ENPH 455 Final Report

Design of a New Blood Pressure Monitor

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Abstract:

The goal of this thesis is to design a new blood pressure monitor that overcomes existing obstacles facing traditional oscillometric and auscultatory blood pressure monitoring methods. In the course of this project, shortcomings of current monitors and proposed non-invasive monitoring methods were analyzed. A modified photoplethysmography (PPG) based device, analogous to finger-tip PPG pulse oximetry devices, was proposed as a way to continuously monitor blood pressure. A reflectance mode PPG design using light in the near infrared (NIR) range, and placed medially at the wrist over the radial artery was developed to provide a signal most heavily correlated with blood pressure. Making use of suggestions from existing research, an additional photodetector was included for the purposes of determining the pulse transit time (PTT) of the wave to further corroborate a blood pressure prediction. Open source PPG signals with corresponding blood pressure measurements were selected to test the relationship between PPG signals and blood pressure. Data processing methods were experimented with until the Savitzky-Golay filter was chosen for its amplitude and slope preserving capabilities. Various features were extracted from the cleaned PPG including the systolic peak amplitude, diastolic peak amplitude, dichroic notch location and the augmentation index. These features along with basic patient information such as weight and age were fed into a 2 hidden layer backpropagation network and trained separately to predict the systolic and diastolic blood pressures. Systolic blood pressure was predicted to within 13.2±11.3mmHg and diastolic blood pressure was predicted to within 8.2 ± 6.8mmHg, outside the Association for the Advancement of Medical Instrumentations (AAMI) guidelines of 5±8mmHg. Failure to achieve results within the guidelines was likely due to the small size of the training dataset, and relatively large amounts of error in the signals. It was determined that the device designed could be made small enough to fit in a simple flexible wristband, have battery life of 5 days, store with ease in excess of 1000 readings (approximately 2 weeks) and be made at a price of approximately $44. Thus it was concluded that if the accuracy of such a device could be improved, this device could be a commercially viable alternative to traditional blood pressure monitors and provide a more complete profile of an individual's blood pressure. Future considerations for work on this project should include a refinement of the neural network to obtain blood pressure measurements within AAMI standards, the verification of accelerometer motion correction, physical prototyping, and the development of a computer or phone based application to store and analyze long term trends in measurements.

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Acknowledgements

I'd like to thank my supervisor, Dr. Kayll W. Lake for his guidance and encouragement throughout the completion of this thesis. A special thanks is also due to my good friends, Andrew Frizado, Alex Friedlan, Curtis Shewchuk and Stewart Reid, without which my sanity might not remain.

Introduction:

High blood pressure has long been known to increase the risk of cardiovascular diseases such as coronary heart disease, stroke, and heart failure [1]. More recently, there has been growing evidence that high blood pressure also increases one's risk factor for dementia and renal disease[1][2]. The prevalence of hypertension has increased worldwide from an estimated 594 million effected adults in 1975 to 1.13 billion affected adults in 2015 [3]. Given that the number of those affected by hypertension is expected to increase to 1.56 billion by 2025, it is clear there is a need for accurate and ubiquitous blood pressure monitoring [4]. However, technological innovation in the field of blood pressure monitoring has remained relatively stagnant. Older technologies such as automatic oscillometric devices and sphygmomanometers continue to be the dominant sources of blood pressure measurement [4][5]. Meanwhile, the accuracy of even these time-tested devices remain subject to a number of biases and come with unignorable variability [4][6][7]. A new blood pressure monitor that overcomes the limitations and challenges of existing machines is needed.

Current State of Blood Pressure Monitoring:

Accuracy Limitations:

There are various limitations to both the auscultatory and oscillometric devices listed above. Blood pressure measurement techniques using a cuff often heavily rely on accurate cuff-sizing, with poorly fitting cuffs causing skewed results [4]. Measurements using these methods are also susceptible to biases such as the whitecoat effect and cuff-inflation hypertension which both lead to overestimated levels of blood pressure and therefore overtreated patients [4]. If being tested by a physician on a sphygmomanometer, blood pressure results can be skewed by terminal digit bias [4]. Blood pressure has also been shown to depend on factors such as whether or not the patient is talking or actively listening, whether the cuff is over clothing or not, the posture of the patient and activity and stress levels immediately before measurement [7]. A recent study carried out from 2011 to 2014 testing the accuracy of home blood pressure monitors found that approximately 30% of devices attained results outside of the ±5mmHg error recommended by AAMI guidelines [8]. Additionally,

studies done outside of Canada have also found limited accuracy of home blood pressure measurement devices [9][10].

Measurement Routines:

Recognizing the limitations of single blood pressure measurements at the doctor's office as indicators of overall cardiovascular health, there are two alternative methods that provide more useful measurements. The first, home blood-pressure monitoring, solves the problem of white-coat hypertension by allowing the user to get into a more relaxed and natural state before taking a measurement. However, this assumes that the user follows all the operational guidelines recommended by the doctor for accurate blood pressure measurements and still does not account for general blood pressure variability throughout the day [11][12]. A solution to this problem comes from the second measurement method, ambulatory blood pressure monitoring. Ambulatory blood pressure monitoring (ABP monitoring) involves taking frequent measurements throughout the day and has been shown to be a better predictor of cardiovascular risk than single blood pressure measurements from a clinic [13]. Limitations with this method arise from the fact that ABP monitoring is usually only done for one full day before the results are sent back to a doctor meaning that day to day variation in blood pressure is not captured. Additionally, the reoccurring automatic inflation and deflation of the cuff is often distracting, may disrupt sleep, and does not account for blood pressure changes due to activity levels.

