NON-CONTACT HEART RATE MONITOR

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ABSTRACT

The goal of this project was to create a non-contact heart rate monitor using a household camera such as a Raspberry Pi or smart phone camera. The system takes advantage of an algorithm developed by the CSAIL Lab at MIT in 2012. The algorithm has the ability to amplify small color changes in everyday videos. The system takes advantage of this by amplifying the color change in the face due to oxygenated blood flow. The system then counts the number of heart beats in the video and determines the subjects heart rate. The system works and has about a 6% error as compared to an "off the self" pulse oximeter.

1. MOTIVATION

There were two motivating factors going into this project. One was to create a system to monitor a new-born baby heart rate in a hospital or home setting. The other was to create a system that could use everyday household equipment to create an ubiquitous medical device.

1.1. Baby Monitor

The motivation for creating a new-born baby monitoring system is that with this system the newborn will have no machine contact. In effect, there will be less spreading of germs between infants. Neonatal babies do not have a fully developed immune system and thus are very susceptible to infection [1]. In a hospital setting, measuring the different new-born's heart rate with the same conventional contact heart rate monitor increases the risk of infection to the baby. Imagine a new system in place where a camera is mounted atop the new-born's crib in the hospital. In this situation there is no contact with a machine that has also been touched by other humans and babies, decreasing risk of infection. Plus there is less setup time. All that is necessary is to put the baby to sleep in the crib.

1.2. Consumer Device

Today, conventional methods to measure heart rate require specialized equipment that could be costly. The gold standard to measure a patient's heart rate is an EKG machine. These machines provide a tremendous amount of information about the condition of the heart. However, they are big, bulky, and expensive ($1,000 - $5,000); thus making them not suitable for consumer use and are typically only seen in a hospital setting [2]. The everyday consumer product to measure heart rate are usually seen in smart watches or Fitbits. These can range from about $150 to $500. They use red LEDs and photodetectors to measure the blood flow in and out of the wrist or finger. These LEDs only have one purpose and are specialized for this application [3]. The system mentioned in the paper would alleviate this problem because it uses pre-existing equipment (smart phone camera) to measure the user's heart rate.

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2. BACKGROUND

This system takes advantage of an algorithm developed at MIT to amplify small changes in movement and color changes in videos. The algorithm has four main components: spatial decomposition, temporal filtering, amplification, and reconstruction [4].

2.1. Spatial Decomposition

The first step in processing the video to amplify color changes, is to spatially decompose the video. By dividing up the video into its different spacial components we have better control on the amplification step. For instance, if we are interested in only amplifying color changes in a flat region of the video we can choose to only amplify the low frequencies in the spacial decomposition. Conversely, by amplifying the high frequencies in the spatial decomposition, will amplify color changes on a region with many edges in the video.

2.2. Temporal Filtering

The next step is to run each video segment from the decomposition in the previous step through a band-pass filter. The filter is set to ensure we only amplify changes in which we are interested in. For example, if we want to see the blood flow in the face during a resting heart rate we will need a band pass filter from 50 beats per min (0.83 Hz) to 70 beats per min (1.17 Hz). This introduces the first draw back of the system. The system must know if the user is at a resting heart rate or excited heart rate before it processes the video, ultimately making the system not automatic.

2.3. Amplification and Reconstruction

In its most basic form the amplification stage multiplies each video segment by a constant. In doing so, we magnify the color change due to blood flow in the face. After amplifying the signal, we combine all the spatial decomposed video segments and return one final video.

3. HEART RATE DETECTION

The heart rate detection algorithm was the main part of my project. I devised three different methods to calculate the heart rate from the videos processed with the MIT's motion magnification algorithm. They all are based on a similar concept: count the number of local maxima in red pixel intensity values and divide by the length of the video. The three methods to detect local maxima are using a gradient in the red pixel intensity, a built in Matlab peak detection algorithm, and preprocessing the video to crop it to flat region on the face. Each method has its own advantages and disadvantages. Processing time for all methods run under a minute, using a 2 core 2.60 GHz processor and 8 GB RAM.

3.1. Gradient Detection

The gradient method works by calculating the gradient of red pixel intensities between every frame in the video. In doing so, we can count the number of local minima and maxima by counting the number of times the gradient drops below a certain threshold. Since we are only interested in maxima we must divide the count by 2. This ensures we do not double count the heart beat. Then by dividing by the length of the video we can compute the heart rate.

