Video-Based Heart Rate Measurement Using Short-time Fourier Transform

Yong-Poh Yu, Ban-Hoe Kwan, Chern-Loon Lim, Siaw-Lang Wong, P. Raveendran
Department of Electrical Engineering, Faculty of Engineering
University of Malaya, Kuala Lumpur, 50603, Malaysia
Email: richieyyp@yahoo.com, banhoe@gmail.com, limchernloon@gmail.com, wong.siawlang@gmail.com, ravee@um.edu.my

Abstract— **Non-invasive heart rate measurement is essential in medical and sport sciences. Typically, the first stage of heart rate measurements is obtained from non-invasive sensors. In this paper, the data from video sequences of a subject cycling are processed using short-time Fourier transform (STFT) to indicate the heart rate of the subject. The choice of using STFT is its ability to provide more accurately localized temporal and frequency information, especially for the rapidly changing heart rate pattern during the exercise routine. Experimental results show the proposed method can provide an acceptable result and the root mean square error is less than 2.5 beats per minute (BPM) for heart rate variations between 80 BPM and 130 BPM.**

I. INTRODUCTION

Human heart rate is measured as the number of heart beats per minutes (bpm). It is an important parameter used to reveal the health condition of an individual. The pattern of the measured heart rate can be used to indicate levels of fitness, the presence of disease, stress or fatigue and even blockages in the artery due to diabetes or high cholesterol level.

Currently, the most common method used for human heart rate measurements is using the Electrocardiography (ECG) machine. The electrodes are attached to the surface of the skin around the wrist and chest of the subject. The electrical activity of the human heart is captured through the attached electrodes. Heart rate measurements using ECG machine is a contact based method which might not be suitable for skin-burned patients and person with autistic disorder (sensitive to touch).

In year 2007, Garbey *et al.* introduced a new approach for human cardiac pulse measurement based on thermal signal analysis of the major blood vessels near the skin surface [1]. The modulation of the temperature measured from these blood vessels is caused by the variations in blood flow. In the same year, Pavlidis *et al.* measured the human heart rate and breath rate through bio-heat modeling of facial imagery using a thermal camera [2]. The cardiac pulse detection at the forehead proposed by Gatto was extracted from the video infrared thermography [3]. This approach is based on the principle that the variations of blood flow during the cardiac cycle will cause the fluctuation of thermal energy released by the body tissue.

Takano and Ohta developed a system in 2007 to measure the human heart rate and respiratory rate based on the images from the Charge-Coupled Device (CCD) camera [4]. The variations of the average brightness in the region of interest within the subject's skin were recorded. These data were processed through a sequence of operations which involve interpolation, low pass filter and Auto-Regressive (AR) spectral analysis in order to obtain the heart rate and the respiratory rate. In the following year, Verkruysse *et al.* measured human respiration and heart rates through remote sensing of plethysmographic signals under ambient light using digital camera [5].

Jonathan and Leahy utilized the camera on the smartphone to capture a series of video frames of a human index finger [6]. The reflections of plethysmographic signals obtained from these video frames were used to compute the human heart rate. The engineering model created by Shi *et al.* was used for cardiac monitoring through reflection photoplethysmography [7]. This non-contact model is made up of a light source that consists of a Vertical Cavity Surface Emitting Laser (VCSEL) and a photo-detector that consists of a high-speed silicon PiN photodiode.

Photoplethysmography (PPG) is a non-invasive and inexpensive method to measure the variations of blood volume through the variations of light absorption or reflection. The variations of blood volume in the blood vessels are due to the contraction and relaxation of heart muscles during each cardiac cycle. The relationship between the blood volume pulses and the light in reflection PPG has been investigated by some of the researchers in [8], [9] since a few decades ago. The principle of PPG is based on the fact that body tissue is less opaque than the blood [9]. Therefore, the increase in blood volume will reduce the intensity of the reflected light from the trans-illuminated tissue. The variations in blood volume will change the intensity of the reflectance accordingly. Therefore, the human heart rate which is the same as the frequency of cardiac cycle can be measured from the plethysmographic signals captured in the video.

