ArterialNet: Arterial Blood Pressure Reconstruction

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***Abstract*—Accurate and continuous monitoring of arterial blood pressure (ABP) is vital for clinical hemodynamic monitoring. However, current methods are either invasive, requiring insertion of catheters, or provide limited information, lacking comprehensive ABP waveforms. Cuffless wearable solutions, combined with deep learning, offer potential but face challenges in accurately reconstructing ABP waveforms and estimating systolic and diastolic blood pressure (SBP/DBP) due to individual variability. We propose a custom pre-trained backbone and a tailored optimization function to address these challenges. Our method demonstrates superior performance in ABP waveform reconstruction and accurate SBP/DBP estimations, while significantly reducing subject variance. To validate the effectiveness of our approach, we conducted comprehensive evaluations using both in-clinic data and a pioneering study involving remote health monitoring with cuffless data. Our results surpass previous efforts, demonstrating a root mean square error (RMSE) of 5.41 ± 1.35 mmHg and a minimum of 58% lower standard deviation (SD) across all measurements. These outcomes highlight the robustness and precision of our method in accurately estimating SBP/DBP and reconstructing ABP waveforms. Furthermore, we assessed the performance of our solution in non-clinical settings using the CTRAL BioZ dataset. The evaluation yielded an RMSE of 8.66 ± 1.13 mmHg for ABP, proving the potential of ABP reconstruction under remote health settings.**

***Clinical Relevance*—ArterialNet is a competitive alternative to replace invasive arterial lines via reconstructing ABP waveform with accurate physiological predictions from peripheral pulsatile recordings.**

I. Introduction

Hemodynamic monitoring is critical in clinical outcomes and patient safety by providing early warning signs of cardiovascular-related adverse events such as cardiogenic shock [1]. Continual tracking of arterial blood pressure (ABP) is the basis of accurate monitoring in perioperative and postoperative settings. However, this monitoring, which records a continuous and accurate hemodynamic data stream, is invasive, through the insertion of arterial lines. Alternatively, non-invasive blood pressure cuffs provide periodic measurements that serve as a surrogate for hemodynamic changes (in this case blood pressure changes) but collect sparse, limited readings [2]. Thus, arterial lines are always preferred in critical settings despite potential secondary complications, such as bleeding and infection [3]. Conversely, in remote health settings, the invasive nature of A-line makes it impractical for hemodynamic monitoring with ABP waveform.

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Recently, there has been a growing interest in cuffless wearable sensors that utilize peripheral pulsatile recordings to offer convenient and non-invasive continuous blood pressure (BP) measurement through beat-to-beat estimation. By leveraging deep learning (DL)-based regression algorithms, these cuffless approaches have demonstrated precise and correlated predictions for systolic and diastolic blood pressure (SBP/DBP) values, meeting the standards of the medical industry [2]. Moreover, DL-enhanced sequence-to-sequence (seq2seq) modeling has improved ABP sequence reconstruction by mapping pulsatile signals to the ABP waveform [3]. However, the significant variability in BP modeling between individuals hinders an accurate DL solution for everyone.

While there have been limited attempts for personalized ABP monitoring in clinical settings, these efforts only work on some subjects but inflict significant errors on others. Additionally, models solely trained on waveform reconstruction often result in inaccurate estimations of physiological characteristics such as SBP and DBP.

This work involves leveraging a custom pre-trained backbone and implementing a tailored optimization function, followed by applying transfer learning to develop personalized ABP monitoring. Instead of designing a pre-trained model specifically for the task, we utilized seq2seq models as backbones for signal modality transformation, enabling us to develop downstream tasks for waveform reconstruction and SBP/DBP estimations. In this study, we propose ArterialNet, a framework for ABP reconstruction that is independent of the specific backbone used, and we make the following contributions:

- A feature extractor that captures temporal dependencies by extracting long sequences of previous cardiac cycles and removes subject dependencies, allowing us to minimize covariate shifts [4].
- A hybrid objective function that evaluated both waveform and statistical reconstruction losses. This approach helped the ArterialNet understand the distribution of correct ABP waveforms and achieve accurate estimations of both morphologies and amplitudes.
- A subject-invariant regularization that enables training multiple subjects in parallel and guides the backbone's convergence to an extrapolated cohort instead of any individual.

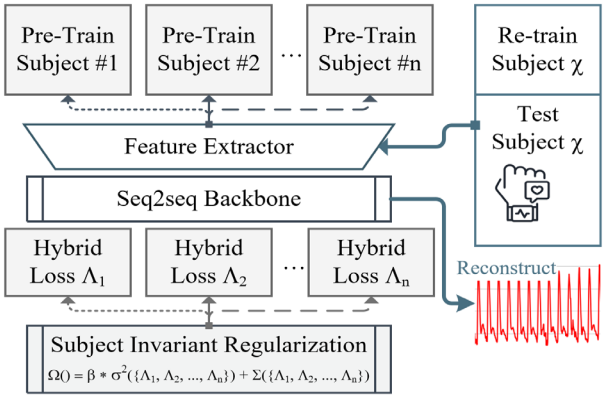

Figure 1: Overview of the proposed ArterialNet, an ABP Modeling Framework pre-trained with multiple subjects and then calibrated with a new subject using a subset of one's recordings.

