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Research Article

Monitoring Personalized Trait Using Oscillometric Arterial Blood Pressure Measurements

Young-Suk Shin

Department of Information and Communication Engineering, Chosun University, 375 Seosuk-dong, Dong-gu, Gwangju 501-759, Republic of Korea

Correspondence should be addressed to Young-Suk Shin, ysshin@chosun.ac.kr

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The blood pressure patterns obtained from a linearly or stepwise deflating cuff exhibit personalized traits, such as fairly uniform peak patterns and regular beat geometry; it can support the diagnosis and monitoring of hypertensive patients with reduced sensitivity to fluctuations in Blood Pressure (BP) over time. Monitoring of personalized trait in Oscillometric Arterial Blood Pressure Measurements (OABPM) uses the Linear Discriminant Analysis (LDA) algorithm. The representation of personalized traits with features from the oscillometric waveforms using LDA algorithm includes four phases. Data collection consists of blood pressure data using auscultatory measurements and pressure oscillations data obtained from the oscillometric method. Preprocessing involves the normalization of various sized oscillometric waveforms to a uniform size. Feature extraction involves the use of features from oscillometric amplitudes, and trait identification involves the use of the LDA algorithm. In this paper, it presents a novel OABPM-based blood pressure monitoring system that can monitor personalized blood pressure pattern. Our approach can reduce sensitivity to fluctuations in blood pressure with the features extracted from the whole area in oscillometric arterial blood pressure measurement. Therefore this technique offers reliable blood pressure patterns. This study provides a cornerstone for the diagnosis and management of hypertension in the foreseeable future.

1. Introduction

Blood pressure (BP) is a vital sign, which along with body temperature, heart rate, and respiratory rate provides various physiological statistics about the body. Small changes in the BP over a period of time can provide clues about cardiovascular and respiratory abnormalities in a patient. Oscillometry is one of the widely used methods to determine the blood pressure [1–7]. The oscillometric method of measuring blood pressure uses the amplitude of cuff pressure oscillations from a linearly or stepwise deflating cuff and is given as two values, the systolic and diastolic pressures. The cuff pressure oscillations consist of waveforms. The systolic pressure is the pressure associated with contraction of the heart, and indicates the maximum amount of work per stroke needed for the heart to pump blood through the arteries [8]. In contrast, diastolic pressure is the pressure in the large arteries during relaxation of the heart left ventricle [9]. The diastolic pressure indicates the amount of pressure that the heart must overcome in order to generate the next beat [8].

There have been ongoing studies to develop reliable measurements of blood pressure [3–7]. These researches have focused on improving the accuracy of blood pressure measurements. However, a large number of cardiovascular diseases such as arrhythmia can make it difficult to obtain accurate blood pressure measurements [3]. To determine the true BP level, many BP measurements need to be taken over a long period of time and problems affected by the white-coat effect have to be solved. The white-coat effect is usually defined as the difference between the BP measured at home and at the office. White-coat effect can be influenced by anxiety, a hyperactive alerting response, or a conditioned response. The white-coat effect typically causes the office BP to be higher than the home BP and is present in a high percentage of hypertensive patients [10]. If there are personalized traits in blood pressure measurements, problems such as noises caused by cardiovascular diseases like arrhythmia or problems of the white-coat effect may be overcome. Therefore, this study proposes the oscillometric measurement-based automatic blood pressure pattern identification system to explore personalized traits prior to obtaining reliable blood pressure measurements. The proposed approach demonstrates the feasibility of personalized trait identification with 85 people.

This paper aims to explore blood pressure pattern identification to find personalized traits in oscillometric arterial blood pressure measurements using the linear discriminant Analysis (LDA) algorithm. Section 2 introduces a review of related work. Section 3 develops a representation of personalized traits with features from the oscillometric waveforms. It consists of four steps. The first step introduces the database used for this research. The second step presents a preprocessing technique for obtaining uniform sized oscillation waves, and the third step develops a personalized traits representation via oscillations of amplitude features from uniform sized oscillation waves. The fourth step describes data reduction and feature extraction using LDA in the appearance-based approach. Section 4 presents the performance of the blood pressure patterns identification model via the LDA algorithm. Finally, this study discusses the advantages and applications of personalized trait monitoring.

