DSP Final Project:

Heart Rate Detection using Consumer Camera and MATLAB

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Heartrate Detection

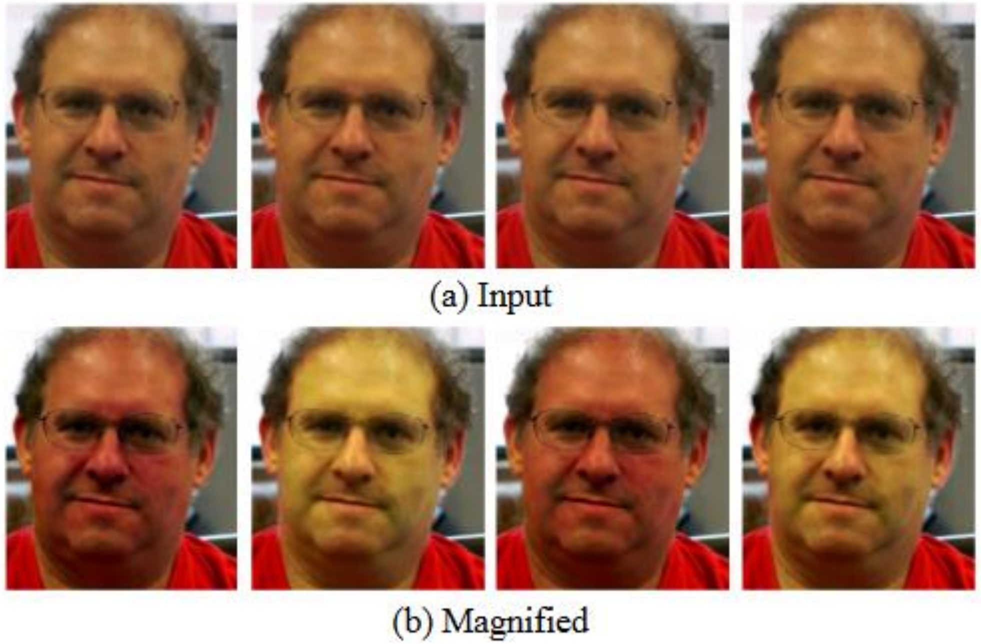
Vital signs are incredibly important in understanding the condition of the patient and how their body reacts to disease and the treatment they are receiving. Currently, most of these measurements must be taken with sensors which contact the patient. Measurement methods that require contact can be physically intrusive, cause irritation to the patient, spread unnecessary infections, and be cumbersome for the mobility of the patient or the health care workers who treat them. *So, how can we do this without contact?*

Initial Thoughts

- Having a static frame, with assumptions that our test subject will not move is not adaptable enough for our liking.
- Implement a face tracker.
- Use information gained from Project 1.
- Use FFT to find peaks of frequencies.

Research (Eulerian Video Magnification)

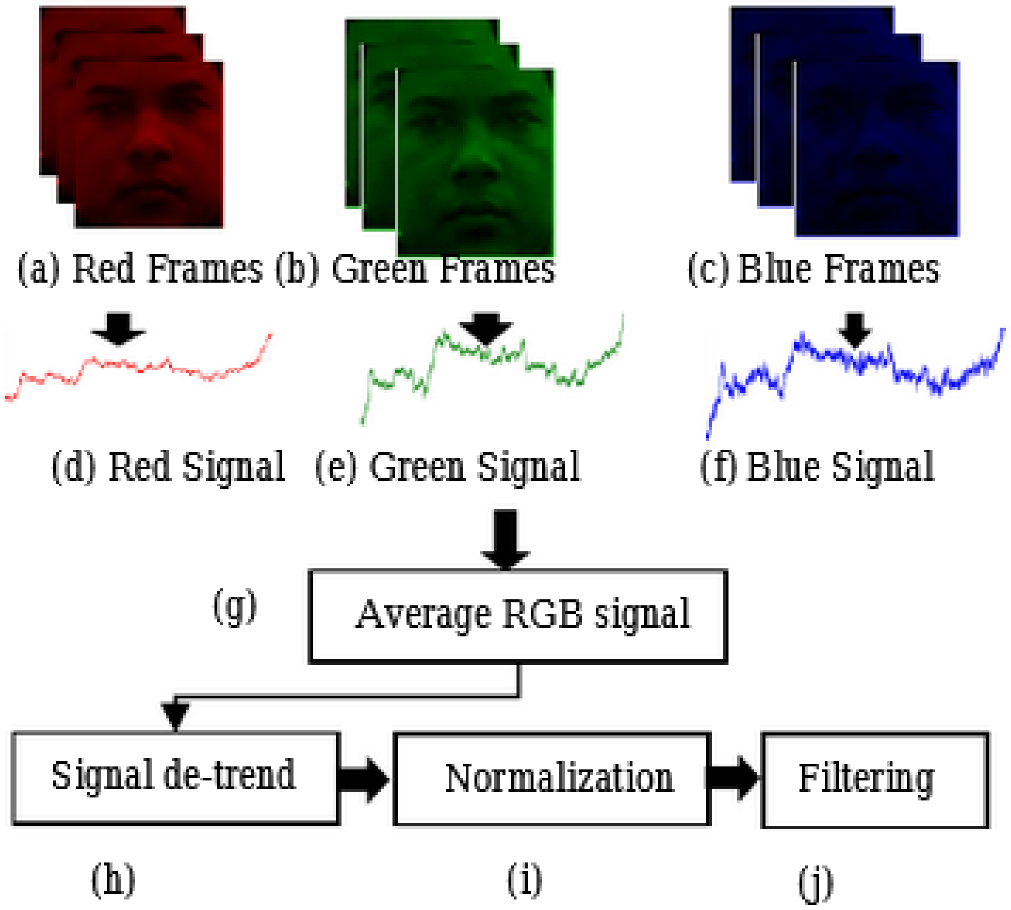
"…takes a standard video sequence as input, and applies spatial decomposition, followed by temporal filtering to the frames. The resulting signal is then amplified to reveal hidden information. Using our method, we can visualize the flow of blood as it fills the face and amplify the signal to reveal small motions. Our technique can run in real time to show phenomena occurring at temporal frequencies selected by the user. [1,3]"