Heart rate measurement from video sequences is considered as low cost since the color video can be captured using any available video recording device such as video camera, webcam or mobile phone. This remote and noncontact (without using any special device) heart rate measurement is very suitable for home-based health care applications and telemedicine.

978-1-4673-6361-7/13/$31.00

Poh *et al.* developed a new technique that can extract the human heart rate from the facial region in videos recorded by webcam [10], [11]. This contact-free approach is based on automatic face tracking and the use of blind source separation on color channels within the facial region. Besides that, the proposed method is robust to motion artifacts and able to extract the heart rate of multiple people at the same time. The modification of this technique can be found in [12].

Poh *et al.* had shown that the human heart rate can be measured from digital color video recordings under normal ambient light [10], [11]. However, the whole frontal face is used as the Region of Interest (ROI) which includes the regions with less or without blood vessels such as the eyes, hair and nostrils. They used a video with duration of 60 seconds to compute the average heart rate variability for this entire duration.

Anyway, for a heart rate pattern that changes rapidly (for instance, during a workout), a method that could measure the heart rate variation by giving the temporal information is much more desired. In this paper, the video frames captured during a cycling exercise by a subject are used in developing a predictive model to indicate the heart rate of the subject.

II. PROPOSED METHOD

In this section, we begin with a discussion on how the video data was obtained followed by data analysis using STFT.

A. Data Collection

In this paper, the area between the eyes and the upper lip of the mouth in a video frame was chosen as the ROI. The distance between both eyes is used as the reference to estimate the size and location of ROI.

The experiments were set up under office fluorescent lights with indirect sunlight as the source of illumination. A video camera (24-Bit RGB, 8 bits per channel) with a resolution of 720 x 576 pixels and 25 frames per second is used in recording a subject cycling for duration of 3 minutes. Fig. 1 shows the subject cycling during the experiment. The subject was seated at a distance of about 60 cm from the camera. The exercise routine of three minutes was divided equally into three phases. The subject was at rest in the first phase which lasted for a minute. During this phase, the heart rate of subject was almost the same throughout the period. In the second phase, the subject began cycling and the heart rate started to increase. This phase lasted for a minute. In the third and last phase, the subject continued to increase the speed and at some point began to maintain the speed where the heart rate variation at this point was minimal. The data obtained from the experiments were then analyzed using our proposed method.

Fig. 1: Subject cycling during the experiment

B. Data Analysis

The ROI of each frame for the three RGB components was extracted. The process begins by obtaining the mean of all pixel values for each component where

μ_R: the mean of all pixel values for red component
μ_G: the mean of all pixel values for green component
μ_B: the mean of all pixel values for blue component

This was repeated for sixty seconds for each phase. The total number of sample values was 1500 for each component in each phase. We then used independent component analysis to separate the collected data (RGB components) into their different sources [13], [14]. The source with the highest spike of power spectrum was selected to be used as the time-series input data for the short-time Fourier transform (STFT).

For a time-series data of $x[n]$, the STFT at time n is given as

$$X(n,\omega) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\omega m} \qquad (1)$$

where $w[n]$ is the analysis window.

The discrete STFT is obtained by sampling $X(n,k)$ as

$$X(n,k) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\frac{2\pi k}{N}m} \qquad (2)$$

Where $\omega = \frac{2\pi k}{N}$

The results of the proposed methods were compared to the heart rate readings obtained from Polar Heart Rate Monitor since it is the one of the most accurate instantaneous heart rate measurement devices at this moment [15],[16].

Fig. 2 summarizes the techniques used in our proposed method.

III. EXPERIMENTAL RESULTS

The proposed algorithm was implemented using MATLAB. Fig. 3 shows the comparison between the estimated heart rate (using proposed method) and the actual heart rate (based on Polar Heart Rate Monitor readings) for three different phases.

