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A Multi-Wavelength Optical Sensing Framework for Calibration-Free Wearable Blood Pressure Monitoring

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***Abstract*—Blood pressure (BP) is a key indicator of cardiovascular health, with hypertension leading to significant morbidity and mortality worldwide. Continuous monitoring of BP is essential for early detection of cardiovascular disease, however current tools are either cumbersome, unreliable, or not suited for long-term use. Traditional cuff-based BP measurement, while reliable, is impractical for continuous monitoring. Recent advances using photoplethysmography (PPG) waveforms offer an alternative, but they face challenges such as limited interpretability, high computational complexity, and susceptibility to motion artifacts. In this paper, we introduce a novel multi-wavelength optical sensing framework designed for calibration-free wearable blood pressure monitoring. Our system utilizes a broad spectrum of wavelengths and interpretable features, combined with machine learning, to estimate systolic (SBP), diastolic (DBP), and mean arterial pressure (MAP). The framework was tested in a proof-of-concept study involving 9 subjects across varied postures and BP levels, demonstrating accuracy comparable to standard cuff-based techniques. This approach eliminates the need for continuous calibration and provides a scalable, interpretable solution for real-time, wearable BP monitoring.**

***Index Terms*—blood pressure, wearable, calibration-free, spectroscopy, multi-wavelength, PPG**

I. Introduction

Blood pressure is one of the most commonly monitored vital signs, critical for monitoring overall health [1]. Hypertension, or high blood pressure, is a leading contributor to morbidity and mortality in the United States, where nearly half of adults are affected [2]. The CDC has reported a stark increase in hypertension over the last decade, with prevalence rising from 10.2% in 2011-2012 to 48.1% in 2022 [2]. Despite increased prevalence and awareness, blood pressure control remains unsatisfactory [3]. As a result, ubiquitous tools for detecting and managing blood pressure, especially outside the clinic, have become increasingly desired.

An effective approach to managing and reducing blood pressure-related diseases is early detection, timely treatment, and continuous monitoring. The oscillometric method, commonly used in clinical settings, relies on an inflatable cuff to measure oscillations in arterial wall pressure during deflation, similar to manual Korotkoff sound-based measurements [4]. However, this method has limitations, including discomfort from cuff inflation [5], inaccuracies in certain populations [6], improper usage [7], [8], and the inability to provide continuous monitoring [9]. These drawbacks have driven the development of cuffless methods to alleviate this burden.

To date, there has been a large amount of research on cuffless blood pressure monitoring; exhaustive reviews can be found in [10] and [11]. Traditionally, PPG is used alongside ECG to calculate pulse transit time (PTT), the time it takes for an arterial pulse wave to travel between two points. This measure correlates directly with blood pressure—shorter transit times generally indicate higher pressure due to stiffer arterial walls [12], [13]. However, systems based on PTT require initial and ongoing calibration with an oscillometric cuff to account for individual physiological differences, such as tissue composition and vascular elasticity [14], [15]. While this approach has enabled more continuous monitoring of blood pressure without the constant need for a cuff, it also faces challenges, including the ongoing need for cuff calibration [16], difficulty in calculating PTT with abnormal ECG signals [17], and the need for advanced algorithms to filter noise, especially in motion-sensitive PPG waveforms [18].

Recent research has increasingly focused on estimating blood pressure using advanced signal processing and machine learning techniques solely from PPG waveforms. These approaches extract features from fiducial points of the PPG waveform and utilize physiological models [19], machine learning regression [20], [21], and deep learning [21]–[23] to predict blood pressure with reasonable accuracy. Several calibration-free devices, such as those by Aktiia [24], Corsano [25], and Valencell [26], claim to provide accurate blood pressure readings using PPG and machine learning algorithms without the need for traditional cuff calibration. However, none of these devices have received FDA approval.

Despite promising progress in calibration-free PPG-based monitoring, challenges remain. Accurate predictions depend on the precise extraction of PPG waveform features, which requires high-fidelity data, a high sampling rate, and advanced denoising techniques—factors that can impact battery life in practical applications and may be impractical in a wearability-constrained and noisy environment [27]. Additionally, deep learning models used in this context often lack explainability, a critical factor for clinical use.