Objectives:

The main goal of this project is to design a new ambulatory blood pressure monitoring device which makes use of new measurement techniques to overcome obstacles and shortcomings encountered by the traditional blood pressure monitoring devices discussed above. Having reviewed the relevant literature on this topic, more specific objectives may be set. This design aims to produce a competitively priced product that is accurate, automatic, discrete, inobtrusive, and provides a better cardiovascular health profile for the patient. After reviewing current blood pressure monitors and standards, the following list of quantifiable objectives has been developed:

1. The product should be priced within the $30 to $200 range to remain competitive with existing monitors [14]–[16].
2. The device should be able to provide a systolic and diastolic blood pressure measurement to within 5 ± 8mmHg, consistent with the AAMI standard [17].
3. The device should be able to be worn for at least one full day without needing to recharge or offload data.
4. The device should be able to take readings at least every 20-30 minutes and store at least 72 readings (corresponding to a 24 hour period).
5. The device should be able to be worn easily and while sleeping.
6. The blood pressure monitor should be able to account for variability in physical activity throughout the day to alert one when readings might be spurious.

Methodology:

With the objectives of this thesis clarified, a design plan can be laid out. First, four different proposed methods of non-invasive blood pressure measurement are described and compared. A device that offers the most promise in fulfilling the design objectives is selected to move forward with. The theory of operation of this device and method of blood pressure prediction are then explored in depth to determine the technical requirements of this method. A preliminary device design is then proposed and justified, developing first from the data acquisition phase through to the data analysis phase. Tests that can be done without the completion of a prototype are then completed and reviewed in order to validate components of the design. Areas to improve the prototype design are then elaborated on for possible future work on this project.

Proposed Device Review:

Four potential technologies were uncovered in research that show promise in accurately measuring blood pressure in a non-invasive, inobtrusive and frequent fashion. These devices are described briefly below.

Giant-Magneto-Resistance (GMR):

The proposed device uses a GMR sensor (a very sensitive magnetic sensor) to measure the Modulated Magnetic Signature of Blood (MMSB) – a signal which reflects the volumetric change in blood flow and which is therefore related to the pulse pressure waveform [18]–[20]. This waveform, measured in two places, can be related to blood pressure through the pulse transit time (PTT).

Photoplethysmography (PPG):

This method uses PPG – a method for measuring the change in blood volume with an infrared light – to obtain a waveform as the volume of blood in an artery changes with the passage of a pressure wave. The time delay between two such waveforms can be related to blood pressure through the PTT. Research has also shown that through the use of a neural network, a direct relation between a PPG signal and the pulse pressure waveform can be obtained [21]

Ultrasound Time Delay:

The ultrasound time delay method operates on the principle that sound travels more quickly through liquid under higher pressure. By analyzing the time it takes for an ultrasound wave to travel through an artery and return via reflection off the back inside face of the artery, the pulse pressure waveform can be obtained.

Doppler Ultrasound:

Doppler ultrasound uses the change in frequency of a reflected ultrasound wave to determine the speed and direction of blood flow. This data has shown some correlation with blood pressure and could allow for non-invasive, frequent blood pressure monitoring [22][23].

Device Selection:

The above devices were evaluated against their potential to fulfill the objectives of the project and compared to each other to decide which blood pressure measurement technique to move forward with. The ultrasound time delay method and the doppler ultrasound method were ruled out due to their comparative complexity, the price of ultrasound transducers, and the

need for a signal enhancing transmission gel between the skin and transducer. GMR and PPG were relatively similar in their supposed ability to predict blood pressure. However, there was more research to suggest the efficacy of the PPG method over the GMR method, the PPG method costed slightly less than the GMR method, and PPG is not subject to noise from the Earth's magnetic field as GMR is. Therefore PPG was determined to be the most promising method for non-invasively measuring blood pressure.

Theory:

Photoplethysmography:

Overview:

PPG is an optical technique that is used to measure a change in volume. In a medical setting, PPG is commonly a feature of an already ubiquitous device, the pulse oximeter, and is used to measure the level of blood perfusion to the extremities. PPG is also the method by which many fitness watches measure heart rate, as it provides an inexpensive and relatively accurate way to record the pulse pressure wave of blood. PPG devices obtain such measurements by first shining a green or infrared light on a segment of skin. A light sensor is then used to detect either the amount of light transmitted through the skin (transmittance mode PPG) or the amount of light reflected by it (reflectance mode PPG). As the volume of arteries and blood vessels increase with the passing of a blood pulse pressure wave, the amount of light reflected and transmitted will change. This change is recorded by the PPG. A cleaned sample PPG signal is shown in Figure 1.

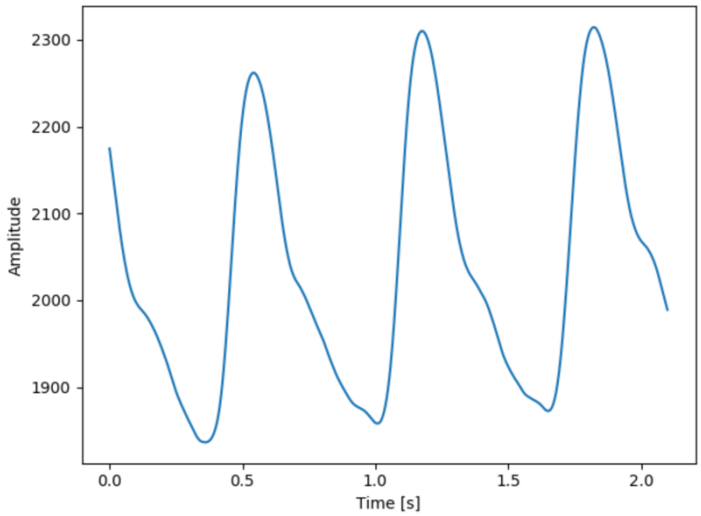

Figure 1: A filtered reflectance mode PPG signal showing change in arterial volume.