Research (Real Time Heart Rate Monitoring from Facial RGB Color Video Using Webcam)

“Before applying PCA, ICA and FFT the Red, Green and Blue signals in Fig. 2(d-f) formed from all red, green and blue image frames in Fig. 2(a-c) are filtered by Hamming window (128 point, 0.6-2 Hz, for normal HR 36-120) for heart rate [2]”

“HR = 60* f bpm = [60 x (number of Peaks/Time)] bpm 60 x (25/20) bpm = 75 bpm. [2]”



Research (BSS)

"…noise removal from physiological signals is blind source separation (BSS). BSS refers to the recovery of unobserved signals or "sources" from a set of observed mixtures with no prior information about mixing process. Typically, the observations are acquired from the output of a set of sensors, where each sensor receives a different combination of the source signals. There are several methods of BSS and in this paper we will focus on BSS by Independent Component Analysis (ICA) [13]. ICA is a technique for uncovering the independent source signals from a set of observations that are composed of linear mixtures of the underlying sources. [4]"

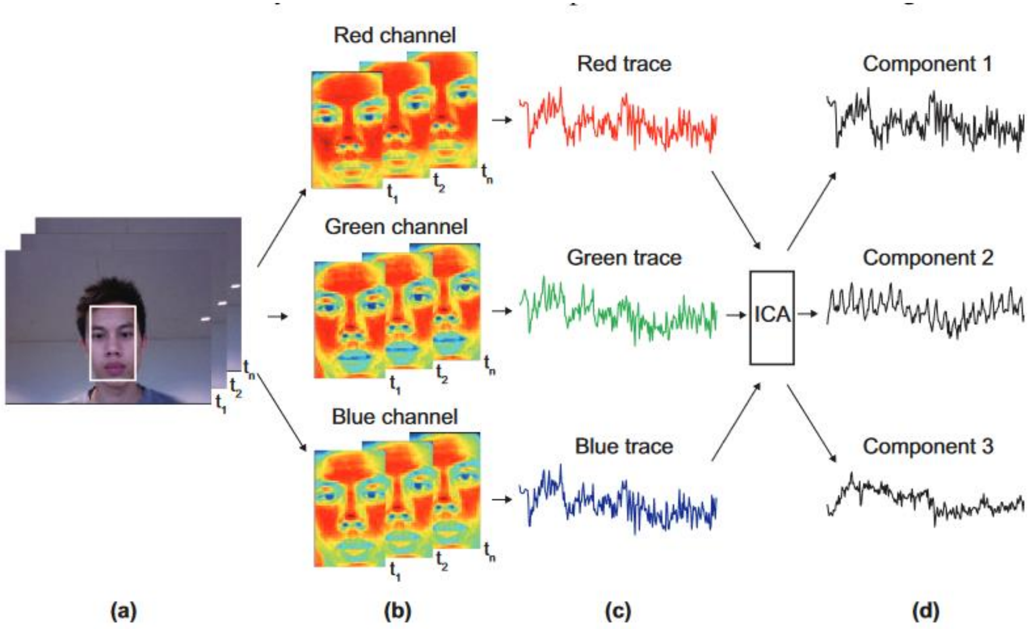


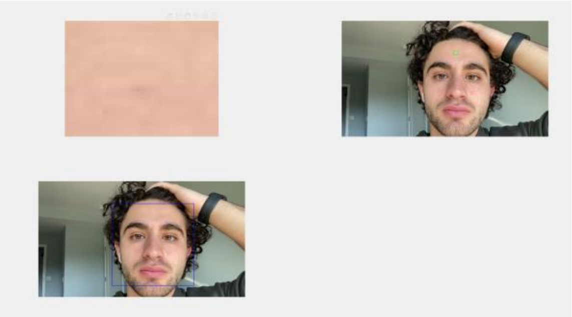
Fig. 2. Cardiac pulse recovery methodology. (a) The region of interest (ROI) is automatically detected using a face tracker. (b) The ROI is decomposed into the RGB channels and spatially averaged to obtain (c) the raw RGB traces. ICA is applied on the normalized RGB traces to recover (d) three independent source signals.

Filtering

- Based on prior research, we determined that .8 – 3 Hz correlates to 40 – 180 BPM.
- Designed a 2nd order Butterworth filter to keep our heart rate within those ranges
- Other filter types can be tested, and We chose Butterworth as:
  - It is an IIR filter, and the order required for a given bandwidth is much lower than with a FIR filter. Lower order usually means less computations.
  - It has flat pass-band and stop-bands compared to other IIR structures that show ripples. This avoids favoring certain frequencies over others in the valid range. [6]

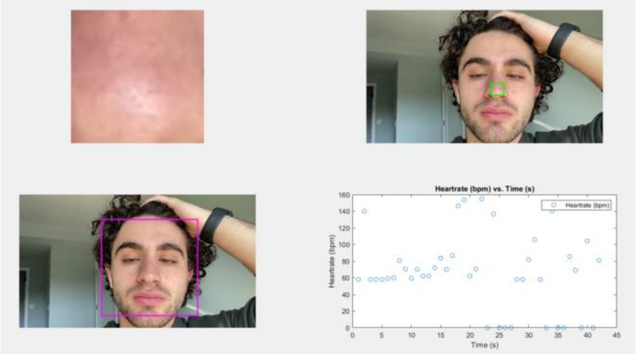
```
% Apply a bandpass filter to the pulse signal
% Define the passband frequency range (e.g., 0.8-3 Hz = 40 - 180 bpm)
fpass = [0.8, 3];
fs = frameRate;
% Design a Butterworth bandpass filter
[b, a] = butter(2, fpass / (fs / 2), 'bandpass');
% Apply the filter to the pulse signal
roiFiltered = filtfilt(b, a, roiRed);
```

