An Investigation into the Relationship between Inflection Area and Blood Pressure in Plethysmography Signals to Develop A Passive Blood Pressure Monitoring Device

Senior Design Project Report

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0.1 Introduction

0.1.1 Purpose of Project

The purpose of this report and the encompassing project is to design a photoplethysmography (PPG) signal processing algorithm that can be used to track the cardiovascular health of a patient. The algorithm is intended for use in consumer-grade health-monitoring watches which contain PPG sensors. An Empatica E4 smartwatch [1] was used to gather data to build this algorithm. The algorithm is, at the time of writing, intended for use specifically with the Empatica E4 wristwatch. The principles of this algorithm, however, can be extended to any health-monitoring watch that contains a PPG sensor. The general goal of the algorithm is to automatically gather key qualitative measures from the PPG signal, such as cardiac output, vessel elasticity, and blood pressure, as well as to use these measures to make prediagnostic decisions regarding cardiovascular health of the wearer.

Since wearable technology is becoming increasingly common for the average consumer [2], creating new algorithms that operate upon biometrics gathered by these watches impacts a large amount of people. A universal user need with these health-monitoring wearables is for the continuous monitoring of cardiovascular health. While the common health-monitoring wristwatch can access heart rate (HR) and heart rate variability (HRV), current health-monitoring wearables do not gather secondary cardiovascular metrics such as blood pressure or vessel elasticity. Secondary health monitor metrics could be used to make a user aware of health issues that should be monitored, such as poor peripheral perfusion or pre-hypertensive blood pressure. Since clinical methods represent more accurate versions of health monitor metrics, these calculated metrics should not be used to make a direct diagnosis. An algorithm that calculates these secondary metrics does so by analyzing primary PPG measurements and then performing calculations on them to arrive at more specific biometrics. One such secondary metric, the inflection point area (IPA) as well as its relationship to blood pressure will be examined [3] in this report. The following section provides background on key PPG fundamentals including hardware, signal metrics, and IPA.

0.1.2 PPG Signal Overview

PPG signals are recorded by shining a light source on the surface of thin skin near a blood vessel and measuring the scattering of light that occurs. The light is scattered due to the pulsatile nature of blood within the vessel and the quantity of scattering can be used to infer information about a patient's cardiovascular system. PPG signals are taken in medical environments via a device attached to a patient's fingertip. This allows for noninvasive measurement of cardiovascular health. PPGs, however, can also be measured at the wrist using a similarly noninvasive method. The PPG, when measured at this location, is sometimes referred to as the blood volume pulse (BVP). This measurement method has found footing in modern wearables in the form of smartwatches that record biometric data. The PPG signal has seen an increase in prevalence since its integration into wearable technology and its analysis is becoming increasingly relevant both clinically and commercially [2]. A number of secondary biological metrics are said to be estimable from a PPG signal, including blood pressure, vascular distensibility, and peripheral resistance [4]. These metrics stem from simpler signal calculations, such as signal width, area, and height. Although these metrics can typically be analyzed easily by

professional physicians, an automatic algorithm that performs this analysis could bring clinical cardiovascular health monitoring to a larger audience. The noninvasive measurement methods of the PPG signal compounded with its relation to overall cardiovascular system health makes it a prime target for passive analysis algorithms.

A generic PPG signal can be seen below in fig. 1. Although the Y axis of the signal technically refers to the scattering of light, a PPG plot can generally be thought of as blood flow volume over time. This is why a PPG signal is also commonly referred to as a blood volume pulse signal. The PPG signal itself can be separated into two distinct sections. The rising section is referred to as the anacrotic phase, and the falling section is referred to as the catacrotic phase. The anacrotic phase is related to systole, where the heart muscle contracts and outputs blood. The catacrotic phase is related to diastole, where the heart relaxes and fills with blood, preparing for the next systole. A visible "dicrotic notch" is present on healthy patients with compliant arteries and occurs during the diastolic duration of a BVP waveform. The dicrotic notch is caused by the closing of the aortic valve after systole, which leads to a transient increase in arterial pressure, forming a peak. The location of the dicrotic notch in a PPG waveform has been shown to change over time for patients. The height of the dicrotic notch is also typically dampened with increased age [5]. One important clinical consideration for the PPG waveform is the possibility of no peak occurring at all and instead a simple bump, as seen in fig. 1 occurring. This is known as an "incisura" and is a critical component of the BVP/PPG signal.

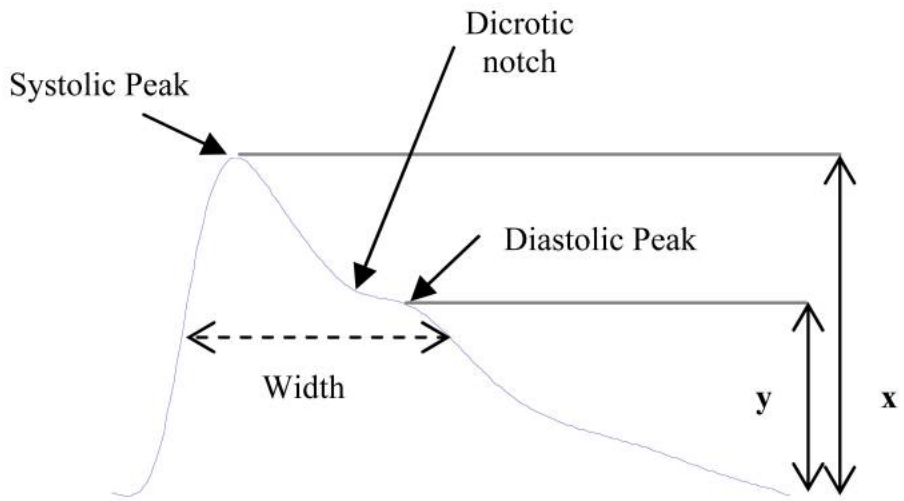


Figure 1: A normal PPG waveform taken at the fingertip [4].

A number of metrics gained from the PPG signal have proven to be clinically relevant. For a detailed analysis on many useful metrics that can be found from the PPG signal and the corresponding papers that expand further upon these metrics, *On the Analysis of Fingertip Photoplethysmogram Signals* is an excellent source [4]. In summary, systolic peak amplitude, dicrotic notch, pulse width, half-amplitude pulse width, and diastolic peak are each important aspects of a PPG signal that can be manipulated to yield clinically relevant results. Pertaining to this report is a specific PPG signal metric that has found clinical relevance in measuring vascular distensibility and blood pressure, the inflection point area ratio (IPA).

The IPA (fig. 2) is the relationship between the area underneath the PPG curve after the dicrotic notch and the area under the PPG curve before the dicrotic notch for a given pulse. Mathematically, this relationship can be seen in (eq. 3). This ratio is related to age, which is correlated with total peripheral resistance and vascular distensibility [5][6].

$$A1 = \int_{a}^{notch} PPG(t)dt \tag{1}$$

$$A2 = \int_{notch}^{b} PPG(t)dt \tag{2}$$

$$IPA = \frac{A2}{A1} \tag{3}$$

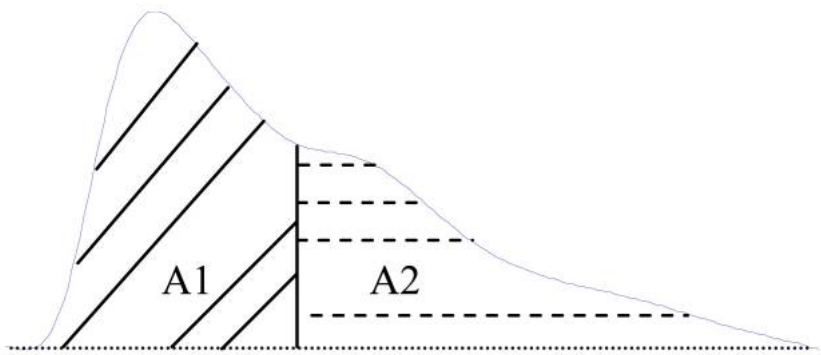


Figure 2: Inflection point area ratio

0.1.3 PPG Analysis Algorithm Overview

Since the IPA ratio was determined to have the highest potential for an overall cardiovascular health assessment metric from the PPG signal for the purposes of this report, an algorithm was created to extract the IPA ratio for a given PPG signal. The PPG signal would be retrieved from a health-monitoring smartwatch. The overall calculation algorithm is pictured in figure 3. The basic structure of the diagram indicates steps for determining metrics of a PPG signal to calculate IPA. The diastolic trough, systolic peak, and dicrotic notch locations are all necessary considerations to determine IPA for a PPG signal. Any errors in the generation of these critical points for a waveform are grounds for exclusion from the IPA calculation. Since IPA calculation is meant to take the place of procedures or measurements that currently take several minutes or more to perform, the exclusion of individual PPG waveforms is allowable in favor of calculating an accurate IPA.

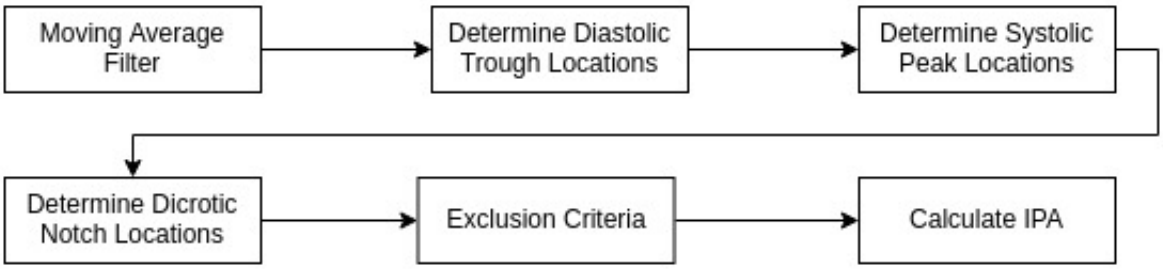


Figure 3: Block diagram for basic IPA calculation.

Once calculated, the purpose of gathering the IPA ratio in this algorithm is to determine effects or correlations with a patient's simultaneously gathered blood pressure. If correlation is observed between the two metrics, then a case could be made for the usefulness of the IPA ratio as a clinically relevant health metric obtainable via health-monitoring smartwatches.

