Cuffless Blood Pressure Estimation Using Finger-to-Toe Differential Pulse Transit Time and Random Forest Regression

T Omari[1], A Collet[2], S Carlier[2,3]

[1] University of Temouchent, Temouchent, Algeria
[2] University of Mons, Mons, Belgium
[3] Department of Cardiology, CHU HELORA, Kennedy Site, Mons, Belgium

Abstract

Managing hypertension effectively requires monitoring blood pressure (BP) continuously and over extended periods. Although ambulatory BP monitoring (ABPM) is the current clinical gold standard for 24-hour assessment, it repeatedly inflates a pneumatic cuff throughout the day and night, disrupting sleep and leading many patients to abandon the device before the recording is complete. In this work, we propose a cuffless alternative that estimates systolic (SBP) and diastolic (DBP) blood pressure from the differential pulse transit time (dPTT) measured between the finger and the toe, combined with heart rate and age, using a Random Forest (RF) regression model. We evaluated the method on 1000 subjects drawn from the publicly available pulse-wave database (PWDB), using 10-fold cross-validation. The RF model achieved a mean absolute error (MAE) of 6.28 mmHg for SBP and 4.07 mmHg for DBP, with R^2 values of 0.717 and 0.578 respectively. Bland–Altman analysis revealed near-zero bias in both cases (0.06 mmHg for SBP and -0.02 mmHg for DBP), and the British Hypertension Society (BHS) protocol assigned grade B for SBP and grade A for DBP. These results suggest that finger-to-toe dPTT, combined with a small set of automatically acquired features, offers a practical and comfortable path toward continuous cuffless BP monitoring.

1. Introduction

Hypertension remains one of the most prevalent and dangerous cardiovascular risk factors worldwide, affecting over one billion people [1]. Detecting and managing it reliably requires more than a single office measurement: BP fluctuates throughout the day and drops during sleep in healthy individuals, a phenomenon known as nocturnal dipping. When this dipping pattern is absent, the cardiovascular risk increases significantly. For this reason, 24-hour ABPM is considered the gold standard in clinical practice, as it captures the full diurnal BP profile and reveals masked hypertension that office readings often miss [7].

Despite its diagnostic value, ABPM has a well-known drawback: it operates by inflating a cuff around the upper arm every 15 to 30 minutes, day and night. During waking hours this is merely inconvenient, but during sleep the repeated inflations frequently wake patients, reducing both sleep quality and recording compliance [8]. In elderly patients or individuals with sleep disorders, this discomfort can be particularly limiting, sometimes rendering the nocturnal portion of the recording unreliable.

These practical limitations have driven growing interest in cuffless BP monitoring. Among the physiological signals explored for this purpose, pulse transit time (PTT) has attracted considerable attention. PTT is conventionally defined as the travel time of the pulse wave between a proximal arterial site (e.g. the aortic valve, identified via the ECG R-wave) and a distal site, and it is inversely related to pulse wave velocity (PWV) through the Moens–Korteweg equation [3]. When the time delay is instead measured between two *distal* sites, as is the case here between the finger and the toe, neither site provides a proximal reference; the resulting quantity is technically the difference between two PTTs (heart-to-toe minus heart-to-finger) rather than a true PTT, and is accordingly termed a differential pulse transit time (dPTT) [9, 10]. Since PWV rises with arterial stiffness, and arterial stiffness is itself a strong determinant of BP, dPTT carries meaningful information about the haemodynamic state of the patient. Measuring dPTT between the finger and the toe takes advantage of the full length of the peripheral arterial tree, integrating contributions from both the upper and lower limb vasculature and maximising sensitivity to central aortic stiffness. Importantly, this measurement requires only two optical or impedance sensors placed at the extremities, with no cuff, no ECG reference, no mechanical actuation, and no discomfort during sleep.

Several groups have investigated PTT-type measures for

cuffless BP estimation, using approaches ranging from simple linear models [4] to neural networks. However, few studies have combined physics-inspired feature engineering with ensemble learning methods such as Random Forests [5], and even fewer have done so on a large-scale vascular simulation database. The PWDB [6], which contains one-dimensional blood flow simulations for 4374 virtual subjects across a broad demographic range, provides an ideal controlled environment for this type of evaluation, free from the ethical and logistical constraints of clinical data collection.