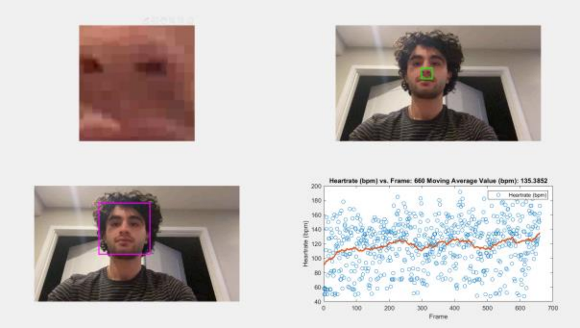
Initial Testing



Initial ROI from Facial Recognition

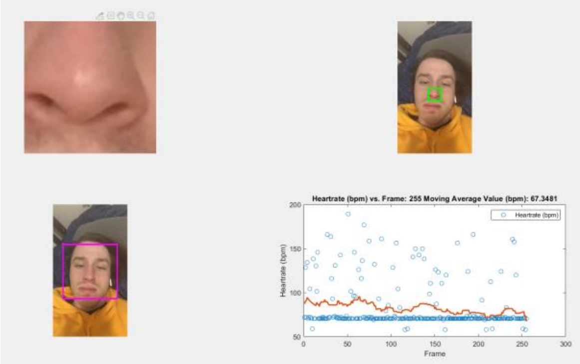
Heart rate Extracted

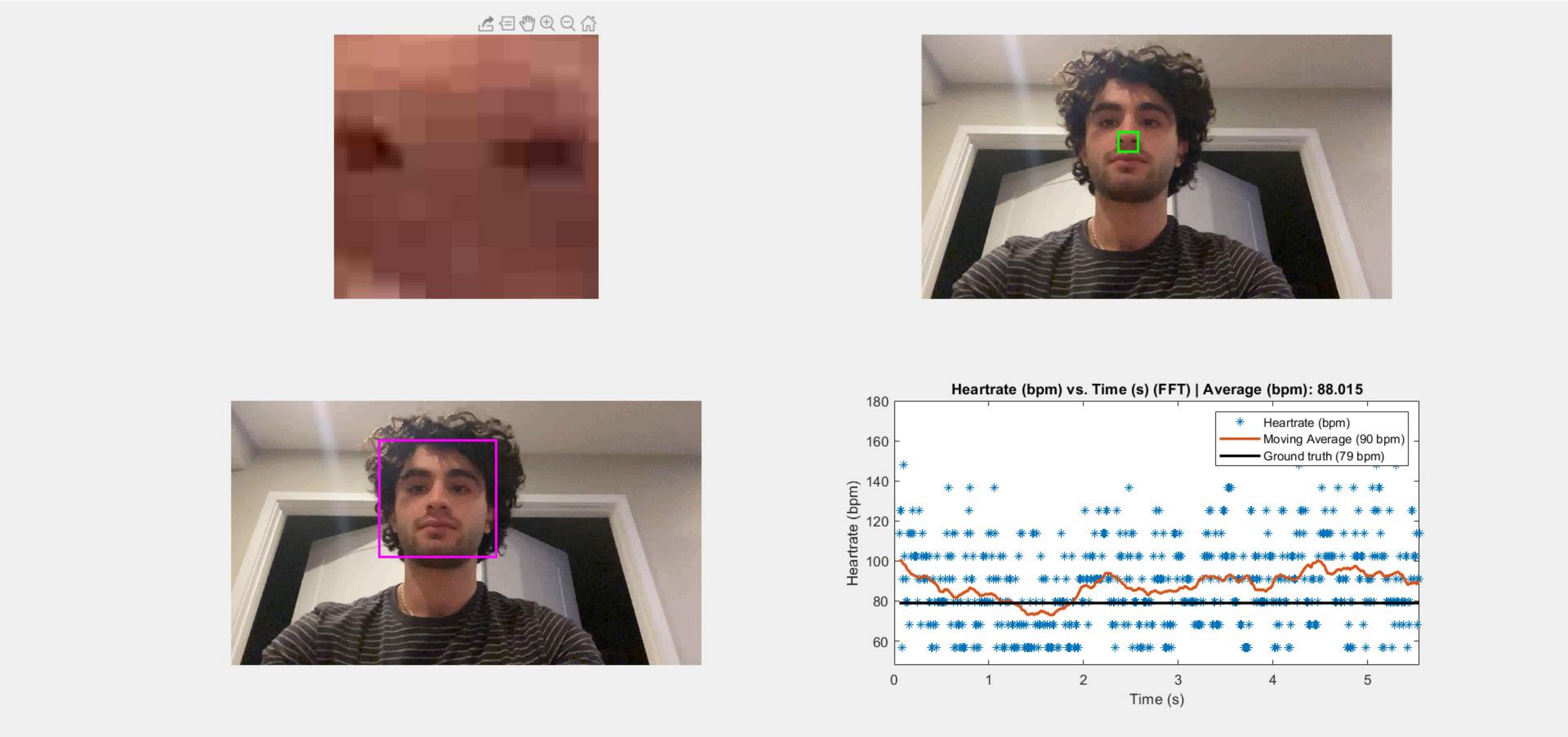




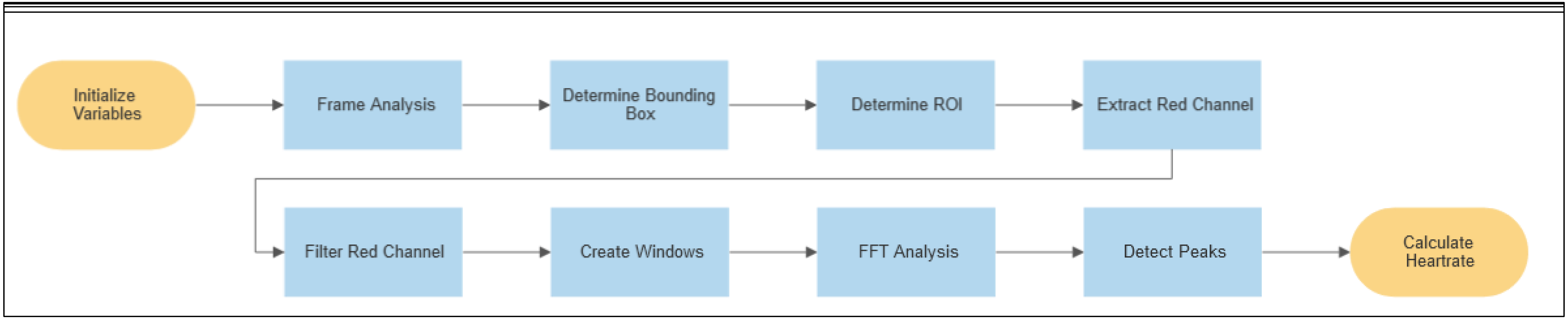
Moving Average Added

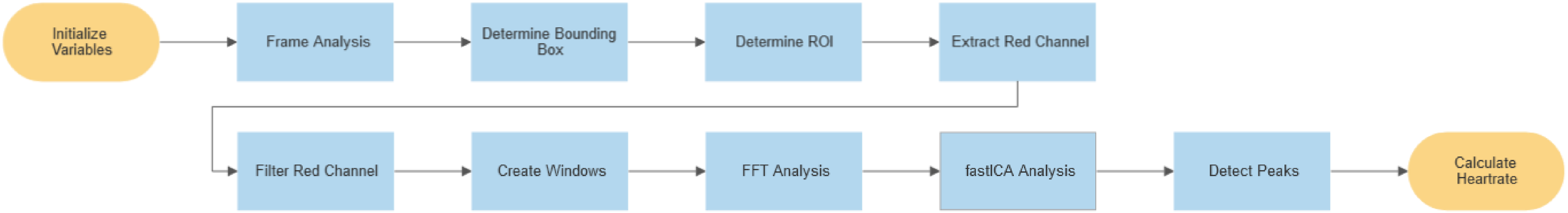