2. Related Work

Blood pressure best predicts cardiovascular risk. Therefore, a variety of studies have been proposed to improve the accuracy of blood pressure measurements [3–7, 11–14]. Many studies use the oscillometric method to measure the blood pressure [1–7, 11, 12]. The oscillometric method is used to find the peak values of the oscillation waveform, which are determined as the oscillation amplitudes obtained from the pressure of the linearly deflating cuff. This method has virtually no complications and needs less expertise; it is less unpleasant and painful for the patient. In [1–7, 11, 12], blood pressure measurements based on the oscillometric method typically only use single-point estimates for both systolic blood pressure and diastolic blood pressure. Recently, BP measurements in [13, 14] were introduced: the confidence interval estimate of the systolic blood pressure and diastolic blood pressure. In [13], the confidence interval estimate performed well only when sample size is large. The confidence interval estimate used in [14] requires independent and identically distribution of data. But these methods also have to measure single-point estimates for systolic and diastolic blood pressure and can reflect on sensitivity to fluctuations in BP measurements.

In this paper, we have attempted to extract personalized blood pressure patterns of oscillation amplitudes rather than measure single-point estimates for systolic and diastolic blood pressure. During feature extraction, we focus on the more uniform features of the oscillation amplitudes in each person.

3. Methodology

This section describes a new blood pressure patterns identification technique to find personalized traits in oscillometric arterial blood pressure measurements using the LDA algorithm. This work consists of four steps. First, data collection is described. Second, oscillometric waveforms of various sizes are normalized to a uniform size. Third, features based on the oscillation amplitudes are developed. Finally, the LDA algorithm is applied to identify blood pressure patterns.

3.1. Data Collection

Experimental data has been provided by the blood pressure research team of the University of Ottawa in Canada. The database consists of blood pressure data using auscultatory measurements and pressure oscillations data obtained from the oscillometric method. The blood pressure data measured using the auscultatory method was obtained by two trained nurses. The oscillometric method is similar to the auscultatory technique, but it uses a pressure sensor instead of a stethoscope to record the pressure oscillations within the cuff. This method requires an external inflatable cuff, which can be placed around the left wrist at heart level. The cuff is inflated starting from below the diastolic pressure until the cuff pressure exceeds the systolic pressure. The cuff pressure is first increased until it exceeds the systolic pressure and then deflated until it reaches certain pressures at fixed or variable intervals [7].

The database consists of a total of 425 (85×5) records with five recordings per subject from 85 male and female subjects. Subjects met various blood pressure criteria: 10% of participants had BP below 100 mmHg systolic, 10% had BP above 140 mmHg systolic, 10% had BP below 60 mmHg diastolic, 10% had BP above 100 mmHg diastolic, and the remainder had BP distributed between these outer limits. The subjects' ages ranged from 10 to 80 years. Subjects were allowed to relax in a waiting room area for 15 minutes and the measurement room was organized to be conducive to accurate blood pressure measurements. The subjects were told not to talk or move during the readings. Five records per subject were acquired, and measurements were repeated for one minute with a one-minute rest period. Figure 1 shows one example of an oscillation pattern extracted from the cuff pressure acquired from the oscillometric method.

