IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 2, 2020, accepted March 12, 2020, date of publication March 19, 2020, date of current version April 6, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2981903

Cuffless Blood Pressure Estimation Using Single Channel Photoplethysmography: A Two-Step Method

SYED GHUFRAN KHALID[1,2], HAIPENG LIU[1,2], TAHIR ZIA[3], JUFEN ZHANG[2], FEI CHEN[4], (Senior Member, IEEE), AND DINGCHANG ZHENG[1,2]

[1]Research Centre for Intelligent Healthcare, Faculty of Health and Life Sciences, Coventry University, Coventry CV1 2HF, U.K.
[2]Faculty of Health, Education, Medicine and Social Care, Anglia Ruskin University–Chelmsford, Chelmsford CM1 1SQ, U.K.
[3]The Royal Marsden Hospital, London SW3 6JJ, U.K.
[4]Department of Electrical and Electronic Engineering, Southern University of Science and Technology, Shenzhen 518055, China.

Corresponding authors: Syed Ghufran Khalid (syed.khalid@coventry.ac.uk) and Dingchang Zheng (dingchang.zheng@coventry.ac.uk)

This work was supported by Anglia Ruskin University under Ph.D. studentship to Syed Ghufran Khalid. The work of Fei Chen was supported by the National Natural Science Foundation of China under Grant 61828104.

ABSTRACT Traditional cuff-based blood pressure (BP) monitoring procedure causes inconvenience and discomfort to the users. To overcome these limitations, cuffless BP estimation based on pulse transit time (PTT) and single-channel photoplethysmography (PPG) has been proposed. However, existing studies based on PTT and PPG for BP estimation did not achieve AAMI/ISO standard criteria for BP measurement (mean difference within ±5mmHg and SD of difference within ±8mmHg) under each BP category (Hypotensive, Normotensive and Hypertensive). This study aims to validate an innovative two-step method for PPG-based cuffless BP estimation. A combined database was derived from two online databases (Queensland and MIMIC II) to cover a wide range of corresponding BPs. In total, there were 18010 raw PPG signal segments (5 seconds for each) with corresponding BPs, separated into two halves for training and testing of algorithms (independent datasets). Each PPG signal segment was pre-processed to extract 16 signal features. Later, three significant features have been selected using multicollinearity test. The traditional generic (trained with uncategorized BP) algorithm and two-step algorithm (specifically optimized for each BP category) were developed using machine learning. Generally, the two-step algorithm achieved the AAMI/ISO standard in estimating systolic BP (mean ±SD: 0.07±7.1 mmHg, $p<0.001$) and diastolic BP (−0.08±6.0 mmHg, $p<0.001$). Categorically, the two-step method also achieved standard accuracy in all BP categories except Hypotensive systolic BP whereas generic algorithm did not conform to standard accuracy in any BP category except Hypotensive diastolic BP and Normotensive categories. Compared to the traditional generic algorithm, the two-step algorithm specifically designed for three different BP category patients and achieved standard accuracy for cuffless BP estimation.

INDEX TERMS Cuffless BP, pulse transit time, Photoplethysmography & categorical BP estimation.

I. INTRODUCTION

Blood pressure (BP) is a vital sign that reflects the state of the cardiovascular system. BP is commonly measured for the diagnosis of cardiovascular health. Abnormal BP indicates various cardiovascular anomalies, including heart attack, stroke, peripheral arterial diseases, kidney failure, and vascular dementia [1]. Presently, automatic cuff-based BP measurement devices have been routinely used in clinics and hospitals [2], [3]. However, the cuff-based BP measurement procedure causes inconvenience and discomfort due to frequent cuff inflation around the arm or wrist, especially for multiple BP measurements.

To overcome these limitations of cuff-based BP, many cuffless BP technologies have been proposed, including pulse transit time (PTT) or pulse arrival time (PAT), vascular transit time (VTT), tonometry, and pulse wave velocity (PWV) using magnetic sensors as shown in Table 1 [4]–[7].

The PAT is a travel time of the pulse from the heart to the peripheral artery of the finger which is measured by the R-wave of electrocardiography (ECG) and the peak of photoplethysmography (PPG) signal. The PTT is the time delay

The associate editor coordinating the review of this manuscript and approving it for publication was Yongtao Hao.

TABLE 1. Summary of key publications regarding cuffless BP estimation techniques.

Authors	BP Estimation Method	SBP		DBP	
		(Mean ± SD) mmHg	Correlation (r)	(Mean ± SD) mmHg	Correlation (r)
D. Buxi et al	PAT	0±13.0	Not Available	Not available	Not Available
M. Kachuee et al.	PAT	8.2±5.4	0.6	4.3±3.5	0.5
M.Park et al.	PTT	0.3±9.9	Not Available	-1.0±8.2	Not Available
P.M.Nabeel et al.	Magnetism	Not Available	0.7	Not available	0.8
S.N.Shukla	VTT	Not available	Not Available	Not available	Not Available
Y. Zhang, & F. Zhimeng	SVM	11.2±9.0	Not Available	12.0±10.3	Not Available
K.Atomi et al.	Regression	1.5±8.4	0.8	Not available	Not Available
A. Visvanathan et al.	Regression	Not available	Not Available	Not available	Not Available
S.G.Khalid et al.	Regression	-1.1±5.7	Not Available	-0.3±5.6	Not Available

between ECG R-wave till the onset of the first derivative of PPG. The vascular transit time (VTT) is an alternate for PTT which was measured between fingertip with PPG and the chest via phonocardiography [8]. In recent times, various studies used a mobile phone camera to estimate BP whereas some of the studies used different algorithms include the Windkessel model and neural network [9]. Many of these technologies achieved AAMI/ISO standard accuracies (mean difference no greater than ±5mmHg and SD of difference no greater than ±8mmHg) in terms of overall accuracy [4], [5], [10]. However, these technologies require at least two sensors, which makes them unsuitable for wearable applications. The PPG signal, which detects the volumetric changes of blood, has been widely used in wearable healthcare technologies. Some studies have attempted to use PPG for BP estimation [11]–[13]. However, none of the proposed studies achieved AAMI/ISO standards. Thus, a new algorithm to accurately estimate BP from PPG is necessary for wearable BP estimation.