To date, there has been limited work on wearable devices utilizing wavelengths across the visible spectrum for blood

pressure measurement. Liu *et. al* [28] and Botrugno *et. al* [29] proposed multi-wavelength PPG algorithms for cuffless blood pressure monitoring, employing principal component analysis and neural networks, respectively. While these approaches have demonstrated performance comparable to, or even surpassing, single and dual-wavelength PPG sensors, they still face several limitations, including the need for individual calibration [28], operation within a relatively narrow spectral band [28] [29], reduced wearability [28], and limited interpretability of the resulting models [28] [29].

There is a growing body of work suggesting that additional contextual sensors that increase spectral resolution may improve optical biomarker detection, especially in the presence of noise [30]. In this paper, we introduce a multi-spectrum spectral framework using an off-the-shelf wearable for calibration-free BP monitoring. This framework employs interpretable features combined with machine learning techniques to estimate mean arterial blood pressure (MAP), systolic blood pressure (SBP), and diastolic blood pressure (DBP), achieving accuracy comparable to existing methods. We evaluate this framework in a n=9 feasibility study, spanning a range of BP values to demonstrate its effectiveness and generalizability.

The contributions of this work include: (1) the development of a novel multi-spectrum spectroscopy framework that leverages wavelengths across the visible spectrum for calibration-free BP monitoring; (2) the implementation of classical machine learning techniques that utilize easily interpretable features to estimate MAP, SBP, and DBP, achieving accuracy comparable to traditional methods; and (3) a comprehensive evaluation of the proposed framework in a n=9 feasibility study to validate its effectiveness and generalizability.

II. Framework Design

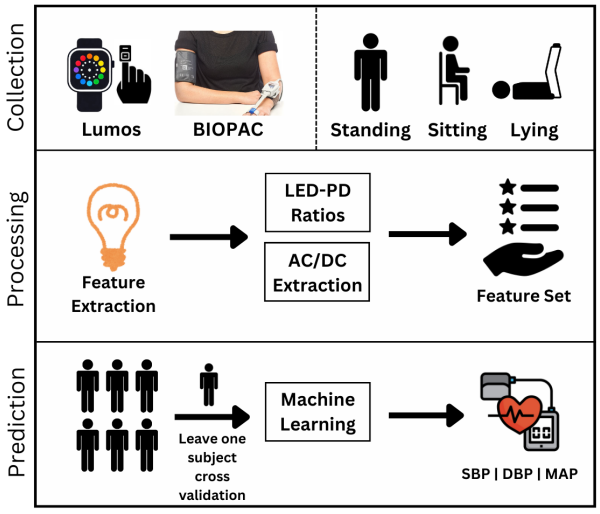


Fig. 1: Blood Pressure Prediction Framework

An overview of the system architecture used to collect multi-wavelength spectral data and convert these measurements to SBP, DBP, and MAP values relative to ground-truth is shown in Figure 1.

We utilized Lumos [31], an off-the-shelf wearable device, for multispectrum optical measurements. Lumos utilizes LEDs and photodiodes (PDs) ranging from 400nm-1000nm, allowing for a wide sensing spectral resolution that current commercial wearable devices do not provide. The device can be configured in several form-factors through the use of a detachable strap; we utilized a fingertip and wrist form-factor for this study. Regardless of configuration, spectral measurements are recorded in reflectance mode. Lumos functions by recording the PD responses for each LED that is turned on during its operation cyclically. Thus, for a sensor array of 9 PDs and 10 LEDs, there are 90 sensor readings every 1.7 seconds.

For ground-truth measurements, the BIOPAC NIBP100E was used [32]. The NIBP100E is a data acquisition system that uses arterial occlusion of the fingers along with occasional arm cuff calibration to provide continuous, beat-to-beat, blood pressure waveforms and downstream values (SBP, DBP, MAP). The system is FDA and CE-approved and is used commonly in academic settings, with an accuracy of $\pm$5mmHg. We conducted a proof-of-concept study with 9 subjects to evaluate feasibility of our framework. The BIOPAC NIBP100E was positioned on the participant's right arm, while an arm cuff was placed on the left arm for initial calibration. The Lumos devices (configured for finger and wrist placement) were worn on the left arm after calibration to avoid blood pressure distortions caused by upstream or downstream arterial occlusion from the NIBP finger cuffs. This setup allowed for accurate, distortion-free readings between arms, with continuous data collection from all devices.

