Lab Report
Advanced Bio-Electronics

Eulerian Video Magnification

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Abstract— In this experiment, we use The EMV algorithm in order to measure HR from different parts of the body. In the first part of the experiment the heart rate is extracted from an ECG text file and a magnified video of a face. The two HR values are compared to each other, where the ECG serves as the value of reference. The results of this first part of the experiment demonstrate that the EMV algorithm, combined with an additional algorithm, can calculate the HR with impressive precision. In the second part of the experiment, the EMV algorithm was used in order to calculate the HR from a video of a foot, both at rest and after exercise. Because ECG measurements were not available for the second part of the experiment, a Fitbit smartwatch HR measurements served as the value of reference, and the relative error of the HR extracted from both videos were below 4% (table 6 and table 7). Although the results of both parts of the experiment are impressive, we conclude that the EMV method for HR measurement is quite limited.

1. INTRODUCTION

Because the human eye does not have a wide range of Spatio-temporal sensitivity it is necessary to use another tool- in our case, a video, to enhance the ability to see subtle change and transformations in the body's behavior. Video magnification is an image processing tool, that is useful for acquainting with delicate changes in the video. The Eulerian [1] technique is helpful by amplifying the changes in selected frequencies so that the input goes through spatial decomposition (Laplacian\Gaussian), followed by temporal filtering to the frames. Subsequently the bands added back to the input sequence (in a feedback as will be shown here in the figure), and by reconstruction of the mentioned process we get the amplified output.

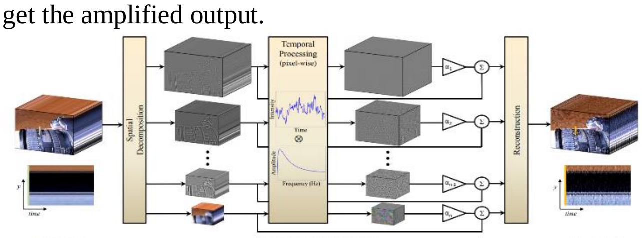

Figure 1: overview of the technique- first the input video is imported to MATLAB. Second, spatial decomposition brings the frames to specific several frequency bands, while using the Laplacian pyramid technique. Third, temporal processing is used with temporal filter for each one of the achieved bands. Fourth, a magnification factor is applied. Fifth, summing the results with the original bands in a feedback to get the amplified output.

In order to apply the technique on a Video, specific parameters have to be decided in advance, these parameters that should be defined for the magnification are: (1) the relevant range, represented by the frequencies ω_l and ω_h; (2) an amplification factor α; and (3) a spatial wavelength λ_c, which defines the spatial frequency cutoff.
The α factor, has to be chosen with taking into consideration the λ_c, which is the minimal threshold of wavelength, so that it is still suitable with the previously chosen α factor.
By defining the parameters correctly, the required mission can be achieved, for example, in breathing monitoring, as in the video which follows the baby's breathing, it is possible to control the type of magnification performed on the video.
We can use the Eulerian method to different clinical purposes as will be describes throughout this report. While choosing the suitable parameters, we are able to make use of the Eulerian video magnification to discover the changes in the breathing or the flow of blood in people's faces\blood vessels.

2. METHODOLOGY

2.1 **PART 1**:

Materials:

1. "Tamir's Video"- An MP4 video of Tamir's face, supplied by the university, with a sample rate of 30fps.
2. ECG measurement taken at the time of the filming of "Tamir's Video", describing the HR in the form of mV versus time with sample rate of 1kHz supplied as txt file by the university.
3. Matlab codes for the EMV program provided by the university.

2.1.1 Editing the video:

Before using the EMV program to magnify the heart rate in our video, we trimmed to video to 15 seconds starting at the moment the photographer turned the ECG measurement on. additionally, we cropped the area of the video to specify the area of interest to the face only, demonstrated in figure 4.

2.1.2 Calculating the HR from the ECG file:

In order to calculate the HR, a MATLAB function, called 'ECG2HR' was written. the function includes the following steps:

1. Load the EGC text file and select the left column only as directed by the instructor.
2. In order to distinguish between the relevant higher peaks to the lower peaks, square the ECG data.
3. Finding the R peaks and the peaks' location using the MATLAB function 'findpeaks', specifying the min peak height to be $0.4mV^2$. (the value selection for the min peak height was chosen based on the visualization of the squared ECG data).
4. using the locations of the peaks, create a vector of the distances between the peaks.
5. Convert the distances from 'Sample Distance' to 'Time Distance' by dividing the distance vector by the sampling frequency- 1kHz.

