Data-Driven Estimation of Blood Pressure Using Photoplethysmographic Signals

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Abstract— **Noninvasive measurement of blood pressure by optical methods receives considerable interest, but the complexity of the measurement and the difficulty of adjusting parameters restrict applications. We develop a method for estimating the systolic and diastolic blood pressure using a single-point optical recording of a photoplethysmographic (PPG) signal. The estimation is data-driven, we use automated machine learning algorithms instead of mathematical models. Combining supervised learning with a discrete wavelet transform, the method is insensitive to minor irregularities in the PPG waveform, hence both pulse oximeters and smartphone cameras can record the signal. We evaluate the accuracy of the estimation on 78 samples from 65 subjects (40 male, 25 female, age 29±7) with no history of cardiovascular disease. The estimate for systolic blood pressure has a mean error 4.9±4.9 mm Hg, and 4.3±3.7 mm Hg for diastolic blood pressure when using the oximeter-obtained PPG. The same values are 5.1±4.3 mm Hg and 4.6±4.3 mm Hg when using the phone-obtained PPG, comparing with A&D UA-767PBT result as gold standard. The simplicity of the method encourages ambulatory measurement, and given the ease of sharing the measured data, we expect a shift to data-oriented approaches deriving insight from ubiquitous mobile devices that will yield more accurate machine learning models in monitoring blood pressure.**

Index Terms— **Machine Learning, Discrete Wavelet Transform, Blood Pressure, Mobile Health, Big Data**

I. Introduction

Monitoring blood pressure (BP) is an active field of research. Home measurement is more accurate in predicting health problems than in-office sampling [1], hence simple, easy-to-use devices are desirable. Recent developments focus on measurements that cause the least amount of discomfort to patients, as improved convenience leads to higher acceptance rate [2]. An ideal sensor is thus non-invasive, light-weight, unobtrusive, and trivial to place, which point towards cuffless, optical methods [3].

A photoplethysmograph (PPG) is a device to optically obtain a volumetric measurement of an organ. Peripheral volumetric changes and arterial BP are linked [4], but there is no simple, continuous relationship [5]. The placement of the PPG device is crucial: finger BP may be different from arterial BP in the arm [6], but strong correlation is apparent if the circumstances are given – for instance, during sleep [7]. Even given a high correlation with the BP wave, explicit mathematical models get complex as they attempt to incorporate free parameters, such as arm position and motion [5]. Machine learning methods address this problem by automatically extracting the relationship between BP and the PPG waveform. The seminal work in this field modelled the relationship between peripheral BP and blood volume pulses with linear auto-regressive with exogenous variable model and an artificial neural network for the nonlinear components [8]. Type-2 fuzzy logic also produced error rates below 10 % [9]. Previous data-driven methods like [10] collect a lot of data and show good accuracy. It includes invasive BP measurement as the gold standard and professional PPG sensor, which makes it restricted to hospital settings and usually need to collect PPG signals for a long time like 30 minutes. This makes it difficult to collect a large enough quantity of data to validate such methods and make the data-driven approach really useful.

We continue the line of work using machine learning, combining the approach with wavelet transforms. We perform single-point measurement with a pulse oximeter or a smartphone, which translates to an ability to improve accuracy by collecting more data from millions of potential users outside a controlled clinical experiment. We use a data-driven methodology with no explicit mathematical models which leads to resilience to adapt to different application scenarios.

We must also point out the limitations of our approach. We process the data off-line, hence continuous estimates are not yet feasible [11]. Until more data become available, sampling is restricted to a calm, seated position. The arm position relative to the heart is especially important [9], [5], [12]. As measurements leave a clinical setting and smartphones enable PPG recording, patients need more guidance to obtain a clean signal, as even the contact force with the sensor matters [13].

II. Methods

We acquire a PPG signal from a single-point measurement on the finger using an Android application (Section II-A), and extract periodic characteristics by a discrete wavelet transform (Section II-B). Using the wavelet coefficients and other characteristics of the data, we select a small subset of features by automatic means (Section II-C). A support vector regression estimates systolic and diastolic BP readings using the selected subset of features (Section II-D). This workflow was applied on the PPG signals obtained by the pulse oximeter and by the phone camera, on both SBP and DBP, leading to a total of four workflows[1].

