Constactless Measurement of Heart Rate on iPad

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Abstract. This paper describes implementation of a contactless heart rate estimation algorithm on iPad. Our method is based on plethysmographic signal detection of skin colour changes. We had to overcome the iPad low computational performance to achieve real time processing and solve other challenges. The presented solution accuracy is comparable with professional sport testers. We point out possible extensions of the application at the end of this paper.

Keywords: heart rate measurement, iPad, mobile application

1 Introduction

Many people are concerned about their health and lifestyle. The heart rate is one of the main vital signs and is widely spread in many areas as sport, medical diagnosis, biometric identification or lie detectors - polygraphs. Last but not least is human curiosity. Who is not interested in his own heart rate after 20 push-ups or double Espresso?

Today, the wearables technology is capable of measuring heart activity, blood pressure, health condition, etc. and it is making its way to consumer products and gadgets. Computer miniaturization, smaller battery requirements and growth of computational power of mobile devices are expanding the area of use. The described application running on an iPad offers an low cost alternative compared to many more expensive gadgets. In addition the pulse rate estimation is contactless.

2 Related Methods

Many of noninvasive professional medical devices are based on plethysmographic signal detection. The heart muscle is pumping blood to blood vessels resulting in periodic skin colour changes. This is caused by changes in a blood volume in the capillaries and slightly different optical properties of the oxidized and non oxidized blood.

Professional medical devices (like pulse oximeter) are based on photoplethysmography (PPG) [8]. This equipment is attached to a finger using dedicated source of light. Red and infrared LED diodes are emitting light and appropriate light detectors are measuring intensities. Hemoglobin saturated by oxygen is absorbing light better than hemoglobin bounded by carbon dioxide. This method provides measurement of oxygen saturation [1]. Plethysmographic signal is visible in tiny changes of skin colour. These changes are not noticeable by naked eye, but a standard video camera captures these changes and converts them to a useful signal.

The signal is noisy because of ambient light and it has to be cleaned. Poh [4] suggests to preprocess the signal by Independent Component Analysis (ICA) by splitting the RGB signal to three linearly dependent signals. Finally, the Fast Fourier Transformation (FFT) is used for frequency analysis. The most significant frequency is considered as heart rate estimate.

Another estimation method is the Eulerian Video Magnification (EVM) [6]. It allows to visualize periodic movements and colour changes. For example, it is possible to highlight changes of skin colour according to heart activity. This method is computationally expensive and is not suitable for an iPad implementation.

3 Heart Rate Estimation Algorithm

The main goal of our algorithm was to deliver the heart rate estimation under 10 seconds interval in an ambient source of light. We are using the built-in iPad camera and the iPad available computational resources. The camera is running at 30 frames per second. We also took advantage of the Graphical Processing Unit (GPU) of iPad with the face detection algorithm. It provides the basic face detection functionality. To successfully detect the colour changes additional facial landmarks like corners of mouth, eyes and center of nose need to be identified. We have used the Flandmark library [7]. The facial landmarks detection is done on a face image normalized to a resolution 40×60 px. For further processing even smaller image containing mainly forehead, nose and cheeks is cut out. Mouth is not included in the image mainly to its susceptibility to a movement. Weighted average colour of the image is computed. Especially areas under the eyes are the most important and has the bigger weight. The time series containing the colour changes is then extracted.

3.1 Measured signal

The mathematical model for the heart rate detection is based on finding the plethysmographic sine signal in a window of measured data. The measured signal format is depicted in a formula 1. In general, we are looking for parameter w of the model representing the weights of RGB colours, a_0 is a time independent coefficient and the a_1 is the time dependent gradient. Simply speaking, we are generating all possible sine signals, which may represent a reasonable plethysmographic signal and choose the most suitable heartbeat frequency ω.

$$signal(t) = \sin(\omega t + \varphi) + a_0 + a_1 t + noise \quad (1)$$

3.2 Basic model

Initially we force the method to generate a sine sequence with ω in the range from 40 to 180 bpm (0.67 to 3 Hz) and φ in the range 0 to 2 π. The minimization is leading to picking up the parameters with minimal error where ω and φ are fixed. Minimization problem is solved by Least Square method defined by formula 2, where w is the colour vector of RGB signal. Results are represented in figure 1.

$$\arg\max_{w,a_0,a_1} \sum_{t=0}^{T-1} [x^T(t) \cdot w - a_0 - a_1 t - \sin(\omega t + \varphi)]^2 \quad (2)$$

3.3 Optimized Model

In every step of the described algorithm huge amounts of data are generated because of fixing parameters φ and ω. The computational power of an iPad is not sufficient and therefore we had to optimize the algorithm by modifying the original formula 2. The new error is described by formula 3. Term $B^T b$ is not significant, because it is constant and we are looking for minimal solution. The size of the matrix $A^T A$ is 5×5 and the size of the vector $A^T b$ is 5×1 instead of $fps \cdot t \times 5$ and $fps \cdot t \times 1$ used before. Because of the size reduction the computation is much faster. Main advantage of this modification is possibility to fill matrices recurrently.