3.2. Preprocessing

The number of oscillation waveforms extracted from the cuff pressure varies according to physiology, geometry of the heart, hypertension, gender, and age (see Table 1). Table 1 shows a partial example of varying number of oscillation waveforms extracted from the cuff pressure. The systolic and diastolic pressures are the average values acquired by two nurses with auscultatory measurements. We can find a similar number of oscillation waveforms in 5 measurements of the same subject. That is, the same person can have similar number of oscillation waveforms. We attempt to use normalization to reduce variations of corresponding

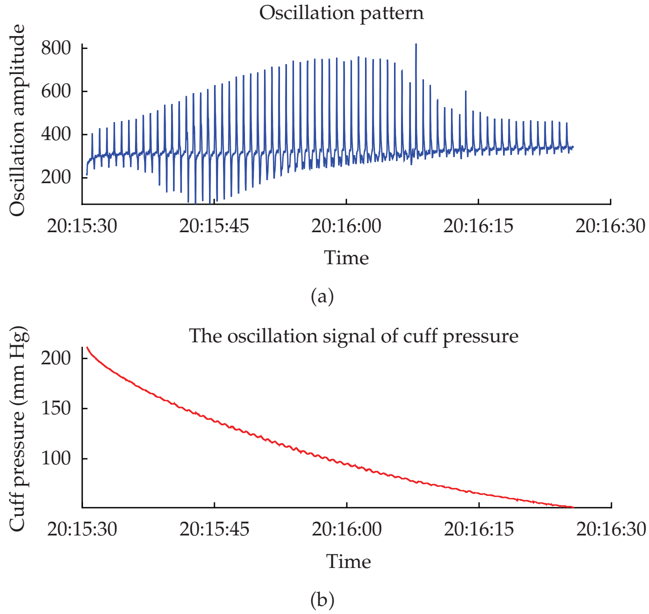

Figure 1: Oscillation pattern extracted from the cuff pressure with the oscillometric method.

oscillation waveforms for different oscillation waveforms of the same person. A blood pressure pattern means a varying number of oscillation waveforms in one record for one-minute. Training set is defined as X. Given the training set $X = \{W_i\}_{i=1}^{N}$, containing N blood pressure patterns where each blood pressure pattern $W_i = \{W_{ij}\}_{j=1}^{N_i}$ consists of a number of oscillation waveforms W_{ij}, the normalization is applied as follows:

$$\varphi = \mathrm{sqrt}\left(\sum_{j=1}^{N_i}\left(W_{ij}\right)^2\right),$$
$$W_i^* = \frac{W_i}{\varphi}. \tag{3.1}$$

3.3. Feature Extraction

The proposed feature extraction technique extracts features of mean amplitude (MA), maximum positive amplitude (MPA), and maximum negative amplitude (MNA) based on database with the number of oscillation waveforms.

To implement the proposed approach, we segment a normalized oscillation pattern into 29-sample windows (at least including a single beat in the minimum oscillation waveforms) to obtain the feature windows. That is, a blood pressure pattern is divided into 29 sections and each divided section has to include at least a single heartbeat. In this study, 29 sections are defined for including at least a single heart beat on the training set, X. Blood pressure patterns larger than the minimum number of oscillation waveforms in a blood pressure pattern represent multiple heart beats within a given window. One-feature window means one section in 29 sections. Figure 2 shows four heart beats detected within a given

Table 1: Oscillation waveforms of various sizes extracted from the cuff pressure.

Subjects	age	Gender	Reading number	Number of oscillation waveforms acquired from cuff pressure for oscillometric method	Blood pressure by auscultatory method Systolic	Diastolic	Note
S1	50	Male	1	4591	127	98	Prehypertension
			2	4679	128	98	
			3	4684	126	98	
			4	4705	126	98	
			5	4698	125	99	
S2	22	Female	1	3457	113	67	Normal
			2	3499	104	68	
			3	3530	112	66	
			4	3551	104	61	
			5	3523	108	65	
S3	54	Female	1	3721	145	88	Stage 1 hypertension
			2	3845	142	83	
			3	3892	143	84	
			4	3935	140	80	
			5	3979	135	78	
S4	34	Male	1	8401	131	82	Prehypertensive
			2	8500	131	86	
			3	8746	130	79	
			4	8808	131	78	
			5	8948	130	82	
S5	36	Male	1	3957	109	67	Normal
			2	4069	106	71	
			3	4159	104	72	
			4	4220	103	71	
			5	4218	108	70	
S6	43	Female	1	3991	109	69	Normal
			2	4106	112	69	
			3	4041	109	70	
			4	4139	112	69	
			5	4100	114	71	

