HeartSense: Estimating Heart Rate from Smartphone Photoplethysmogram Using Adaptive Filter and Interpolation

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Abstract. In recent days, physiological sensing using smartphones is gaining attention everywhere for preventive health-care. In this paper, we propose a 2-stage approach for robust heart rate (HR) calculation from photoplethysmogram (PPG) signal, captured using smartphones. Firstly, Normalized Least Mean Square (NLMS) based adaptive filter is used to clean up the noisy PPG signal. Then, heart rate is calculated from the frequency spectrum, which is further fine-tuned using different interpolation techniques. Experimental results, show that the overall HR calculation improves significantly due to the proposed 2-stage approach.

Keywords: Photoplethysmography · Heart rate · Adaptive filtering · Noise removal · Interpolation

1 Introduction

Personal healthcare and wellness have emerged as a powerful market segment and has empowered active research in that domain. Several approaches have been used to measure physiological parameters and record them for further study by healthcare professionals and care-givers. Early devices came with connectivity to personal computers which allowed data logging and display. This was replaced with Bluetooth and Zigbee enabled devices that can transmit wireless data to gateway devices or the user's mobile phone for local logging or remote logging via server connectivity.

Although the above model brought in ease of use for both the user as well as the care-givers and physicians, the cost of ownership and maintenance of such devices lies largely with the users, preventing their mass penetration especially in developing countries.

The above problems created the need for alternative approaches. One such approach is to use smartphone sensors for monitoring physiological parameters [3]. Though such readings may not be used for diagnostic purposes, they can provide indicative value to the user. Since in developing countries, the patient to doctor ratio is highly skewed, and the cost of owning multiple devices is relatively high, such approaches are more viable.

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The sensors available on a smartphone platform that can be used for physiological sensing includes accelerometer, microphone and camera where the camera can be used for capturing photoplethysmography (PPG) signal unobtrusively.

PPG is defined as the volumetric measurement of blood flow in body organs [1]. In principle the volume of blood flowing at a capillary is a function of the rate at which the heart pumps blood to the body. Hence, the PPG signal over time reflects the heart-rate value of a person. Equipped with camera and flash, smartphones are able to capture fingertip PPG signal [7]. Although this is true in theory, the mobile camera based PPG suffers from several practical issues. Firstly, most mobile phones have a camera that can capture video at a maximum rate of 30 frames per second (fps), yielding a very low sampling-rate data, compared to medical grade PPG (100 Hz[1]). Secondly, since the mobile PPG technology works on reflected light rather than transmitted light, oftentimes the signal quality is poor [6]. Thirdly, user movement and pressure variance causes artifacts, which adds to the noise, resulting into inaccurate heart-rate detection. Finally, turning on the LED flash continuously for longer period increases the temperature of the region surrounding the camera, causing thermal noise in captured video. In this paper, we demonstrate the behavior of Normalized Least Mean Square (NLMS) filter and it's effects of noise cleaning on noisy phone PPG signals. In addition, we have also explored different interpolation techniques to fine-tune peak detection in frequency domain analysis for improved HR calculation.

2 Extraction of Smartphone PPG

There are many techniques available in the literature to extract PPG signal in reflective mode using smartphones. Most of them include capturing of a video stream by placing the fingertip of the user on the smartphone camera with flash on. PPG signal is extracted as a time series data, by analyzing the change in intensity of 'RED' component in each frame of the captured video. Three such methods have been used in the current context for comparative studies.

2.1 Method 1 (PPG_{avg})

This method, proposed by Pal et al. [7] selects a region of $m \times m$ pixels from the center of each frame of captured video. The value of PPG signal for l^{th} frame is represented by the mean value of all the 'Red' pixels in that selected region.

2.2 Method 2 (PPG_{area})

Kurylyak et al. calculates a person specific threshold (T) for each video by analyzing the first few frames as in [6]. The value of PPG signal for l^{th} frame is calculated by

$$PPG_{area}[l] = \frac{number\ of\ Red\ pixels > T}{total\ number\ of\ Red\ pixels} \quad (1)$$

[1] http://itee.uq.edu.au/~davel/uqvitalsignsdataset/download.html.

2.3 Method 3 (PPG_{rad})

Extending Method 2, Kurylyak et al. [6] proposed a newer methodology to extract better PPG signal that fits a circle in the region of each video frame, where the pixel values cross the threshold. The value of the PPG signal of that frame is represented by the radius of the circle.