This method had an advantage in that I could set the threshold of when the blood changed from flowing into, to out of the face. With this threshold I was able to have greater control of detecting a heart beat and was able to look at every frame rather than every other frame as in the peak detection method. This resulted in a higher resolution of the heart rate giving us a more accurate reading of the high heart rate which can be seen in table 1.

The disadvantage is that the threshold needed to count the heart beats varies from video to video. Thus it is unable to automatically detect the heart rate: it requires user input and trial and error to determine the correct threshold.

3.2. Peak Detection Method

The peak detection algorithm calculates the frobinous norm of the red pixel intensity values at every other frame. Storing this information in a vector, allows us to run a peak detection algorithm previously created by Matlab – *findpeaks()* – to count the number of local maxima or heart beats. We can also plot this vector to show the blood flow in the face. This is known as a photoplethysmogram or PPG [5]. As seen in figure 3, this gives us a measure to compare against standards in the market place today.

The advantage of this method is that we can run the same code on every video, making it robust to minor changes between different videos due to skin color, lighting, etc. However, the disadvantage is we must look at every other frame rather, decreasing the resolution of the heart rate signal. This is because looking at every frame creates small variations in the signal creating noise or jitter. As seen in figure 1, this creates false positives in the peak detection and increases the detected heart rate.

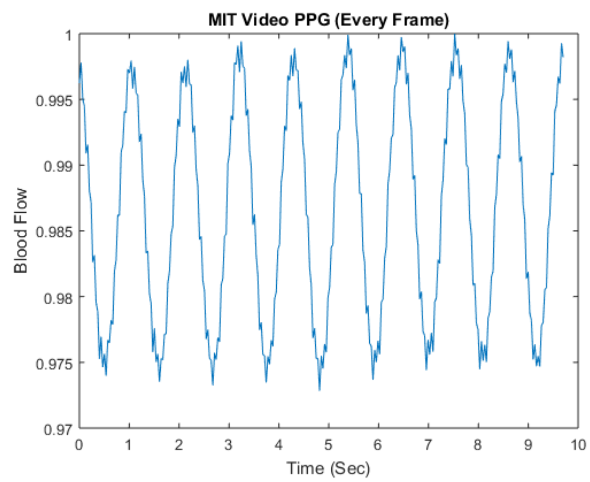


Fig. 1. Plotted PPG Vector at Every Frame

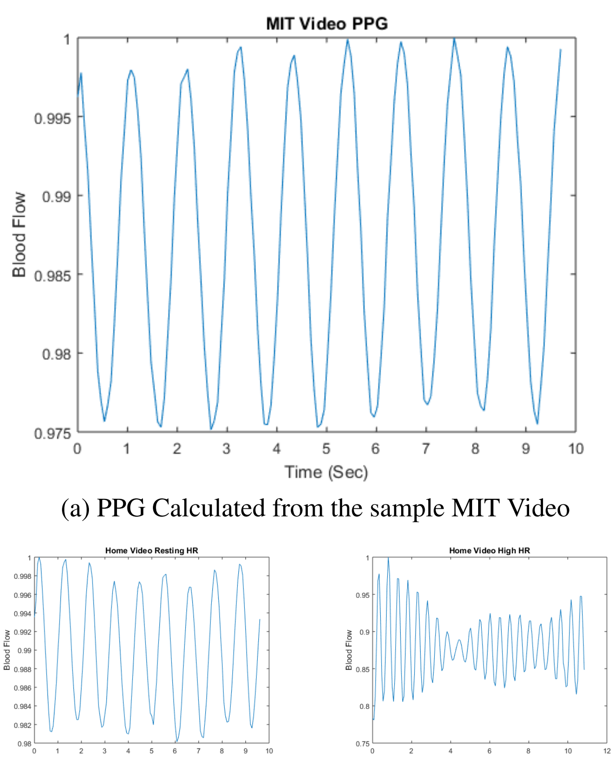
3.3. Video Cropping

The video cropping method does some preprocessing to the raw video before it is sent to MIT's algorithm. The cropping is done manually and is cropped to a region on the face where the blood flow is most apparent. This is usually a flat region on the face around the forehead. After video is cropped it is processed with the peak detection algorithm to detect the user's heart rate. By cropping the video, we make the system more robust to noise. This can be seen in the results where the home video with a high heart rate had a lot of noise due to poor lighting conditions. In table 1 notice the video cropping method had a lower error than just the regular peak detection method.