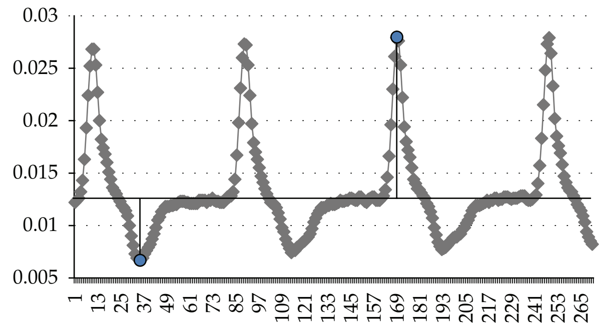

Figure 2: Four heartbeats detected in the segmented one-feature window from one subject.

window. We extract three features from the oscillation amplitudes in the segmented feature window: mean amplitude, maximum positive amplitude, and maximum negative amplitude. The circle marks of Figure 2 display the maximum positive and negative amplitudes extracted in the segmented feature window. We define the following for three features; MA means the averaged oscillation amplitudes in the segmented one-feature window; MPA means the amplitude of the maximum upper pulse from the oscillations in the segmented one-feature window; MNA describes the amplitude of the maximum lower pulse from the oscillations in the segmented one-feature window.

Figure 3 shows the feature extraction results of one subject with the mean amplitude and maximum positive and negative amplitudes in each feature window. The mean amplitude can reduce noise signals within the feature window, and the maximum positive and negative amplitudes exhibit personalized traits in the period of high or low cuff pressure. Figures 4 and 5 show the feature extraction results of six subjects in Table 1 with maximum positive and negative amplitudes in 29 feature windows, respectively. Figures 4 and 5 show the averaged results of five readings obtained from the oscillometric blood pressure measurements of each subject. Subjects S2, S5, and S6 of Figures 4 and 5 are normal (BP: <120/80 mmHg), whereas blood pressure subjects S1 and S4 are prehypertensive (BP: 120/80 to 139/89 mmHg) and S3 is stage 1 hypertensive (BP: 140/90 to 160/100 mmHg) blood pressure subject. In Figures 4 and 5, stage 1 hypertensive or prehypertensive subjects display a steep-slope pattern in front of the feature windows compared to normal subjects. Especially, older subjects show higher amplitudes based on the MPA features. In the MNA features, stage 1 hypertensive or prehypertensive subjects show lower amplitudes compared to normal subjects.

3.4. Identification

Linear discriminant analysis is used for data reduction and feature extraction in the appearance-based approach. LDA searches for feature vectors in the fundamental space that best discriminates among classes [15]. LDA describes a linear combination of feature vectors that produces the largest mean differences between the target classes. Features of the heartbeat applied for human identification from electrocardiogram (ECG) [16–18] are similar to features extracted from oscillometric arterial blood pressure measurements. Features extracted from oscillometric measurements are classified with an appearance-based approach based on LDA. Appearance-based approach is usually taken by different two-dimensional views

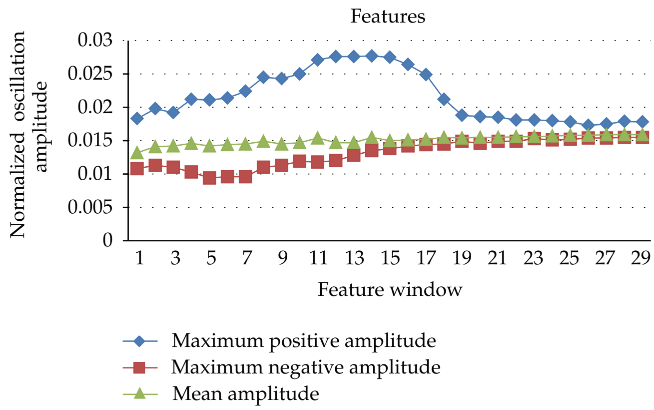

Figure 3: Features extracted with mean amplitude and maximum positive and negative amplitudes in the segmented feature windows from one subject.