   Now, in order to convert to BPM, we used the following equation:

$$[BPM] = \frac{60}{[Time\ Difference]} \quad (1)$$

   We multiply by 60 to change the time units from seconds to minutes.

for clarification, the 'ECG2HR' function returns the ECG_HR in the form of a vector. In order to receive a single heart rate value, a mean calculation of the vector is performed.

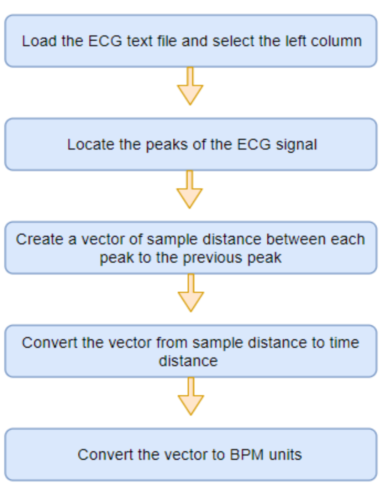

Figure 2: Block diagram describing the algorithm of the ECG heart rate calculation process.

2.1.3 Finding the HR from the magnified video:

The main idea which was used during the heart rate extraction from the video is the mean RGB behavior as a function of time.
The magnification of the video causes color enhancement. Therefore, at a time of a heart pulse, the RGB values would have a peak.
This principle is used in order to locate the heart beats, leading to the calculations of the heart rate.

In order to find the HR from the magnified video, a MATLAB function, called 'video2HR' was written, the function includes the following steps:

1. Calculate the mean RGB level for every frame in the video.
2. Select one color out of the RGB which the optimal one for peak detection (the least noisy).
3. Find the peaks and the peaks' location using the MATLAB function 'findpeaks', specifying the min peak height to the mean value of the selected color vector.
4. Create a vector of the distances between the peaks.
5. Converting the distances from 'Sample Distance' to 'Time Distance' by dividing by the sample rate (which is 30fps).
6. Convert to time distance vector to a BPM vector, using equation (1).

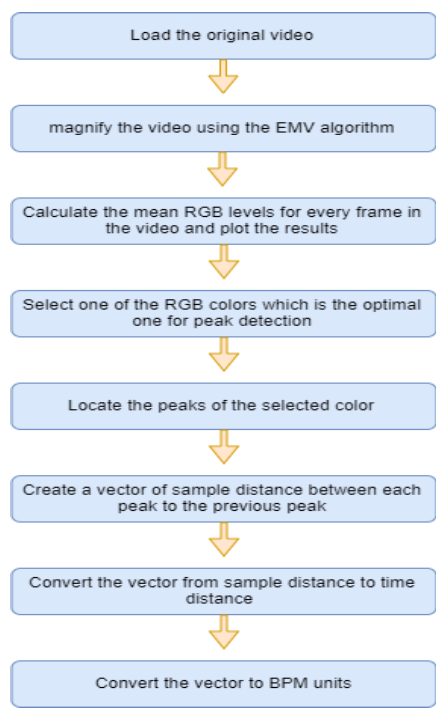

Figure 3: Block diagram describing the algorithm of the magnified video HR calculation process.

2.1.4 Selecting the magnification parameters:

we selected to magnify the video using the function "amplify_spatial_Gdown_temporal_ideal", given by the supplied MATLAB code.
Below are the values chosen for the magnification video:

Parameter	α	$level$	$\omega_l\ (Hz)$	$\omega_h\ (Hz)$
Value	150	8	1.0846	1.23

Table 1: The values of α, $level$, ω_l and ω_h used to magnify the video.

The values described in table 1 were chosen with the aid of table 2.