Once recorded, the PPG signal can be related to blood pressure through the use of a neural network. Additionally, if two detectors spaced apart along an artery are used as shown in Figure 3, the PTT can be obtained from the time delay between the detector signals. This can be fed into an empirical algorithm to determine blood pressure or into a neural network containing other PPG signal features.

PPG Signal Features:

There are many features of the PPG that seem promising in their correlation to blood pressure [30]. These include the systolic amplitude, pulse width, pulse area, peak to peak interval, augmentation index, diastolic peak location/peak, and dichroic notch location. A graph of an ideal PPG signal with some of these features labelled can be seen in Figure 2.

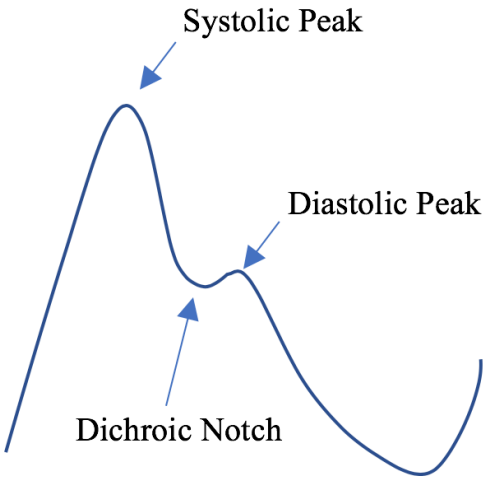

Figure 2: A PPG signal with systolic peak, dichroic notch, and diastolic peak labelled.

The pulse width of the wave can be seen as the full width at half the systolic max of the wave. The augmentation index is the height of the diastolic peak divided by the height of the systolic peak. The dichroic notch location refers to its distance from the foot of the systolic peak.

Wavelength:

The wavelength of light used on a PPG device has a large effect on the signal quality and utility of the data. The two most frequently used wavelengths in PPG are those in the green range, 500-600nm, and near infrared wavelengths (NIR), 800-1000nm [24]. The penetration depth of green light in human skin is approximately 1.2mm while the penetration depth of infrared light is approximately 2.5mm [25]. This implies that light in the NIR range will provide larger signals than light in the green range for transmittance mode PPG. Conversely, green light has been shown to have a larger signal to noise ratio than NIR light for reflectance mode PPG. Although green light may provide a larger signal than NIR light for reflectance mode PPG, it's limited penetration depth means that the signal is largely influenced by superficial blood flow rather than the deep-tissue and even arterial blood flow that NIR light is influenced by [24]. As a result of this, green light reflectance mode PPG is more susceptible to contact pressure. A recent study has even suggested that the change in the green light PPG signal is due to the compression of once disperse capillaries from an arterial volume change and not the arterial volume change in itself [26].

PPG Mode:

The mode of PPG used has an effect on the quality of signal obtained. Reflectance mode PPG is generally more susceptible to motion artefact than transmittance mode PPG [24]. However, transmittance mode PPG needs a relatively thin body part, such as the fingertip, earlobe or septum for signals of ample magnitude [24]. In contrast, reflectance mode PPG can be placed almost anywhere where blood vessels and arteries are near the surface of the skin.

The amount of light transmitted through the skin is commonly modelled using the Beer-Lambert Law. Assuming a non-scattering and homogeneous medium, the law is given as follows:

$$I(t) = I_0 e^{-\epsilon CV} \quad (1)$$

Where $I(t)$ is the intensity of the transmitted light, I_0 is the intensity of the incident light, ϵ is the absorption coefficient, C is the concentration of chromophore, and V is the volume of the medium [24]. This law can be used to predict the amount of light expected to reach the sensor and can therefore be used to estimate light power requirements and detector sensitivity requirements.

The amount of light reflected through the skin is slightly more complicated to model given the variety of paths backscattered light can take. The estimation of the intensity of light reflected back to the photodetector is therefore non-trivial to predict. However, Monte Carlo simulations have been effective in predicting the 'banana-shaped' envelope of light travelling through the skin [27][28]. Based on this banana shaped envelope, one study was able to predict that for a 940nm wavelength light source and a penetration depth of 3mm, the optimal light detector distance is 3 to 4mm away [27].