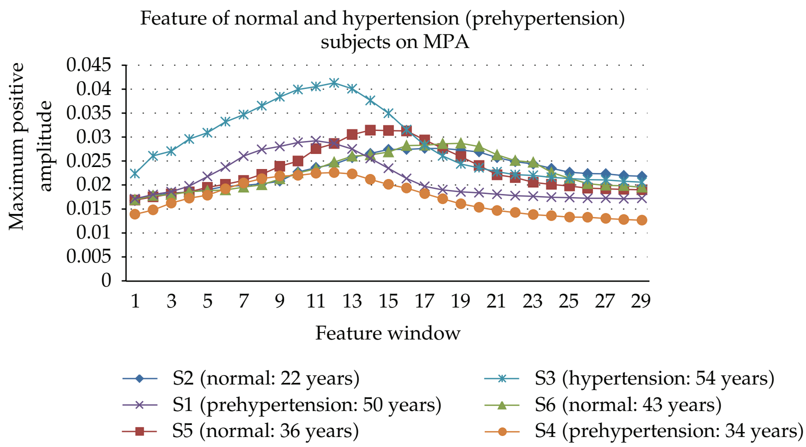

Figure 4: Features extracted with maximum positive amplitude averaged from five readings in the feature windows for normal and hypertension (prehypertension) subjects with respect to age.

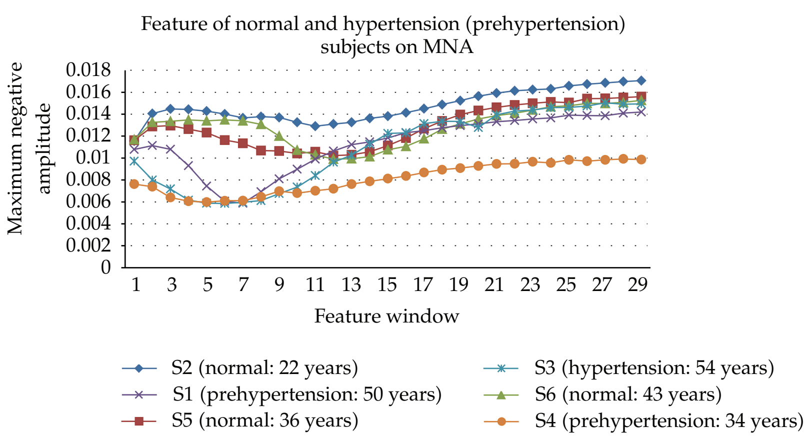

Figure 5: Features extracted with maximum negative amplitude averaged from five readings in the feature windows for normal and hypertension (prehypertension) subjects with respect to age.

of the object of interest. These methods based on the applied features can be subdivided into two approaches: local and global approaches. This study applies global appearance-based method. The main idea is to project the original input data onto a suitable lower-dimensional subspace that represents the data best for a specific work. Selecting optimization criteria for the projected data is the goal to best identify personalized trait.

Given a training set $X = \{W_i^*\}_{i=1}^{C}$, containing C classes with each class $W_i^* = \{w_{ij}^*\}_{j=1}^{C_i}$, consisting of a number of features, w_{ij}^*, there are a total of $N = \sum_{i=1}^{c} C_i$ oscillation patterns. We define two measures for all samples of all classes. S_{WT} is defined as within-class scatter matrices of the training feature set. S_{BT} is defined as between-class scatter matrices of the training feature set. S_{WT} and S_{BT} are given as

$$S_{\mathrm{WT}} = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{C_i}\left(w_{ij}^* - \mu_i\right)\left(w_{ij}^* - \mu_i\right)^T,$$
$$S_{\mathrm{BT}} = \frac{1}{N}\sum_{i=1}^{c}\left(\mu_i - \mu\right)\left(\mu_i - \mu\right)^T. \tag{3.2}$$