Video	α	λ_c	ω_l (Hz)	ω_h (Hz)	f_s (Hz)
baby	10	16	0.4	3	30
baby2	150	600	2.33	2.67	30
camera	120	20	45	100	300
face	100	1000	0.83	1	30
face2 motion	20	80	0.83	1	30
face2 pulse	120	960	0.83	1	30
guitar Low E	50	40	72	92	600
guitar A	100	40	100	120	600
shadow	5	48	0.5	10	30
subway	60	90	3.6	6.2	30
wrist	10	80	0.4	3	30

Table 2: the values of α, λc, ω_l and ω_h which were used to produce the various output videos in the article [1].

we can see from the table that in order to magnify a heart pulse like in the case of 'face' and 'face2 pulse', a high value for α is preferred, hence we decided to select 150 for α.
The parameter 'level' is related to the parameter 'λc', the 'level' value was selected by trial and error.
The parameters ω_l and ω_h are representing the bandwidth of the temporal filter. Their values were chosen by the aid of ECG_HR vector, hence, there is a direct conversion between BPM to Hz:

$$1[BPM] = 0.0167[Hz] \quad (2)$$

Using this relation, we chose the parameters ω_l and ω_h, according to the minimum and maximum heart rate values in the ECG_HR converted to Hz.

	BPM	Hz
Min ECG_HR	65	1.08
Max ECG_HR	73.8	1.23

Table 3: conversion between BPM to Hz of the minimum and max values of the ECG_HR.

The above-selected frequencies supplied the best results compared to other frequency bands we have tried, any other selection of frequencies was accompanied by additional noise.

2.2 **PART 2:**

In this part, we extracted the heart rate from a video of a human foot. To do so, we used the following materials:

1. A healthy and athletic 30 years old man, height 1.73m, weight 68kg.
2. iPhone 11 Camera (video sample rate 30 fps).
3. Fitbit smartwatch, Blaze model, that enables heart rate tracking.
4. the EMV Matlab code, supplied by the university
5. the Matlab algorithms written in part 1.

In this part of the experiment, the exact same algorithm described in figure 3, is used in order to calculate the HR from the magnified video. Unlike before, we do not have the ECG results for reference. So, in order to assess the results of this part, the Fitbit smartwatch HR measurement at the time of the video recording will serve as the value of reference. If the algorithm's HR results are relatively close to the smartwatch's measurement it will be possible to conclude that the HR measurement from the magnified video is successful.
In addition, in order to further access the results, HR will be extracted from two videos. The first one will be taken while our volunteer is at rest, and the second after our volunteer's exercise. The expected HR results should be much lower for the first video, at rest, compared to the second video taken after the exercise.

2.2.1 Selecting the magnification parameters:

We selected to magnify the video using the function "amplify_spatial_Gdown_temporal_ideal", given by the supplied MATLAB code.
Below are the values chosen for the magnification video:

Parameter	α	$level$	$\omega_l\ (Hz)$	$\omega_h\ (Hz)$
rest	130	9	0.83	1
after workout	130	9	1.83	2

Table 4: The values of α, $level$, ω_l and ω_h used to magnify the video.

In both cases, we selected the values of α and the $level$, based on a number of trails until we received the clearest magnified video.
The selection of ω_l and ω_h for 'rest' is based on the values used for 'face' in Table 2.
For the selection of ω_l and ω_h for 'after exercise', we increase the values of 'rest' by 1Hz, corresponding to the expectation of a higher HR.

3. RESULTS

3.1. RESULTS - Part 1.A:

The effect of the EMV algorithm on the original video is presented by 30 evenly scattered frames of both videos, as can be seen in figure 4 and figure 5.

figure 4: 30 frames of original video.

figure 5: 30 frames of magnified video:

In order to calculate the HR from the magnified video, we start off by examining the mean RGB level behaviors as a function of time, to ensure the magnified video's RBG behavior is optimal for peak detection.
As displayed in figure 6, we can see that both the green and the blue levels are smooth and display clear pulses, for that reason we continued the HR calculations with the green color levels.

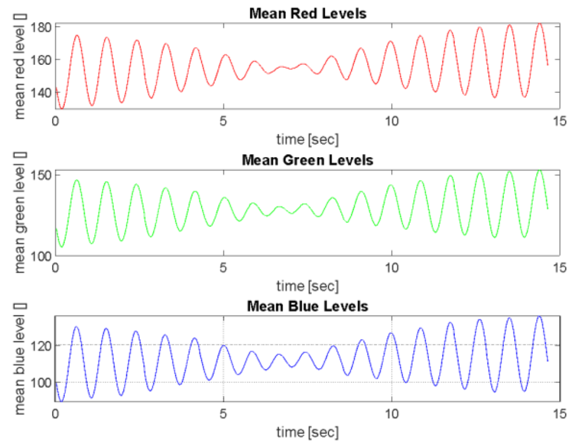

Figure 6: RGB levels behavior of the magnified video as a function of time.
Each time instance represents a frame, and the mean is referred to the mean presence of the given color in all the pixels of the frame.