0.2 Methods and Results

0.2.1 Data Gathering

In order to process a PPG/BVP signal and test the efficacy of an algorithm for determining IPA ratio, a significant amount of human BVP data was required. A standard protocol was drafted to help guide the individual acting as researcher to collect controlled data. Parameters documented by the researcher for a given test subject included sex, age, height, weight, smoking status, and general cardiac health. BVP data was gathered from each subject using an Empatica E4 Smartwatch [1] while simultaneously gathering blood pressure using an Omron blood pressure cuff [7]. In order to most accurately assess BVP for a subject, the smartwatch was fit snugly to each subject's wrist for the measurement period. The comfort of fit was determined to be a relevant factor because of the necessity of long periods of wear for passive data collection with the Empatica smartwatch in clinic. Once the watch was suited comfortably on the arm, the blood presure cuff was fitted with the air hose leading down the brachial artery, 1-2 cm from the inside of the elbow. The measurement process is shown below in table 1.

Time of Action (sec)	Researcher Action
Before start	Record patient metrics
Before start	Apply E4 Watch and BP Cuff
0	Start Empatica recording
30	Start first BP measurement
109	Start second BP measurement
188	Start third BP measurement
218	End test

Table 1: Data gathering protocol visual for researcher action corresponding to time for a single session.

After affixing both devices, the subject was instructed to keep their back supported, arms resting on the table in front of them with both palms facing down, and feet flat on the ground. These instructions were based on those outlined in the Omron cuff instruction manual and specified to ensure an accurate blood pressure measurement [7]. Due to significant previously measured motion artifact noise in the Empatica smartwatch BVP signal, subjects were instructed to limit movement of their right arm as much as possible.

28 healthy individuals were subjected to the data gathering protocol (n=28). The patient population was limited to students attending Denmark Technical University. As a result, the age range of patients varied from 21 to 30 years of age. Variation in height and weight were reasonably representative of the general population [8].

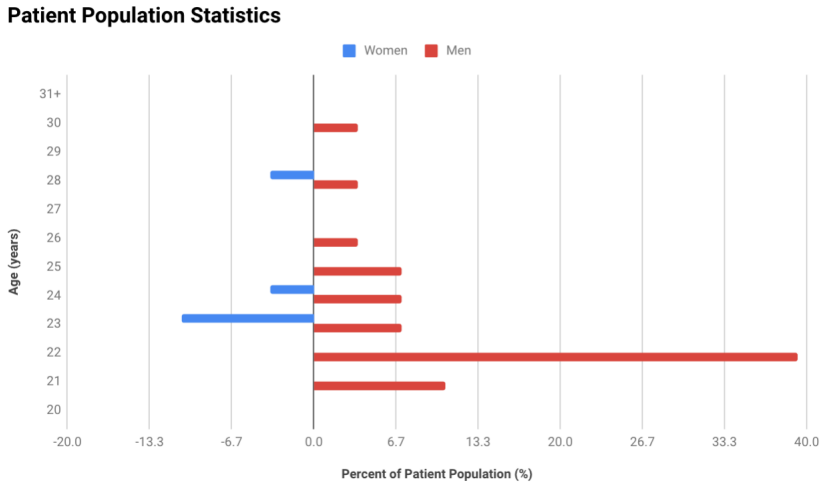


Figure 4: Visual representation of patient population based on sex and age.

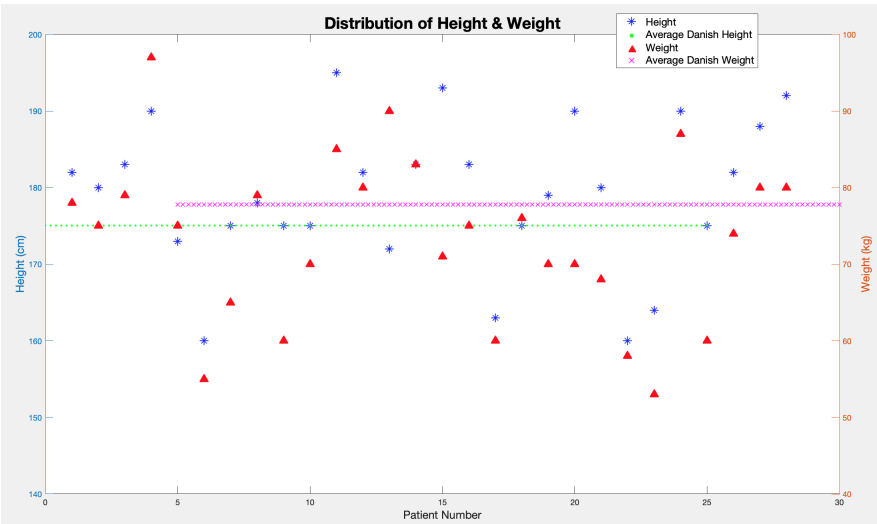


Figure 5: Distribution of patient population's Height and Weight compared with average Danish metrics [8].

0.2.2 Data Retrieval and Storage

Retrieval Methods

In order to retrieve and analyze data gathered with the Empatica E4 smartwach, it was necessary to create an interface between the site's data storage system and any programs created by researchers for analyzing patient Empatica BVP data. Empatica provides a user data portal on their website that allows users to download CSV (comma separated value) files containing their biometric data (BVP, heartrate, accelerometer data, etc). The CSV files are stored in a zip file for each session gathered by the Empatica E4 smartwatch. A session is defined as the entire duration from the moment a watch syncs with a user's phone via Bluetooth to the moment that the user chooses to stop data tracking via the Empatica app. Once the phone which was synced with the Empatica device during collection is connected to the internet it automatically sends all collected user session data to Empatica's database, where it can be downloaded locally by the user from the website's data portal.

Empatica's website utilizes a basic watch session ID number to allow navigation of a user's watch sessions. This site navigation protocol presented a clear opportunity for creating a research data pipeline. A Python script was created (fetch_every_session.py) to scrape the Empatica website and download all sessions logged by a given user so that they could be analyzed via MATLAB scripts used in the following sections of this report. Upon running the web-scraping script, an authenticated request to Empatica's storage database is made, requesting any sessions that are present on the site but missing from the researcher's computer. Zip files are then downloaded for each watch session and saved locally to the researcher's computer before being extracted into timestamped folders. Fig. 6 shows a block diagram for the function of the script.

Data Storage and Manipulation

The web-scraping script was set up to run every 20 minutes via a crontab BASH script on a researcher-created Ubuntu DigitalOcean server. This allowed for a constantly updated pool of all Empatica sessions for a given user readily available for analysis and signal processing. The result of running the script is a set of timestamped folders, with one folder for each Empatica session. This folder structure is shown in the second directory row of fig. 7. Once N total sessions have been downloaded to the server for a patient, a second Python script(create_subset.py) can be run by a researcher to subset these timestamped data sessions. The goal of this second script is to subset any range of patient Empatica watch sessions into a smaller data subset ready for analysis via MATLAB or Python scripts. This script's output takes the form of a folder specific to each of a set of M total patients used in the study for this report. Essentially the create_subset.py script is run and a researcher titles its ouptut based on the patient whose data is contained in the subset. The subsetting script also copies a user-specified list of scripts into each subset watch session directory to allow for quick analysis and feature extraction via MATLAB, Python, or any other user-created script. The bottom row of fig. 7 shows the files contained in each session for a given patient allowing for analysis. For the signal processing performed in this paper, a single MATLAB script was ultimately used for analysis of BVP signals. This meant the most minimal option for analyis saw a MATLAB script copied into every patient watch session directory. However, any of the scripts contained in the Project Root directory may be copied into every session for a given patient watch session.

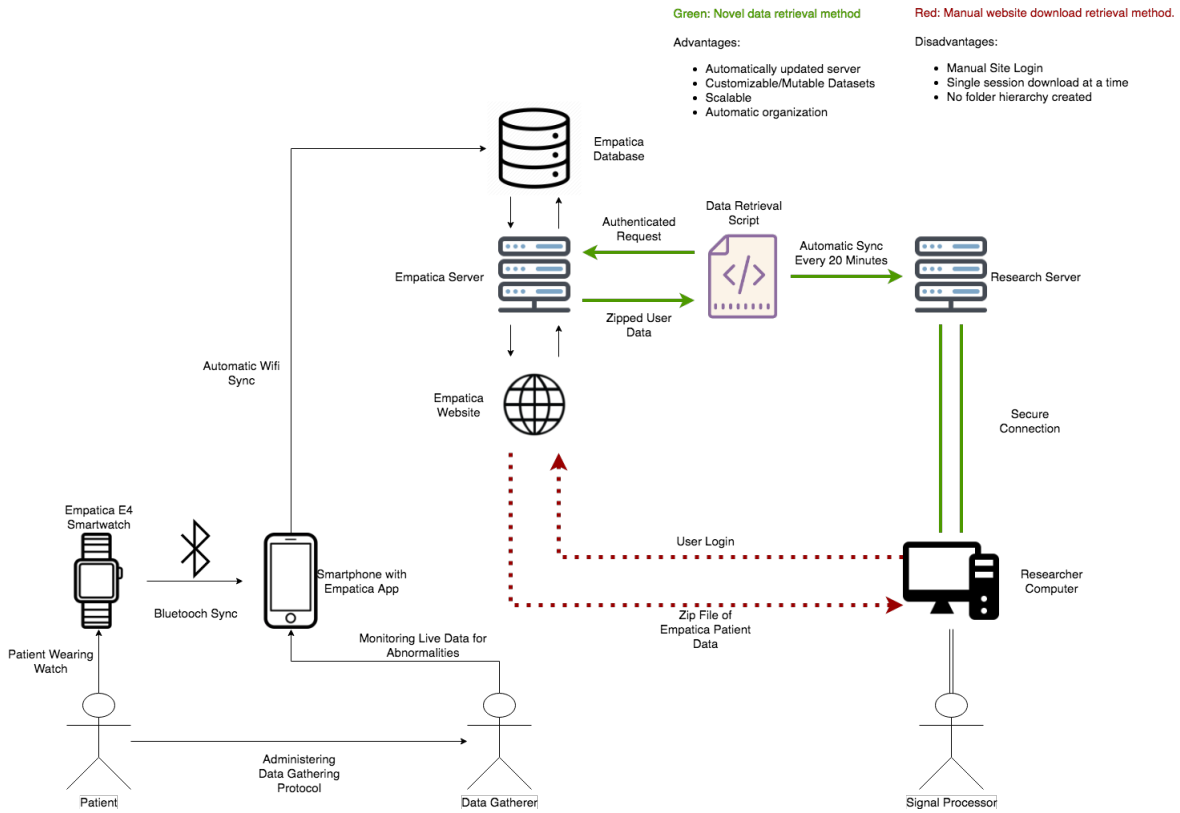


Figure 6: Map of data collection pipeline.