3 Filtering and Interpolation for Cleaner PPG Signal

As mentioned earlier, smartphone PPG signals get corrupted by several noise sources. In this section, we propose a 2-stage approach to clean up the noise for better HR estimation. Firstly, we investigate the usage of adaptive filter to enhance the Signal to Noise Ratio (SNR) in time domain, followed by different interpolation techniques to further fine-tune HR estimation in frequency domain.

3.1 Normalized LMS Based Filtering

LMS (Least Mean Square) filters encompass a class of adaptive filters, which tries to match a desired filter, by calculating the filter coefficients which leads to least mean squares of the error signal.

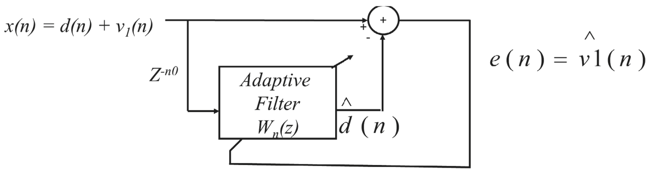


Fig. 1. Normalized Least Mean Square Filter

However, LMS filter has one inherent difficulty in estimating the step size μ. To mitigate this issue, Hayes et al. [4] presented the concept of normalized LMS (NLMS) where β, a normalized step size, typically within the range $\{0,2\}$ is introduced. As shown in Fig. 1, $x(n)$ is the noisy raw PPG signal, i.e. the *desired signal* $d(n)$ corrupted by noise $v_1(n)$. A delay z^{-n_0} is introduced to the input signal to obtain a reference signal, which is applied to the adaptive filter to get the *estimated signal* $\hat{\mathrm{d}}(\mathrm{n})$ close to $d(n)$.

3.2 Interpolation

Heart rate is calculated by searching the dominant peak in the frequency spectrum of the signal. For frequency domain peak estimation, it's often common to have a coarse estimation of the dominant peak, followed by fine search around that to get the accurate peak location using interpolation. In this paper, we have explored two interpolation techniques.

1. *Linear Interpolation:* A simple linear interpolation was employed to fine tune the frequency domain resolution of PPG signal. This can serve as an ultra-light reconstruction technique, while porting HeartSense to smartphones.
2. *Jacobsen Interpolation:* Jacobsen et al. presented the following interpolation technique for fine resolution frequency estimation in DFT domain [5].

$$\hat{\delta} = Real[\frac{(R_{k-1} - R_{k+1})}{(2 * R_k - R_{k-1} - R_{k+1})}] \tag{2}$$

Later Candan [2] proposed a finer version of Jacobsen Intepolation technique as follows.

$$\hat{\delta} = \frac{\tan(\pi/N)}{\pi/N} * Real[\frac{(R_{k-1} - R_{k+1})}{(2 * R_k - R_{k-1} - R_{k+1})}] \tag{3}$$

However, in our approach, we chose N=512[2], which makes $\frac{tan(\pi/N)}{\pi/N} \rightarrow 1$. Hence we have limited our experimentation to Jacobsen interpolation.

4 Experimental Setup

A total of 11 subjects having male to female ratio of 7:4, with an age distribution of 22-40 years volunteered in our experimentation. During data capture, the subjects were asked to be in rest position, seating on a chair in an air-conditioned room for half a minute at the beginning. Later they were asked to make some light but predefined body movements while seating to add artifacts in their PPG signal for another half a minute, making the data collection duration of one minute per subject. Ground truth heart rate for all the subjects was recorded using a CMS 50D+ digital pulse-oximeter[3] from their right hand middle finger. Smartphone video for every individual was also collected simultaneously from the index finger of the same hand, while keeping the LED flash on. Videos were collected using the native camera app of iPhone4, iOS 6. All the videos are recorded in the highest resolution i.e. 1280×720 at 30 fps. A total of 11 videos were collected from 11 subjects. All the 3 algorithms (PPG_{avg}, PPG_{area} and PPG_{rad}) were applied to extract 3 sets of PPG signals per video file.

5 Results

Our experimental results are broadly classified into two major sections, 1) Effects of NLMS filtering on raw phone captured PPG data and 2) Effects of interpolation techniques in estimating HR on NLMS filtered data.

[2] At 30 Hz, 512 samples amount to 17 sec video.
[3] www.pulseoximeter.org/cms50d.html.

5.1 Effects of NLMS Filtering on Raw Phone Captured PPG Data

The delay parameter plays an important role in the NLMS filter. As the delay increases, the correlation of the *noise in actual signal* with the *noise in the delayed signal* drops, resulting in increasing SNR. As shown in Fig. 2, SNR of the filtered PPG signal is improving along with an increase in delay till a *delay of 12 data points*.