For cuffless BP estimation, generic regression-based supervised machine learning algorithms have been proposed, including Support Vector Machine (SVM), Multiple Linear Regression (MLR), and Regression Tree. Zhang and Feng suggested SVM as the best algorithm for cuffless BP estimation from PPG signal waveform features [11]. However, the study unsuccessful to achieve the AAMI/ISO standard (11.6 ± 8.2 mmHg & 7.6 ± 6.7 mmHg for systolic BP (SBP) and diastolic BP (DBP)). Atomi *et al.* applied a linear regression algorithm on the self-collected dataset, but there was a contradiction found between the ages of participants enrolled for the training dataset and testing dataset. The training dataset only included aged individuals, whereas the testing dataset was collected from young individuals [12]. Visvanathan *et al.* also extracted PPG signal features and achieved accuracy measured in percentage for MLR (93.2 & 76.4) and SVM (51.6 & 53.6) algorithms for SBP & DBP [13]. Nevertheless, these studies failed to conform to AAMI/ISO BP standards. Khalid *et al.* suggested that the regression tree is the best estimating algorithm which achieved overall standard accuracy and better accuracy under each BP category for cuffless BP, but this study is limited to Queensland database only [14]. A cuffless BP estimation device has been proposed that achieved AAMI/ISO standard in mean difference (3.8 mmHg for SBP and 4.6 mmHg for DBP), but the technical details have not been revealed [15]. Moreover, in all the published studies, the BP estimation accuracies have not been evaluated separately in various clinical BP categories (Hypotensive, Normotensive and Hypertensive). The classification machine learning algorithm is another type of supervised machine learning algorithm used to predict a specific group of data under study [16].

Researchers also attempted the classification algorithm to predict BP of four different age groups from PPG signal. The classification algorithm achieved more than 90% accuracy for SBP and DBP [17]. A two-step approach (consists of different type classification and regression algorithms) were tested on ECG to estimate cuffless BP but the accuracy was not under AAMI/ISO standards [18].

This study aimed to evaluate and compare overall accuracy of an innovative two-step BP estimating algorithm (highly optimized for specific BP categories) and traditional generic algorithm (training and testing data contained uncategorized corresponding BP). Their accuracy of BP estimation would also be evaluated separately in three different BP categories (Hypotensive, Normotensive and Hypertensive).

II. MATERIALS AND METHODS

The flow diagram in Fig. 1 illustrates the major steps of the proposed method:

1. Derive and select input PPG signal segments and the corresponding BPs (SBP and DBP) from the combined database.
2. Pre-process the raw PPG signal segments by noise filtration, baseline foot unification, and signal normalization.
3. Extract waveform features from the pre-processed PPG signal segment and selects significant features.
4. Divide the combined database into two halves for training and testing dataset. Each half of the datasets are independent of each other.

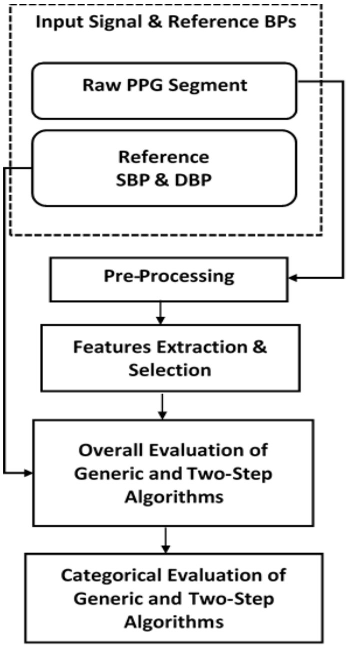

FIGURE 1. **The flow diagram illustrates the essential parts of this study. The combined database (dashed line rectangle) contained raw PPG signal segments along with reference SBP and DBP. Each raw PPG signal segment was pre-processed by noise filtration, baseline correction and signal normalization to extract signal features for BP estimation. Generic and two-step algorithms were developed with significant PPG signal features and reference BP. Algorithms were evaluated in terms of overall and categorical BP estimation accuracies.**

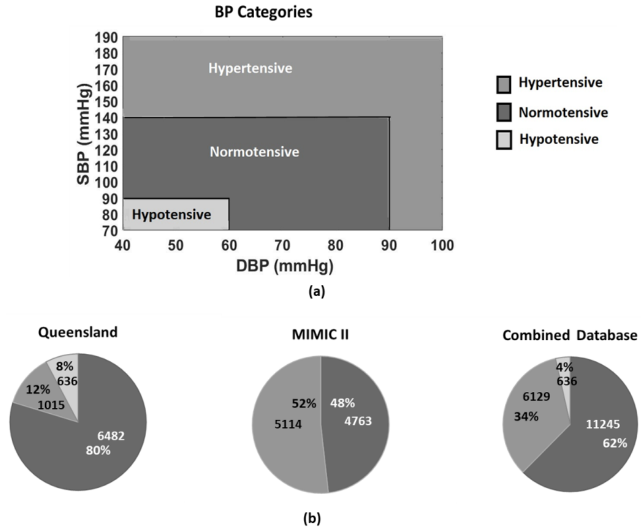

FIGURE 2. **BP classification chart and reference BP categorical distribution: a) BP is classified into three BP categories (Hypotensive, Normotensive and Hypertensive) [12] and b) reference BP categorical distribution in individual databases (Queensland and MIMIC II) and combined database. Note: The data distributions in Fig. 2(b) present good quality signal segments extracted from original databases (Queensland and MIMIC II).**

5. Develop a traditional generic algorithm with a regression-based supervised machine learning algorithm and an innovative algorithm with a two-step approach using the training dataset.
6. Evaluate the overall and categorical BP estimation accuracy of both generic and two-step algorithm on the testing dataset.

