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Heart Rate Measurement using The Change of Color of Skin over Time Due To Blood Flow

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Abstract - **Heart Rate is an important medical parameter in case of maintaining one's health. There are some apps available in the market that can calculate the heart rate of a person by using a Smartphone camera. No external pulsometers are required. But, these applications also consists of different issues in measuring proper pulse, like motion, noise in capturing the video, premature ventricular contraction and many more. Also some human errors like low or high pressure on the mobile camera, misplacement of finger over the camera leads to countable amount of error in measurement of Heart Rate. In our case of study, we have developed an application using existing algorithms that can cut down these errors up to an extent and gives the user almost error less Pulse of him or her by using the video of change of color of skin over time. We have captured video to get the PPG using smart phone and used tan 1st order Butterworth (IIR) band pass filter with frequency domain analysis and Hann windowing for leakage reduction.**

Keywords - **PPG, Heart Rate, BPM, Sampling, FFT, Filter, Skin.**

I. INTRODUCTION

Cardiovascular problem is one of the major concerns in present days as most of the people die from heart related problem each year. In 2018, heart related problem caused death 35% of the total death which is more than 18 million people. The number is increasing alarmingly and sources claimed that the total estimated global cost of cardiovascular disease was $863 Billion in 2010 and it might likely to increase by 2030 by $1044 Billion. The normal Heart Rate of human is about 60 BPM to 200 BPM. Here, in our study, we have focused on PPG signal that is measured from change of brightness of skin caused by change of blood flow on the skin over time.

We have assumed the range of interest of heart rate is from 40 BPM to 230 BPM. First target is to obtain noise free PPG signal from a video on the Red plane and thereby counting the peaks from the normalized signal and the resultant value is multiplied by 60 (1 Minute) to calculate the heart rate which is an important parameter for health monitoring. This process is easy to implement, convenient, user friendly, portable and in expensive.While capturing the red contact video of fingertips, miss touch errors can produce significant variation in real result as noise gets incorporated in it. Similarly, high pressure and low pressure on camera can produce improper and incorrect PPG signal and therefore, the result can be incorrect. These error factors can be treated as noise and needs to be removed up to a level to keep up the originality of a signal to give the correct BPM.

II. PIPELINE

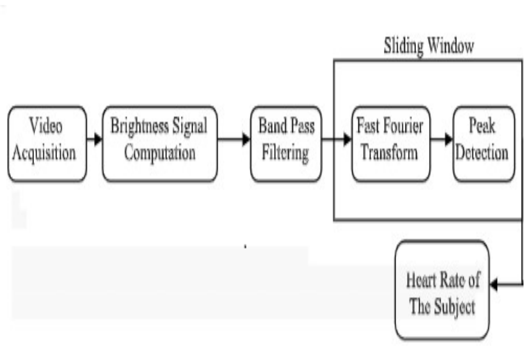

Fig.1. Processing pipeline to extract the heart rate over time from a video sequence of the fingertip skin.

III. METHOD

1. Video Acquisition:

In this step, we record the video of the fingertip skin; keeping in mind the finger pressure on the camera is moderate. And then the video is sampled. We have already assumed that the target signal can be achieved between 40 to 230 BPM. Hence, the highest and lowest sampling frequency is 0.667 Hz and 3.833 Hz. According to Nyquist Sampling Theorem, the sampling frequency should be at least double of the highest frequency value to get the whole range of frequencies without aliasing. Hence, the sampling frequency should be greater than or equal to 7.667 Hz. Generally a Smart

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Phone camera records a video at about 25 FPS to 30 FPS, which is more than three times than the minimum required sampling frequency according to Nyquist Sampling Theorem.

2. Brightness Signal Computation:

In this step, the Red brightness level of each pixel of each frame is calculated. With these values of Brightness, a signal is generated. The signal we want to process is the brightness of skin over time. We cannot ensure that all pixels in each frame of the video will contain same brightness level variation that we are looking for. We want the rest of the processing pipeline to be computationally light for faster execution. Therefore, we have chosen all pixels into a single average brightness value per frame. Hence, the n-th sample of the red brightness function can be expressed as:

$$B[n] = \frac{1}{W.H} \sum_{x}^{H} \left(\sum_{y}^{W} \left(v[n, x, y, 1] \right) \right)$$

Where, W is the width of the image in pixels, H is the height of the pixels & v [n, x, y, 1] represents the light level of red plane (index 1) at [x, y] coordinates of frame n in the video.As the frame size is constant over time, and we are only interested in the shape of the signal, not in its amplitude, we could even omit the division by total number of pixels.