The visualization of the peaks of the green color level, detected by our algorithm are displayed in figure 7, where they are compared to the peaks detected in the ECG.

Comparison between ECG HR to magnified video HR:

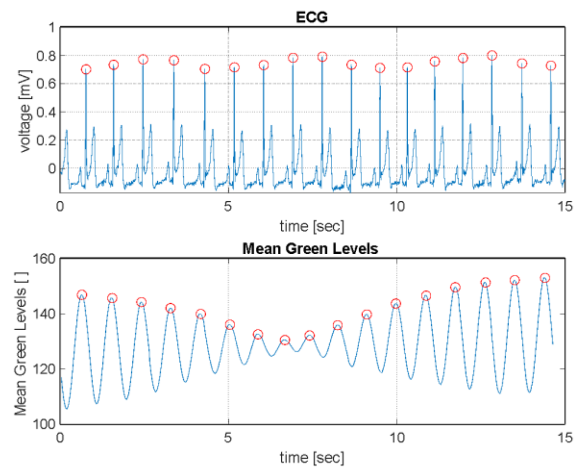

Figure 7: the peak detection of the ECG measurements as a function of time compared to the peak detection of the magnified video's mean green level as a function of time**.**

Using the sample distances between the detected peaks, a HR vector is calculated. The HR vectors for both the ECG and the magnified video are presented in figure 8.

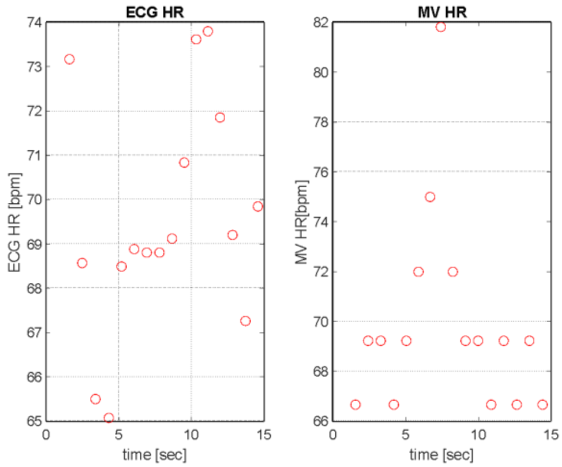

Figure 8: comparison between HR_ECG and HR_MV as function of time. Each point's location in time matches a heart pulse (a peak in the ECG or the green color level).
The value at a given point represents the distance between the current peak to the previous peak in the unit of BPM.

	Mean [BPM]	Standard deviation [BPM]
ECG HR	69.7	2.56
Magnified video HR	69.9	3.9
The Relative Error	0.33%	

Table 5: the average values of the HR, the standard deviation and the Relative Error, relative to the ECG.

3.2. RESULTS- Part 1.B:

The results obtained with the same magnification parameters as part 1.A, except for wl=1.8 Hz, wh= 2.1Hz:

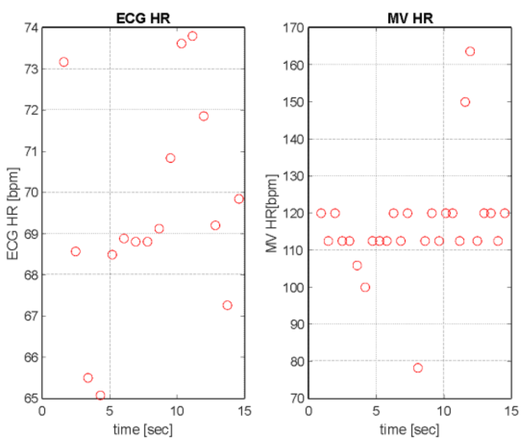

Figure 9: comparison between HR_ECG and HR_MV as function of time, for the requested temporal passband wl=1.8 Hz, wh= 2.1Hz.