In (3.2), w_{ij}^* denotes the jth sample of class i, c is the number of classes, μ_i is the mean of class i, and c_i denotes the number of samples in class i and μ is the mean of all classes. The LDA approach [19] finds a set of basis vectors described by φ that maximizes the ratio between S_{BT} and S_{WT}:

$$\varphi = \arg\max \frac{\left|\varphi^T S_{\mathrm{BT}}\varphi\right|}{\left|\varphi^T S_{\mathrm{WT}}\varphi\right|}. \tag{3.3}$$

One method is to assume that S_{WT} is nonsingular and the basis vectors φ correspond to the first N eigenvectors with the largest eigenvalues of ${S_{\mathrm{WT}}}^{-1}S_{\mathrm{BT}}$. LDA-based feature representation, $y = \varphi^T w^*$, is produced by projecting the normalized input features (w^*) from the oscillation amplitudes onto the subspace spanned by the N eigenvectors.

4. Experimental Results

To evaluate the performance of our approach, we conducted our experiments with the pressure oscillations data (measured using oscillometric method) provided by the blood pressure research team of the University of Ottawa in Canada. For the experiment, we used 425 records with five readings per subject obtained from 85 subjects; the training set consisted of 255 records with three readings per subject obtained from 85 subjects; the testing set consisted of the remaining 170 data readings excluded from the training set, two readings per subject obtained from 85 subjects. The blood pressure data measured using the auscultatory method provided indirect information for analyzing the subjects recognized by the oscillometric method in our experiment.

The experimental results were evaluated with the performance of LDA by using the nearest neighbor algorithm. The Euclidean distance was used for the similarity measure. To find the optimal LDA-based features, our implementation used the five sets of features from Figure 3 to test their discrimination power. One set included all of the features, whereas

Table 2: Subsets of features extracted using the oscillometric method.

Subset	Feature
I	Mean amplitude (MA)
II	Maximum positive amplitude (MPA)
III	Maximum negative amplitude (MNA)
IV	MPA + MNA
V	MA + MPA + MNA

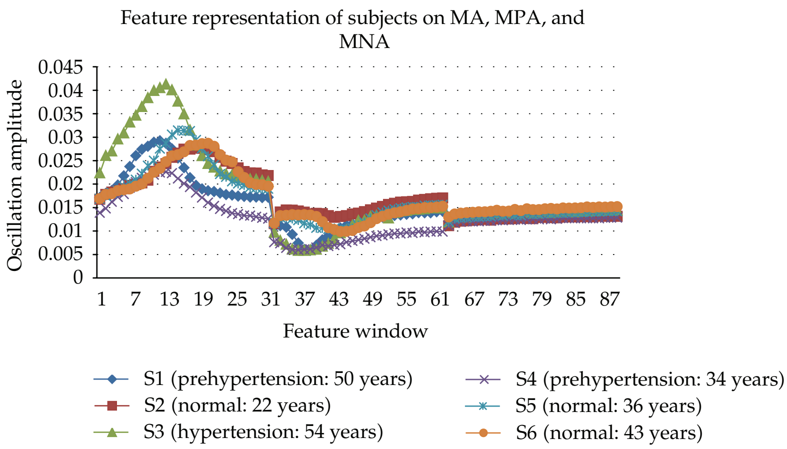

Figure 6: Features extracted with mean amplitude and maximum positive and negative amplitudes in the feature windows from normal and hypertension (prehypertension) subjects.

the other four sets included a subset of these, as shown in Table 2. Subset IV concatenates the features of the maximum positive and negative amplitudes, and subset V concatenates the features of the mean amplitudes and maximum positive and negative amplitudes into one vector.