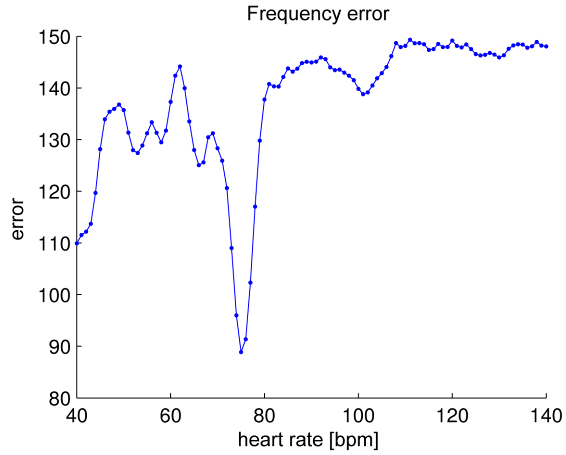

Fig. 1. This figure represents error for frequency spectrum. Frequency with minimal error (in our case approximately 75 bmp) is heart rate estimation.

$$err = x^T A^T A \ x - 2b^T A \ x + b^T b \quad (3)$$

Another improvement is the usage of optimisation for finding the minimum. For this task we are using Grid search [2]. The search space is regularly sampled and only the area around the raw minimum is searched in detail. This method does not guarantee reaching the global minimum.

3.4 Algorithm improvement

The all above mentioned optimisations still require higher than iPad computational power to achieve real time performance. The original algorithm weakness is the fixation of the parameters ω and φ. However, the algorithm can be further simplified by estimation of linear combination of colour vectors. The formula 4 decomposes the term $sin(\omega + \varphi)$. Optimisation task 7 has 4 arguments to optimise but now we are fixing just parameter ω. The results are more accurate because φ is not sampled.

$$\sin(\omega t + \varphi) = \sin(\omega t)\cos(\varphi) + \cos(\omega t)\sin(\varphi) \quad (4)$$
$$A = \cos(\varphi) \qquad B = \sin(\varphi)$$

$$s(t) = x^T(t) \cdot w \quad (5)$$
$$p(t) = -A' \sin(\omega t) + B' \cos(\omega t) \quad (6)$$
$$\arg\max_{A',B',a_0,a_1} \sum_{t=0}^{T-1} [s(t) - a_0 - a_1 t + p(t)]^2 \quad (7)$$

Rearranging the computation this way is leading much faster processing, because we fixed only the parameter ω. The colour vector w is computed as an average colour vector in the original algorithm. During the experiments we verified that the green element of RGB is the most significant for plethysmographic signal [8]. This is related with the light reflection of hemoglobin in green light spectrum.

More information about the algorithm is mentioned in [3].

4 Experiments

To verify accuracy of the application we compared it with a sport tester Polar RS800sd [5] with a chest strap. Sport testers accuracy is $\pm 1\%$, which is the same as a typical ECG accuracy.

For the purpose of testing we have recorded more than 30 videos in a duration of around 30 seconds. We recorded 7 males and females in the age between 20 and 70 under different light conditions with a soft ambient light and still camera. The test video recordings included the sport tester Polar RS800sd readings.

During the tests we have found the application results in good agreement with the reference tester see the figure 2. We have found the application sensitive to poor light conditions. The results were also affected one the user does not hold the iPad in a fixed position, shaky hands etc. Trustworthiness of results is expressed by colour based on standard deviation.

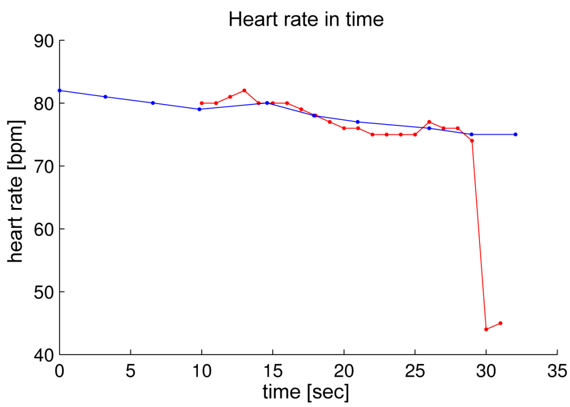

Fig. 2. Blue line is the annotation of captured video. Red line is the estimated heart rate. Last two values are not correct. This kind of error can be removed by threshold.

5 Conclusion

We are presenting a new algorithm for contactless estimation of heart beat rate running on iPad. The algorithm requires about 10 seconds to show stable results. Results with similar accuracy as a sport tester with chest strap can be achieved by reasonable light conditions and still camera.

Further we want to enhance the application with additional services, such as an estimated age from image. Based on the age and the current heart rate it is possible to examine users health. Heart beat rate application can prevent "White coat symptom" when used at home. In company of medic personal many people become nervous and their heart rate or blood pressure may be increased. Accumulating the estimates to a knowledge database and combining it with medical staff such application can improve the personal health care and bring it to a new level.

This work confirms that tablets and mobile phones can be used as simple medical assistants. The new wearable devices may also create new opportunities for contactless heart beat estimation.

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