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[1]The Android application that collected the data, the Mathematica and RapidMiner processing pipeline are shared at https://github.com/thmedialab/DataDrivenBP.

A. PPG signal collection on human subjects

Since our approach is data-driven, we had to obtain a relatively large number of PPG readings matched with SBP/DBP values. The number of subjects is critical. We recruited 65 volunteers, 40 male and 25 female subjects. Their age varied from 22 to 65, with a mean age of 29±7. They had no history of cardiovascular disease. We collected a total of 78 records, 13 volunteer recorded two times in different days.

Every subject had normal blood pressure, the mean SBP was 109.8±11.9 mm Hg, and the mean DBP was 70.6±10.5 mm Hg, as measured by an ordinary electronic blood pressure cuff model A&D UA-767PBT with error ±3 mm Hg. Sampling of PPG was performed while the subjects were seated with both an Android phone and an oximeter Etcomm HC-801 that sends data to phone via Bluetooth with sampling rate 20 Hz. The camera picture format was YUV420sp, which we converted to RGB888. Each channel shows the PPG channel, but we found that the green channel is the clearest, confirming the findings of earlier studies [14], [15]. The subjects' forearms were resting on the table at heart level to steady the hand with finger sensors attached to the index finger of the left and right hand. The pulse oximeter was placed on the right index finger. The participants held the phone in their left hand, placing the left index finger on the camera lens. A custom-developed application on the phone collected the data simultaneously from the camera and the pulse oximeter. Synchronising the beginning of the recording, we obtained pulse signals from both the camera lens and the pulse oximeter for a total of 120 seconds. Subjects were often not familiar or comfortable with the phone measurement procedure initially, adding excessive noise to the signal in the first sixty seconds. There we only process the remaining sixty seconds of the signal starting from the 60th second.

B. PPG signal and discrete wavelet transform

PPG and arterial blood pressure are coupled in mid-term signals, meaning between four to thirteen heartbeats [16], [5]. This observation hints at an optimal sampling window of twenty to ninety seconds. Given that we are interested in low-frequency data, and the time window is clear, we find detrending is unnecessary. Heart rate and respiratory rate are not directly relevant [17], these frequencies are not of interest in the processing.

A discrete wavelet transform (DWT) is a wavelet transform for which the wavelets are discretely sampled. Shannon wavelets are efficient for DWT, and they excel at finding periodic characteristics with a correctly chosen support length. In this study, we use the DWT function, with Shannon Wavelet evaluated on the equally spaced interval [-80, 80] in Mathematica to extract the DWT coefficients of the recorded 60s period PPG signal.

C. Optimal feature selection

To construct a mathematical model or an automated learner, we must identify those characteristics – features – of the data that are relevant to the problem. Using wavelet analysis, Teng and Zhang (2003) suggested using two coefficients of a transform with a Mexican hat mother wavelet, together with the systolic upstroke time and the diastolic time of the pulse [18]. Others proposed normalized harmonic area and the amplitude of PPG [19], [11]. We use the systolic upstroke time and the diastolic time, gender, age, together with thousands of DWT coefficients obtained in Section II-B. The calculation of systolic upstroke time and the diastolic time is done on the continuous wavelet transform with Mexican hat wavelet smoothed series using MinDetect and MaxDetect function in Mathematica.

The approach we use is using a linear support vector machine for feature selection, and later a non-linear support vector machine to train a model for prediction [20]. Combining a linear method with a nonlinear learner resonates well with the relationship between a PPG signal and BP, a similar system achieved high accuracy [8]. We use forward feature selection [21] – stop adding features when none of the alternatives improves upon the merit of a current feature subset based on the predictions of the underlining learner.

D. Machine learning with automated parameter tuning

Our aim is a form of regression: we would like to fit the feature set describing the PPG signals and the subjects to the corresponding SBP and DBP values.