We demonstrated our pre-trained ArterialNet achieved higher accuracies for both ABP reconstruction and SBP/DBP estimation than previous works on prediction and reconstructions tasks from data captured from both intensive care unit (ICU) patients and non-ICU subjects via a cuffless bio-impedance-based wearable device.

II. Related Works

The existing literature on ABP measurement has focused on minimizing reconstruction loss of ABP waveforms using pulsatile recordings or derived features. Many studies reconstructed ABP by incorporating at least two pulsatile recordings from different parts of the human body, as pulse transit time (PTT) is inversely correlated with BP vitals [5] For example, Hill et al. used a modified V-Net backbone to impute ABP waveform using electrocardiography (ECG) and photoplethysmography (PPG) recordings [6].

Maintaining two recording sites may be challenging, so other solutions have been developed with single-channel pulsatile recordings and reported competitive performance. For example, Ibtehaz et. al. applied a modified U-Net backbone with raw PPG waveform recordings [7]. However, neither approach failed to minimize errors and variances in SBP/DBP estimations. In contrast, our ArterialNet integrates seamlessly with various single-channel PPG seq2seq backbones, such as U-Net and transformer, to elevate performance in both ABP reconstruction and SBP/DBP estimations.

III. Methods

In this section, we discussed data preparation, and the proposed ArterialNet, illustrated in Figure 1, beginning with the feature extractor, data is provided to the seq2seq backbone, optimized by a hybrid objective function and the subject-invariant regularization, and ultimately both waveform and SBP/DBP estimates are generated. We also share the implementation and experiment setup (next section) at https://github.com/stmilab/ArterialNet. We discuss the components further in the following section.

A. Feature Extractor

We designed the feature extraction encoder as a dilated convolutional neural network (CNN) that includes both convolutional layers (convlayers) and fully connected layers (fclayers). The convlayers consist of two 1D convolutional layers with dilation, each followed by a leaky rectified linear unit (ReLU). Meanwhile, the fclayers comprised three fully connected linear layers with another leaky ReLU activation function. We applied one-dimensional batch normalization between every layer of both the convlayers and fclayers.

B. Seq2seq Backbone

ArterialNet was flexible to incorporate both approaches as backbones. We chose an improved U-Net variant [8] and a transformer as they achieved state-of-the-art on several related works.

C. Hybrid Loss Function

We selected root-mean-squared error (RMSE) as the reconstruction loss criterion and denoted the loss function as λ, the hybrid loss function as Λ, the predicted and reference waveform as $\hat{\theta}$ and θ, respectively. We implemented a non-gradient function to the 5 statistical features (Ψ) {mean, standard deviation, skewness, minimum, and maximum} from θ and $\hat{\Psi}$ from $\hat{\theta}$, respectively. Then, we defined a weight hyperparameter α [0,1] to adjust statistical importance and guide the ArterialNet to learn the distribution of ABP waveforms with the following hybrid loss function (1):

$$\Lambda(\hat{\theta}, \theta) = (1 - \alpha) * \lambda(\hat{\theta}, \theta) + \alpha * \lambda(\hat{\Psi}, \Psi). \quad (1)$$

The hybrid loss function calculated and returned the modified reconstruction loss of predicted and reference waveforms.

D. Subject Invariant Regularization

We implemented a subject-invariant regularization layer to minimize the impact of subject-dependent features when pre-training ArterialNet with multiple subjects. To achieve this, we adopted Krueger's variance risk extrapolation (REx) theory [9] and a regularization layer that calculated the regularized loss (Ω) of all training losses ($\{\Lambda_1, \Lambda_2, ..., \Lambda_n\}$) by adding weighted variance (σ^2) to the sum (Σ) in equation (2):

$$\Omega(\hat{\theta}) = \beta * \sigma^2(\{\Lambda_1, \Lambda_2, ..., \Lambda_n\}) + \Sigma(\{\Lambda_1, \Lambda_2, ..., \Lambda_n\}). \quad (2)$$

We defined the weight hyperparameter β [0, ∞) to control the magnitude of extrapolation. This regularization layer applied variable weights to different subjects and manipulated the rate of backpropagation of ArterialNet to different training data. This regularization strategy ensured that the model was optimized for the extrapolated (subject-invariant) population instead of the observed training subjects, thus minimizing subject-dependent features. To validate the success of extrapolation, we evaluated it on a held-out subject.