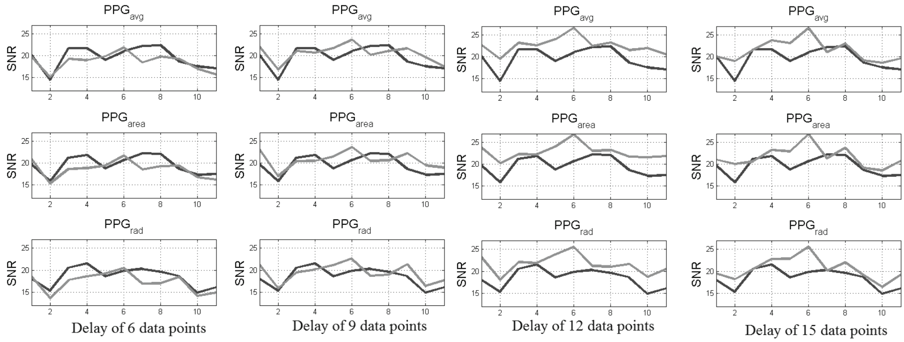


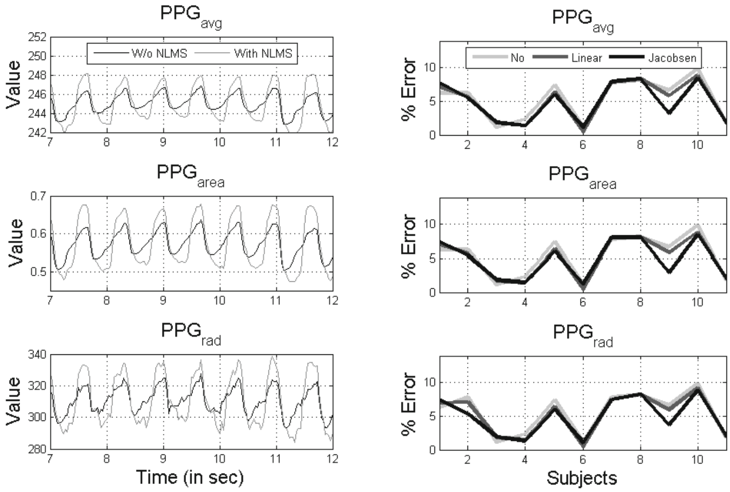
Fig. 2. SNR for Different Delay Parameters for 11 Subjects and 3 PPG Extraction Algorithms(the *darker* and *lighter* line represents *unfiltered* and *filtered* PPG respectively)

However, as the delay becomes comparable to the time period of signal, the signal also tends to become uncorrelated. Hence the SNR starts to deteriorate. In our case, the drop in SNR is visible for a delay of 15 data points. So we fixed a delay of 12 data points for the rest of our experimentation. Given our data rate of 30 Hz, a delay of 12 data points would correspond to 40 %-80 % cycle period, for a heart range of 60-120 respectively.

The effect of NLMS filtering on a typical noisy PPG signal is shown in Fig. 3(a). It is evident that the peaks and troughs in the filtered signal is far more prominent in the filtered signal. So for the rest of the experiment, we incorporate NLMS filtering on the raw PPG signal first and then investigate the effect of different interpolation techniques.

5.2 Effects of Interpolation Techniques in Calculating Heart Rate

Interpolation techniques are used to fine tune the dominant peak location in the frequency response. We have explored 2 different interpolation techniques (linear and Jacobsen interpolation) against 3 PPG extraction methods. As shown in Fig. 3(b), HR estimation improves when interpolation is applied. However, it can also be observed that the performance of Jacobsen interpolation technique outperforms others.



(a) Effects of NLMS Filtering on PPG data for 3 PPG extraction methods

(b) % Error in Heart Rate Calculation using Different Interpolation Techniques

Fig. 3. Effect of NLMS filtering and Interpolation

6 Conclusion and Future Work

In this paper, we have demonstrated a two-stage approach, i.e. noise cleaning in time domain and peak frequency estimation in frequency domain by applying NLMS filtering and different interpolation techniques respectively. Jacobsen interpolation technique has outperformed *'No Interpolation'* and *'Linear Interpolation'* techniques. Hence, according to our experimentation, irrespective of various smartphone PPG extraction procedures, NLMS filtering followed by Jacobsen interpolation is the most optimum method to find HR from smartphone PPG. Our future work includes analyzing the effects of NLMS filtering on PPG signal captured using other smartphone models. We also aim to explore extraction of other physiological parameters, e.g. respiratory rate, blood oxygen content (SpO_2) and blood pressure from the clean PPG signal obtained using the proposed methodology.

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