A frame from a video shows the intently of blood in fingertip

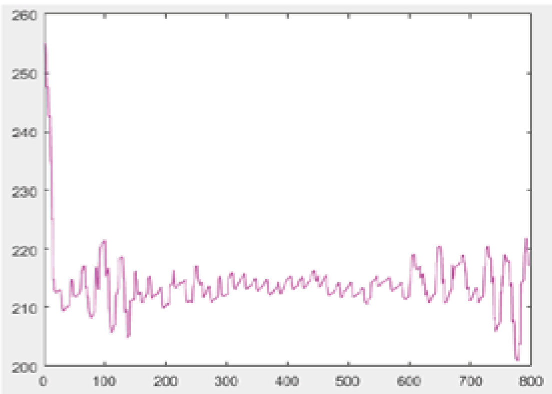

Fig.2. The Brightness Signal (X axis : Frames, Y axis : Density).

3. Band Pass Filtering:

After the signal from the brightness level from the pixels of each frame has been achieved, a band-pass filter has been applied. This band-pass filter attenuates frequencies outside the interest band. This reduces the noise in later processing and makes the resultant heart rate smoother. In our case a First order Butterworth filter is designed. The cut-off frequencies have been set to contain within our band of interest, i.e. 40 BPM to 230 BPM.

An initial piece of 1 second is cut off the filtered signal. It is an approximation of time it takes for the filter to completely remove the constant signal offset (Fig. 3). If this initial piece is not removed, we might get bad readings of heat rate during the stabilization time. Other types of filters can be applied. Butterworth filter has been chosen because, it is an IIR filter and the order required for a given bandwidth is much lower than that it a FIR filter. Lowe order generally means less computation. It has flat pass-bane and stop-bands compared to other IIR structures that show ripples. This avoids favouring certain frequencies over others in the valid range

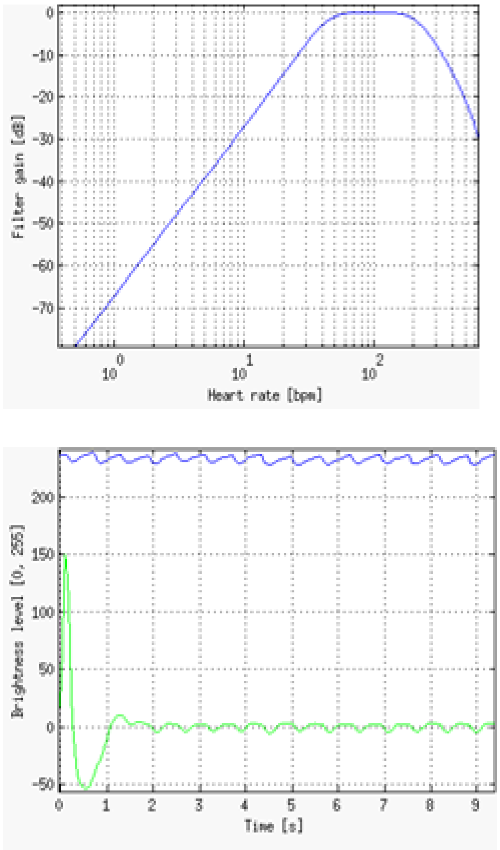

Fig.3. On the left, the filter frequency response. On the right, original Signal (blue) vs. filtered signal (green). Notice the transient during the First second.

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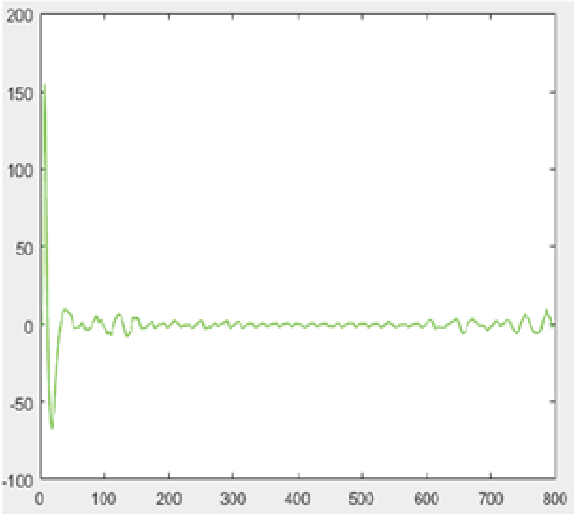

Fig.3a. Filtered and stabilized brightness signal (X:Frames Y: Density).