We use the support vector regression machine [22] with RBF kernel for regression on the selected features. An SVM learner has parameters, most notably, the cost of making a wrong prediction. It is expected that high accuracy will require a large value for the cost parameter, as the number of training examples is not especially high by machine learning standards. As we are able to restrict the range of parameter settings, a greedy search in the parameter space is feasible to tune the learner. We use the Optimize Parameters Operator with linear steps to do the grid search to automatically tune the parameters of SVM in 10-fold cross-validation.

We changed the number of available training data from 20% to 100% and calculated the corresponding errors to analyse the sensitivity of the learner as an estimate of possible improvements through data collection.

III. Results

Table I shows the outcome of feature selection.

Figure 1 plots the mean error for all configurations when changing proportion of training data. The final mean error of estimating the SBP and DBP is close: 4.9±4.9 mm Hg for SBP, and 4.3±3.7 mm Hg for DBP. The gap was larger in the case of the phone-obtained PPG, with values of 5.1±4.3 mm Hg and 4.6±4.3 mm Hg, but the standard variance of the error was identically small, even with a small portion of the training set. Except phone-obtained PPG estimate of SBP, other three estimates are within the AAMI standard [23].

We did t-tests on the predicted SBP/DBP value with oximeter/phone camera data during 10-fold cross validation and the actual values. We got p-values of 0.8297, 0.9199 for SBP and DBP with oximeter, and 0.6565, 0.9402 for

	Pulse oximeter		Phone camera	
	Systolic	Diastolic	Systolic	Diastolic
Selected features	Gender and 11 DWT coefficients	Gender and 20 DWT coefficients	Gender and 13 DWT coefficients	Gender and 22 DWT coefficients

TABLE I

OVERVIEW OF THE SELECTED FEATURES. THE 2804 ORIGINAL FEATURES INCLUDE 2799 DWT COEFFICIENTS, THE UPSTROKE TIME, DOWNSTROKE TIME, THE HEART RATE, AGE, AND GENDER. THE AUTOMATED FEATURE SELECTION FOUND DIFFERENT OPTIMAL FEATURES FOR ESTIMATING SBP AND DBP.

SBP and DBP with phone camera. All p-values indicate the predicted sample mean is the same with the actual value sample mean.

IV. DISCUSSION

Contrary to our expectations, the number of selected features was strikingly low. Barely a dozen DWT coefficients suffice to achieve high accuracy with a linear predictor. This finding hints at the amount of irrelevant information in the signal: less than one percent of time-frequency decomposition is relevant.

Gender was included for predicting SBP and DBP with both sources of PPG signals. Interestingly, heart rate was not selected in any of the cases, confirming earlier findings that BP and heart rate are not directly relevant [17].

As expected, the error rate drops as the number of training examples increases. The decrease in error rate is not sharp, although we must keep in mind that even the complete data – 78 training samples – are few for a learning algorithm. The overall error rate was similar for the PPG signals obtained by the pulse oximeter and the phone camera: the learning workflow is insensitive to noise, and therefore a device already owned by most people can act as a recorder. There seems to be no statistical difference in mean error between all the experiments $\geq$ 60 % data for training, there could be overfitting which could only be overcome by a lot more data.

Since generalisation performance depends on model complexity, we also plot the number of support vectors for each case in Figure 2.

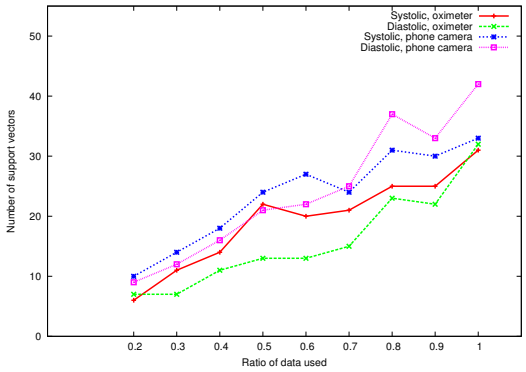

Fig. 2. The number of support vectors as the function of training data available

The model complexity is in line with our expectations. Since nearly all blood pressure readings were different, an estimator must consider most training examples in building the model. With all examples included, we found between 31 and 42 support vectors, which is 40% to 54% of the number of examples. This indicates a relatively complex model, and the scaling of the number of support vectors is near-linear with the ratio of training examples included. Naturally, on the noisier samples obtained by the phone the number of support vectors was consistently higher. We expect that including more overlapping blood pressure readings, the curve would flatten out, and the overall complexity would decrease.

