series as $60/\text{IBI}$. Analysis of HRV was performed by power spectral density (PSD) estimation using the Lomb periodogram. The low frequency (LF) and high frequency (HF) powers were measured as the area under the PSD curve corresponding to 0.04–0.15 and 0.15–0.4 Hz, respectively, and quantified in normalized units (n.u.) to minimize the effect on the values of the changes in total

power. The LF component is modulated by baroreflex activity and includes both sympathetic and parasympathetic influences. The HF component reflects parasympathetic influence on the heart through efferent vagal activity and is connected to respiratory sinus arrhythmia (RSA), a cardio respiratory phenomenon characterized by IBI fluctuations that are in phase with inhalation and exhalation. We also calculated the LF/HF ratio, considered to mirror sympatho/vagal balance or to reflect sympathetic modulations. Since the HF component is connected with breathing, the RR can be estimated from the HRV power spectrum. When the frequency of respiration changes, the center frequency of the HF peak shifts in accordance with RR [20]. Thus, we calculated RR from the center frequency of the HF peak f_{HFpeak} in the HRV PSD derived from the webcam recordings as $60/f_{\text{HFpeak}}$. The respiratory rate measured using the chest belt sensor was determined by the frequency corresponding to the dominant peak f_{respeak} in the PSD of the recorded respiratory waveform using $60/f_{\text{respeak}}$.

7.1 GSM network

Global System for Mobile communication (GSM) [Theodore S. Rappaport, 2002] is a standard for digital communication. GSM uses the Time Division Multiple Access (TDMA). The switching system is responsible for performance call processing and subscriber-related functions. The concept of cellular service is the use of low - power transmitters where frequencies can be reused within a geographic area.

8. RESULT

A face-based heart rate monitoring technique is proposed to evaluate heart rate variation without physical contact. Face reflectance is first processed in MATLAB from a single image and then heart rate evaluation is conducted from consecutive frames according to the periodic variation of reflectance strength resulting from variations in haemoglobin absorptivity across the visible light spectrum as each heartbeat increases/decreases the blood volume in the blood vessels of the face. To achieve evaluation, JADE algorithm

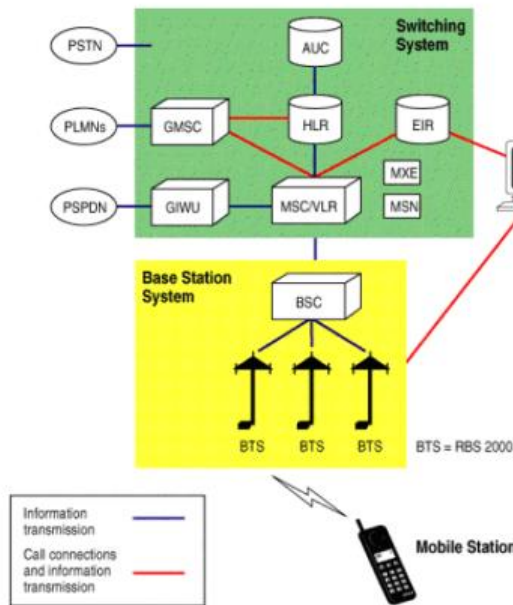


Fig.5 GSM Network

was been used to acquire the primary heart rate signal while reducing the effect of changes to ambient light. The proposed approach outperforms the current state-of-the-art in terms of providing accurate measurement with a smaller degree of variance, thus demonstrating its applicability in real world environments. For the non-real time characteristic of the proposed method, it is more useful to be used for Traditional Chinese Medicine (TCM) or for similar analytic systems than for emergency systems. Suppose if the heart beat is abnormal immediately the information is given to that area doctor or hospital using GSM modem, so that the patients can immediately take the necessary steps.

9. CONCLUSION

Our proposed approach is found to outperform the current state of the art, providing greater measurement accuracy with smaller variance and is shown to be feasible in real-world environments. To achieve a robust evaluation, ensemble empirical mode decomposition of the JADE algorithm is used to acquire the primary heart rate signal while reducing the effect of ambient light changes.

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