A. ONLINE DATABASES

The Queensland database consists of vital sign parameters, including PPG and the corresponding BPs, extracted from 32 patients during anesthesia [19]. This database has less number of Hypertensive and Hypotensive signal recording data. The MIMIC II data (extracted from 250 individual data) also contained physiological measurement data with a large amount of Normotensive and Hypertensive corresponding BPs but did not contain Hypotensive corresponding BPs [20]. Therefore, a combined database has been created that contained both (Queensland and MIMIC II) data recordings. The combined database is a large-scale one that covers a wide BP range. The corresponding BP values were classified into three BP categories (Hypotensive, Normotensive and Hypertensive) according to the reference BP chart in Fig. 2(a). Each database has unequal data distribution among different BP categories, as shown in Fig. 2(b). Besides, both Queensland and MIMIC II databases have a large amount of missing data and unacceptable signal recordings. Thus the PPG recordings from both the databases segmented into 5 seconds signal segments. The manual check has been performed for each recording according to the selection criteria to stack good quality signal segments only [14]. The Queensland and MIMIC II databases contained total 8133 and 9877 good quality PPG signal segments with corresponding BPs, with the combined database covering all the three BP categories. The Queensland database provide Hypotensive (636 (8%) segments), Normotensive (6482 (80%) segments) and Hypertensive (1015 (12%) segments) BP categories while the MIMIC II database provide Normotensive (4763 (48%) segments) and Hypertensive (5114 (52%) segments) BP categories.

Besides more data, the combined database covered all the three BP categories, as shown in Fig. 2(b).

B. PPG SIGNAL PRE-PROCESSING

Savitzky-Golay filter was applied on each PPG signal segment to eliminate high-frequency noises, as illustrated in Fig. 3(b). It is a moving average filter which removes optimization process considered 3-neighbours (K=3) around the query point, and the distances have been high-frequency noises while preserves the sharp edges of PPG signals [21]. Respiratory activity which affects signal baseline deleted from each PPG signal segments. The data from Queensland and MIMIC II databases are different in sampling rate and amplitude. Therefore, the width and height of each PPG beat were normalized, as shown in Fig. 3(b) and (c). The Queensland database contains non-continuous reference BPs whereas MIMIC II database contains continuous reference BP waveforms which only requires noise filtration to get SBP peaks and DBP onsets.

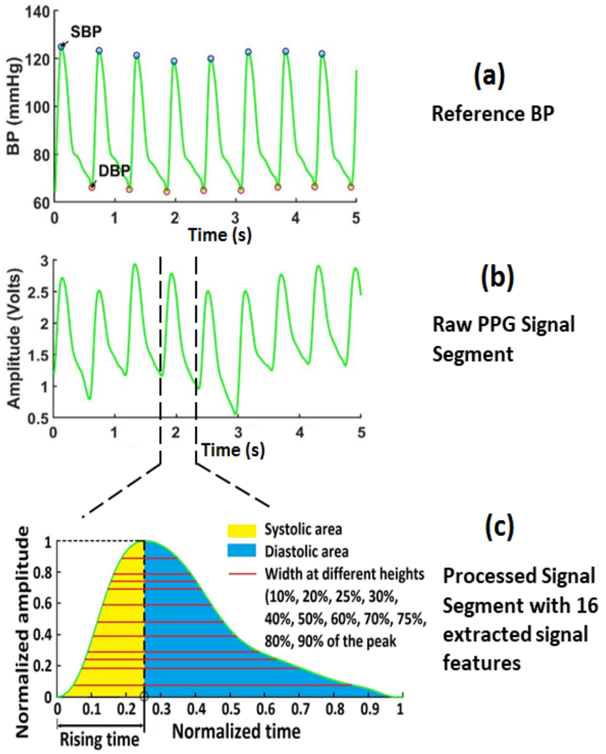

FIGURE 3. Pre-Processing of raw PPG signal segment to normalized signal pulses and extracted PPG signal features: a) A 5s signal segment represent BP pulses with systolic peaks and diastolic onsets (marked with blue and red circles). b) A 5s signal segment of aw PPG pulses; (c) The features were extracted from pre-processed (filtered, baseline corrected and normalized) pulses.

C. FEATURES EXTRACTION AND SELECTION

Initially, 16 time-based signal features were extracted from pre-processed PPG signal segments: Systolic Area (the area under first onset and the systolic point of pulse), Diastolic Area (the area under systolic point till second onset of pulse, Total Area (Systolic Area + Diastolic Area), Width10% (Width of pulse at 10% of peak amplitude), Width20%, Width25%, Width30%, Width40%, Width50%, Width60%, Width70%, Width75%, Width80%, Width90%, Rising Time (time to reach systolic peak) and Reflection index (Diastolic Area/Systolic Area) as shown in Fig. 3(c). The pulse areas of the PPG pulse indicates changes in vascular tone [22]. Pulse rising time feature correspond to change in BP [23]. Visvanathan *et al.* added a pulse rising time feature with other feature to estimate cuffless BP [13]. The PPG pulse widths are related to systemic vascular resistance [24].

In this study, the most significant PPG pulse features (Total Area, Rising Time and Width 25%) were selected by statistical multicollinearity test. This statistical test was used to detect the presence of collinearity among PPG signal features, which lead to the unreliable machine learning model [25].

The variance inflation factor (VIF) is the key parameter to detect multicollinearity among features [25]. The VIF value of each feature >10 indicates that the feature is collinear with other features. Low VIF (<10) value corresponding to the significant features that were selected to develop a reliable machine learning algorithm.