To simulate varying blood pressure conditions, measurements were taken while participants were seated, standing, and lying down with their legs elevated. Each position was held for approximately 3 minutes, totaling 9 minutes per subject. During this time, the BIOPAC device continuously recorded SBP, DBP, and MAP values on a beat-to-beat basis. This study was approved by the Institutional Review Board of University of Virginia (IRB-HSR #240068).

Systolic, diastolic, and MAP values were time-aligned with the nearest respective Lumos measurements for direct comparison. The following features were then used for training on each row corresponding to a single Lumos measurement (90 columns) and output targets (SBP, DBP, MAP):

1) LED-PD values - representing sensor readings corresponding to individual LED and photodiode (PD) responses during a Lumos cycle.
2) LED-PD AC and DC extraction - 5th-order high-pass and low-pass Butterworth [33] filters, with a cutoff frequency of 0.1 Hz, were applied to extract the alternating current (AC) and direct current (DC) components from each LED-PD signal.
3) Inter-beat interval - time between successive peaks for each LED-PD waveform.
4) Ratios of above features - to provide normalization or relationness, ratios of all the above features were taken.

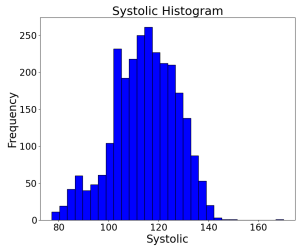
Model	Finger (Subject-specific)			Wrist (Subject-specific)			Finger (Generalized)			Wrist (Generalized)		
	MAP MAE (SD)	Diastolic MAE (SD)	Systolic MAE (SD)	MAP MAE (SD)	Diastolic MAE (SD)	Systolic MAE (SD)	MAP MAE (SD)	Diastolic MAE (SD)	Systolic MAE (SD)	MAP MAE (SD)	Diastolic MAE (SD)	Systolic MAE (SD)
XGBoost	4.14 (0.52)	4.36 (0.41)	5.37 (0.69)	4.09 (0.50)	4.23 (0.47)	5.30 (0.97)	7.04 (2.43)	7.21 (2.14)	9.50 (3.35)	6.92 (1.69)	6.76 (1.70)	10.21 (3.25)
CatBoost	4.15 (0.60)	4.37 (0.55)	5.31 (0.76)	4.04 (0.62)	4.33 (0.55)	4.99 (0.95)	6.71 (2.31)	6.99 (2.22)	9.30 (3.29)	7.19 (2.20)	6.48 (1.60)	10.26 (3.03)
LightGBM	4.18 (0.57)	4.53 (0.54)	5.31 (0.88)	4.11 (0.53)	4.27 (0.54)	5.62 (1.40)	7.31 (2.33)	7.58 (2.11)	10.20 (2.92)	7.47 (2.22)	7.23 (2.08)	11.42 (3.91)
RandomForest	4.39 (0.65)	4.75 (0.72)	5.22 (0.82)	4.24 (0.60)	4.26 (0.48)	5.67 1.77)	7.53 (2.44)	7.89 (2.45)	10.65 (2.84)	8.55 (2.70)	7.52 (1.65)	13.19 (5.23)
GradientBoosting	5.07 (0.28)	5.43 (0.27)	6.80 (0.82)	5.07 (0.25)	5.37 (0.15)	7.27 (1.01)	7.12 (2.32)	7.34 (2.10)	9.60 (3.17)	7.20 (1.95)	6.74 (1.72)	10.19 (3.17)

TABLE I: Top five models' performance for MAP, diastolic, and systolic measurements on the finger and wrist.

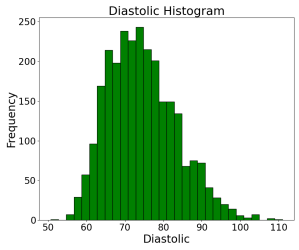
These features were chosen based on the assumption that physiological factors—such as skin thickness, skin-tone, and vascular elasticity—which require re-calibration or advanced non-linear modeling in systems solely relying on traditional PPG, can be effectively captured using additional wavelengths that are utilized in Lumos. The simplicity of these features was intentional to prioritize interpretability.