Figure 6 shows the feature extraction results obtained from six subjects in Table 1 and the mean amplitudes and maximum positive and negative amplitudes are concatenated into one vector. S2, S5, and S6 are normal blood pressure subjects, and S1, S3, and S4 are prehypertension or hypertensive blood pressure subjects. This shows the averaged results of the five readings for the oscillometric blood pressure measurements obtained from each subject. The feature windows describe feature windows 1 to 29 extracted from the maximum positive amplitudes, feature sections 30 to 57 extracted from the maximum negative amplitudes, and feature sections 58 to 87 extracted from the mean amplitude. The stage 1 hypertensive subject (S3) displays steeper maximum positive amplitude than that of the normal subjects. Prehypertensive or stage 1 hypertensive subjects generally display lower maximum negative amplitude than that of normal subjects. This shows that the averaged features of the five readings taken from each subject are plotted in a personalized uniform pattern. The results of the final LDA-based experiments are listed in Table 3. We can see that using all of the features provides the best blood pressure pattern identification rate, and subset IV shows good performance, while subset I shows the worst performance. LDA does not go beyond 85 for the dimensionality of the LDA space. Since we use 85 classes, this gives us an upper bound of 85-dimensional LDA space.

Table 3: Experimental results of LDA.

Subset	Recognition rate (%)
I	34.30
II	67.44
III	72.09
IV	93.02
V	94.70

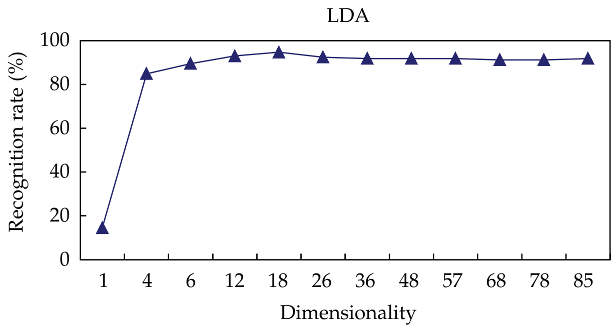

Figure 7: LDA recognition performance according to dimensionality via LDA algorithm with nearest neighbor classifier.

Figure 7 shows the recognition results based on the dimensionality that yields the best identification rate. We achieved the best blood pressure pattern identification rate of 94.7% for the first 18 eigenvectors. Thus, the first 18 eigenvectors are estimated to the optimal decision boundary to best identify personalized trait using LDA in this study.

5. Discussion

This study aimed to explore a new blood pressure patterns identification model for personalized traits monitoring of oscillometric arterial blood pressure measurements using the linear discriminant analysis algorithm. A blood pressure patterns identification model was used for the oscillometric arterial blood pressure measurements, which successfully discriminated personalized traits for the LDA algorithm. Our best recognition result showed a recognition rate of 94.7% for the first 18 eigenvectors. This means that the optimal LDA-based 18 eigenvectors in oscillometric arterial blood pressure measurements can effectively represent personalized traits.

The personalized traits of the oscillometric arterial blood pressure measurements can be represented for the features extracted from the whole domain of one oscillation pattern. Especially, the integration of the three feature streams extracted from each segmented feature window for the whole domain of one oscillation pattern enhances the recognition performance. In our experiment, the integration of the feature streams extracted with the maximum positive and negative amplitudes largely improved the recognition rate. In the three feature streams, while the maximum positive and negative amplitude feature streams showed strong effects on the recognition performance, the mean amplitude showed a weak effect. We propose that the maximum positive and negative amplitude features can effectively represent personalized traits of oscillometric arterial blood pressure measurement.

Features extracted from each segmented feature window in the oscillometric method may support the monitoring and diagnosis of hypertensive patients because stage 1 hypertensive or prehypertensive subjects display a steep-slope pattern in front of the feature windows compared to normal subjects.

Our approach offers a simple and inexpensive means of monitoring personalized trait with blood pressure patterns in oscillometric arterial blood pressure measurement. Based on these results, this study has established a new blood pressure monitoring system for health care monitoring in oscillometric arterial blood pressure measurements. Our research has the potentiality for the diagnosis and management of hypertension and provides a foundation of a new biometric modality using blood pressure patterns.

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