IV. Experiments and Results

We evaluated the effectiveness of ArterialNet in generating accurate ABP waveforms by comparing its performance with the previous methods. We provide a detailed description of the datasets and experimental setup used, report the results of our experiments, and discuss the insights and findings that were obtained.

We evaluated the performance with absolute values and standard deviation (SD) of RMSE, mean-absolute-error

Table 1: Performance evaluation of proposed ArterialNet versus related studies on both ABP waveform reconstruction and physiological estimations.

Table of ABP Reconstruction Evaluation on ICU Data Collections collected with PPG and/or ECG												
Method	Dataset	# of Subjects	Total data (hours)	Performance Metrics (RMSE and MAE in mmHg, no unit for R)								
				ABP (SD)			SBP (SD)			DBP (SD)		
				RMSE	MAE	R	RMSE	MAE	R	RMSE	MAE	R
LSTM [12]	MIMIC	42	-	6.04 (3.26)	5.98	0.95	2.58	-	-	1.98	-	-
V-Net [6]	MIMIC III	264	1923+	5.82	-	0.96	-	-	-	-	-	-
U-Net [7]	MIMIC II	942	354	-	4.60 (5.04)	-	-	5.73 (9.16)	-	-	3.45 (6.15)	-
Transformer [13]	MIMIC	241	150~241	-	-	-	-	4.01 (5.93)	0.90	-	2.97 (3.87)	0.84
ArterialNet U-Net	MIMIC III	56	733	5.78 (1.45)	4.52 (1.91)	0.92 (**0.04**)	5.76 (1.93)	4.30 (1.97)	0.89 (0.05)	4.65 (1.68)	3.38 (1.68)	0.87 (0.04)
ArterialNet Transformer	MIMIC III	56	733	**5.41** (**1.35**)	**4.17** (**1.29**)	0.91 (0.04)	5.26 (**1.35**)	4.15 (**1.32**)	**0.90** (**0.03**)	4.01 (**1.55**)	3.17 (**1.37**)	**0.88** (**0.01**)

(MAE), and Pearson's correlation coefficient (R) between reconstructions/estimations and references.

A. Dataset Selection

1) ICU Data Collection

We utilized the Medical Information Mart for Intensive Care III (MIMIC-III) waveform dataset [10], which contained 22,317 pulsatile PPG, ECG, and associated ABP waveform records. To create a suitable dataset, we screened patients via their electronic health records (EHR) and removed the following: 1) Patients with extreme hemodynamics (e.g., extreme respiratory rate, oxygen saturation, etc.); 2) Patients with missing or flat recordings; 3) Patients with narcotic or illicit drug use, organ failure, or major internal bleeding during check-in. We established a cohort of 61 patients, with a median age of 65 years old and a range of 25-87, comprising 34 females. The list of patients is available in our repository.

2) Non-ICU Data Collection

We conducted a study involving 20 healthy participants (45% male) between the ages of 18 and 40 years old to collect data from a non-ICU environment (IRB2020-0090F, Texas A&M University). We used a bioimpedance-based cuffless device [11] to compare against reference waveforms collected by a Finapres NOVA. Each participant completed an 8-minute protocol consisting of 0.5 minutes of rest, 3 minutes of gripping a hand to raise BP, 1 minute of placing a foot in ice water to lower BP, and 3.5 minutes of rest to recover BP. Each participant repeated the protocols 4 times per visit and had 7 visits scheduled at least 24 hours apart.

B. Data Preparation

With collected pulsatile waveforms, we first applied a finite impulse response (FIR) bandpass filter of (0.5-8 Hz) to remove artifacts without distorting the signals. Then, we performed phase shifting to align pulsatile recordings features and ABP waveform labels and then segmented them into cardiac cycles based on maximum slopes [11].

C. Experiment Results

We selected five patients who are normotensive at admission {27172, 47874, 94897, 56038, 82574} from the MIMIC-III waveform cohort. We then pre-trained ArterialNet using four random patients and validated it on the remaining patient. After thorough hyperparameter tuning (we reported all tuning scope in our repository), we selected the best-performing pre-trained ArterialNet, which had a batch size of 512, a learning rate of 1e-5, and was trained for 75 epochs.

1) MIMIC Experiments

We used transfer learning to retrain the rest 56 patients individually and performed the same hyperparameter tuning. We evaluated ArterialNet's performance on waveform reconstruction by comparing it against related studies with the following seq2seq backbones: long short-term memory (LSTM) [12], V-Net [6], U-Net [7], and Transformer [13]. Due to each study being conducted on a separate and undisclosed cohort, we have included their individual findings, alongside our own results, in Table 1.