The similar prediction accuracy between data from oximeter and phone camera might guarantee the quality of less rigorous data collection by a cell phone camera alone. Future research in this area might be made possible with the availability of open research frameworks like HealthKit by Apple Inc. that can enable large-scale health data collection.

V. CONCLUSION

Purely data-driven modelling is tempting: even using a noisy PPG obtained on a smartphone, we achieved a mean error of 5.1$\pm$4.3 mm Hg for estimating SBP, and 4.6$\pm$4.3 mm Hg for estimating DBP. The workflow automatically selected a small number of salient features, and tuned the learner to find the best estimators. Given the simplicity of data collection and the widespread use of smartphones, potentially millions of end-users can get involved, paving the way of big data analysis in blood pressure monitoring.

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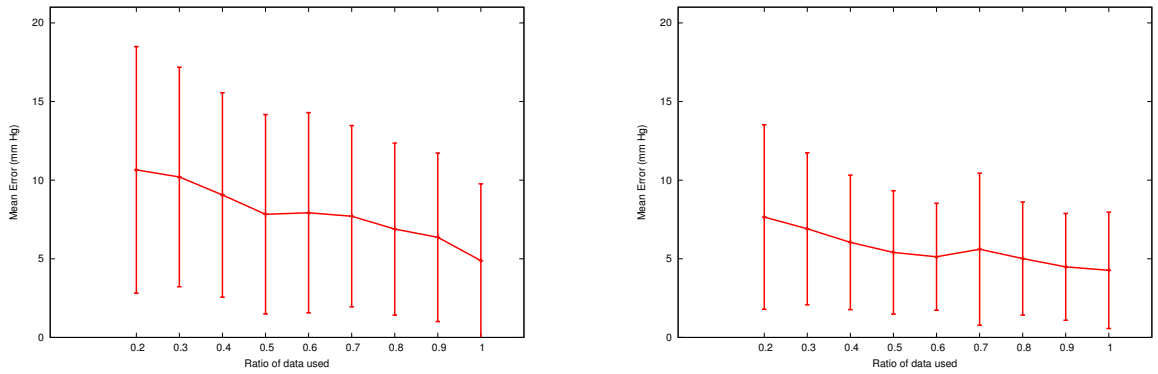
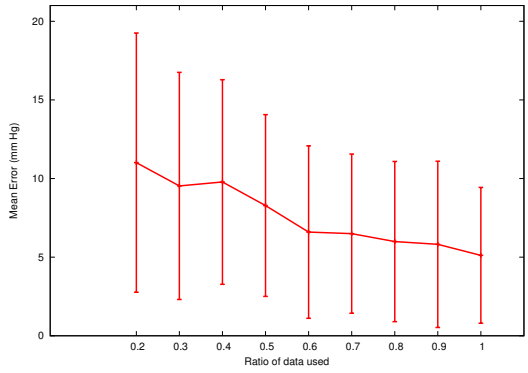
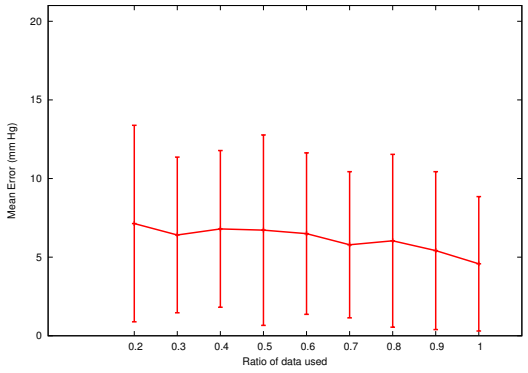


(a) Systolic blood pressure, oximeter

(b) Diastolic blood pressure, oximeter



(c) Systolic blood pressure, phone camera



(d) Diastolic blood pressure, phone camera

Fig. 1. Mean error and error bars for estimating the systolic and diastolic blood pressure. The PPG signal was either obtained by a pulse oximeter – (a) and (b) – or by a phone camera – (c) and (d).

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