4. RESULTS

I used three separate videos to test my system. First was the MIT supplied video which can be downloaded with their algorithm. This video represented the baseline for my experiments. It was recorded with ideal lighting conditions and standard point and shoot camera [4]. The other two videos were recorded at home and were taken with an iPhone 5s camera. One was recorded with a resting heart rate and the other with high a heart rate. The high heart rate introduced the most noise to the system and can be seen in regions such as the chest. The noise can be due to a multitude of factors but most importantly the lighting. I found that conventional lighting caused flickering in the video due to the alternating current from the power line. This is where the cropping method really helped in narrowing the color change to just the face.

Figure 2 shows the PPG calculated for each video. These figures are very similar to figure 3 which is a PPG measured from the standard pulse oximeter around the ear [5]. The fact that these two figures are similar proves that what we are measuring in the video is in fact the user's heart as compared to random noise.



(a) PPG Calculated from the sample MIT Video

(b) PPG Resting Heart Rate (c) PPG High Heart Rate

Fig. 2. PPGs Calculated from Various Videos using the Peak Dection Methon. Section 3.2

Notice in figure 4 the high heart rate PPG is not as similar to figure 3 (sample PPG from pulse oximeter). This is due to the noise created by imperfect lighting conditions. Cropping the video to a flat region on the face results in figure 4. Here the plot is more similar to the sample PPG from the pulse oximeter, showing the cropping method reduces noise in the heart rate detection.

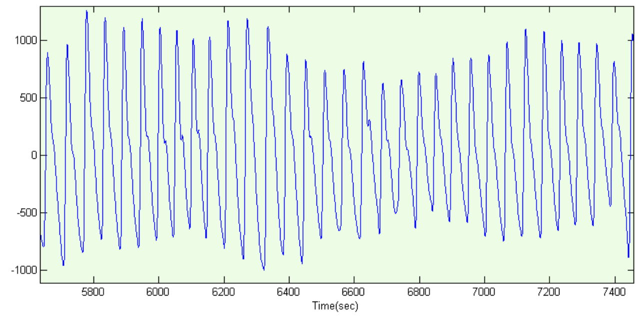


Fig. 3. Sample PPG from Pulse Oximeter

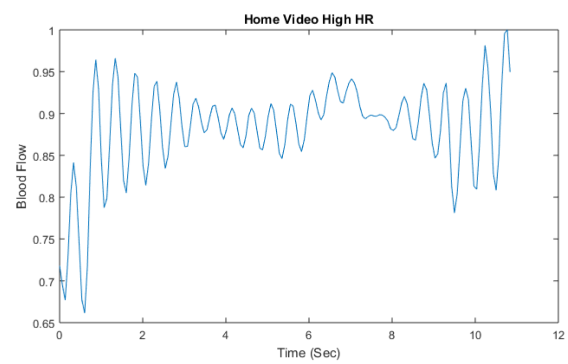


Fig. 4. PPG of High Heart Rate on Cropped Video

Table 1 shows the heart rate calculated by each method. Here the measured heart rates were taken with a pulse oximeter and are believed to be the user's true heart rate to base the error on.

Video	Measured HR	Gradient Method (% Error)	Peak Detection (% Error)	Flat Region (% Error)
MIT Sample	53 BPM	46 BPM (13%)	56 BPM (6%)	56 BPM (6%)
Home Resting HR	61 BPM	61 BPM (0%)	57 BPM (7%)	57 BPM (7%)
Home High HR	123 BPM	119 BPM (3%)	116 BPM (6%)	127 BPM (3%)

Table 1. Calculated Heart Rate using Various Methods

4.1. Outside Testing

I took two videos of my face outside while moving my head in the video. One video I tried to move my head from side to side and up and down very minimally. The next video I introduced more movement. The small movements of my head did not throw the measurements off too much and can be seen in table 2. However, moving my head a lot introduced too much noise and the algorithm was unable to return a heart rate. This is apparent when viewing the video – *testVid78.avi*.

Video	Measured HR	Gradient Method (% Error)	Peak Detection (% Error)	Flat Region (% Error)
Small Movements	73 BPM	61 BPM (16%)	61 BPM (16%)	72 BPM (1%)
Large Movements	78 BPM	N/A	N/A	N/A

Table 2. Calculated Heart Rate from Outside Videos

5. FUTURE WORK

To take this project further, the next step would be to add in a face detection algorithm to crop the video before detecting the user's heart rate. As we have seen in the cropped video method explained in section 3.3, this would make the system more robust to noise and environmental changes. Next, we can implement this system on a Raspberry Pi or smart-phone application. If this is to be implemented on a Raspberry Pi be sure to use a regular camera lens and not the one with out an infrared filter. The infrared filter is critical in filtering out noise and allows the system to better detect the user's heart rate.

6. REFERENCES

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