New video test




Heartrate (bpm) vs. Time (s) (FFT) | Average (bpm): 88.015
Heartrate (bpm)
Moving Average (90 bpm)
Ground truth (79 bpm)
Heartrate (bpm)
Time (s)
180
160
140
120
100
80
60
0
1
2
3
4
5

Our Process


Initialize Variables
Frame Analysis
Determine Bounding Box
Determine ROI
Extract Red Channel
Filter Red Channel
Create Windows
FFT Analysis
Detect Peaks
Calculate Heartrate


Initialize Variables
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Create Windows
FFT Analysis
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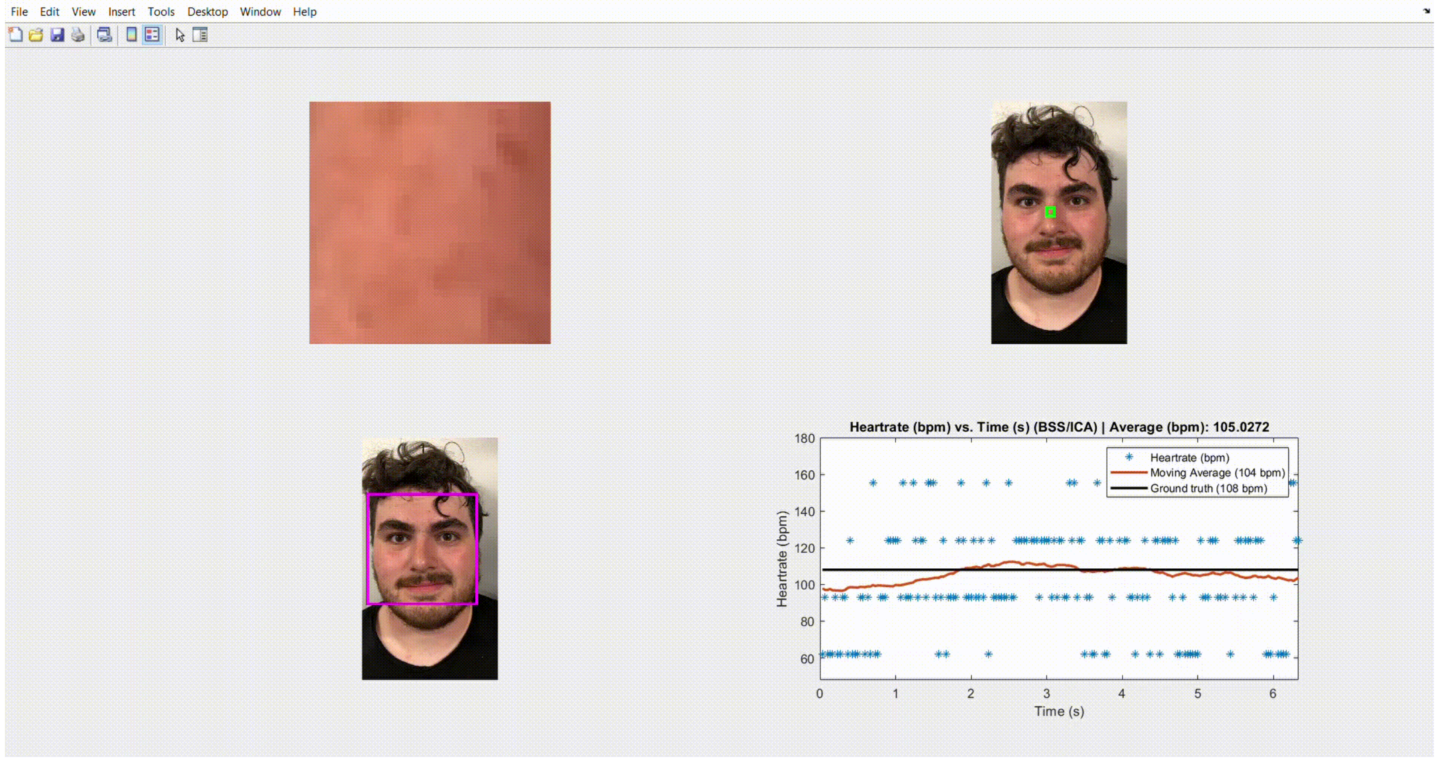
Detect Peaks
Calculate Heartrate