Pulse Transit Time:

PTT is defined as the time it takes for a pulse pressure wave to traverse an arterial segment. The PTT of a blood pressure pulse is typically measured as the time delay between the R-wave peak measured from an ECG at the heart to the PPG wave peak measured at the fingertip. The PTT of a pressure wave, and the pulse wave velocity (PWV) it directly corresponds to have been shown to correlate to blood pressure through a variety of relations [6]. This is due to the fact that the speed at which a pulse pressure wave travels through an artery is related to the arterial stiffness and that such arterial stiffness is related to blood pressure. The greater the arterial stiffness, the greater a patient's blood pressure tends to be. The relationship between PTT and arterial stiffness is given by the following equation:

$$\mathrm{PTT} = \frac{1}{\sqrt{\frac{\rho}{A}\mathrm{C(P)}}} \tag{2}$$

where ρ is the density of blood, A is the cross-sectional area of the artery, and $\mathrm{C(P)}$ is the arterial compliance as a function of pressure [6]. $\mathrm{C(P)}$ is given as:

$$\mathrm{C(P)} = \frac{\mathrm{A_m}}{\pi P_1 \left(1 + \left(\frac{P - P_0}{P_1}\right)^2\right)} \tag{3}$$

where $\mathrm{A_m}$, $\mathrm{P_1}$, and $\mathrm{P_0}$ are empirical constants, and P is the arterial pressure. As compliance is merely the inverse of stiffness, it is clear that a larger PTT implies an increased arterial stiffness which implies a larger arterial pressure.

Many empirical models exist to relate pulse transit time to blood pressure. One study [29], conducts an analysis on the accuracy of a number of models. A few of these models are listed below:

$$\mathrm{BP} = \mathrm{a} * \ln(\mathrm{PTT}) + \mathrm{b} \tag{4}$$

$$BP = a * PTT^{-1} + b \quad (5)$$

$$BP = a * PTT + b * HR + c \quad (6)$$

where BP is either systolic or diastolic blood pressure, PTT is the pulse transit time of the signal, HR is the heart rate of the patient, and a, b, and c are empirical constants that must be determined [29]. Equation 6 was found to provide the best accuracy in predicting blood pressure. Given the inclusion of empirical constants that vary by individual in this model, predicting blood pressure in this way will require semi-frequent calibration.

Neural Networks:

Neural networks consist of layers of nodes connected by weights which are trained to accept an input vector and output a desired result. Their popularity has increased recently in part because of their ability to characterize and predict outcomes in data sets where the relationship between data points is poorly understood. Previous attempts at relating the PPG signal to blood pressure using a neural network have typically used a feed-forward architecture with various back-propagation algorithms [21][31]. They have also used input features ranging from well-recognized PPG waveform characteristics, to the phase and magnitude of the waves at various points [21][31].

Preliminary Design:

Moving ahead with the choice to use PPG to measure blood pressure, the design of the device was broken down into 3 sections, Data Acquisition, Data Processing, and Data Analysis. The following are discussed below.

Data Acquisition:

The data acquisition component of this design is a critical step along the way to obtaining valid blood pressure measurements. It was decided that in order to obtain reasonable blood pressure results, the PPG waveform, the PTT and an accelerometer signal representing the

motion disturbances experienced by the sensor would need to be acquired. To accomplish this, a simple design was proposed involving 2 infrared photodiodes spaced a small distance apart (1-2cm) along the length of an artery, one infrared LED placed between them, and an accelerometer. An illustration of this system can be seen in Figure 3.

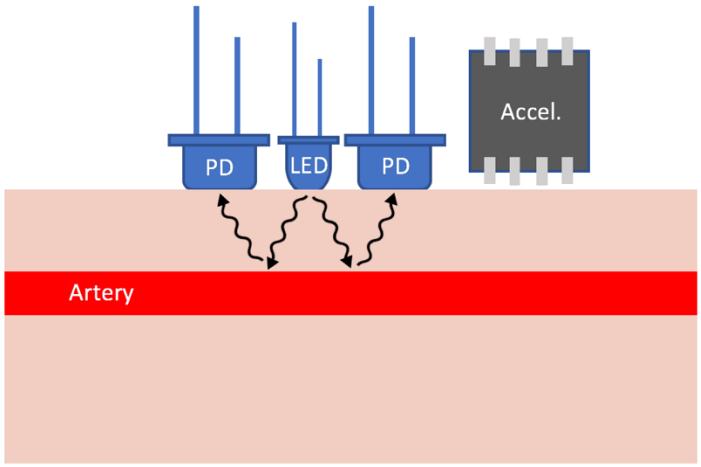

Figure 3: A schematic diagram of the data acquisition system where the objects labelled "PD" represent the photo diodes and the object labelled "Accel." represents the accelerometer attached to the light sensors.

Wavelength:

The wavelength of light selected for this design is in the near infrared (NIR) range (800nm-1000nm). Wavelengths in this range pass through the skin better than their frequently mentioned alternative – green light – making NIR light better for measuring deep-tissue blood flow [24]. NIR PPG is also less sensitive to visible light, device contact pressure, and blood oxygen content meaning, it will yield waveforms that are more stable over time and between skin tones [6].

PPG Mode:

Despite its greater vulnerability to motion artefact, reflectance mode PPG was selected over transmittance mode PPG for its flexibility in device placement location – an important consideration for a device that will be worn all day [24].

Device Placement:

Given the short penetration depth of NIR light, the PPG device must be located where an artery is near the surface of the skin [32]. Measurements taken medially at the wrist - over the radial artery in particular - are ideal as the arteries are very near to the surface here (2.74mm), and such location would not provide any more discomfort than a watch [33]. PPG signals from the wrist however, are typically susceptible to greater levels of motion artefact than other locations meaning that greater motion correction and filtering will need to be applied [32].

Accelerometer:

For a device that will be worn all day, the presence of motion artefacts in the signal is inevitable. Therefore, an accelerometer was selected as a noise correction device. The accelerometer was chosen to be attached to the PPG module so as to measure the motion-related disruptions in the PPG signal and to adjust accordingly.