Once files were secured onto the research server and subsetted for easy data analysis, they could be manipulated as necessary to allow for processing of BVP signals. Aggregate data analysis could be performed for a range of patients as desired, single patients' BVP signals could be analyzed, or any of the other Empatica signals analyzed which are measured concurrently with BVP in the E4 smartwatch. Typical workflow for BVP signal analysis saw file transfer via the Unix scp command in keeping with secure shell connection methods established for connecting to the server. Once retrieved with their appropriate analysis scripts a range of patient BVP signals could easily be processed and analyzed.

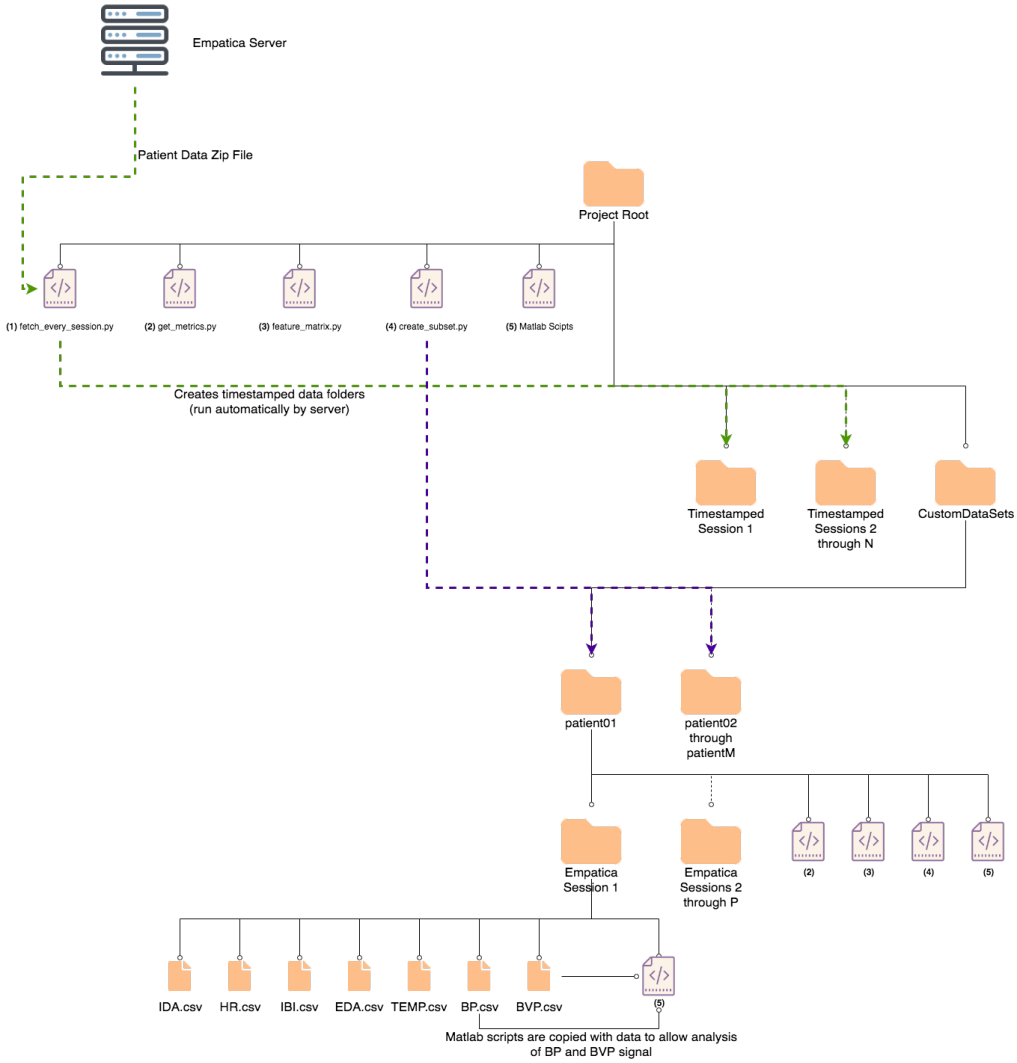
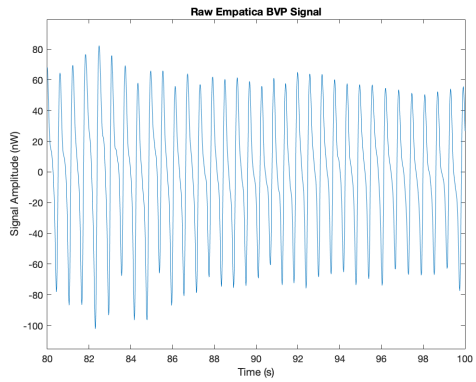


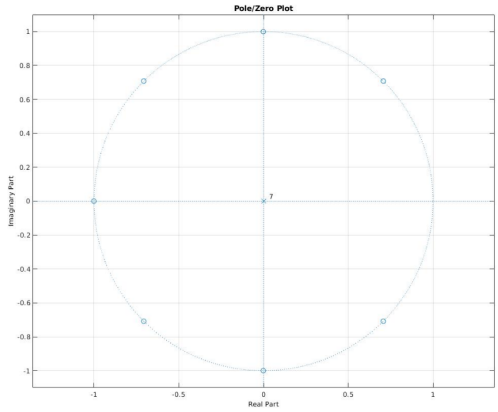
Figure 7: Folder hierarchy of research server created via data pipeline.

0.2.3 Moving Average Filter

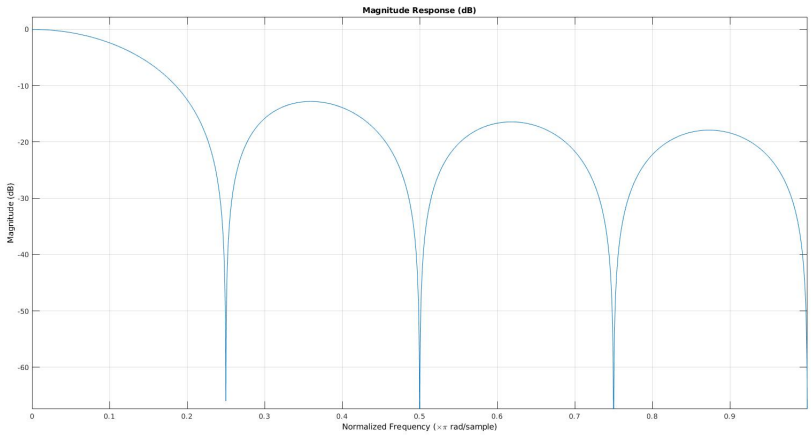
A raw Empatica BVP signal can be seen in fig. 8a. For the purpose of removing any small peaks or troughs that would create critical point false positives in a BVP signal, a moving average filter with a window length of 8 samples was applied to the signal. The sampling frequency of the Empatica E4 watch's BVP signal is 64 Hz, and an 8 sample window length was determined empirically to produce BVP waveforms that contained the fewest false positive critical points for a given signal while still preserving the shape of the BVP signal. A plot of the poles and zeros of this moving average filter can be seen in fig. 8b along with the magnitude response in fig. 8c.



(a) Raw Empatica Smartwatch BVP signal.



(b) Pole-zero plot for moving average filter used on Empatica BVP signal.



(c) Magnitude response of moving average filter used on Empatica BVP signal.

Figure 8: Moving average filter

0.2.4 Critical PPG Points: Diastolic Troughs

The first necessary BVP signal critical point for IPA calculation is the location of each diastolic trough within the signal. The diastolic troughs of a PPG signal can then be used to calculate pulse interval. The pulse interval is the distance between consecutive diastolic troughs within a PPG signal and is used frequently in health-monitoring smartwatches to determine heart rate. Knowing the location of every diastolic trough within a PPG signal allows for the signal to be split from one large BVP signal into a series of individual BVP waveforms like the two shown in fig. 1. This allows for easier waveform morphology analysis and determination of waveform boundaries. Once diastolic troughs have been determined, the algorithm iterates through each waveform, looking for other critical points.

The algorithm created in this report to calculate the location of diastolic troughs utilized a minimum peak height threshold specific to each BVP signal. The threshold below which a diastolic trough could be detected was determined to be an an amplitude offset of 8 nW below the mean of a given BVP signal, shown in fig. 4. The threshold being based on an individual signal's mean allows for some adaptability of the threshold between different signals. This thesholding method was chosen since user BVP data was

shown to have a large amount of diastolic trough height variability between patients.

$$Threshold = mean(PPG(t)) - 8 \tag{4}$$

MATLAB's *findpeaks* function was used as a sweeping peak finding algorithm for an inverted copy of the BVP signal. The function was used with no exclusion parameters other than minimum peak height based on the previous threshold, since exclusion criteria will be specifically analyzed before IPA calculation. False positives at this stage of the algorithm are not troubling as exclusion criteria for the IPA applied later in the algorithm are meant to take care of any false positive diastolic troughs that might be detected in the signal. Once diastolic troughs have been found for the signal, further analysis is performed within each waveform bounded by two consecutive diastolic troughs. This means that, for the following sections describing other critical points in the BVP signal, methods will be described within the scope of a single BVP waveform.

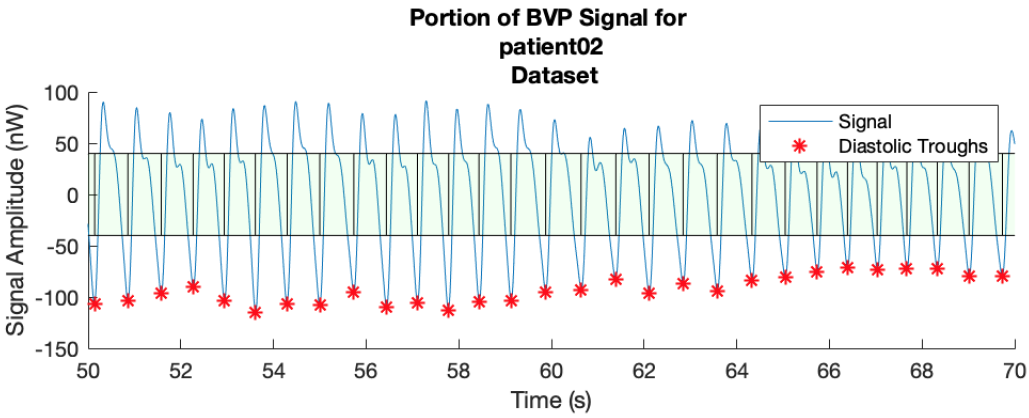


Figure 9: Detected diastolic troughs for Empatica BVP signal region.