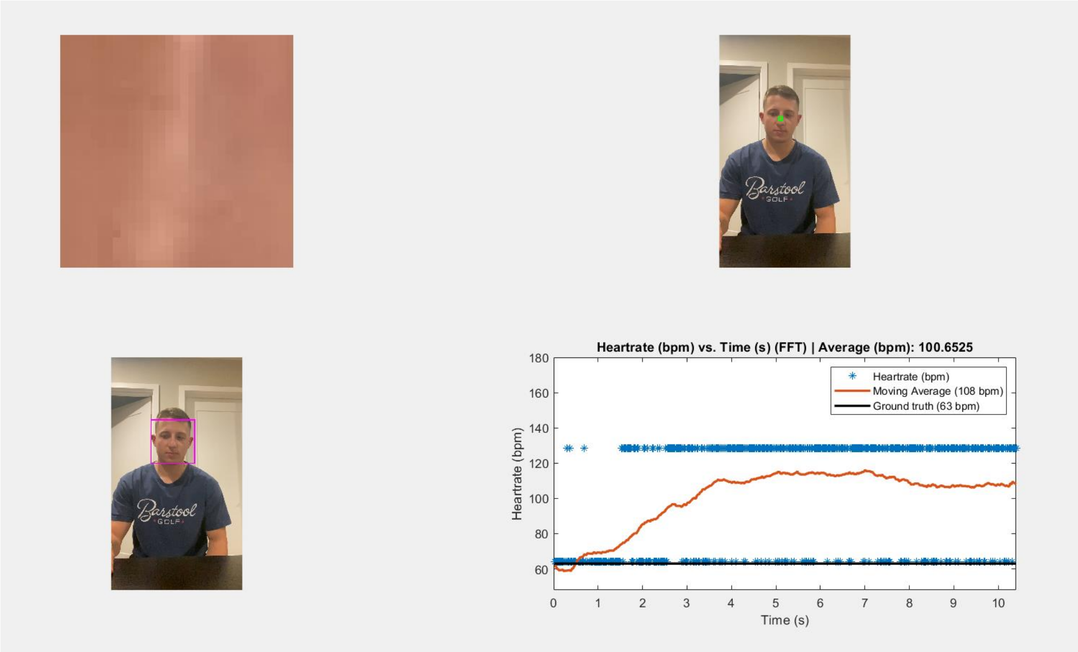
Current State

- This sample's heartrate had a ground truth of 108 BPM measured after working out.
- As the video goes on, the sample's heartrate decreases which is evident in the gif shown.
  - Moving average was helpful to see the change in heartrate over video sample.