Data Processing:

Sources of Noise:

Once the PPG signals and accelerometer information is obtained, it must be properly managed and altered before analysis. The objective of this component of the design is to clean the data and prepare it for further analysis. The major sources of noise PPG signals are subject to are a 60Hz power supply noise, motion artefacts, and breathing. To reduce and eliminate these sources of noise, previous studies using PPG have used bandpass filters with ranges from 0.5Hz to 12Hz [29][34]. There is also research which suggests the implementation of a signal correcting accelerometer can provide a PPG signal more robust to motion [35].

Selection of Data:

As a physical prototype is out of the scope of this design project, the testing of digital signal processing methods was carried out on open source PPG data. The dataset used in the processing and analysis stages was developed specially for the purpose of researching the relationship between PPG signals and blood pressure, making it ideal for the purposes of this project [34]. The PPG data contained in this set has been filtered using a bandpass filter

(0.5Hz-12Hz) and comes with corresponding blood pressure measurements and important patient medical information (ie. weight, age, sex). Additionally, data in this dataset has been subject to other signal quality scrutiny such as a test for the skewness values of the signal. If a negative skewness value was detected – indicative of a heavily distorted PPG signal – the signal measurement was retaken. A sample signal from this data set can be seen in Figure 4.

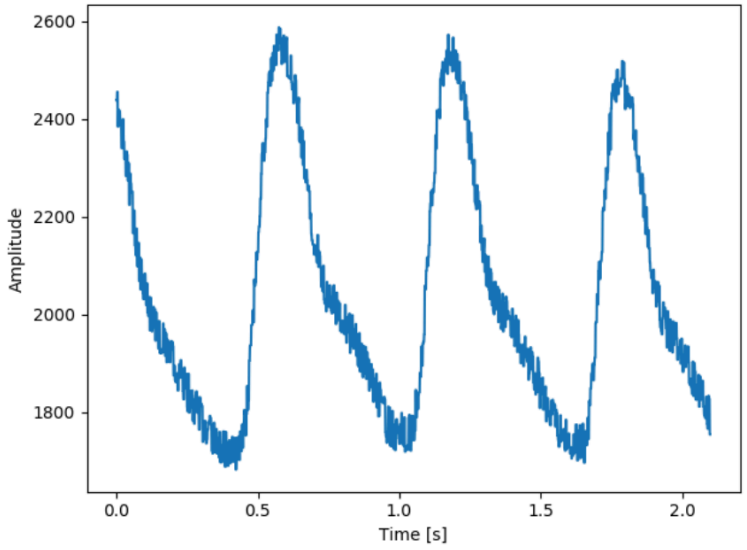

Figure 4: A sample signal from the PPG dataset.

Digital Filtering:

Different digital filtering techniques were tested on the signals in the dataset noted above. A moving average filter was experimented with using various window sizes, however it was found to cause too much signal degradation (in the form of its poor response to the sharp spikes in PPG signals). A Savitzky-Golay filter was then tested and found to provide appropriate amounts of smoothing while maintaining the original shape of the waveform. A window size of 99 and a polynomial fit order of 2 was found to provide sufficient smoothing of the noisy signal. A graph comparing the moving average filter to the Savitzky-Golay filter is given in Figure 5.

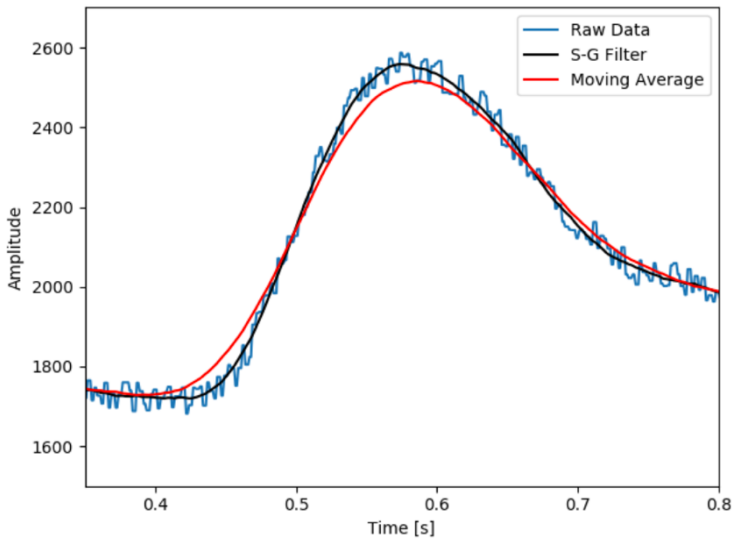

Figure 5: A graph showing the effect of the Savitzky-Golay filter and the moving average filter on raw PPG data.

Amplification:

Typical devices use amplifiers with a gain on the order of magnitude of approximately 10^3 [36]. Amplification will be performed prior to avoid attenuation of the true PPG signal and to maintain a high signal to noise ratio.

Data Analysis:

Feature Extraction:

There are two aspects of the data analysis section of this project – feature detection and blood pressure prediction. Various functions were developed in Python to extract important features of the processed PPG signal. After consulting the relevant literature, the features chosen to be extracted were the systolic peak amplitude, diastolic peak amplitude, dichroic notch location, augmentation index, full-width at half-max, level of random noise, skewness index, and the spacing between systolic and diastolic peak locations. Initially, the relative significance of the variety of features obtained was unknown – it was only after a neural network was trained on the features that I was able to determine which features were the most important for blood pressure prediction. After the relevant signal attributes were gathered, they were combined

with the patient medical data which included their sex, age, weight, body mass index (BMI), and heart rate. The combined data matrix was then normalized to increase training speeds and keep network weights low. The order of the combined data matrix rows (neural network input vectors) was then randomized to improve the generalizability of the network.