0.2.5 Critical PPG Points: Systolic Peaks

The systolic peak within a PPG waveform is another useful signal component for profiling cardiovascular behavior. The systolic peak is also necessary for finding both the dicrotic notch within a waveform and calculating the waveform's IPA ratio. For this algorithm, systolic peaks for patient BVP waveforms were determined within a waveform of the BVP signal in a manner similar to the one used to find diastolic troughs over the whole signal range. MATLAB's *findpeaks* function was used with no exclusion criteria to allow for every peak within a waveform to be initially included. From this point further scrutiny could be given to each peak to detemine if it did in fact represent a systolic peak.

If the moving average filter has been applied adequately to a signal there should, at this stage, be at most two peaks within a BVP waveform. The first peak would represent the systolic peak of the waveform and the second would represent the diastolic peak. However, in many instances and especially with age, the diastolic peak is not a true "cresting" peak of the signal, but rather a bump in the signal that represents a peak of the signal's first derivative. This incisura behavior can be seen in the portion of the BVP signal shown in fig. 9 and fig. 10. In this instance only one peak is detected within the waveform and the dicrotic notch location must be determined with slightly more care. In both of these cases, however, the first peak that occurs within a waveform represents the systolic peak of the waveform. Fig. 10 shows the results of the algorithm

when attempting to locate systolic peaks of the Empatica BVP signal. Once the systolic peak location is determined within a waveform, it is possible to determine the location of the dicrotic notch for that waveform.

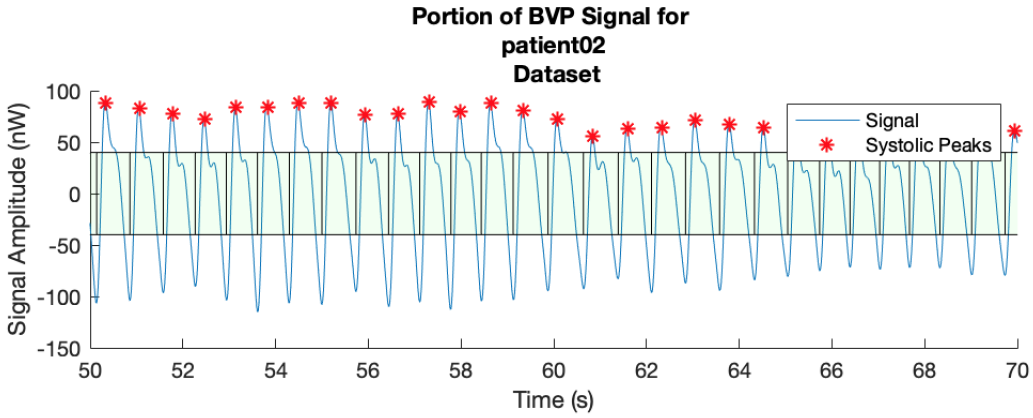


Figure 10: Detected systolic peaks for Empatica BVP signal region.

0.2.6 Critical PPG Points: Dicrotic Notches

Due to the possibility of a BVP waveform having either one or two peaks, there are two cases that must be considered when searching for a dicrotic notch within the waveform. 1) One waveform peak exists and the dicrotic notch is an incisura. 2) Two waveform peaks exist and the dicrotic notch is nested between the first and second peak of the waveform.

In order to create an algorithm that can catch the dicrotic notch for both of these cases, systolic peak location must be known for a waveform. Since a dicrotic notch occurs at a peak of the first derivative of a BVP waveform and only after a systolic peak has occurred, the algorithm takes the first peak of the BVP waveform's first derivative that occurs after the location of the determined systolic peak and determines it to be a dicrotic notch. In other words, a dicrotic notch is determined as the first location after the waveform's systolic peak where the second derivative of a BVP waveform crosses zero from negative to positive. Using the second derivative allows for determination of dicrotic notches both as incisuras such as those shown in fig. 11 and peaks such as those shown in fig. 12. Fig. 13 shows the derivative plots for an Empatica BVP signal.

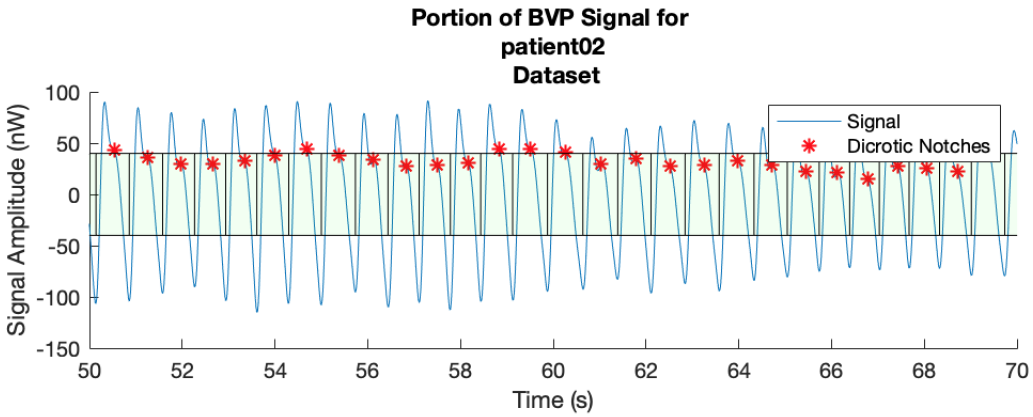


Figure 11: Detected incisura dicrotic notches for Empatica BVP signal region.

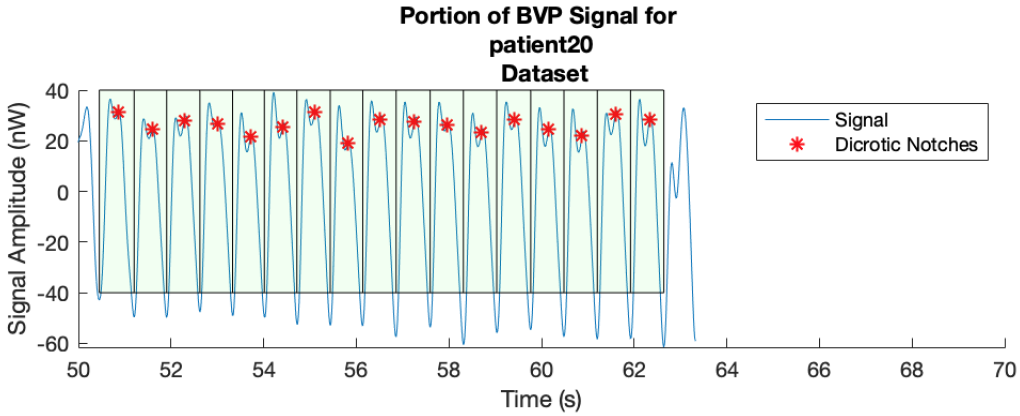


Figure 12: Detected peaking dicrotic notches for Empatica BVP signal region.

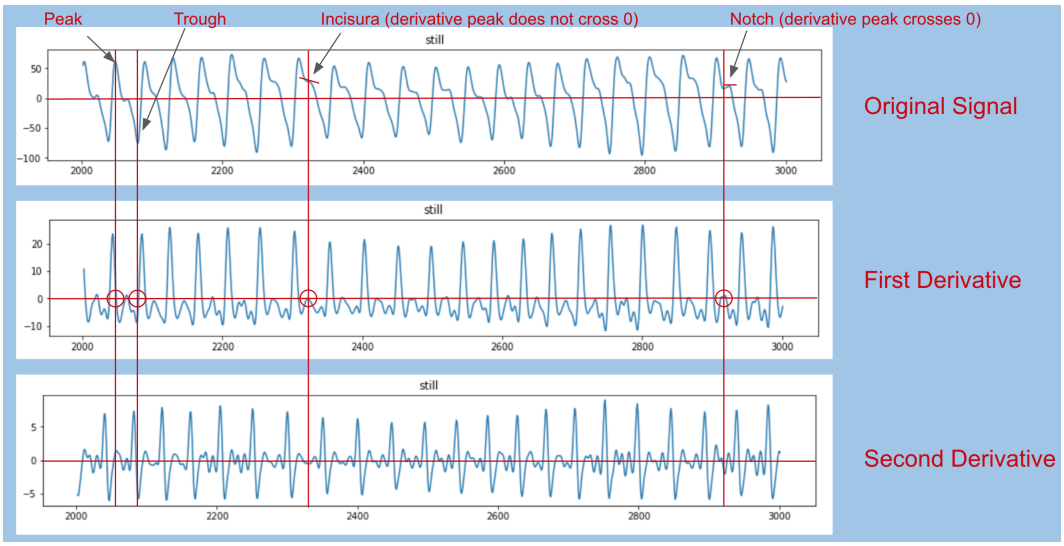


Figure 13: Plot of Empatica smartwatch BVP signal and its first and second derivative showing critical point evaluation locations. X axis is sample number and Y axis is signal amplitude in nW for the first plot.

0.2.7 Exclusion Criteria

Since the algorithm up to this point has detected diastolic troughs, systolic peaks, and dicrotic notches, there remains one final exclusionary step before the IPA can be calculated for a patient. Exclusion criteria applied before calculating IPA are meant to catch any final errors that may have resulted from the detection of critical points for the signal. These critical point errors that would be grounds for excluding a waveform from IPA ratio calculation can take several forms.

- Late and low dicrotic notch detection causing incorrect low IPA calculation
- Early and high dicrotic notch detection causing incorrect high IPA calculation
- Moving average filter not removing false waveform peaks
- BVP signal containing more than two valid peaks
- Watch amplifier errors caused by motion artifacts from the patient
- Waveform length being too short/long i.e., failure of diastolic trough detection

Filtering each waveform against these exclusion criteria can allow for an IPA calculation that is more robust than the algorithms that detect its preliminary components. This is why it is safe to have several false positives for the previously found critical points. If a waveform fails to meet these exclusion criteria it should not undergo IPA ratio calculation. This allows the algorithm to only capture those BVP waveforms that are clinically relevant for IPA calculation and gather a more accurate IPA profile over time to assess patient cardiovascular health. Fig. 14 shows the exclusion criteria in effect for a region of a patient BVP signal. The exclusion criteria are able to filter out a given waveform based on its morphology as well as its systolic peak height compared with neighboring waveforms. In essence, the exclusion criteria provide a method for critical examination of a waveform before calculating its IPA ratio.