To evaluate the performance of various machine learning models in predicting blood pressure, we used a combination of regression techniques. The tested models included tree-based algorithms such as random forest, gradient boosting, XGBoost, CatBoost, and LightGBM models, as well as linear models such as Ridge, Lasso, and basic linear regression. Variance thresholding was used to remove low-variance features, which were then scaled using RobustScaler, allowing the model to be resistant to outliers. Recursive feature elimination using a random forest model as the base estimator was used to reduce the feature set to the most relevant predictors prior to training. We utilized two models for each target variable per form-factor: a generalized model on the entire cohort and a subject-specific model that corrected for individual biases following training. These results are discussed in Section III.

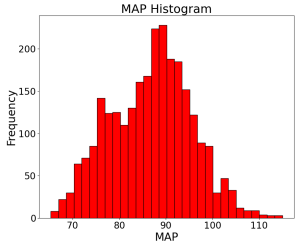
III. Evaluation



(a) Systolic Histogram



(b) Diastolic Histogram



(c) MAP Histogram

Fig. 2: Data distribution among three output target variables.

A summary of input statistics for the collected subject data can be found in Fig 2a, 2b, and 2c. The systolic values appear to follow a relatively normal distribution, with fewer data points observed in the hypertensive range. Diastolic values, conversely, are skewed towards lower blood pressure, while MAP displays a more symmetric, normal distribution. Given that the population is expected to be predominantly normotensive, these results align with expectations.

We implemented leave-one-subject-out (LOSO) cross-validation to ensure the models had the ability to predict an entirely new subject's data after training. Mean absolute error (MAE) and its standard deviation (SD) were calculated for each model to quantify performance and model stability across various features and target variables. Table I demonstrates the models' performance at predicting each blood pressure metric for the finger and wrist, using both our generalized and subject-specific model. Performance is relatively strong across all models in both configurations, with MAP and diastolic MAEs outperforming systolic. Our subject-specific models performed extremely well across form-factors and targets.

To contextualize these results, we present them relative to current international standards. IEEE, the British Hypertension Society (BHS), and the Association for the Advancement of Medical Instrumentation (AAMI) each have standards regarding the performance of blood pressure estimation models; these standards are utilized by regulatory agencies during evaluation of these devices.

	BHS Compliance (%)			
Target	$\leq$ 5 mm	$\leq$ 10 mm	$\leq$ 15 mm	Grade
SBP (W)	59.8	88.0	97.0	B
DBP (W)	65.8	92.5	99.2	A
MAP (W)	68.9	93.5	99.4	A
SBP (F)	57.4	86.1	96.0	B
DBP (F)	64.5	92.7	99.3	A
MAP (F)	68.0	93.1	99.1	A

TABLE II: BHS compliance and grades for wrist (W) and finger (F) measurements.

a) BHS classifies performance based on compliance percentage, or how much of a percentage of the predicted values fall within three thresholds: 5mmHg, 10mmHg, and 15mmHg. Our subject-specific wrist and finger systolic predictions score a B based on this classification, and an A for all other predictions. These results are summarized in Table II.

	IEEE and AAMI Results				
Target	**MAD**	**ME**	**SD**	**IEEE Grade**	**AAMI**
SBP (W)	5.06	0.88	6.67	B	Compliant
DBP (W)	4.32	0.40	5.47	A	Compliant
MAP (W)	4.05	0.56	5.15	A	Compliant
SBP (F)	5.26	0.37	6.94	B	Compliant
DBP (F)	4.40	0.52	5.52	A	Compliant
MAP (F)	4.14	0.32	5.32	A	Compliant

TABLE III: IEEE and AAMI results for wrist (W) and finger (F) measurements.

b) IEEE and AAMI have similar standards, with different implementations. IEEE grades devices based on their mean absolute difference (MAD). Similar to the BHS classifications, we score a B in subject-specific wrist and finger systolic predictions, and an A in all other predictions. Finally, AAMI determines compliance by checking the mean error (ME) as well as the standard deviation (SD). Across all predictions, we are AAMI compliant. These results are summarized in Table III.