Neural Network:

The is to be fed into an artificial neural network created using the keras API and trained with the corresponding blood pressure measurements taken with the PPG signal data. A 2 hidden layer, stochastic gradient descent backpropagation network will be used for its tendency to minimize error and ability to fit curves to continuous functions. The quantity of nodes in hidden layer 1 and hidden layer 2 will be varied until the accuracy of the network ceased to improve. The first layer will use a sigmoid output function in hopes that this layer would 'select' the important features. The second layer will use a rectified exponential linear unit (RELU) output function in hopes that this layer would scale the useful features to the appropriate levels of blood pressure. A schematic of the neural network architecture is given in Figure 6.

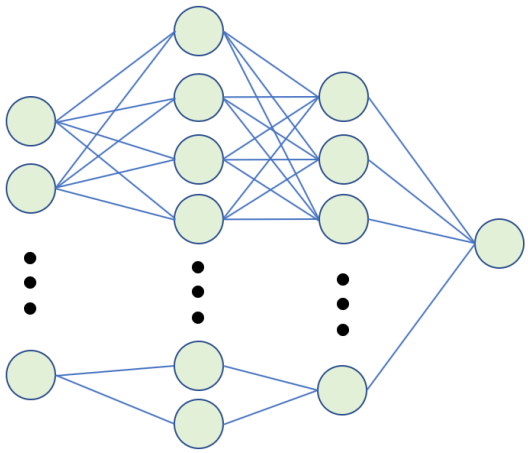

Figure 6: A schematic of the simple backpropagation network used to predict systolic blood pressure and diastolic blood pressure.

Additional Design Considerations:

Housing:

The final design of this blood pressure monitor requires the integration of the separate subsystems discussed above. In order to meet the ergonomic objectives of this project, the electronic components of the device should be contained in a flexible wrist-band-like housing. The housing should allow for the photodiodes and LED to contact the skin directly to improve signal quality and magnitude. The housing should also protect the photodiodes from external infrared light sources so as to avoid causing interference in the PPG signal.

Power Requirements:

A sample parts list has been created (see Appendix C) to estimate the power requirements of the system. The infrared LED selected will draw a relatively large amount of current while in operation – approximately 36mA. When powered on, the OLED display will draw 16mA. To improve the battery life of this device, when not taking measurements, these components will be powered off. Assuming measurements are taken once every 20 minutes, and that the PPG signal length taken is 10 seconds, the proposed device is estimated to require 0.43mAh of capacity for every hour of operation. This corresponds to an average power consumption of 2.2mW, with a peak current demand of 52mA. Therefore, given the current requirements, a high discharge, rechargeable battery will be required to power this device. Two 3.7V lithium polymer rechargeable batteries placed in series were selected to fulfill this demand. With a rated capacity of 60mAh for each battery, the battery life of the device will be approximately 5 days.

Data Storage:

The calculated blood pressure will be stored on a micro SD card connected to the microcontroller. Readings stored on the SD card could then be downloaded and viewed in the broader context of one's blood pressure history. This will allow for a more complete picture of the blood pressure of an individual. As only four entries will be logged on the micro SD card at one time – systolic blood pressure, diastolic blood pressure, the date, and the time– the micro SD card will not require much memory to store many data points. In order to store 504

entries (one reading taken every 20 minutes for one week), a text file of approximately 25Kb is required. This means that only a very small external memory device is required to meet the memory requirements of this device – a 1Mb micro SD card should do.

Display:

Blood pressure values will also be available for immediate reading from an OLED display. To reduce power consumption by the OLED display, which can quickly deplete a small battery, the OLED will only display for a short period when fresh measurements are taken. Given that such a device is designed to be all day – including while sleeping – the display function will be able to be turned off in order to reduce disruptions.

Final Design Summary:

The final preliminary design of this device, most broadly, will consist of a PPG data acquisition unit, and a data processing and analysis unit. The PPG data acquisition unit will consist of one high intensity 940nm wavelength LED, two high sensitivity photodiodes, and an accelerometer. This module will be placed so as to measured blood pressure via reflectance mode PPG from the radial artery at the wrist. The signal will be fed into an amplifier with a gain of approximately 1000 and filtered using a Butterworth bandpass filter (0.5-12Hz). The filtered signal will then be digitally processed aboard a small microcontroller, first by digitally smoothing the signal with a 2^{nd} order Savitzky-Golay filter, and then by applying various feature detection algorithms to the signal. The detected features, along with general patient medical information will be fed into a neural network which will predict the systolic and diastolic blood pressure of the patient. These blood pressure values will be displayed to the patient for a brief time on an OLED display after which the data will be logged with the corresponding date and time to the on board microSD card. The data on the card can then be uploaded to a computer to be saved and analyzed in the broader context of one's blood pressure history.

Test Results:

A total of 653 PPG signals were used to train and validate the neural network with a 70-30 training-validation set split. After varying the learning parameters (learning rate, momentum and clipping) to find an optimal value, the network was capable of predicting diastolic blood pressure to within 8.2±6.8mmHg after 150 epochs and systolic blood pressure to within 13.3±11.3mmHg after 300 epochs. These measurements are not within the acceptable limits of the Association for the Advancement of Medical Instrumentation (5±8mmHg) [17]. The error curves for both neural networks can be seen in Figure 7.