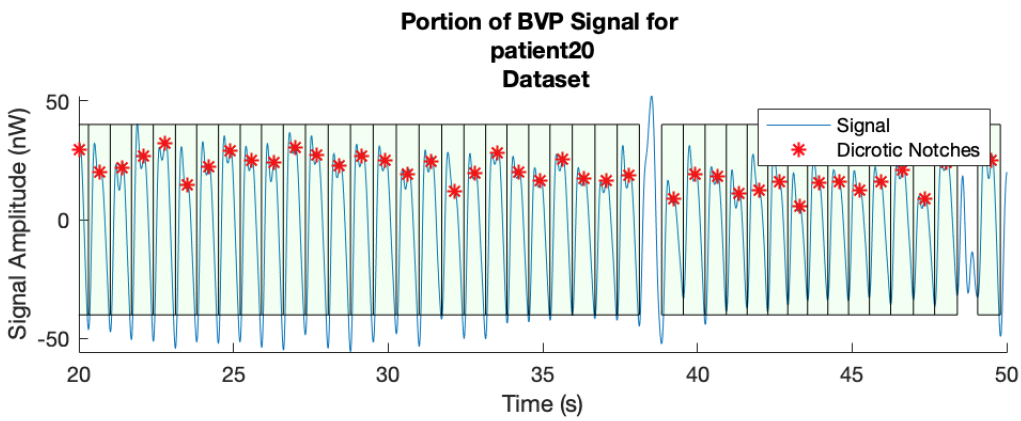


Figure 14: Exclusion criteria removing an undesirable waveform from calculation of IPA.

0.2.8 IPA Calculation

Once a BVP waveform has been cleared as relevant through the use of exclusion criteria, the IPA for that waveform can be calculated. Using eq. 3, the systolic area of the waveform and diastolic area of the waveform can be compared to yield the IPA ratio. This can be repeated through every waveform of a signal using the exclusion criteria to gather a clinically relevant profile over time for each patient. Fig. 15 shows the signal from fig. 14 along with its corresponding IPA ratio. Note the interpolation instead of IPA calculation at the excluded waveforms. Fig. 16 shows another IPA calculation for a patient with a higher IPA indicating a larger portion of the PPG signal being comprised of diastolic, or relaxing, cardiovascular activity.

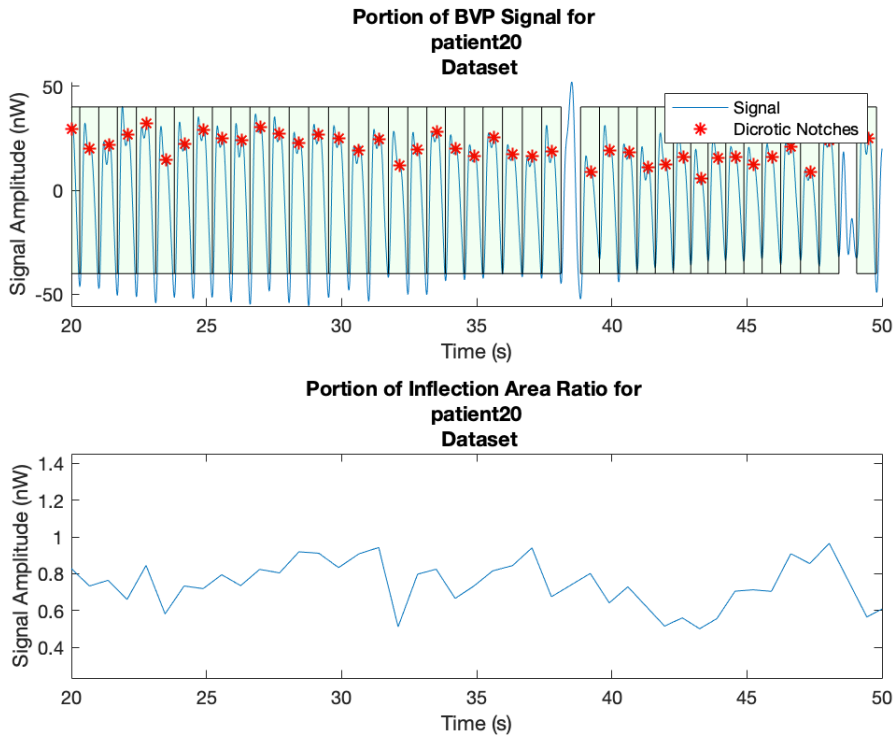


Figure 15: Calculation of IPA Ratio for BVP signal region.

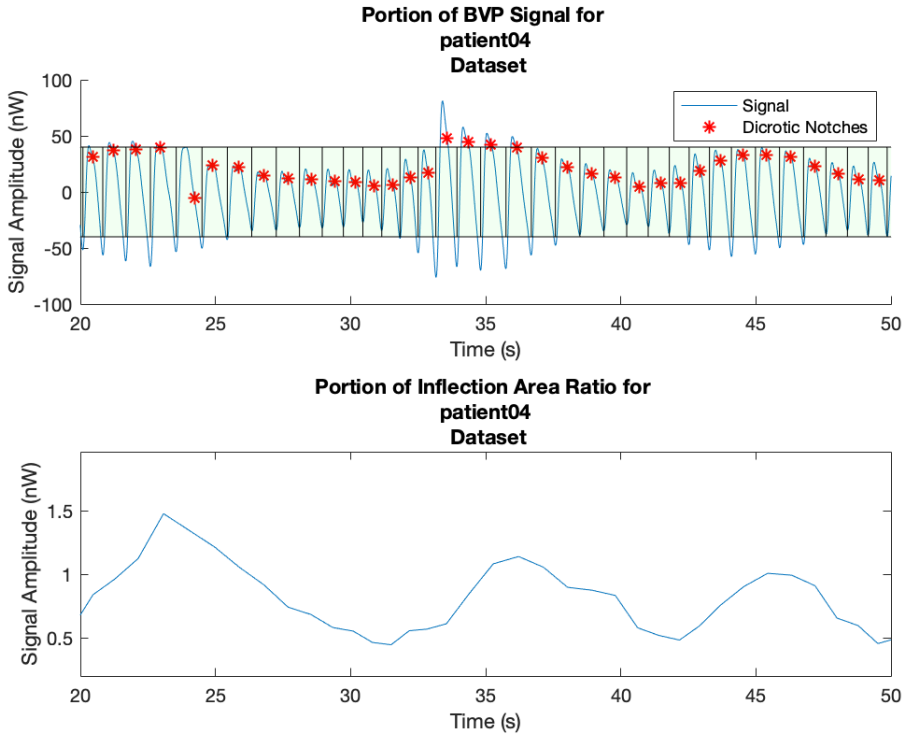


Figure 16: Patient with higher IPA ratio due to higher diastolic BVP waveform area.

0.2.9 Blood Pressure Correlation

While gathering BVP data for each patient, a simultaneous blood pressure measurement was performed. The goal of this simultaneous measurement was to attempt to assess the correlation between IPA ratio (a calculated secondary biometric signal) and blood pressure (a primary measured biometric signal). An analysis of each patient (n=26) was performed in order to determine correlation between IPA ratio and systolic blood pressure. Fig. 17 shows a plot of the IPA ratio's relation to systolic blood pressure. Note that the plot contains every systolic blood pressure measurement for each patient so the total number of data points is larger than the actual number of patients undergoing testing.

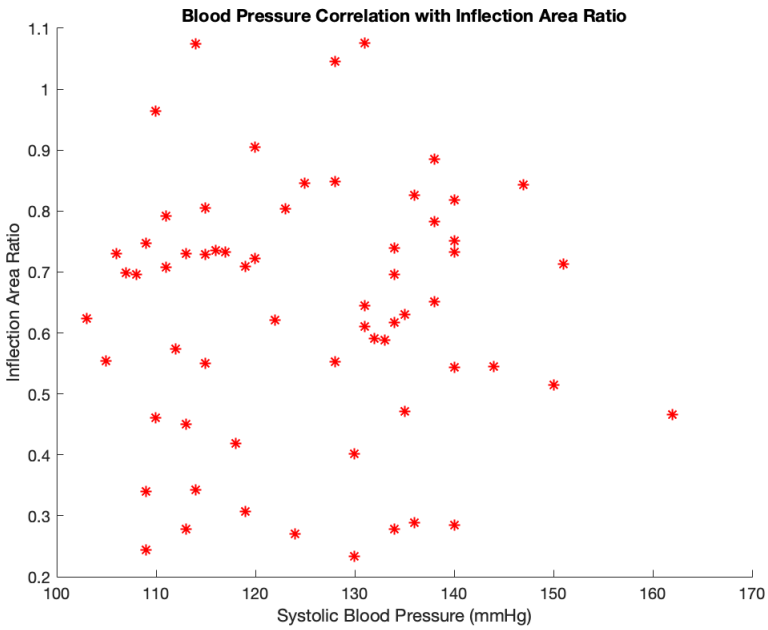


Figure 17: Relationship between IPA ratio and systolic blood pressure (n=26).

Due to a low range of participant age variability, analyzed in fig. 17, a separate analysis for blood pressure correlation was performed for a patient of age 70. Fig. 18 shows a similar plot representing the systolic blood pressure correlation with IPA ratio for this patient. A near complete lack of correlation between systolic blood pressure for the patient and their corresponding IPA ratio profile can be seen ($r^2 < 0.05$).

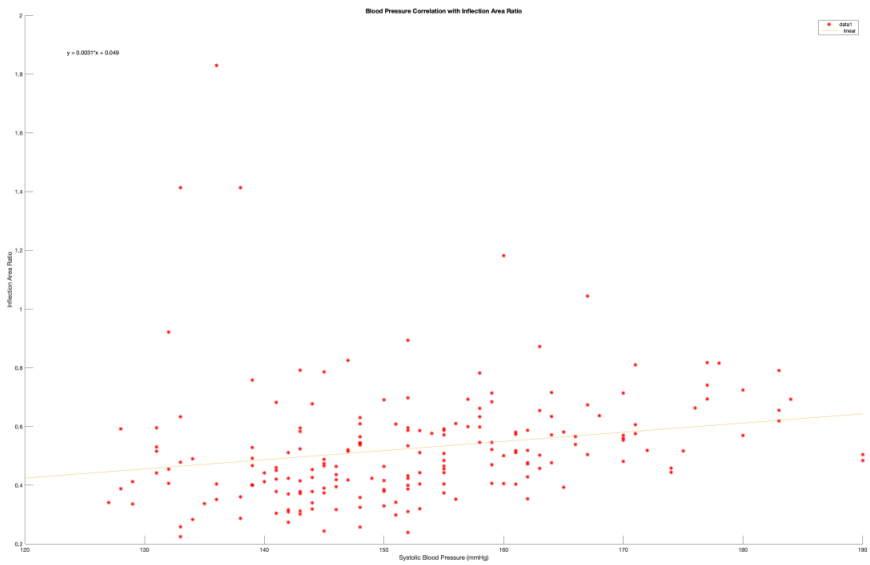


Figure 18: IPA ratio correlation with systolic blood pressure for an older patient (n=1). Note that due to excessive computational time for this individual dataset, the figure was not recompiled despite having slightly smaller text, but is labelled exactly the same as in fig. 17.