2.Fast Fourier Transform:
The Discrete Fourier Transform is used to translate the signal from the time domain to the frequency domain. The Fast Fourier Transform (FFT) algorithm in used to save the processing time when computing the DFT. While the computational complexity of the DFT is O(n2) for a sat of n points, the FFT gets the same result with O(nlog2(n)), which means a huge speed-up when n is high. The FFT of a real signal is a complex signal in which each complex sample represents the magnitude and phase of the corresponding frequency. In our case, phase is not needed. Only the magnitude has to be deal with. The Frequency vs. Amplitude graph is shown below.

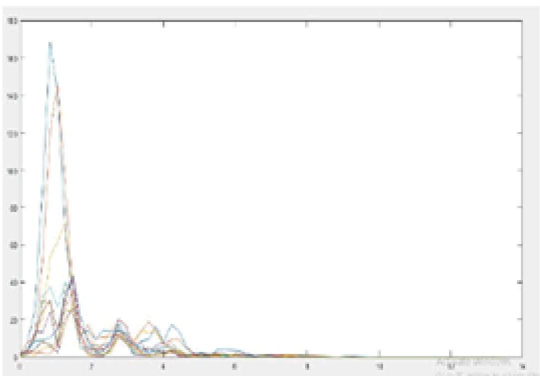

Fig.4. The Frequency vs. Amplitude Graph off FFT component.

3.Peak Detection:
Once the FFT is computed, magnitude peaks in the interest band are spotted. A sample is taken as the peak if is either larger than its two neighbours or equal to infinity. Among the resulting peaks, the highest peak position is sought out. Finally it is translated to the corresponding frequency in FFT vector.

4. Sliding Window:
In order to give a continuous estimation of heart rate, the FFT and the following step (Peak Detection) are repeated every 0.5 seconds. This computation is always performed over a window containing the last 6 seconds of signal samples. Virtually the window moves over the signal and this is why it is called 'sliding' or 'moving' window.

The 6 seconds is not arbitrary. The window length directly affects frequency resolution and thus the accuracy of our estimation. The FFT signal sampled N times at a sampling frequency Fs is N bins long. All the bins together cover a bandwidth of Fs. So the frequency difference between two consecutive bins is Fs/N. This is the frequency resolution (Fr). As the Sampling frequency can be written as the number of window samples divided by the total time it took to sample them (the window duration), we can say that:

Frequency Resolution = (Sampling Frequency)/(Number of window samples)
= 1/(Duration of window taken)

There fore, the higher the windows duration, the better the frequency resolution. The accuracy will be better, as it is half of the resolution in this case. However, increasing the windows decreases time accuracy. In the trivial case, in which, the whole signal length is picked as the windows length. If a peak is detected in the FFT, it is impossible to tell when that tone started within the signal or how long it lasted. Whatever number we give will be a maximum of a windows length away from the real value.

Another problem of long windows is that it will force the user to wait for an equally long period to get a first reading after starting up the measurement In Summary, with a 6 second window, we get a tolerable 6 seconds startup delay that gives a fair time accuracy of 6 seconds and a fair frequency accuracy of 5 BPM (half the FFT resolution). Computing an estimate every 0.5 seconds does not improve the time accuracy of the output, but it increases the time resolution of reading. It produces more heart rate output samples per second that will provide a more continuous and frequent reading. With this, we are incrementing the time resolution of the reading but not its accuracy, which stays limited by the time resolution of the FFT.

5. Leakage Reduction:
The DFT works ideally with infinite-time signals. A time-limited signal of length N is equivalent to infinite-time counterpart by a rectangular signal of length N and amplitude 1. Frequency-wise, this results in convolving the infinite-time signal spectrum by the rectangular signal spectrum, producing leakage.

In order to reduce leakage, before computing the DFT, the input signal is multiplied by a function whose boundaries are zero. These forces the resulting boundary values to zero. The multiplying function is usually called "window". It must not be confused with the sliding window that we have talked about in the previous section. There are many window functions in the literature, each having their own virtues and disadvantages. Here the Hann window is particularly chosen because it offers good resolution and good leakage rejection.