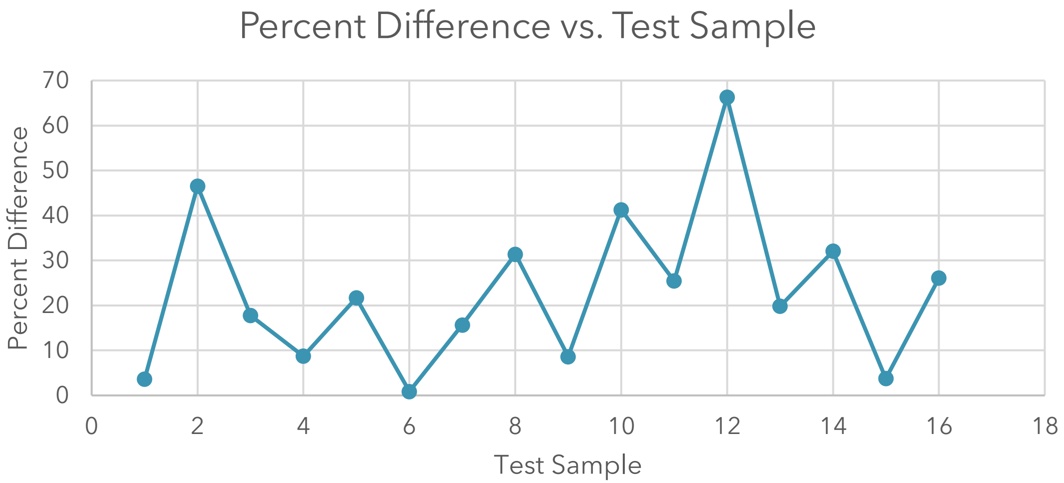


ROI Refinement and Highest Percent Error

- Analyzing the high percent errors, like this example, you can see that his nose is glossy/oily, probably leading to worse results.
- This test occurred shortly after a workout, leading to the extra gloss.
- Lighting, reflection, and data recording are a huge factor.

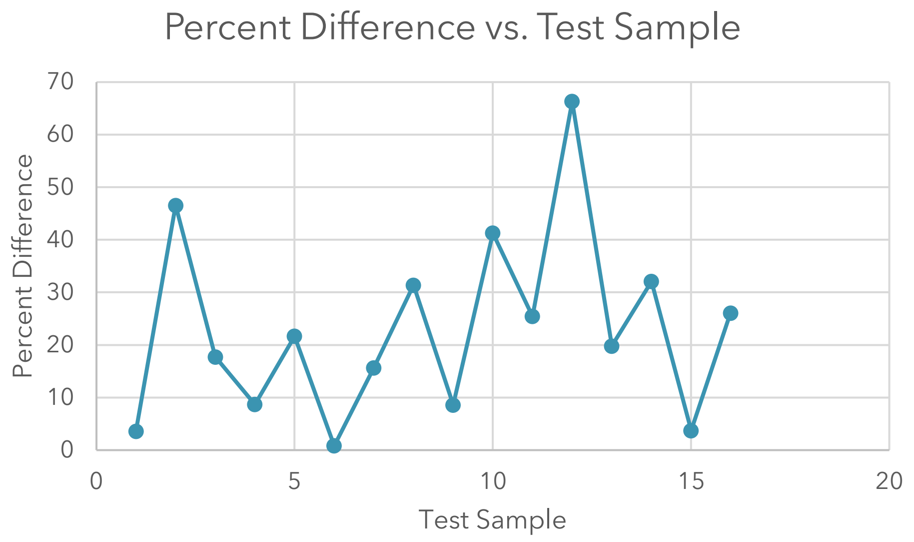


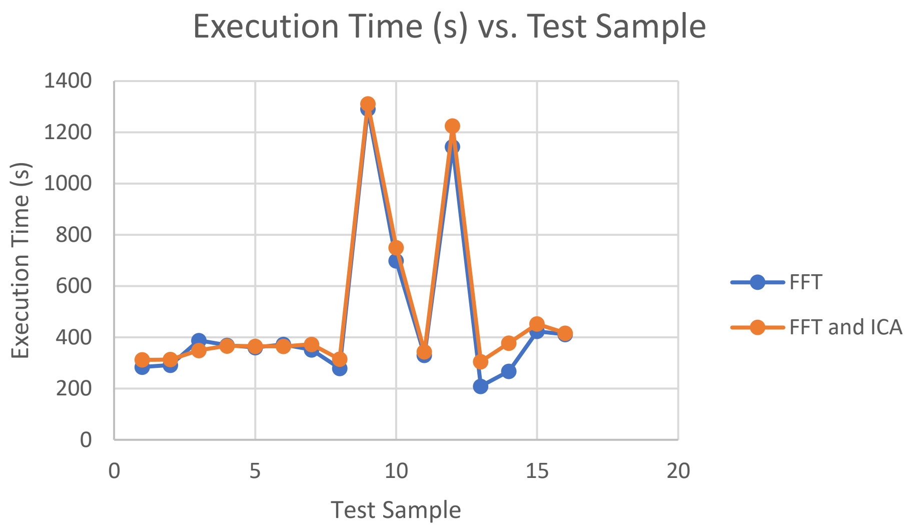
Success Rate



- 16 tests were conducted:
  - 13 different people
  - Before and after workouts
  - Different recording cameras
  - Different heart rate sensors (apple watch, Fingertip Pulse Oximeter, manual)

- Highest Percent Error was 66.3%
- Lowest Percent Error was 0.84%
- Average Percent Error was 23.1%