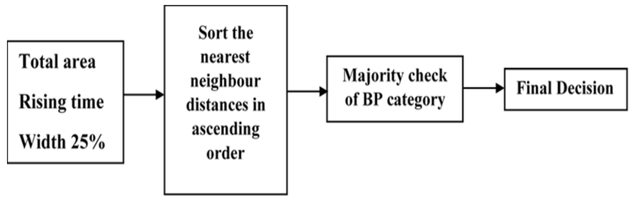

FIGURE 4. The simplified flow diagram of the KNN classification algorithm: algorithm analyses the features and measures the distances between the query point and 3-neighbouring points in the Minkowski metric. Majority checks have been performed to identify which BP category obtain the majority.

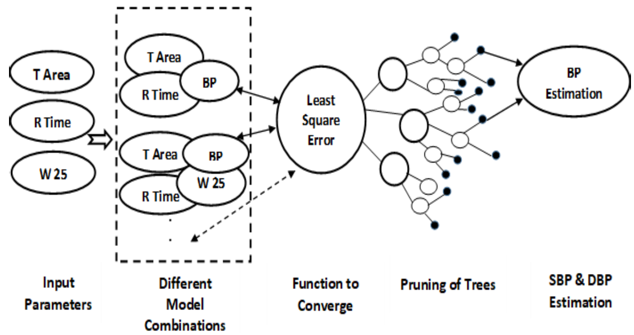

FIGURE 5. The flow diagram of Regression Tree algorithm shows different significant features (Total Area, Rising Time and Width 25%) combination were used with least square error function that leads to the pruning and splitting of the tree into branch nodes. Each node (small black colour filled circles) that attached with the branch node contains estimation results [12].

D. MACHINE LEARNING ALGORITHMS USED TO ESTIMATE CUFFLESS BP

1) K-NEAREST NEIGHBOR (KNN) CLASSIFICATION ALGORITHM

The KNN algorithm is widely used as a benchmark classification technique. It measures the distances between the query point and the neighbouring points of the training dataset. In this research, the KNN algorithm measured using the Minkowski metric from the query point. The algorithm sort the measured distances in ascending order and check the majority of distances belongs to which BP category as shown in Figure 4. The selected BP category from majority checks has been classified as predicted BP category.

2) REGRESSION TREE

The traditional generic algorithm was developed with Regression Tree machine learning algorithm, trained with significant features and corresponding BP categories as shown in Figure 5. The previous study revealed that the Regression Tree is the best algorithm for PPG-based cuffless BP estimation [14]. It is a non-parametric type of machine learning algorithm which is used to estimate BP. This algorithm has relatively short training time as compared to the SVM algorithm. Leaf nodes of Regression Tree carry decision from the root node. Regression Tree was developed with binary data splits but leaf nodes carry decision in the numeric form [26]. It splits the dataset with pre-set optimization criteria which subject to the minimum leaf size and tree depth for each

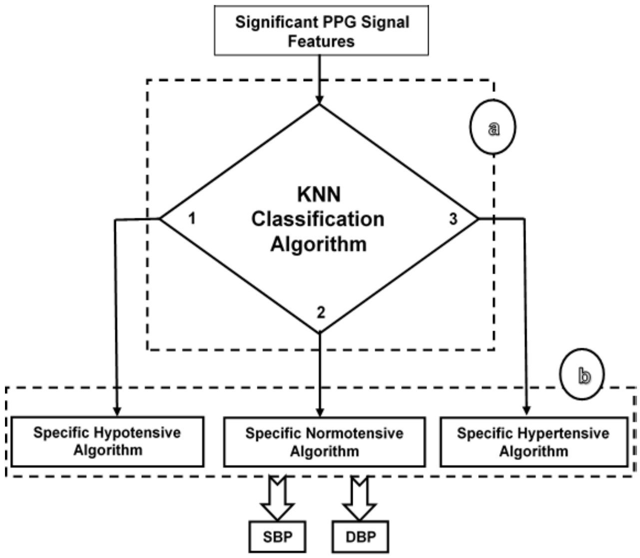

FIGURE 6. The diagram shows the working principle of two-step approach developed for cuffless BP estimation from PPG only: a) first step used KKN classification algorithm to identify BP category of PPG signal features; b) the second step which consists of specific BP algorithms estimate SBP and DBP.

predictor variable (Total Area, Rising Time and Width 25%). The stopping criteria for tree split to create a pure node depends upon the mean square error (MSE), as shown in equation (1).

MSE (observed response) < MSE (observed response from all data) x tolerance (1)

A pure node corresponds to the observed response MSE, which is less than MSE of total dataset multiplied with the tolerance [26]. To achieve optimization, Regression tree algorithm splits tree branches to reduce prediction error as shown in Fig. 5.

3) SPECIFIC BP ALGORITHMS

Specific BP algorithms were developed with Regression Tree algorithms which were trained with specific BP category (Hypotensive, Normotensive and Hypertensive) data only. The combined dataset has been separated into three BP categories. Each category divided equally to make training and testing dataset. Later, training dataset from each category was used to train specific BP algorithms.

E. TWO-STEP BP ESTIMATING ALGORITHM

The Innovative two-step algorithm designed explicitly to specific BP categories with highest possible optimization of Regression Tree algorithm. The aim to develop this algorithm is to get better categorical accuracy in three BP categories.

1) STEP 1

In the first step, as indicated in Fig. 6(a), the K-nearest neighbour classification algorithm identifies one of the BP categories (Hypotensive (1), Normotensive (2) and Hypertensive (3)) using significant PPG signal features.

2) STEP 2

In the second step, which is presented in Fig. 6(b), one of three specific BP algorithm which belongs to the classified BP category in step 1 estimate SBP and DBP.