	Mean [BPM]	Standard deviation [BPM]
ECG HR	69.7	2.56
Magnified video HR	116.6	14.5
The Relative Error	66%	

Table 6: the average values of the HR, the standard deviation and the Relative Error, relative to the ECG.
for the requested temporal passband wl=1.8 Hz, wh= 2.1Hz.

3.3. RESULTS- Part 2:

the effects of the EMV algorithm on the original videos are presented by 30 evenly scattered frames, as can be seen in figures 9 - figures 12**.**

The Fitbit smartwatch HR measurements during the filming of the videos are demonstrated in figure 13 and figure 16.

Figure 9: 30 frames of original video at rest.

Figure 10: 30 frames of magnifies video at rest.

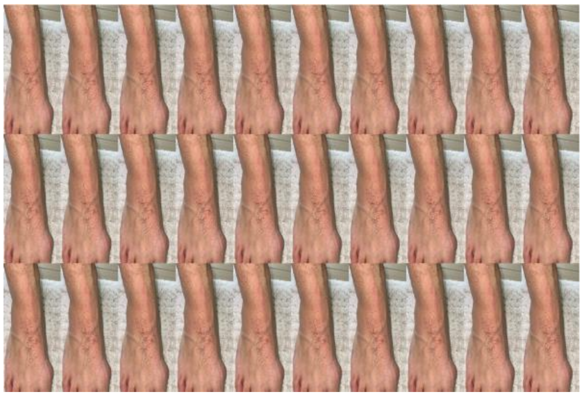

Figure 11: 30 frames of original video after exercise.

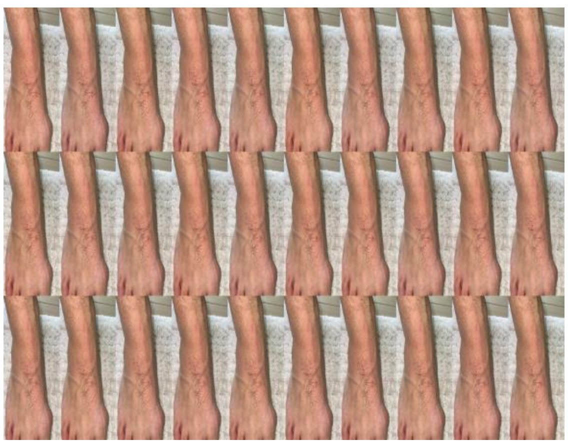

Figure 12: 30 frames of the magnified video after exercise.

Figure 13: the HR at rest is 61 BPM according to the 'Fitbit' smart watch.

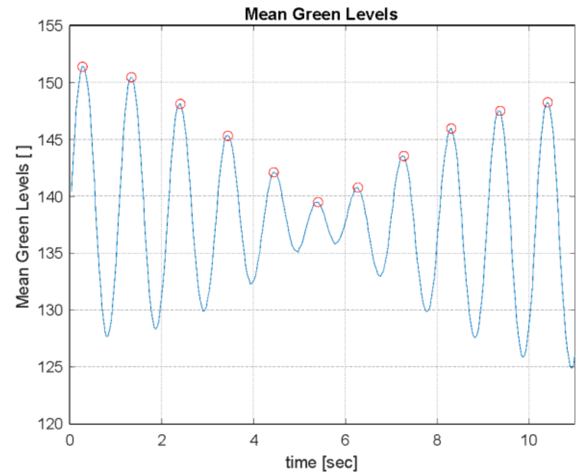

Figure 14: mean green levels of the magnified video at rest as a function of time.

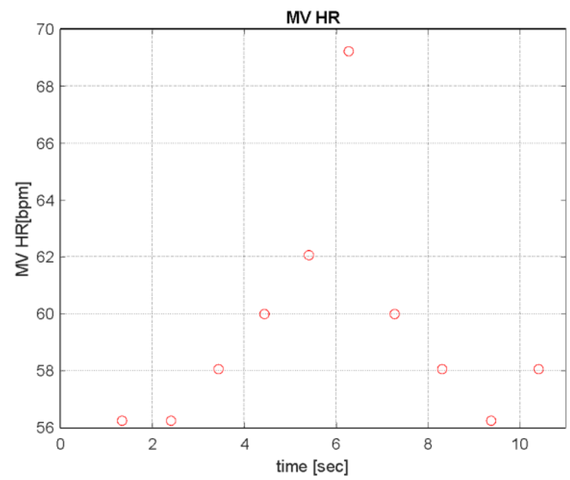

Figure 15: HR_MV of the of the magnified video at rest as a function of time. Each point's location in time matches a heart pulse (a peak in the green color level).
The value at a given point represents the distance between the current peak to the previous peak in the unit of BPM.