The most important features to our models were a combination of LED-PD DC extracted waveforms and their ratios in the 500-700nm range, as well as LED-PD ratios across the visible spectrum and interbeat internal (IBI) ratios in the 500-700nm range. These features were consistent across form-factors, models, and targets. Below are examples of each:

- **Feature 1**: LED633-PD590 / LED670-PD415
- **Feature 2**: LED415-PD680-DC / LED633-PD590-DC
- **Feature 3**: LED633-PD590-IBI / LED670-PD415-IBI

IV. Discussion

Our multi-wavelength optical sensing framework offers several advantages over traditional PPG-based systems for blood pressure estimation. By utilizing wavelengths across the visible spectrum, rather than relying on the traditional single or dual-wavelength approach, our system can allow for better differentiation between various tissue types and components, potentially increasing the accuracy of blood pressure estimation across diverse populations. A multi-wavelength approach may also be more robust against motion artifacts and environmental interference, since all channels may not be affected by noise. Furthermore, the framework is extremely versatile: the device can be fit into multiple form-factors, not just the finger and wrist, and can be equipped with sensors from across the visible and infrared spectrum to tailor sensing using wavelengths that are specific to blood pressure detection.

Our models have uncovered features that suggest a deeper understanding of tissue properties beyond those measured by traditional PPG, potentially improving blood pressure detection. Given the particular relevance of feature ratios, its possible that DC, LED-PD, and IBI ratios capture complementary aspects of light interaction that are not solely correlated with the pulse wave. Notably, while IBI is traditionally associated with heart rate, in this context, it may also capture other AC components related to respiration and skin dynamics, thus providing a normalization to traditional PPG features and improving overall blood pressure detection. Further studies will be conducted to explore these relationships in greater detail.

While our current models benefit from subject-specific training, we expect general-purpose models to perform similarly with sufficient data. While subject-specific models may resemble traditional calibration, they likely learn spectral patterns specific to the individual, thereby eliminating the need for periodic recalibration as required in methods like pulse transit time and allowing for a one-time calibration. Overall, as our training dataset grows, we anticipate that generalized models will achieve performance comparable to subject-specific models. We also observed significant oversaturation in certain photodiodes during our trials, particularly the 820nm PD, which might be relevant for blood pressure detection; we aim to correct this in future studies and expect better performance as a result.

While this study serves as a promising proof of concept for our multi-wavelength optical sensing framework, we acknowledge that significant further validation is required. Our next steps include expanding the study to a much larger and more diverse cohort, encompassing a wider range of blood pressure values, with particular emphasis on hypertensive subjects, as well as various demographic factors including age, gender, and fitness levels. We will also investigate edge cases by exploring blood pressure changes in scenarios such as drug administration effects, stress-induced fluctuations, and exercise-related variations. Given that blood pressure typically decreases during sleep [34], we plan to conduct overnight studies to evaluate our system's performance in detecting and accurately measuring these nocturnal dips. To ensure long-term stability, we will assess the algorithm's accuracy and reliability over extended periods to confirm consistent performance without the need for recalibration. Lastly, we plan to conduct rigorous comparisons against invasive arterial line measurements and other FDA-approved non-invasive devices to validate our system's accuracy.

V. Conclusion

This paper introduces a novel multi-wavelength optical sensing framework for calibration-free, wearable blood pressure monitoring. By leveraging multiple wavelengths across the visible spectrum, combined with machine learning and signal processing techniques, we have demonstrated the ability of the system to provide accurate estimates of SBP, DBP, and MAP. The results of our proof-of-concept study (n=9) indicate that the proposed framework achieves accuracy comparable to current cuff-based methods while maintaining interpretability and robustness across a range of blood pressures. Future work will focus on expanding the cohort size to include a more diverse demographic and exploring the framework's performance in various scenarios, such as during physical activity or in response to pharmacological interventions. Additionally, further validation against invasive and non-invasive gold-standard devices will be necessary to confirm the system's clinical applicability.

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