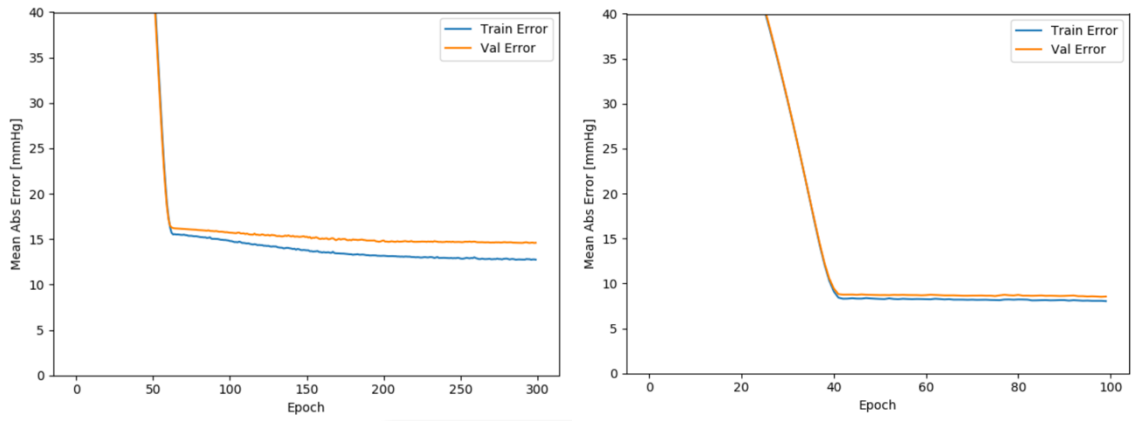

Figure 7: The systolic blood pressure neural network error curve is shown on the left while the diastolic error curve is shown on the right.

The optimal learning parameters were determined to be a learning rate of 0.01, a momentum of 0.002 and a gradient clipping value of 1. A total of 17 nodes in the first hidden layer, and 12 nodes in the second hidden layer were found to provide the best results. While attempting to improve the results of the neural network, a few plots were constructed to display some of the input features and their relationship with systolic blood pressure. A few of these plots are listed in Figure 8.

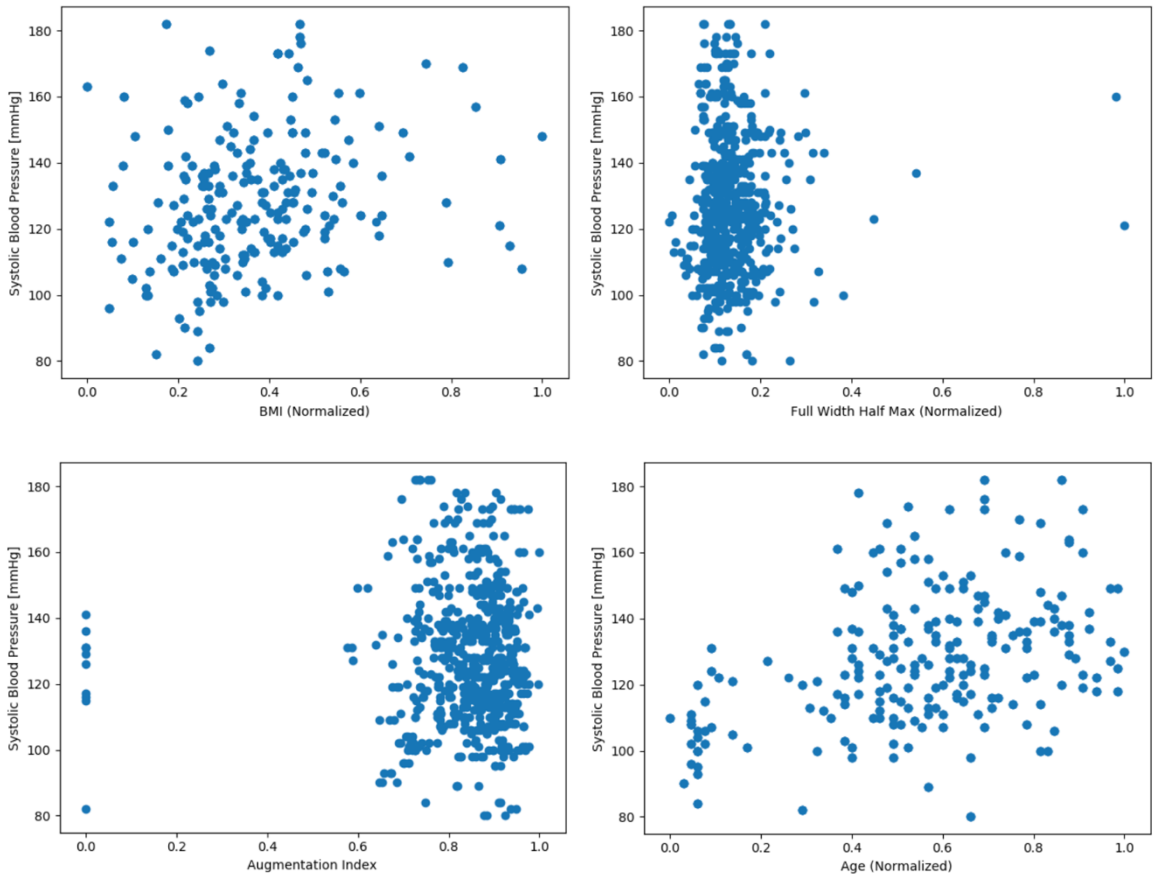

Figure 8: Graphs of systolic blood pressure with various normalized inputs features of the neural network.