F. TRAINING AND TESTING DATASET

The dataset collected from the combined database (18010 segments) was divided into two halves (each contained 9005 signal segments). Both the halves of dataset contained an equal number of corresponding BP under each BP category (318 segments for Hypotensive, 3064 from Normotensive and 5622 from Hypertensive), extracted from the different number of patients recordings to make sure testing dataset completely independent of the training dataset. Half of the dataset was used for the training of generic and innovative BP algorithms and the other half used for the evaluation of the developed algorithms.

G. OVERALL AND CATEGORICAL BP ESTIMATION EVALUATION

The generic (uncategorized Regression Tree algorithm) and two-step BP estimating algorithms were firstly evaluated in terms of overall BP estimation accuracy. Both algorithms were separately applied on test dataset that produced estimated BPs (SBP and DBP) in the response of each set of significant PPG signal segment features. Overall mean difference and SD of differences were calculated. For categorical estimation accuracy evaluation, all the estimated and corresponding data separated into three BP categories. Mean, and SD of differences was calculated under each BP category separately for generic and two-step algorithm.

H. DATA ANALYSIS

Significant PPG signal features were selected by statistical multicollinearity test. In overall and categorical evaluations, the mean difference and SD of BP difference from both the generic and two-step algorithms were compared. Secondly, the p-value using paired t-test of estimated and reference BPs was calculated. Finally, the Bland-Altman plots were drawn between the estimated and reference BPs.

III. RESULTS

A. COMPARISON ANALYSIS OF EXISTING CLASSIFICATION ALGORITHMS

BP category prediction by maximally optimized classification models using a bayesian optimization technique was compared in Table 1. The KNN algorithm is the only classification algorithm which has the highest prediction accuracy ($>$ 90%) as shown in Table 2. Prediction accuracy tested on the testing dataset which is independent of the training dataset.

B. OVERALL BP ESTIMATION ACCURACY OF GENERIC AND TWO-STEP ALGORITHMS

The overall BP estimation accuracies of the generic algorithm and two-step algorithm are compared in Fig. 7(a),

TABLE 2. Prediction performance of classification algorithms to classify BP categories from significant PPG signal features.

Algorithm	Prediction Performance (%)
Discriminant Analysis	71.3
Decision Tree	82.7
SVM	72.4
KNN	91.7

shows that two-step algorithm conformed to AAMI/ISO standard criteria of BP measurement (mean difference no greater than ±5mmHg and SD of difference no greater than ±8mmHg) whereas generic algorithm did not achieve AAMI/ISO standard criteria as their SD of difference for SBP (9.6mmHg), and DBP (9.2 mmHg) exceeded the standard limit of (±8mmHg). However, the generic algorithm shows an acceptable mean difference (±5mmHg). The p-value ($p<0.001$) shows that there is a significant difference between the generic algorithm and the two-step algorithm exist for SBP and DBP. The Bland-Altman plots in Fig. 7(c, e) show that there are agreements between the two-step algorithm and reference method. However, limits of agreement (dashed lines) of generic algorithms in Fig. 7(b, d) are wider than the two-step algorithm.

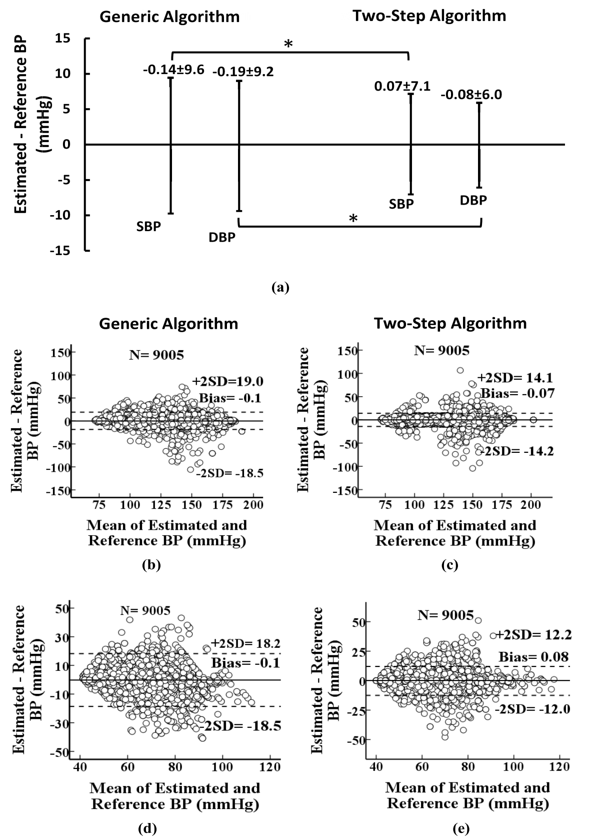

FIGURE 7. Evaluation of overall BP estimation accuracy: a) Overall evaluation of BP estimation accuracy using a testing dataset of the combined database, separately for generic and two-step algorithms. (b-e) Bland –Altman plots for the estimated BPs from the generic and two-step algorithm. (b-c) are for generic and innovative algorithm SBP and (d-e) are for DBP algorithms. Note: * = Significant difference.

C. CATEGORICAL BP ESTIMATION ACCURACY OF GENERIC AND TWO-STEP ALGORITHMS

The BP estimation accuracies of the generic algorithm and two-step algorithm under three BP categories are presented in Fig. 8. For SBP estimation, which is shown in Fig. 8(a) for categorical BP estimation evaluation, the data were categorized into three BP categories (Hypotensive, Normotensive and Hypertensive) according to the reference BP value. The comparison of estimation bias between generic and two-step algorithms was compared separately for each BP category according to AAMI/ISO standard criteria for BP measurement.

For the generic algorithm, mean differences of BP categories were within the standard limit (±5mmHg) except Hypotensive, whereas all the SDs of BP difference exceed the standard (±8mmHg). Contrarily, the SBP accuracy of two-step algorithm achieved standard accuracy in Normotensive BP category (−0.7±5.8 mmHg) and Hypertensive (1.7±7.6 mmHg). However, the accuracy in Hypotensive BP category (−3.0±8.2 mmHg) shows little over the maximum standard limit for SD of difference (±8mmHg).