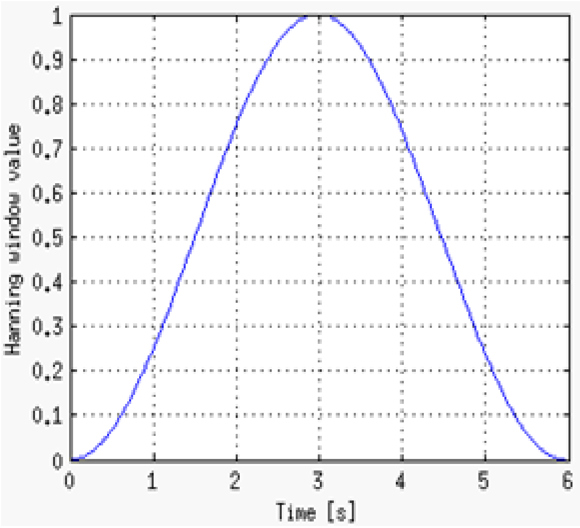

Fig.3. Hann window for the 6-second sliding window.

IV. EXPERIMENTAL SETUP

The fingertip skin is placed over the camera of a Smartphone, with the flashlight of the camera on, similarly shown in the figure Fig. 4a. The video of Blood blow through the skin is recorded up to a length of a minute. This video will be processed through the pipeline stated earlier.

Fig. 4a(Left) and Fig 4b(Right)

When the camera is covered with a finger, the naked eye sees a static red frame, but there are subtle variations caused by the blood flow under the skin that can be recovered processing the video signal.

V. IMPLEMENTATION

The proposed pipeline was implemented using MATLAB 2017a.

System Configuration:

- Intel Pentium G2010 2.80 GHz
- 4 GB RAM
- Windows 7 Professional 64 Bit

VI. RESULTS

For maintaining originality, we have manually captured red image video of fingertips using mobile camera then used that raw *.mp4 file for analysis in MATLAB software. We have captured all videos in average voltage of light and at normal room temperature and at rest physical condition. Then the result is compared with portable wearable BP Machine by MEDISANA. For measuring heart rate, we have used below devices, software and hardware tools:

Smart Phone: Samsung Galaxy J8 Infinity
Android: 9.0.0
Camera: Rear
Software: MATLAB 2017a
Platform: Windows 7 Professional 64 bits

File 1

Right hand, signal_1.mp4, fps=27, Touch error=4, frames=795, HR=82. With touch error, HR=81 so, algorithm works fine and touch error for only 4 frames at the beginning as Figure 4 and throughout the remaining signal train, brightness is consistent and in the range and no straight line in the signal.

File 2

Left hand, signal_2.mp4, fps=28, Touch Error=0, frames=962, HR=77. With touch error (=0), HR=77. Originality of the signal is not lost. So, algorithm is giving expected data if there is no touch error as well.

File 3

Left hand, signal_3.mp4, fps=28, Touch Error=86, frames=811, HR=77. With touch error, HR=80 (Unreliable). Yellowish orange image at the beginning (created flat line) and huge pixel density variation due to finger movement covering the camera so pixel density>200 but sudden up and down.

VII. IMPROVEMENT SCOPE

We are currently working on performance analysis of this application with more test data set in real world keeping in mind further improvement possibilities. We have noted below scopes that will be covered in our next papers with more real world test case analysis: Optimization analysis on upper limit of pixel density (to find a perfect range of brightness signal). Average

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optimum touches % calculation per video for calculating HR.

Introduction of Machine Learning for analyzing touch pattern and thereby decision making.Correlation and Regression analysis. Experimental analysis on different smart phone videos. Factors affecting PPG while capturing video including heat by flash.

VIII. CONCLUSION

This study has opened up new challenges of PPG, digital signal, image processing and filtering where attention to be paid for more accuracy. All the observations mentioned here will be written down in next paper with detail level of mathematical and experimental study with more trial and signal property analysis with variation with factors. We are currently focusing on performance analysis of this algorithm with more test data set in real world keeping in mind further improvement possibilities with other heart parameter measurements which are important data sudden heart attack prediction. For the whole assessment, accurate data/noise free image/noise free signal or test data are highly required as it is very new area and related to health or personal safety.

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