HR according to the Fitbit smartwatch	61 [BPM]
Mean of HR_MV	59.4 [BPM]
The standard deviation of HR_MV	3.9 [BPM]
The relative error of the mean HR relative to the Fitbit HR	2.6%.

Table 7: error analysis for the magnified video at rest.

Figure 16: the HR after exercise is 113 BPM according to the Fitbit smart watch.

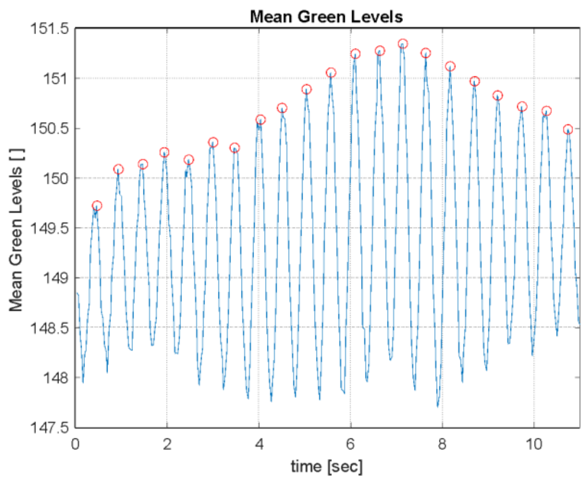

Figure 17: mean green levels of the magnified video after exercise as a function of time.

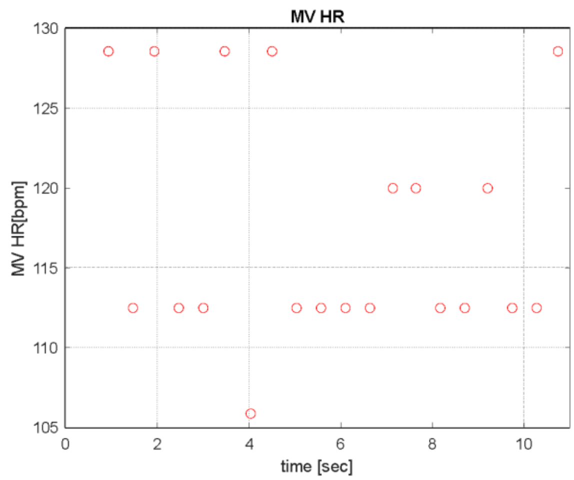

Figure 18: HR_MV of the of the magnified video after exercise as a function of time. Each point's location in time matches a heart pulse (a peak in the green color level).
The value at a given point represents the distance between the current peak to the previous peak in the unit of BPM.

HR according to the Fitbit smartwatch	113 [BPM]
Mean of HR_MV	117 [BPM].
The standard deviation of HR_MV	7.2 [BPM]
The relative error of the mean HR relative to the Fitbit HR	3.9 %.

Table 8: error analysis for the magnified video after exercise.

4. Discussion & conclusions:

4.1 The Results:

According to table 5, the magnified video enables a HR extraction result, that differs from the ECG HR by a relative error of approximately 0.3%, this error is lower than we would expect. Yet, this result is not very surprising considering the way we selected the frequencies, wl &wh for the temporal filter.
As we described in section 2.1.4, the selection of the temporal frequency band for part 1 was "tailored" based on the ECG results.
We suspect the reason of the negligible relative error is due to the usage of prior knowledge of the expected frequency range, which is equivalent to using the knowledge of the expected BPM range. A different choice for the frequencies led to a higher relative error.
On the other hand, in part 2 of our experiment, we specified the frequency parameters without the aid of an ECG measurement. In part 2 the frequency selection was based on the values of table 2 only, meaning prior knowledge was not used in the selection of the magnification parameters.
Yet, even though the magnification parameters were not specifically "tailored" to the expected solution, in both cases (in rest and after an exercise) the algorithm managed to estimate the HR with a relative error smaller than 4% relative to the Fitbit smartwatch HR value. Although the Fitbit's HR measurement is used as the reference in the error analysis of part 2's results, the Fitbit's HR measurement is not ideal. according to the results of the article [2] The mean absolute difference between the Fitbit's HR measurement to the ECG's HR is 5.6±6.4% when the subject is at rest and can be as high as 15.9±18.2%, during exercise, as reported in table 2 of article [2].
additionally, the results of part 2 match our expectation with regards to the mean HR difference before and after the exercise, described in Table 7 and Table 8.
the results of part 1.B represent a case where the video's magnification is done in a temporal frequency band that is out of range, meaning the EMV magnified subtle movement in a frequency band that is higher than the HR's frequency. this selection led to a relative error of 66%, as can be seen in