In this study, we ask whether a compact set of features derived automatically from finger-to-toe dPTT, heart rate, and age — with no need for body dimensions or manual measurements — is sufficient for a Random Forest model to estimate continuously SBP and DBP within clinically meaningful accuracy bounds, as defined by the BHS grading protocol.

2. Methods

2.1. Dataset

We used the pulse-wave database (PWDB) [6], which provides simulated arterial pressure waveforms for 4374 virtual subjects generated by a validated one-dimensional haemodynamic model. For this study, 1000 subjects were randomly selected. The finger-to-toe dPTT was computed from the onset times of the Digital artery and Anterior Tibial artery waveforms, which are provided as precomputed annotations in the database. To exclude physiologically implausible values, we retained only dPTT measurements in the range 0.02–0.5 s.

2.2. Feature Engineering

Seven features were derived exclusively from quantities measured automatically by the acquisition system — namely the raw finger-to-toe dPTT, heart rate (HR), and subject age — without requiring any geometric or anthropometric measurement such as body height or limb length:

- $f_1 = 1/\text{dPTT}$: inverse dPTT, proportional to PWV and therefore to arterial stiffness;
- $f_2 = \ln(1/\text{dPTT})$: logarithm of the inverse dPTT, which linearises the dPTT–BP relationship;
- $f_3 = f_1 \cdot (1 + \alpha \cdot \text{HR})$: a pulse wave reflectance index ($\alpha = 0.02$) that accounts for the chronotropic influence of heart rate on apparent wave speed;
- $f_4 = \text{age} \cdot f_1$: an age-weighted stiffness index reflecting the progressive stiffening of the arterial wall with age;
- $f_5 = \text{HR}$: heart rate, capturing autonomic and haemodynamic variability;
- $f_6 = \text{age}$: subject age, used as a proxy for long-term vascular ageing;
- $f_7 = \text{HR} \cdot \text{age}$: an interaction term that jointly encodes chronotropic and vascular ageing effects on BP.

All features were standardised to zero mean and unit variance prior to model training.

2.3. Random Forest Model

We trained a Random Forest ensemble of regression trees using the MATLAB `fitrensemble` function with the bagging (`'Bag'`) method. Each tree was grown with a minimum leaf size of 3, and the ensemble comprised 300 trees in total. At each split, a random subset of $\lfloor p/3 \rfloor$ features was considered, where $p = 7$. Two separate RF models were trained, one for SBP and one for DBP.

2.4. Cross-Validation

We used stratified 10-fold cross-validation to evaluate generalisation performance. In each fold, the model was retrained from scratch on the remaining nine folds and tested on the held-out fold, ensuring that no information from the test set could influence training.

2.5. Performance Metrics

We report the mean absolute error (MAE), root mean square error (RMSE), coefficient of determination (R^2), mean bias, and standard deviation of the prediction error. Clinical acceptability was assessed using the BHS grading protocol [7], which classifies devices according to the cumulative percentage of predictions falling within 5, 10, and 15 mmHg of the reference.

3. Results

3.1. Prediction Accuracy

Table 1 reports the cross-validated performance metrics for both SBP and DBP. The RF model achieved an MAE of 6.28 mmHg for SBP and 4.07 mmHg for DBP. In both cases the bias was negligible, confirming that the model neither systematically over- nor under-estimates BP across the physiological range.

Table 1. Cross-validated performance metrics for SBP and DBP estimation.

Metric	SBP (mmHg)	DBP (mmHg)
MAE	6.28	4.07
RMSE	7.87	5.13
R^2	0.717	0.578
Bias	0.06	−0.02
Std of error	7.87	5.13

3.2. BHS Grading

Table 2 shows the cumulative error distribution according to the BHS protocol. For DBP, the model attained grade A, with all predictions falling within 15 mmHg and 93.8% within 10 mmHg. For SBP, grade B was achieved, with 94.8% of predictions within 15 mmHg and 81.0% within 10 mmHg.