0.2.10 Statistical Analysis

From a simple analysis of all patients' systolic blood pressures related to IPA ratio, a strong lack of correlation was observed. One possible reason for this was posited to be from the volatility of the IPA ratio calculation compared with the highly steady blood pressure measurement data point. In an effort to reduce error due to this volatility, the median of each patient's set of systolic blood pressures was calculated along with the median of every corresponding IPA ratio. Fig. 19 shows the results of this median-based correlation. This figure demonstrates similar results to those shown in fig. 17, namely a near complete lack of correlation between the two metrics ($r^2 < 0.05$).

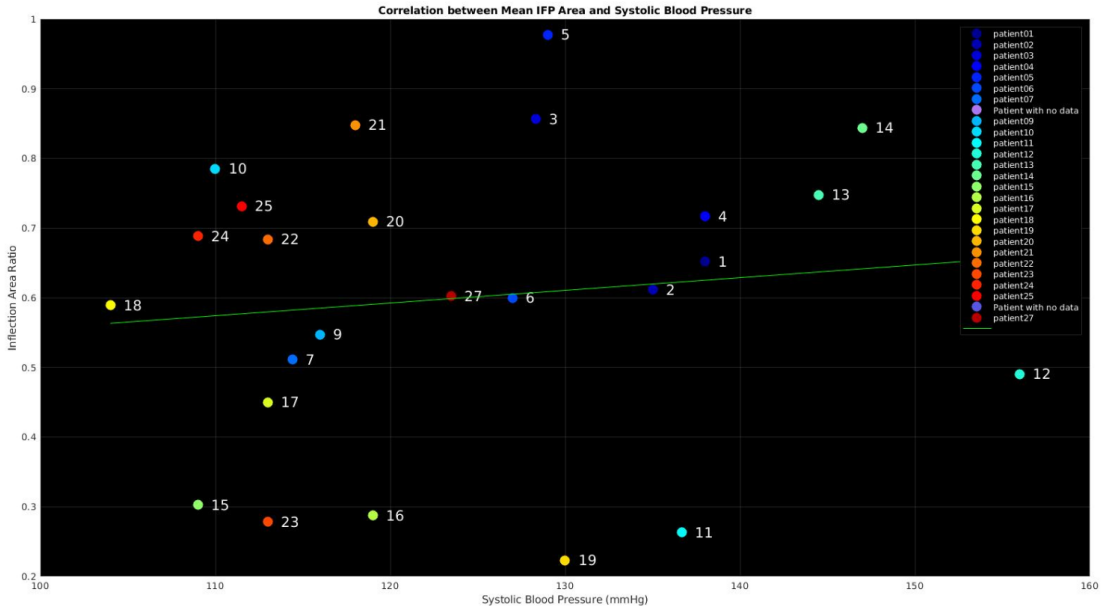
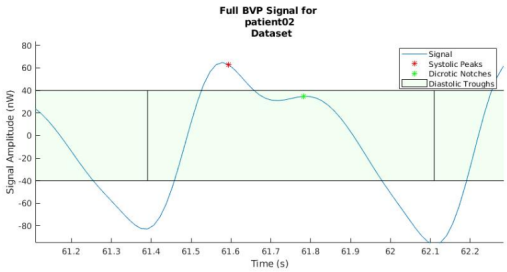


Figure 19: Median value for systolic blood pressure and IPA ratio for each patient.

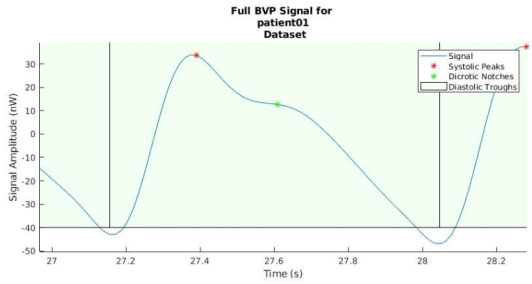
0.3 Discussion

0.3.1 Algorithm Faults

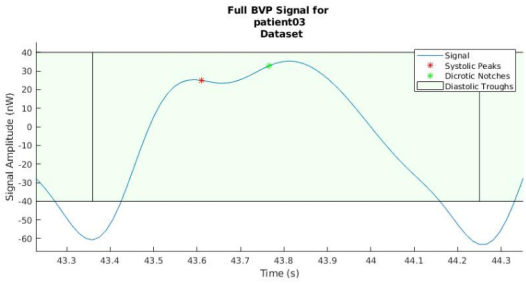
A number of waveform morphologies can cause the algorithm to report abnormally low or high IPAs. Different waveforms types have broadly been categorized into six types (fig. 20).



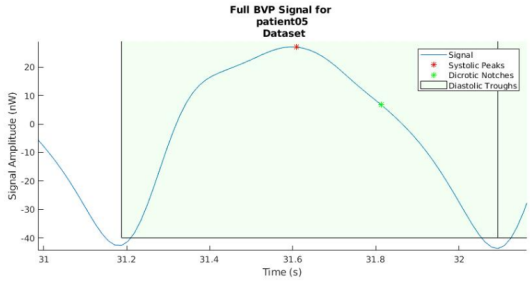
(a) A traditional waveform with a dicrotic peak, type 1, IPA = 0.60



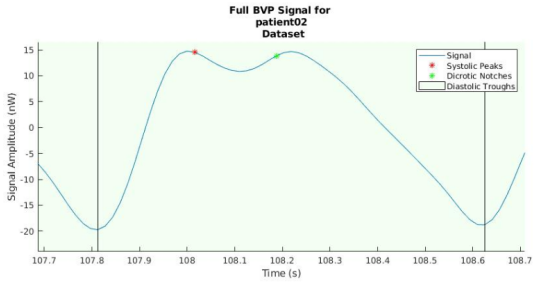
(b) A traditional waveform with only a dicrotic incisura, type 2, IPA = 0.62



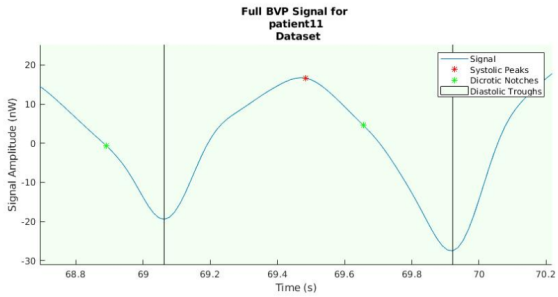
(c) A left justified waveform with a left peak, type 3, IPA = 1.16



(d) A left justified waveform with a left incisura, type 4, IPA = 0.25



(e) A waveform with two peaks of roughly equal height, type 5, IPA = 1.04



(f) A relatively smooth waveform, type 6, IPA = 0.24

Figure 20: Categorized waveform types

These waveforms were taken directly from patient data. The most "normal" of these waveforms in a traditional sense had dicrotic notches much lower than the systolic amplitude (fig. 20a) and fig. 20b). This waveform is most evident of a normal PPG from a healthy patient [4]. This occurred relatively infrequently, with only roughly 25% of patients demonstrating either of these morphologies.

Another observed waveform type had a noticeable incisura or peak before the systolic peak rather than after it(fig. 20c and 20d). Unfortunately, this waveform occurred frequently–in about 50% of patients. A major issue with this waveform type is knowing where to indicate the systolic peak. If there is a noticeable peak before the higher peak value (fig.20c), then which peak is the systolic peak? In the reported algorithm, we identified the earlier of the peaks as the systolic peak. This caused the IPA to be very high for waveforms of this morphology. However, for waveforms with a noticeable incisura before the higher peak (fig. 20d), we chose to identify the higher peak, and not the incisura, as the systolic peak, leading to an extremely low calculated IPA ratio. Seeing as these two waveforms appear to be similar in the time domain, as they have a left justified shape, one of these assumptions of where the systolic peak occurs was determined to be

incorrect as widely different IPA values were reported between the two types.

It might make more sense to identify the systolic peak as simply the highest peak reported, but this would make all IPA measurements very low, and no noticeable dicrotic notch would be present after the systolic peak, which it is clinically expected. In young patients with healthy blood vacsulature, a noticeable dicrotic notch is expected to occur after the systolic peak [4], so this seems wrong. On the other hand, if the first incisura or peak is reported as the systolic peak, then a very noticeable dicrotic notch is reported that is higher in value than the systolic peak. This would cause an extremely high IPA value, which is associated with an increase in age and stiffened blood vessels [6]. This also seems wrong, as all patients were relatively young. This raises the question: which one of these is correct? More research is needed to answer this question, with the opinion of multiple medical doctors being highly preferable.

Additionally, two other types of waveforms were present. Some patients had waveforms where little informaiton on systole and diastole was present at all (fig. 20f). This morphology of waveform also occurred frequently in patients who demonstrated waveform type 4 (fig. 20d) in large quantities. Another morphology of waveform occurs when there are two peaks of roughly the same height, leading to an IPA of 1 (fig. 20e). This waveform occurred frequently in subjects who also had waveform type 3 occur in large quantities.

The variability of the waveform, even for completely still subjects, was a consistent issue faced during testing. In the example below, a patient demonstrates a type 1, type 2, type 3, and type 5 waveform all in a 10 second duration (fig. 21). This seems to indicate that if two peaks are present, the second peak or incisura is always the dicrotic notch, but again the opinion of a medical doctor is needed for more accurate classification. This morphology volatility also indicates that variability is present in the body, hardware, or location where the PPG is measured at. The scattering of light is highly variable, and minute changes in watch positioning might affect the PPG waveform. Patients were instructed to be as still as possible, but the minute change in watch position might still have effects on the waveform. Contact area and distance from sensor to skin may also cause variability. Hardware inconsistencies could also be present, but this is unlikely. It would be good to confirm using different PPG smartwatch measurement hardware if this issue occurs. The change in waveform could actually be a change in blood flow morphology, but this seems unlikely to occur in such a small window of time. Finally, PPG may be better suited to be measured at the fingertip, and a wristwatch could be a generally poor place to extract detail-dependent parameters from a PPG signal, although it can still serve to measure HRV and HR.