For DBP estimation, which is shown in Fig. 8(b), the generic algorithm did not achieve standard accuracy in Hypertensive BP category (0.5±9.5 mmHg) due to higher SD of difference, but the two-step algorithm achieved standard accuracy under each BP category. The p-value ($p<0.001$) from paired t-test also shows that there is a significant difference between generic and two-step algorithm for SBP whereas no significant difference found between generic and two-step algorithm under Hypotensive and Normotensive.

IV. DISCUSSION

A. SUMMARY OF RESULTS

This study proposes to validate the two-step BP estimating algorithm according to AAMI/ISO standard criteria and compare with the traditional generic algorithm in terms of BP estimation accuracy. In general, the method of overall BP estimation accuracy has been followed to check algorithm accuracy. However, in this research, categorical accuracies of both the algorithms were also evaluated. The study revealed that the two-step BP estimating algorithm achieved standard accuracy in terms of overall and categorical BP estimation.

B. THE ADVANTAGE OF TWO-STEP ALGORITHM COMPARED WITH EARLIER RESEARCH

Single PPG provides the possibility of wearable and low-cost BP measurement. Cuffless BP estimation using a single PPG signal has been investigated by other research groups [11]–[14]. Visvanathan *et al.* used PPG features (different set) with linear regression and SVM algorithm [11].

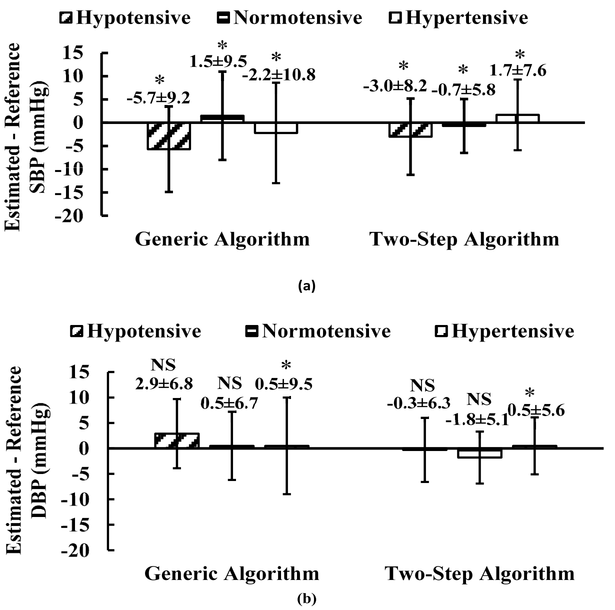

FIGURE 8. Categorical BP estimation accuracy: a) SBP estimation accuracies of generic and two-step algorithm under each BP categories. The data are presented with the mean difference and SD of difference, separately for generic algorithm and two-step algorithm. b) DBP estimation accuracies of generic and two-step under each BP categories. Note: * = significant difference, NS = No significant difference.

Likewise, Ruiz-Rodriquez *et al.* applied a regression model on 525 subjects [27]. However, previously proposed studies did not indicate significant PPG signal features for algorithm development [5], [12], [13]. The two-step algorithm uses significant features which are indicated in this research that used to estimate cuffless BPs. This new method provides the possibility of continuous and wearable BP monitoring without limiting the daily activities of the patients.

Some researchers have inconsistency in their training and testing dataset. They achieved standard accuracy using PPG signal features (different set) for SBP only [11]. Two research group used Queensland database that lacked hypotensive data [11], [28]. Additionally, they did not include a clear BP distribution chart in their published work. Some research studies did not match with the standard criteria of AAMI/ISO standard.

In the current work, firstly, the combined database contained a large amount of data (18010 signal segments in total) to ensure the accuracy of validation. Secondly, the reference BP values covered a wide range across the three BP categories, enabling the estimation of algorithmic accuracy in different BP categories. As far as we know, this is the first time that the accuracy of the PPG-based BP estimation algorithm was evaluated categorically on the combined database.

Clinically, the accurate estimation of hypertensive and hypotensive BP is significant for early diagnosis of many diseases [29]. The high accuracy for normal BP estimation could cover the fact that the majority of current cuffless BP estimation algorithms are inaccurate in hypotensive and hypertensive cases, as the results are shown in Fig. 8(a) and Fig. 8(b).

C. APPLICATION OF TWO-STEP APPROACH

PPG sensors are low-cost and easy to be integrated into smartphones and other daily devices. Therefore, PPG has been widely applied in healthcare monitoring [30]. The proposed innovative algorithm could be applied in low-cost, wearable, and continuous BP monitoring with a single optical sensor without any discomfort to the users. This algorithm is highly efficient and could be incorporated as an android application within the smartphones for telemedicine and other translational applications.

D. LIMITATION AND FUTURE STUDIES

This study had some limitations. Firstly, PPG signal quality has been manually checked to avoid the use of bad quality signal segment during algorithm training, which is not a practical approach. Thus, an advanced PPG signal pre-processing algorithm needs to be developed. Secondly, Queensland and MIMIC II databases, data collected under certain clinical conditions (supine and sitting postures). The effects of physiological conditions, such as posture, movement, and age, were not included. The algorithm testing on a newly collected dataset from different body postures, with different movements, and from different age groups, will be useful for future BP measurement accuracy evaluation. Thirdly, other BP-related clinical parameters (sex, height and weight) could be introduced to train or test the algorithm which might improve the BP estimation accuracy. Only AAMI BP measurement accuracy criteria has been followed instead of compete standard the physiological data were collected by the previous researcehrs.