As is visible from the plots in Figure 8, the relationship between non-PPG related signals (age and BMI) and blood pressure is marginal, and subject to large deviations. The relationship between PPG related signals does not fare well either. Ignoring the few extraneous points on each graph – a by-product of the feature selection algorithms given poor quality data – there appears to be no obvious relationship between the augmentation index and the FWHM of the systolic peak. This was also true when other PPG related features were plotted. This suggests that the neural network has failed to sufficiently predict blood pressure due to a small dataset size and relatively large amounts of random noise.

Future Work:

There are many areas for improvement with this blood pressure design. For example, making use of multiple wavelengths of light to obtain a PPG signal has been shown to provide stronger signals than using a single green or infrared light source. Work should also be done to improve the efficiency of the data processing data processing done on the signals, as the developed algorithms were computationally expensive. The relationship between blood pressure and the relevant PPG parameters should be investigated in more detail to improve the accuracy of blood pressure estimations and their validity. Furthermore, a larger dataset should be constructed to give the neural network a better chance at find the relationship between the PPG signal and blood pressure. Due to the large discharge current required of this device which results in the need for a bulkier battery, more research should be done into ways of reducing the maximum current demand. To fully see the ultimate goal of this project come to fruition, a computer or phone based application would need to be developed that could collect and combine blood pressure data from multiple days to and form a complete blood pressure profile of an individual that is more accurate and robust than single blood pressure measurements from traditional devices.

Word Count: 4883

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Appendix A:

No work prior to September 1st was completed on my thesis project.

Appendix B:

Technical Standard:

A technical standard that has been of great value in this project is the "National Standard for Measurement of Resting and Ambulatory Blood Pressures With Automated Sphygmomanometers" from the Association for the Advancement of Medical Instrumentation (AAMI). The standard referenced in this report was published in 1993. Access via the Queen's server to the 2013 version of this standard was unsuccessful. However, recent references to the 2013 do not conflict with the standards outlined in the 1993 version of the report, suggesting its continued utility [37][38]. A more comprehensive and global standard was looked into, however, only a preliminary (an unfinished) consensus report from the AAMI, the European Hypertension Society (EHS), and the International Organization for Standards (ISO), was available on the topic of automated blood pressure monitoring standards. Therefore, the 1993 version of this standard was deemed valid for the purposes of this report.

According to this standard, for a blood pressure monitor to be consider effective, it must achieve a mean pressure difference of ±5mmHg with a standard deviation of 8mmHg between the reference systolic pressure and the test systolic pressure. The same mean pressure difference of ±5mmHg and standard deviation of 8mmHg between the reference pressure and test pressure is also demanded of diastolic blood pressure. Many studies, including this report, aimed at determining the accuracy of existing blood pressure monitors or new blood pressure monitoring techniques use these error values to validate their devices.

An important note mentioned by the standard on these error requirements is that the patients selected for the study testing the validity of the blood pressure monitor must not introduce a bias. To enforce this, the standard suggests performing multiple studies to reduce errors introduced by a small homogeneous sample size. The diversity in demographic makeup of the dataset selected in the project helped reduce bias associated a small dataset size. Additionally, randomizing which patients were in the training and validation sets in the neural network aided in minimizing this bias. A study size of 85 patients is recommended in order to properly

validate an automated blood pressure monitoring device. A total of 219 patients were included in the dataset used to train and validate the neural network. Given the training-validation ratio of 7:3, only 66 patients were used in the validation of the algorithm, therefore not fulfilling the standard set by this study.

This standard also makes recommendations for the validation of ambulatory blood pressure monitoring devices. An ambulatory blood pressure monitoring device must be able to take accurate readings of pressure (both systolic and diastolic) to within a mean difference of ±5mmHg and a standard deviation of 8mmHg of the reference pressures in supine, seated, and standing positions. This is especially important given that blood pressure can be effected by the posture and level of exertion of a patient. An important aspect of ambulatory blood pressure monitors is the ability to measure blood pressure accurately when the patient is in motion. This standard recognizes the difficulty of performing such measurements given the susceptibility of blood pressure measurements to motion artefact. However, if devices wish to label themselves as accurate during motion, the standard requires they validate their device with reference pressures determined by intra-arterial measurements taken during activity. The accuracy of the device proposed in this report while in motion was unable to be determined due to the lack of an appropriate dataset or a prototype from which to attain a dataset. This standard also mentions that the device must be labelled appropriately such that the ability of the device to function under different circumstances (such as an elevated heart rate or cardiac arrhythmia) is known to the user. As testing of a prototype to this degree was not possible during the course of the project, such labelling was not mentioned.

Word Count: 631

Appendix C:

Sample Parts List:

Table 1: A table with sample parts for the proposed design. Only major parts are included[14]–[16], [39]–[44].

Part	Function	Current Draw (mA)	Voltage (V)	Cost ($)
Arduino Nano 3.0	Microcontroller	2.4	5	28.00
SFH 4545 High Power Infrared Emitter (940nm)	Infrared LED	36	5	0.81
SFH 213 FA Silicon PIN Photodiode	Infrared Photodiode	0.09	5	1.09*2
Adafruit LIS3DH Triple-Axis Accelerometer	Accelerometer	0.002	2.5	5.00
SSD 1306 12864 OLED Display Module	Display	16	3.3-5	3.00
331418 60mA rechargeable lipo mini battery cell	Power Supply	NA	NA	2.00*2
Micro SD 1Mb	Data Storage	NA	NA	1.00
			Total:	43.99