Our ArterialNet, employing both backbones, achieved significantly lower SD than baselines on derived SBP/DBP estimations. Furthermore, our study cohort was significantly larger, demonstrating ArterialNet's superior generalizability across diverse subjects. With Bland-Altman Analysis in Figure 2, we also demonstrated high agreement between ArterialNet's reconstruction and reference waveform for individuals.

2) BioZ Experiment

We repeated the same process to pre-train ArterialNet with five trials, then retrain and test it on the rest of the trials. With the reported hyperparameter tuned results in Table 2, ArterialNet reconstructed correlated waveform, SBP, and DBP and proved the feasibility of waveform reconstruction via peripheral bioimpedance pulsatile. To the best of our knowledge, this is the first ABP reconstruction study with bio-impedance pulsatile on healthy participants.

V. Limitations, Future Directions

We have investigated the adaptability of ABP reconstruction models to new subjects, but minimizing calibration time is another crucial aspect. Therefore, our future work focuses on enhancing the practicality of ArterialNet in clinical settings by evaluating its performance on a diverse patient population. Additionally, we plan to explore various methods to minimize calibration time.

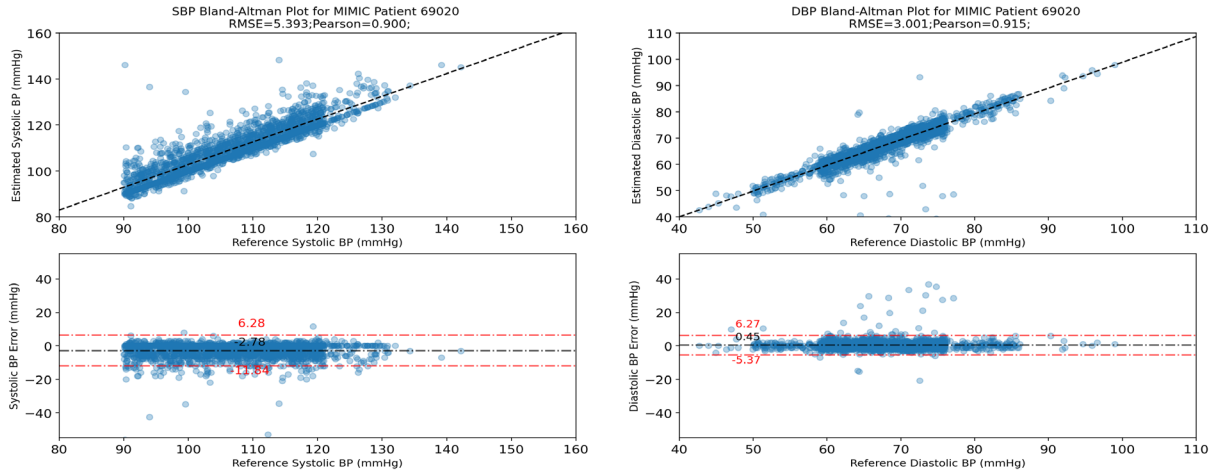

Figure 2: An example of Bland-Altman analysis on estimated systolic and diastolic blood pressure values derived ArterialNet's ABP waveform

Table 2: Performance evaluation of proposed ArterialNet on non-ICU data collections using Bio-Z pulsatile signal

Method	# of Subjects	Total data (hours)	Performance Metrics (RMSE and MAE in mmHg, no unit for Pearson's R)								
			ABP (SD)			SBP (SD)			DBP (SD)		
			RMSE	MAE	Pearson	RMSE	MAE	Pearson	RMSE	MAE	Pearson
ArterialNet U-Net	20	54	8.66 (1.13)	6.90 (1.00)	0.44 (0.10)	12.27 (1.66)	10.57 (1.21)	0.51 (0.10)	8.03 (1.78)	6.63 (1.34)	0.39 (0.09)
ArterialNet Transformer	20	54	8.91 (1.14)	6.93 (0.81)	0.43 (0.12)	14.10 (1.81)	10.69 (1.54)	0.49 (0.10)	9.08 (1.91)	7.85 (1.60)	0.36 (0.10)

VI. Conclusion

We introduce ArterialNet to improve ABP reconstruction and physiological estimations. We evaluated ArterialNet using MIMIC ICU datasets and observed superior performance and significantly reduced SD across all estimations that outperformed baseline methods. Additionally, we present the first exploration of ABP reconstruction using cuffless pulsatile signals and deep learning backbones in non-clinical settings, demonstrating the potential of ABP reconstruction using bioimpedance pulsatile signals. ArterialNet stands as a versatile and flexible pre-trained framework, accommodating various backbones and signal modalities to minimize subject variability and maximize performance in waveform and physiological estimations. We passionately encourage all future endeavors to recognize the significance of both waveform reconstruction and physiological parameter estimations and strive to develop solutions that cater to a wide range of individuals.

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