Table 2. BHS grading protocol results.

	$<$5 mmHg	$<$10 mmHg	$<$15 mmHg
SBP (%)	47.4	81.0	94.8
DBP (%)	67.2	93.8	100.0
BHS grade	B / A	B / A	B / A

3.3. Scatter Plots

Figure 1 shows predicted versus reference BP for SBP and DBP, with points colour-coded by subject age. For both quantities, the predictions track the identity line closely across the full physiological range. The dispersion is slightly larger at high SBP values, reflecting the increased complexity of the haemodynamic state in hypertensive subjects.

3.4. Bland–Altman Analysis

Figure 2 presents the Bland–Altman plots for both SBP and DBP. The mean bias is virtually zero in both cases (0.06 mmHg for SBP, -0.02 mmHg for DBP), and no proportional bias is apparent across the BP range. The limits of agreement (LoA) are $\pm$15.4 mmHg for SBP and $\pm$10.0 mmHg for DBP ($\pm 1.96\,\sigma$). The considerably narrower LoA for DBP confirm its tighter agreement with the reference, consistent with its lower RMSE of 5.13 mmHg compared to 7.87 mmHg for SBP.

4. Discussion

The results presented here suggest that finger-to-toe dPTT, combined with heart rate and age through a small set of physically motivated features, carries enough information for a Random Forest model to estimate BP with clinically relevant accuracy — and to do so without any cuff inflation, ECG reference, or manual body measurement. This makes the approach particularly attractive for unattended 24-hour monitoring, where the discomfort of conventional ABPM is most keenly felt.

The accuracy we observed for DBP (MAE 4.07 mmHg, BHS grade A) is especially encouraging. DBP is tightly linked to peripheral arterial resistance, which is well reflected in dPTT-derived stiffness features. SBP, by contrast, is also shaped by left ventricular ejection dynamics and central wave reflections — physiological mechanisms that dPTT alone cannot fully capture — which explains the somewhat larger errors and the grade B rating.

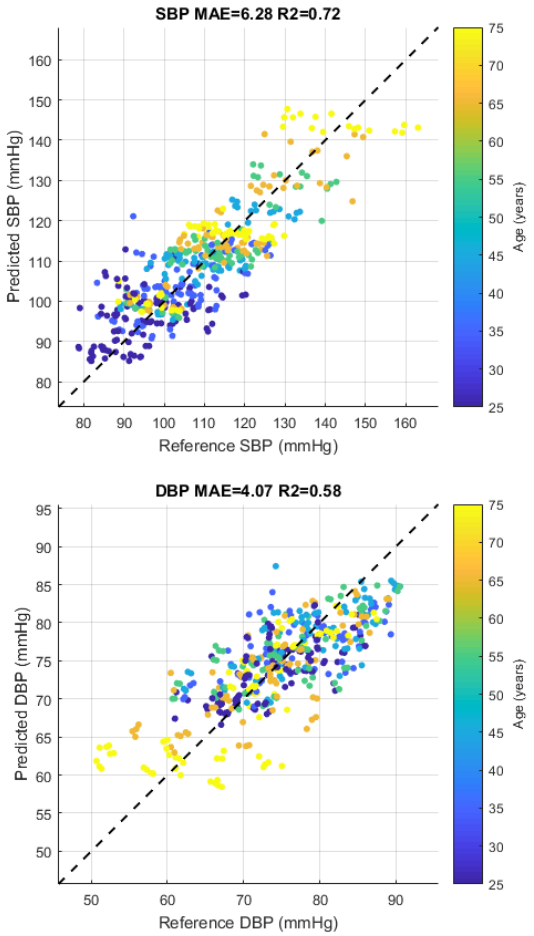

Figure 1. Predicted versus reference BP colour-coded by subject age. *Top*: SBP (MAE = 6.28 mmHg, R^2 = 0.717). *Bottom*: DBP (MAE = 4.07 mmHg, R^2 = 0.578). The dashed line is the identity.