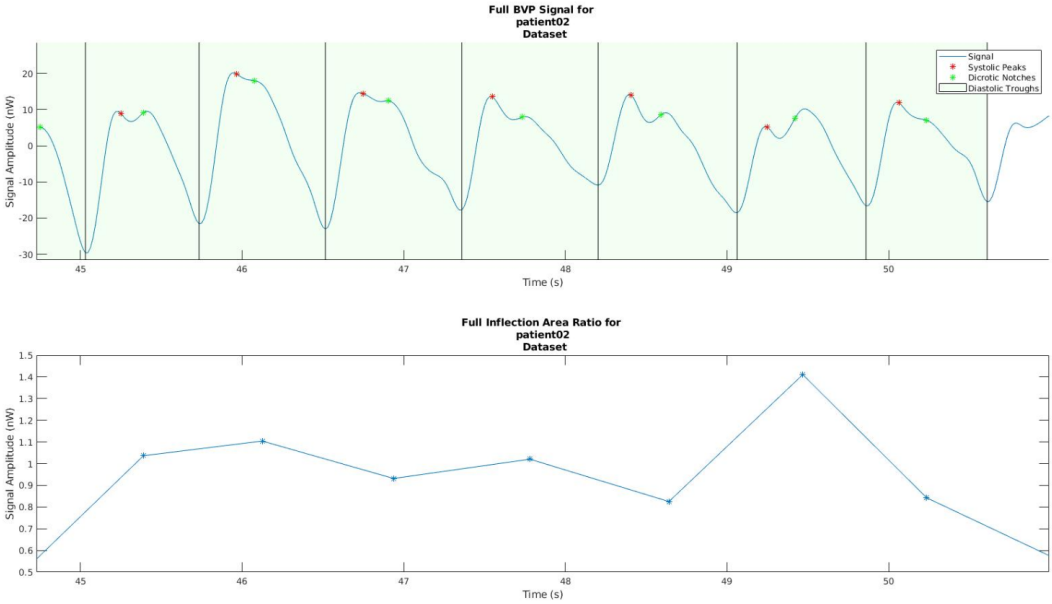
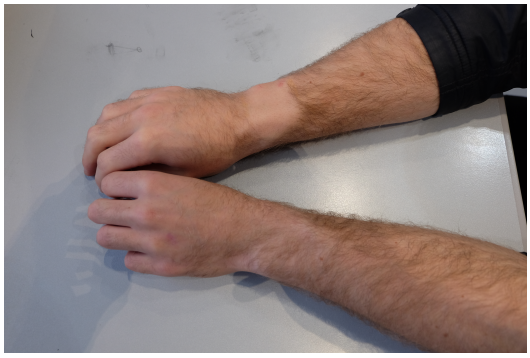


Figure 21: A waveform with type 1, type 2, type 3, and type 5 morphology occuring within 10 seconds

0.3.2 Does wrist-hair affect the signal?

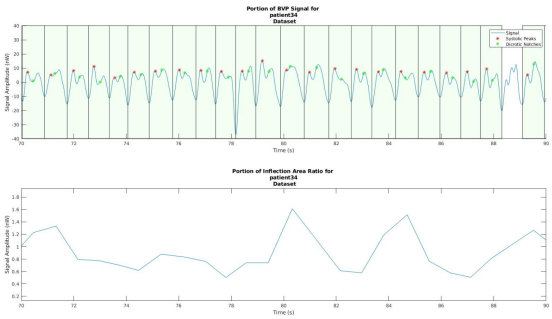
A hypothesis agreed upon after initial observation of signal variability was that wrist hair negatively impacts the signal cleanliness and amplitude. As a side note, since this information was obtained *after* the presentation, it is included in the discussion section as opposed to the methods/results section. Although it was an interesting question, it is pertinent to mention that the question was raised only after the initial report was completed.

To test our hypothesis, two patient PPG signals were recorded for four minutes with blood pressure taken three times. This was done before shaving the wrist of the patient and after shaving the wrist of the patient. A 15s sample of the waveform pre-shave and post-shave were taken. These waveforms can be viewed in fig. 22, along with a picture of the unshaven left wrist and shaved right wrist for comparison.

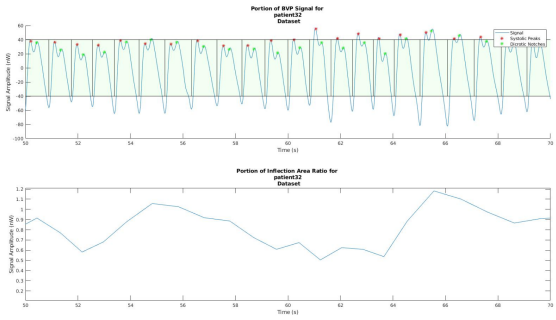


(a) Patient A wrist pre-shave and post-shave

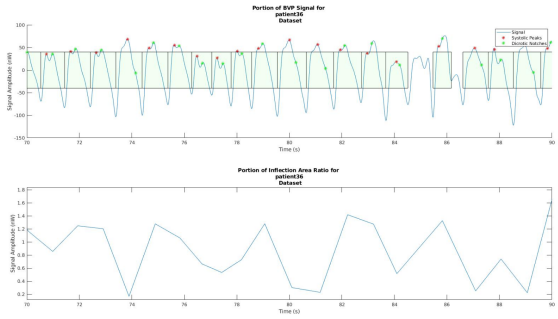
(b) patient B wrist pre-shave and post-shave



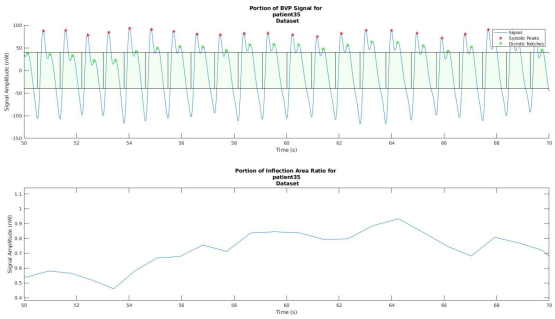
(c) Patient A waveform, pre-shave



(d) Patient B waveform, pre-shave



(e) Patient A waveform, post-shave



(f) Patient B waveform, post-shave

Figure 22: Effect of wrist hair on PPG signal

Note the increase in signal amplitude from pre-shave to post-shave. Patient A displayed a 2.5x increase in systolic amplitude. Patient B displayed a 2x increase in systolic amplitude. This increase in systolic amplitude relative to dicrotic notch amplitude also lowered the IPA. Since the IPA is a ratio, one might think that wrist-hair would not affect it as it would attenuate the systolic waveform at the same rate as the diastolic waveform, but this was observed not to be the case. The use of the EDA (conductance) sensor might help account for this issue, as hairier patients could have their waveform artificially increased based on how the amount of hair affects conductance, but this would not work on the Empatica E4 smartwatch, as the conductance sensor is on the underside of the wrist where far less hair was noted on the patients in question. Even if the sensor were placed on the top of the device, it was observed that hair attenuated the systolic peak more than the dicrotic notch, so accounting for conductance would be much more complex than a simple linear gain factor for the waveform.

A patient using this type of wristwatch for anything other than heart rate detection should have a shaved wrist, especially if these metrics are to be used for clinical diagnosis. The use of a fingertip sensor may provide a more consistent measure of PPG,

although it lacks the portability of a wristwatch. PPG detection on a less hairy part of the body may provide a cleaner signal, which opens up opportunity for a novel PPG sensor on a different location.

0.3.3 Machine Learning Blood Pressure Prediction

The neural network created in this section was undertaken as an effort to determine any final possible correlation between Empatica E4 watch signals and blood pressure in light of the lack of correlation found within the methods of this paper. This study was undergone both after the presentation for this project as well as after gathering additional patient data with the Empatica smartwatch. It is included in the discussion as it strays from the methods previously discussed within this report.

To re-test the initial report hypothesis of blood pressure correlation with smartwatch biometric signals, an artificial neural network (ANN) was created and trained on data from 37 volunteers. In order to optimize training time and computation costs, the entire set of patient data was split into 2 second segments. Varying sampling rates and the fact that the Omron blood pressure measurment device used takes an average of 40 seconds to record BP led to a bit of necessary data cleansing. Each two second segment consisted of 128 PPG samples (Sf=64Hz), eight wrist temperature measurements (Sf=4Hz), eight EDA measurements (Sf=4Hz), one inflection point median, and a patient-specific demographic dataset. Each two second segment was paired up with the nearest systolic and diastolic blood pressure measurement corresponding to that two second segment. This input cleansing gave the ANN an input layer of 150 nodes and an output layer of two nodes, one for systolic and the other diastolic blood pressure. The ANN consisted of 2 hidden layers: the first containing 12 nodes, and the second containing 10 nodes. Matlab's "feedfowardnet" function was used to create the architecture for this neural network.