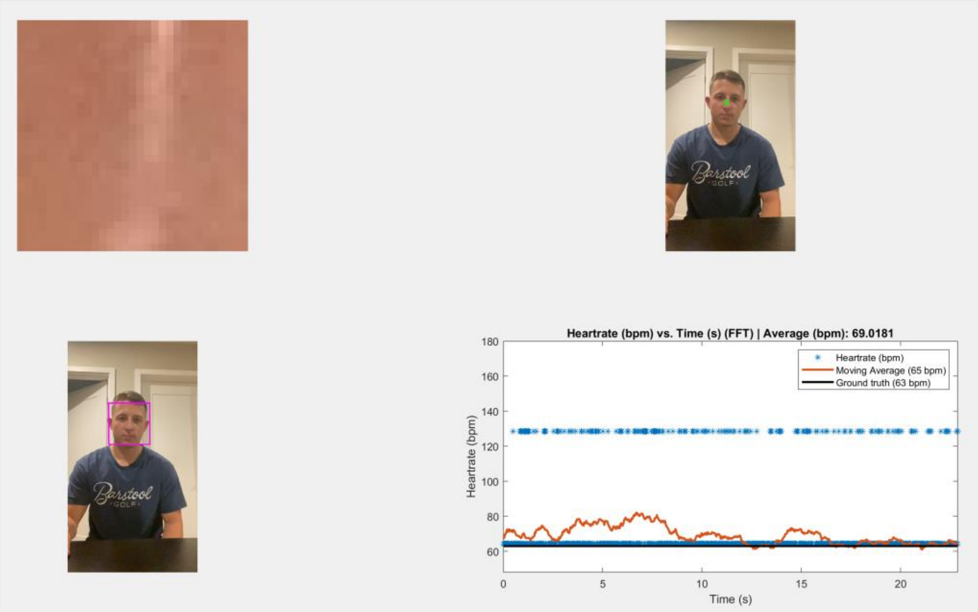




Test Number	Ground Truth	Average Heartrate	Percent Difference	Execution Time (FFT)	Execution Time (FFT, ICA)
1	72.00	74.60	3.61	284.60	312.50
2	108.00	57.71	46.56	291.97	313.79
3	108.00	127.17	17.75	387.98	349.06
4	79.00	72.13	8.69	368.95	366.79
5	108.00	84.60	21.67	360.45	365.79
6	76.00	76.64	0.85	372.07	364.91
7	108.00	124.91	15.66	351.73	373.09
8	88.00	60.40	31.37	279.46	314.70
9	85.00	92.31	8.60	1290.34	1311.11
10	79.00	46.39	41.27	698.22	750.44
11	104.00	77.54	25.45	330.63	343.61
12	63.00	104.77	66.30	1143.87	1223.94
13	88.00	70.57	19.81	209.46	305.43
14	68.00	89.81	32.08	267.88	377.71
15	85.00	88.23	3.73	423.87	452.58
16	130.00	100.03	26.09	411.62	416.73
Average Execution Time				**467.07**	**496.39**

Improving Algorithm for Failure Cases

- Slide 12’s test was rerun instead of extracting the red channel, the entire image was filtered to gray.
- Doing so resulted in a 58% decrease in error.
- How can we incorporate methods to further improve our failures?



Thank you!

Questions?

Resources

[1]U. Upadhyay, “Heartrate Detection using Camera,” Intel Software Innovators, Jun. 03, 2019. https://medium.com/intel-software-innovators/heartrate-detection-using-camera-d34b3289e272 (accessed Apr. 17, 2023).

[2] W. Verkruysse, L. O Svaasand, and J. S. Nelson, “Optica Publishing Group,” opg.optica.org, Dec. 12, 2008. https://opg.optica.org/oe/fulltext.cfm?uri=oe-16-26-21434&id=175396 (accessed Apr. 17, 2023).

[3] H.-Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. Freeman, “Eulerian video magnification for revealing subtle changes in the world,” ACM Transactions on Graphics, vol. 31, no. 4, pp. 1–8, Jul. 2012, doi: https://doi.org/10.1145/2185520.2335416.

[4] M.-Z. Poh, D. J. McDuff, and R. W. Picard, “Non-contact, automated cardiac pulse measurements using video imaging and blind source separation,” Optics Express, vol. 18, no. 10, p. 10762, May 2010, doi: https://doi.org/10.1364/oe.18.010762.

[5] Lee, Cho, Lee, and Whang, “Vision-Based Measurement of Heart Rate from Ballistocardiographic Head Movements Using Unsupervised Clustering,” Sensors, vol. 19, no. 15, p. 3263, Jul. 2019, doi: https://doi.org/10.3390/s19153263.

[6] A. Ahmed, A. El, and R. Elnakib, “Heart rate measurement using webcam Supervised by.” Accessed: Apr. 17, 2023. [Online]. Available: https://engfac.mans.edu.eg/images/files/engpdf/projects/comm/pro2/heart-rate-book.pdf