V. CONCLUSION

This study validated the two-step BP estimating algorithm according to AAMI/ISO standard BP measurement criteria and revealed that the two-step algorithm conformed to standard criteria in terms of overall and categorical accuracy. Furthermore, the two-step algorithm showed better BP estimation accuracy than the traditional generic algorithm in both overall and categorical BP estimation evaluations. The current study shows that the two-step algorithm has the potential to be incorporated into a smartphone for cuffless BP estimation using a single optical sensor.

REFERENCES

[1] C, Höcht, "Blood pressure variability: Prognostic value and therapeutic implications," *ISRN Hypertension*, vol. 2013, pp. 1–16, Jun. 2013.
[2] S. S. Thomas, V. Nathan, Z. Chengzhi, E. Akinbola, Aroul, A. L. Philipose, K. Soundarapandian, S. Xiangrong, and R. Jafari 2014, "BioWatch—A wrist watch based signal acquisition system for physiological signals including blood pressure," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Chicago, IL, USA, Aug. 2014, pp. 2286–2289.
[3] A. De La Sierra, "Ambulatory blood pressure monitoring is a useful tool for all patients," *Hipertens Riesgo Vascular*, vol. 34, no. 1, pp. 45–49, 2017.
[4] D. Buxi, J.-M. Redoute, and M. R. Yuce, "Cuffless blood pressure estimation from the carotid pulse arrival time using continuous wave radar," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Milan, Italy, Aug. 2015, pp. 5704–5707.

[5] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuffless blood pressure estimation algorithms for continuous health-care monitoring," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 4, pp. 859–869, Apr. 2017.

[6] M. Park, H. Kang, Y. Huh, and K.-C. Kim, "Cuffless and noninvasive measurement of systolic blood pressure, diastolic blood pressure, mean arterial pressure and pulse pressure using radial artery tonometry pressure sensor with concept of korean traditional medicine," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Lyon, France, Aug. 2007, pp. 3597–3600.

[7] P. M. Nabeel, S. Karthik, J. Joseph, and M. Sivaprakasam, "Arterial blood pressure estimation from local pulse wave velocity using dual-element photoplethysmograph probe," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 6, pp. 1399–1408, Jun. 2018.

[8] S. N. Shukla, K. Kakwani, A. Patra, B. K. Lahkar, V. K. Gupta, A. Jayakrishna, P. Vashisht, and I. Sreekanth, "Noninvasive cuffless blood pressure measurement by vascular transit time," in *Proc. 28th Int. Conf. VLSI Design*, Bengaluru, India, Jan. 2015, pp. 535–540.

[9] M. Elgendi, R. Fletcher, Y. Liang, N. Howard, N. Lovell, D. Abbott, K. Lim, and R. Ward, "The use of photoplethysmography for assessing hypertension," *NPJ Digit. Med.*, vol. 2, no. 1, p. 60, Jun. 2019.

[10] G. Stergiou *et al.*, "A universal standard for the validation of blood pressure measuring devices," *J. Hypertens*, vol. 36, no. 3, pp. 472–478, 2018.

[11] Y. Zhang and Z. Feng, "A SVM method for continuous blood pressure estimation from a PPG signal," in *Proc. 9th Int. Conf. Mach. Learn. Comput. (ICMLC)*, Feb. 2017, pp. 128–132.

[12] K. Atomi, H. Kawanaka, M. S. Bhuiyan, and K. Oguri, "Cuffless blood pressure estimation based on data-oriented continuous health monitoring system," *Comput. Math. Methods Med.*, vol. 2017, pp. 1–10, Apr. 2017.

[13] A. Visvanathan, A. Sinha, and A. Pal, "Estimation of blood pressure levels from reflective photoplethysmograph using smart phones," in *Proc. 13th IEEE Int. Conf. BioInform. Bio Eng. (ICBB)*, Chania, Greece, Nov. 2013, pp. 1–5.

[14] S. G. Khalid, J. Zhang, F. Chen, and D. Zheng, "Blood pressure estimation using photoplethysmography only: Comparison between different machine learning approaches," *J. Healthc Eng.*, vol. 2018, pp. 1–13, Jan. 2018.

[15] N. Watanabe, Y. K. Bando, T. Kawachi, H. Yamakita, K. Futatsuyama, Y. Honda, H. Yasui, K. Nishimura, T. Kamihara, T. Okumura, H. Ishii, T. Kondo, and T. Murohara, "Development and validation of a novel cuff-less bp monitoring device," *JACC, Basic Transl. Sci.*, vol. 2, no. 6, pp. 631–642, 2017.

[16] S. Suzuki and K. Oguri, "Cuffless and non-invasive systolic blood pressure estimation for aged class by using a photoplethysmograph," in *Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Vancouver, BC, Canada, Aug. 2008, pp. 1327–1330.

[17] B. Zhang, Z. Wei, J. Ren, Y. Cheng, and Z. Zheng, "An empirical study on predicting blood pressure using classification and regression trees," *IEEE Access*, vol. 6, pp. 21758–21768, 2018.

[18] M. Simjanoska, M. Gjoreski, M. Gams, and A. M. Bogdanova, "Non-invasive blood pressure estimation from ECG using machine learning techniques," *Sensors*, vol. 18, no. 4, p. 1160, 2018.

[19] D. Liu, M. Görges, and S. A. Jenkins, "University of queensland vital signs dataset: Development of an accessible repository of anesthesia patient monitoring data for research," *Anesthesia Analgesia*, vol. 114, no. 3, pp. 584–589, Mar. 2012.

[20] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. 215–220, Jun. 2000.

[21] R. W. Schafer, "What is a Savitzky-Golay filter," *IEEE Signal Process. Mag.*, vol. 28, no. 4, pp. 111–117, Jul. 2011.

[22] E. R. J. Seitsonen, I. K. J. Korhonen, M. J. van Gils, M. Huiku, J. M. P. Lötjönen, K. T. Korttila, and A. M. Yli-Hankala, "EEG spectral entropy, heart rate, photoplethysmography and motor responses to skin incision during sevoflurane anaesthesia," *Acta Anaesthesiologica Scandinavica*, vol. 49, no. 3, pp. 284–292, Mar. 2005.