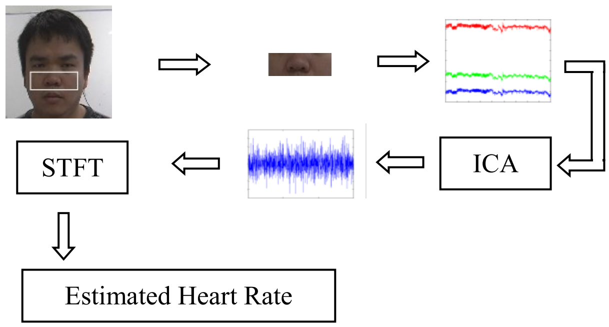

Fig. 2: Proposed method for video-based heart rate measurement

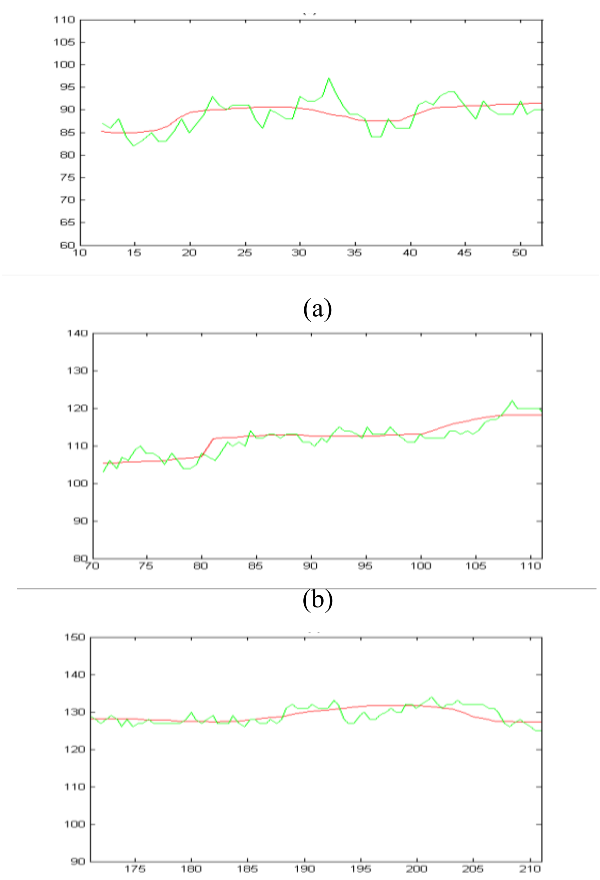

Fig. 3: The Results for (a) first phase (b) second phase, and (c) Third phase. Red color indicates the estimated results from proposed methods. Green color indicates the actual results from Polar Heart Rate Monitor Readings.

The window size of the STFT was set to 500 points, which corresponds to 20 seconds. Overall, the results obtained from the proposed method did not vary much from the actual readings. The respective root mean square errors were 2.1939 (first phase), 2.3235 (second phase) and 2.1939 (third phase).

The power spectrum distribution obtained from STFT is showed in Fig. 4. As compared to Fourier transform, we found that STFT provides better temporal information and hence better results. Fig. 5 shows the comparison of both STFT and Fourier transform. The Fourier transform shows a fixed value for a given time and does not show the time localization. Hence it is not suitable to measure rapidly changing heart rate trends.

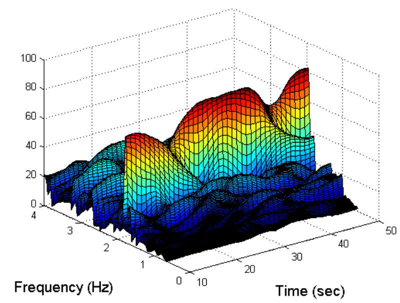

Fig. 4: The power spectrum distribution of second phase obtained from STFT

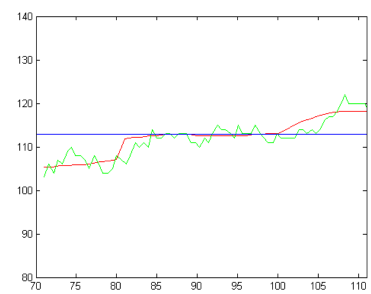

Fig. 5: Comparison between STFT results and Fourier transform result. Red color indicates the estimated results from proposed methods. Green color indicates the actual results from Polar Heart Rate Monitor Readings. Blue color indicates the Fourier transform result.