One result that may seem counterintuitive is that DBP achieves a lower MAE than SBP yet also a lower R^2 (0.578 versus 0.717). This apparent contradiction is readily explained by the difference in dynamic range: DBP spans roughly 45 mmHg in the PWDB cohort, compared to about 85 mmHg for SBP. Since R^2 measures the fraction of total variance explained, a narrower range penalises R^2 even when absolute errors are small. For clinical benchmarking, the MAE-based BHS protocol is therefore the more informative metric.

The near-zero bias for both quantities is an important finding: it means the model is well calibrated and does not drift systematically across the BP range, as confirmed by

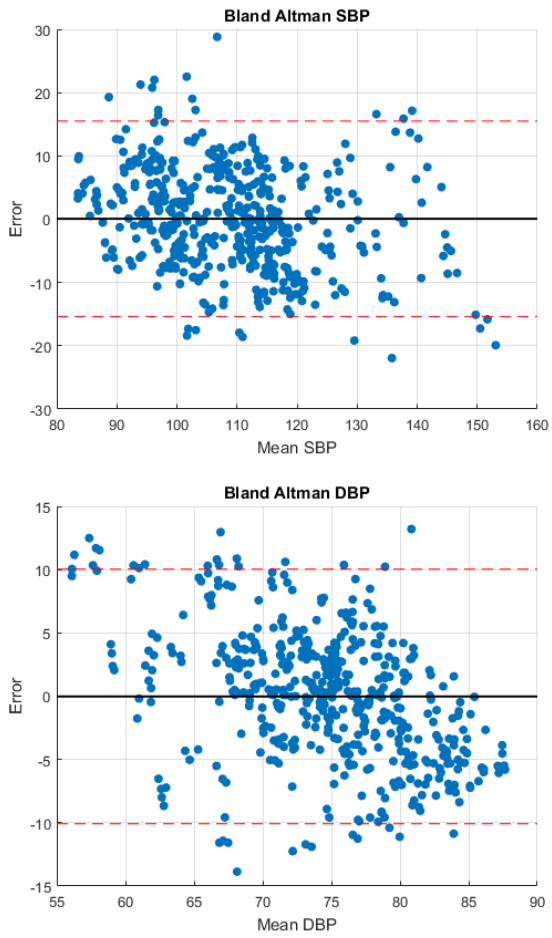

Figure 2. Bland–Altman plots for SBP (*top*) and DBP (*bottom*). The solid line is the mean bias and the dashed red lines are the $\pm 1.96\,\sigma$ limits of agreement.

the Bland–Altman plots. The tighter limits of agreement for DBP ($\pm$10.0 mmHg versus $\pm$15.4 mmHg for SBP) further reinforce its suitability for sleep-time monitoring, where measurement comfort is critical.

From a practical standpoint, the feature set used here is noteworthy for what it does not require. Unlike PWV-based methods that need an estimate of arterial path length — typically derived from body height or inter-sensor distance — our features rely solely on dPTT, HR, and age, all of which can be acquired automatically and continuously by a wearable system. This removes a potential source of measurement error and simplifies deployment considerably.

There are, of course, limitations to acknowledge. The PWDB is a simulation database and does not replicate the full variability of real patients, including effects of obesity, motion artefact, measurement noise, or pathological vascular remodelling. Moreover, HR and age are required as inputs, which implies that a wearable HR sensor and a one-time subject registration step would be needed in practice. Validating this approach on real ambulatory data, ideally over full 24-hour recordings, is the logical and necessary next step.

5. Conclusion

We have shown that a Random Forest model trained on seven automatically derived dPTT features can estimate SBP and DBP with MAE values of 6.28 mmHg and 4.07 mmHg and BHS grades of B and A respectively, with negligible systematic bias. The method requires no cuff, no ECG reference, no body measurements, and no manual intervention, making it a strong candidate for continuous and comfortable ambulatory BP monitoring over 24 hours. Future work will focus on validating the approach in real clinical settings and exploring additional signal features to further reduce SBP estimation error.

Acknowledgments

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Address for correspondence:

T Omari
University of Temouchent, Temouchent, 46000, Algeria
tahar.omari@univ-temouchent.edu.dz