[23] S. R. Alty, N. Angarita-Jaimes, S. C. Millasseau, and P. J. Chowienczyk, "Predicting arterial stiffness from the digital volume pulse waveform," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 12, pp. 2268–2275, Dec. 2007.

[24] A. A. Awad, A. S. Haddadin, H. Tantawy, T. M. Badr, R. G. Stout, D. G. Silverman, and K. H. Shelley, "The relationship between the photoplethysmographic waveform and systemic vascular resistance," *J. Clin. Monit. Comput.*, vol. 21, no. 6, pp. 365–372, Nov. 2007.

[25] M. A. Schroeder, J. Lander, and S. Levine-Silverman, "Diagnosing and dealing with multicollinearity," *Western J. Nursing Res.*, vol. 12, no. 2, pp. 175–187, Apr. 1990.

[26] L. Breiman, *Classification and Regression Trees*. Belmont, CA, USA: Wadsworth International Group, 1984.

[27] J. C. Ruiz-Rodríguez, A. Ruiz-Sanmartín, V. Ribas, J. Caballero, A. García-Roche, J. Riera, X. Nuvials, M. de Nadal, O. de Sola-Morales, J. Serra, and J. Rello, "Innovative continuous non-invasive cuffless blood pressure monitoring based on photoplethysmography technology," *Intensive Care Med.*, vol. 39, no. 9, pp. 1618–1625, Sep. 2013.

[28] X. Xing and M. Sun, "Optical blood pressure estimation with photoplethysmography and FFT-based neural networks," *Biomed. Opt. Express*, vol. 7, no. 8, p. 3007, Aug. 2016.

[29] M. Nitzan, I. Slotki, and L. Shavit, "More accurate systolic blood pressure measurement is required for improved hypertension management: A perspective," *Med Devices(Auckl)*, vol. 10, pp. 157–163, Jul. 2017.

[30] D. M. Bard, J. I. Joseph, and N. van Helmond, "Cuff-less methods for blood pressure telemonitoring," *Frontiers Cardiovascular Med.*, vol. 6, pp. 1–7, Apr. 2019.

SYED GHUFRAN KHALID received the B.S. degree in biomedical engineering from the Sir Syed University of Engineering and Technology, Pakistan, the M.S. degree in medical engineering with specialization in medical imaging and bio-instrumentation from the Royal Institute of Technology, Sweden, and the Ph.D. degree in medical technology from Anglia Ruskin University–Chelmsford, U.K.

He is currently a Research Fellow with Coventry University. He has gained industrial and academic experience in the field of biomedical engineering. He has filed a U.K. patent application for cuffless BP estimation technology. His project has been selected for Innovate U.K. grant for commercialization. His research interests include biomedical instrumentation, physiological measurements, signal processing, machine learning, and statistics. He received multiple BHF travel awards based on the quality of his research abstracts.

HAIPENG LIU received the B.S. degree in electrical engineering and automation and the M.S. degree in biomedical engineering from Zhejiang University, China, in 2012 and 2015, respectively, and the Ph.D. degree in medical sciences from The Chinese University of Hong Kong, in 2018. He is currently a Research Fellow with Coventry University. In recent five years, he investigated biomechanical simulation and its applications in strabismus, cardiovascular diseases, and stroke, with multiple publications in journals and IEEE conferences. His research interests include biomechanics, physiological signal processing, and wearable medical devices. Dr. Liu received the BHF travel awards based on the quality of his research abstract.

TAHIR ZIA received the B.S. degree in biomedical engineering from the Sir Syed University of Engineering and Technology, Pakistan, in 2008, and the M.Sc. degree in mechatronic systems from Kingston University London, U.K., in 2011. Since 2011, he has been a Clinical Engineer with the Clinical Engineering Department of The Royal Marsden NHS Foundation Trust, London, U.K.

JUFEN ZHANG is currently a Medical Statistician with the Medical School, Anglia Ruskin University. She is interested in clinical trials research and epidemiological studies. She is a Chartered Statistician of the Royal Statistical Society.

FEI CHEN (Senior Member, IEEE) received the B.Sc. and M.Phil. degrees in electronic engineering from Nanjing University, and the Ph.D. degree in electronic engineering from The Chinese University of Hong Kong, in 2005. He continued his research as a Postdoctoral/Research Assistant Professor in The University of Texas at Dallas and The University of Hong Kong, and moved to Southern University of Science and Technology (SUSTech) as an Associate Professor in the Department of Electronic Engineering, in 2014. He has published over 80 journal articles and over 60 conference papers. His research interests include speech perception and assistive hearing technology, brain–computer interface, and biomedical signal processing. Dr. Chen received the best presentation award in the 9th Asia Pacific Conference of Speech, Language and Hearing, and 2011 National Organization for Hearing Research Foundation Research Awards in States. He is serving as an Associate Editor of *Frontiers in Psychology*, and an Editorial Member of *Biomedical Signal Processing and Control* and *Physiological Measurement*.

DINGCHANG ZHENG received the B.Sc. degree in biomedical engineering from Zhejiang University, China, and the Ph.D. degree in medical physics from Newcastle University, U.K.

He is currently a Professor of Healthcare Technology and a Research Theme Leader with Coventry University. He is leading research in medical device and technology development with physiological measurements and bio-signal processing, working across multidisciplinary areas with electronic engineers, medical physicists, computer scientists, clinical consultants, industrial partners, guideline makers, and allied professionals at different stages along the pathway of medical device development and commercialization. Prof. Zheng is the winner of the IPEM Martin Black Annual Prize, in 2011, and also the winner of Institution of Engineering and Technology (IET) JA Lodge Award 2009 for Recognizing and Promoting Outstanding Work in the Field of Research and Development in Medical Engineering.