table 6, this is clearly a high error that demonstrates a wrong HR calculation in accordance with our expectation.

4.2 Limitation

In this experiment, we encountered multiple limitations. the most prominent one is the sensitivity to movement in the video.
We had to film the videos for part 2 multiple times in order to receive a video that is steady enough. Initially, the videos suffered from the hand movement of the photographer, those subtle movements affected the behavior of the RBG levels. The RGB functions as a function of time became noisy and unideal for peak detection, which led to wrong HR measurements and faulty results.
In the second try, the photographer placed a steady Stool under the filming hand in order to reduce the hand movement and the results improved significantly.
Another limitation we came across during our experiment was in the parameter selection for the magnification process, in the sense of time consumption:
In our experience, the selection of the parameters includes many trails, and we realized that the parameter selection and optimization can only be performed manually, and not automatically by the program, meaning optimizing the EMV program is time-consuming.
This is a limitation because the parameters need to be changed every time the EMV method is used for a new patient, or even the same subject in a different setting, hence this method is not robust to changes and requires time and effort in order to produce promising results.
Although we can imagine this parameter selection becomes easier and faster with experience, this fact, makes the EMV harder to integrate into outside applications, or frameworks.

4.3 Conclusion:

The objective of this lab was to examine and explore the EMV algorithm, which is an algorithm that serves as a microscope for subtle movement, invisible to the naked eye, enabling HR detection, pulse detection, and more.
In order to examine the algorithm's precision, we extracted an HR from a video of a human's face, using the EMV algorithm, and compared the results to the ECG measurements taken at the time of the video.
In addition, in order to further explore the EMV abilities and limitations, we measured the HR from a video of a human foot, before and after exercise, and compared the results to the HR measurements of a Fitbit smartwatch at the time of the videos.
We observed that the algorithm can measure the HR with impressive precision relative to the ECG HR, under the conditions where the expected HR frequency band is known and used in the process of parameter selection for the EMV magnification. On the other hand, when the selection of the bandpass parameters, wl & wh, is done without prior knowledge, the results can be faulty, and suffer from high errors, as we saw in section 3.2, where the temporal frequencies wl and wh were set too high.
These results led us to conclude that under the conditions where a proper calibration is available, for example with the aid of an ECG machine, the EMV can be a useful and precise tool for HR measurements. For example, the EMV can be used in hospitals to monitor babies' HR, after the EMV frequency parameters are set by the aid of ECG measurements, allowing for a price knowledge of the actual HR frequency band of each baby, the EMV will monitor the HR precisely, thus enabling the ECG machine to be available to the next patient and also enables additional algorithms to track the heart rate in real time and alert if there is suspicious behavior in the HR.
following the results of the second part of the experiment, where we used the EMV algorithm to measure the HR from a video of a human foot, we conclude that the algorithm can achieve good results from other parts of the body besides the face, meaning the program is dynamic and can be used for many purposes and in many different ways.
yet in light of the limitations, we encountered during the experiment, we conclude that in order to ensure good results, a decent amount of time needs to be allocated to the selection of the magnification parameter, comparing between different values until the magnification is optimal. in addition, the filming of the video must be in a static setting where no additional movement besides the desired motion is present in the video. meaning this method is not robust to changes and requires time and effort in order to produce promising results.

REFERENCES

[1] H. Wu. et al. Eulerian video magnification for revealing subtle changes in the world. *ACM Trans. Graph. (Proceedings SIGGRAPH 2012), 65, 31(4), 2012*
[2] Gillinov, Stephen, et al. "Variable accuracy of wearable heart rate monitors during aerobic exercise." Med Sci Sports Exerc 49.8 (2017): 1697-1703.