IV. Conclusion

In this paper, a video-based heart rate measurement using short-time Fourier transform is proposed. Previous works focus on minimal change in the heart rate variations, while this paper deals with rapidly changing heart rate trend. For a rapidly changing heart rate patterns, the temporal information is essential to provide an accurate measurements. The STFT provides this information. Experimental results show that the proposed method can give an acceptable result, for both non-rapidly and rapidly changing heart rate trends.

References

[1] M. Garbey, Nanfei Sun, A. Merla, and I. Pavlidis, "Contact-free measurement of cardiac pulse based on the analysis of thermal imagery," *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 8, pp. 1418-1426, August 2007.

[2] I. Pavlidis , J. Dowdall, N. Sun, C. Puri, J. Fei, and M. Garbey, “Interacting with human physiology,” *Computer Vision and Image Understanding,* vol. 108, pp. 150-170, October 2007.

[3] R. G. Gatto, Estimation of Instantaneous Heart Rate using Video Infrared Thermography and ARMA Models, Ph.D. thesisi, University of Illinois at Chicago, 2009.

[4] Chihiro Takano and Yuji Ohta, “Heart Rate Measurement based on a time-lapse image,” *MedicalEngineering & Physics,* vol. 29, no. 8, pp. 853-857, 2007.

[5] Wim Verkruysse, Lars O. Svaasand, and J.S. Nelson, “Remote plethysmographic imaging using ambient light,” *Optics Express*, vol. 29, no. 8, pp. 853-857, 2007.

[6] E Jonathan and Martin Leahy, “Investigating a smartphone imaging unit for photoplethysmography,” *Physiological Measurement,* vol. 31, no. 11, pp. N79-N83, 2010.

[7] P. Shi, V.A. Peris, A. Echiadis, J. Zheng, Y.S. Zhu, P.Y.S. Cheang, and S.J. Hu, “Non-contact reflection photoplethysmography towards effective human physiological monitoring,” *Journal of Medical and Biological Engineering,* vol. 30, no. 3, pp. 161-167, 2010.

[8] A. B. Hertzman, and C.R. Spealman, “Observations on the figure volume pulse recorded photoelectrically,” *Am. J. Physiol. Meas*., vol. 119, pp. 334–335, 1937.

[9] J. Weinman, A Hayat, and G. Raviv, “Reflection photoplethysmography of arterial-blood-volume pulses,” *Medical and Biological Engineering and Computing,* vol. 15, pp. 22-31, 1977.

[10] M.Z. Poh, D.J. McDuff, and R.W. Picard, “Non-contact, automated cardiac pulse measurements using video imaging and blind source separation,” *Optics Express,* vol. 18, no. 10, pp. 10762-10774, May 2010.

[11] M.Z. Poh, D.J. McDuff, and R.W. Picard,, “Advancements in non-contact, multiparameter physiological measurements using a webcam,” *IEEE Transactions on Biomedical Engineering,* vol. 58, no. 1, pp. 7-11, Jan 2011.

[12] T. Pursche, J. Krajewski, and R. Moeller, “Video-based heart rate measurement from human faces,” in *IEEE International Conference on Consumer Electronics (ICCE),* Jan 2012, pp. 544-545.

[13] J.F. Cardoso, and A. Souloumiac. "Blind beamforming for non-Gaussian signals." In *IEE Proceedings F (Radar and Signal Processing)*, vol. 140, no. 6, pp. 362-370, 1993.

[14] J.F. Cardoso, "High-order contrasts for independent component analysis." *Neural computation* , vol.11, no. 1,pp. 157-192, 1999.

[15] M.B. Wallén, D. Hasson, T. Theorell, B. Canlon, and W. Osika, “Possibilities and limitations of the polar RS800 in measuring heart rate variability at rest,” *European journal of applied physiology*, vol. *112*, no.3, pp. 1153-1165, 2012.

[16] M. Schönfelder, G. Hinterseher, P. Peter, and P. Spitzenpfeil, “Scientific Comparison of Different Online Heart Rate Monitoring Systems,” *International Journal of Telemedicine and Applications*, vol. 2011, 6 pages, 2011