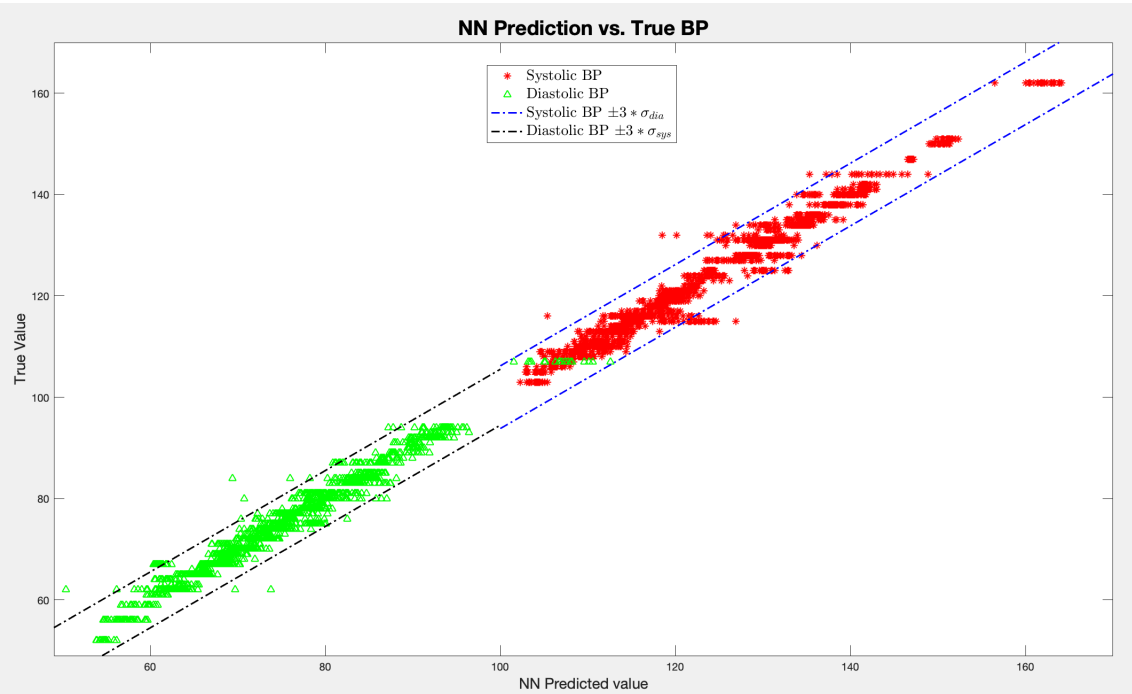


Figure 23: ANN prediction for systolic and diastolic BP plotted against the true BP value (Systolic SD error: 2.0617 || Diastolic SD error: 1.8385)

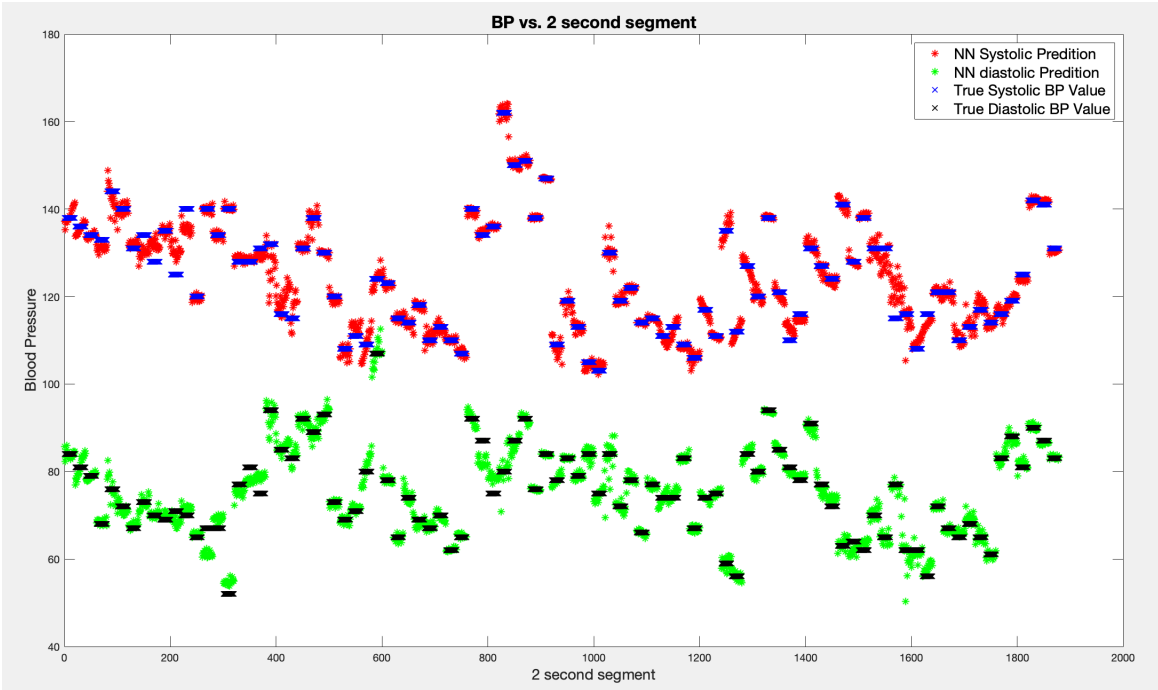


Figure 24: A visualization of each 2 second segment with regards to the how well the ANN predicted the real BP value

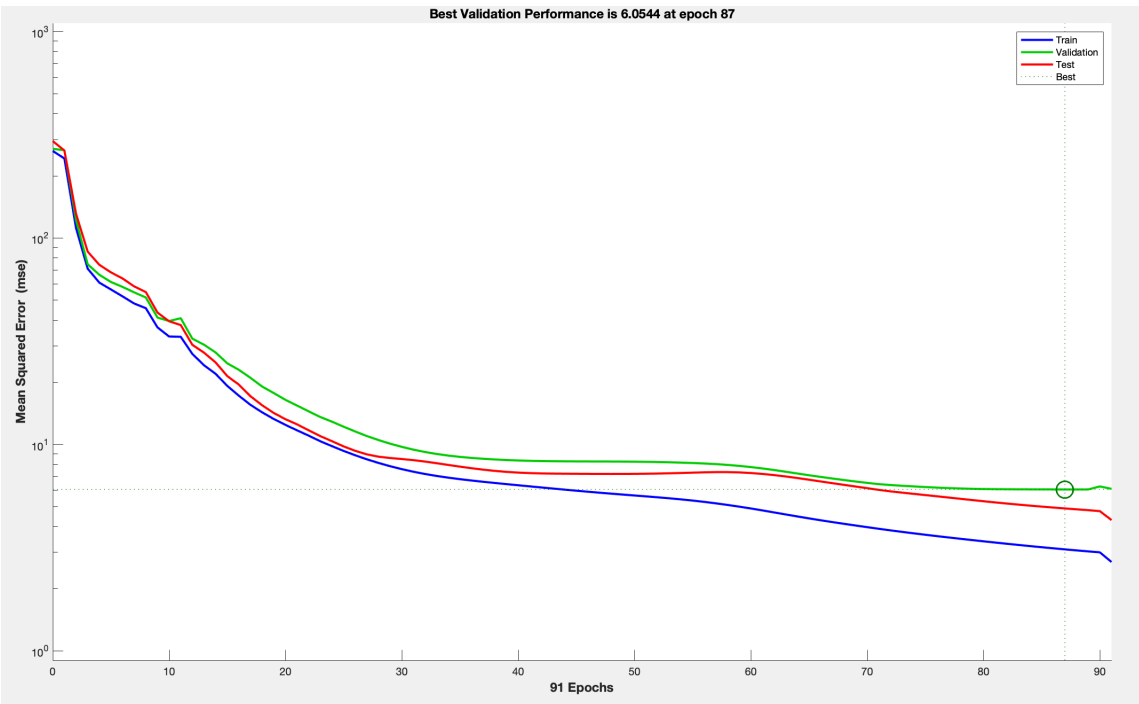


Figure 25: Performance plot of after a particular training session yielding a Means squared error (MSE) of 6.05 on the 87th epoch

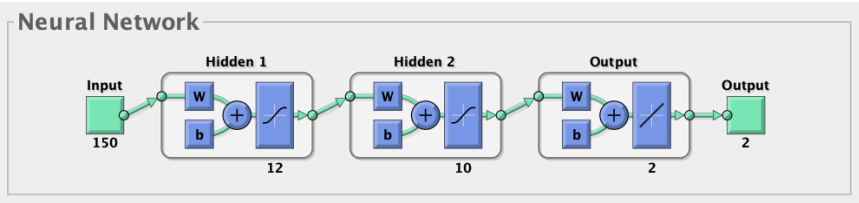


Figure 26: The ANN structural overview

Results of feeding this neural network the patient Empatica data were initially quite promising with the first training round seeing an overall r-squared value of of 0.984 (ranges observed: 0.910 to 0.997) and a mean squared error of 6.05 (ranges observed: 2.85 to 22.45). Training time for the network was consistently under one minute. The Matlab script was built to allow any user-defined input matching the 150 input layer structure and would give a reasonable estimate of systolic and diastolic blood pressure based on only 2 seconds of input data. However, there are two inherent issues with this approach. First, the strategy assumes patient blood pressure is the same for the entire 40 seconds it takes for the Omron device to take a measurement. Secondly, the network selects its training and test sets at random and rotates these at each epoch. While the network is still predicting based on 2 seconds of data from a patient, it may have already seen between 2 and 18 seconds of data from this patient. From a product standpoint, the consumer would not be able to provide validation measurements for the network to tune its weights to. More outside test data would be needed to manually feed the network and each set of data would have to specific to a given patient. Along with this issue, we faced a predicament in the data set being relatively small. The dataset did not encompass a large distribution of age, sex, or regional population as well. Therefore, despite its promising initial results, this strategy would need to massively increase the size of its dataset as well as blood pressure sampling rate in order to be considered clinically relevant.

Another attempt was made using a different neural network structure. The only difference in the second network architecture came in the form of an input layer consisting of 1205 nodes. The justification for this new architecture was to eliminate the network from potentially training and testing on the same 40 second blood pressure measurement. The network was designed to avoid this issue by inputting all of a patient's recorded PPG measurements along with six statistical calculations regarding inflection point area ratio. All other facets of the network were left the same. The major issue with this new architecture was the insufficiently large training and test set. This caused massive over training as early as the first epoch while r-squared values fluctuated from .938 to .367 with a consistent training time of about 10 minutes. In the end, more data and better blood pressure equipment is needed in order to prove the efficacy of either of these strategies.

0.4 Conclusion

While the correlation between blood pressure and IPA ratio was determined to be nil, the IPA ratio is still a clinically useful and insightful waveform. Understanding the component of each individual heartbeat for a patient that is comprised of systolic and diastolic activity remains clinically relevant. Further analysis would likely see correlation of this calculated signal with other measured biometric signals such as peripheral resistance or vascular distensibility. The usefulness of this algorithm extends to other researchers in the

field that have use for determining IPA ratio within a signal as well. The algorithm used in this analysis creates a clinically invaluable feature matrix consisting of every critical point for a waveform as well as its IPA ratio profile over time. The creation of this PPG signal feature matrix could be emphasized as a final product of this report in the form of a program executed by researchers on a specific PPG signal to ease the process of calculating IPA ratio or other metrics. The algorithm also utilized a fully automated statistical analysis process for the gathered PPG signals. This statistical analysis was also performed in a highly scalable framework, allowing for a much larger number of patients to be encompassed in a future study that would ideally compare multiple different patient demographics. Despite an unconfirmed initial hypothesis for the IPA ratio's correlation to a single measured biometric signal, there remains vast potential for the continued analysis and implementation of PPG signals as weaarble health-monitors increase in prevalence and popularity.

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