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ORIGINAL RESEARCH

Automated recognition of hypertension through overnight continuous HRV monitoring

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Abstract Hypertension is a common and chronic disease, caused by high blood pressure. Since hypertension often has no warning signs or symptoms, many cases remain undiagnosed. Untreated or sub-optimally controlled hypertension may lead to cardiovascular, cerebrovascular and renal morbidity and mortality, along with dysfunction of the autonomic nervous system. Therefore, it could be quite valuable to predict or provide early warnings about hypertension. Heart rate variability (HRV) analysis has emerged as the most valuable non-invasive test to assess autonomic nervous system function, and has great potential for detecting hypertension. However, HRV indicators may be subtle and present at random, resulting in two challenges: how to support continuous monitoring for hours at a time while being unobtrusive, and how to efficiently analyze the collected data to minimize data collection and user burden. In this paper, we present a machine learning-based approach for detecting hypertension, using a waist belt continuous sensing system that is worn overnight. Using 24 hypertension patients and 24 healthy controls, we demonstrate that our approach can differentiate hypertension patients from healthy controls with 93.33% accuracy. This represents a promising approach for performing hypertension classification in the field, and also we would improve its performance based on a large number of hypertensive subjects monitored by the proposed pervasive sensors.

Keywords Human-centered computing · Ubiquitous computing · Computing methodologies · Machine learning · Electrocardiogram · Pyramid methods · Healthcare · Heart rate sensing

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1 Introduction

Hypertension is a condition in which one's arteries have consistently elevated blood pressure, also referred to as high blood pressure. Hypertension affects one billion people worldwide (WHO et al. 2015), leading to increased risk of cardiovascular disease, heart attacks and strokes. The World Health Organization estimates that high blood pressure kills nine million people every year (WHO et al. 2015). Problematically, hypertension often does not show any symptoms for many years or even decades. It is a silent killer that damages critical organs of the human body (Poddar et al. 2014). Indeed, many people are not aware they have hypertension (e.g., Li et al. 2016; Wall et al. 2014). In the US, an estimated 13 million people are unaware of their condition (Wall et al. 2014), while in China, 59% of people with hypertension are unaware of their condition (Li

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et al. 2016). Given these statistics, it is clear that we need a technique for recognizing hypertension as early as possible to avoid significant damage to one's body.

In the medical and healthcare community, heart rate variability (HRV) has emerged as a practical, noninvasive tool to quantitatively investigate cardiac autonomic deregulations which result from hypertension (Schroeder et al. 2003). Reduced HRV can be also used as predictor of hypertension (Terathongkum and Pickler 2004). HRV measures the fluctuation between intervals of consecutive heartbeats and is usually detected using the interval variations between consecutive R peak to R peak (R-R interval) values from an electrocardiogram (ECG) recording. Thus HRV analysis is a promising option for detecting hypertension.

Unfortunately, HRV analysis is limited in its usefulness for the many people who are not showing clear symptoms of hypertension. Such patients are at risk and may even have serious sub-clinical effects of hypertension (Feng et al. 2014). Almost all HRV data is collected in a clinical setting, using short (5-min) recordings while a patient is in a resting state, which may miss signs of HRV that occur rarely, or long (24-h) recordings, which require an expensive, lengthy clinical visit. The ability to collect data in the field would address these issues of data collection length and cost. However, the gold standard for sensing during the longer sessions uses a holter monitor, a device that collects high quality data using wet electrodes but is not well suited for field use due to the expertise needed to use it properly. Field options exist, such as apple watch, but have not yet been tested for hypertension detection. A related concern is that existing data analysis techniques are designed for diagnosing hypertension from high quality clinical data, but may not generalize to lower-quality field data. These challenges limit our ability to detect and monitor the progression of hypertension.

In this paper, inspired by the short resting ECG test in clinical settings, we have developed a solution for collecting ECG data overnight while sleeping, with two notable benefits: first, sleep is a resting state with less motion compared to daytime activity, which results in less noise in the data; second, sleep durations are relatively long, so intrinsic subtle changes in dynamicity and complexity of HRV can be adequately reflected in the collected data. Our contributions include:

A waist belt based heart-rate monitoring system to collect ECG data in the field Unlike traditional systems with wet electrodes, the waist belt does not require a constant connection and can be correctly set up by an end user (rather than a medical professional). Unlike existing chest or wrist worn devices that use dry electrodes; the waist belt is expected to have fewer motion artifacts when used while sleeping. An arm moves more than the torso during sleep, and a chest-worn system is likely to be more effected by breathing motions. The tradeoff is that the belt does not collect the full QSR wave of an ECG signal, just heart rate (simple ECG signal). We show that this is an effective solution for capturing diagnostic-quality field data.

A novel algorithm for classifying patients as hypertensive (or not hypertensive) based on the relatively imperfect, long-term data collected using our belt Our algorithm extends past work in HRV analysis for hypertension diagnosis by applying pyramid methods and feature pooling, initially developed for computer vision and signal processing, to collect features over multiple time windows of the data. Our work is similar to the Discrete Wavelet Transform (Boureau et al. 2010), but does not apply frequency filtering to decompose the input signal. Instead we use multiscale temporal resolutions. By building a pyramid at several levels of temporal resolution, and then pooling the resulting features together, we can more effectively recognize whether the input signal is from a subject with hypertension or not.

We now briefly review existing sensors and algorithms for detecting hypertension and a few related conditions. Then, we present the data acquisition process and preprocessing, feature extraction method and feature ranking methods, and our classification approach. Our evaluation shows that our approach has a sensitivity of 93.33% and a specificity of 93.33% on a test set of 30 participants (half of whom were hypertension patients), while a more typical approach using a feature vector that does not use pyramid methods has a 80.00% sensitivity and 93.33% specificity. We end with a discussion of the limitations of our work, a summary of the advantages of the novel waist belt, and opportunities for future research directions, including potential improvements in our approach and its application in practice.

2 Background

Although hypertension profoundly increases an individual's risk of various cardiovascular consequences (Shi and Yu 2013; Natarajan et al. 2014), it can be difficult to detect especially before clinically relevant symptoms that can justify expensive testing are present. However, detecting hypertension early is important to avoid damage to the body before it becomes clinically apparent.

The gold standard for diagnosing hypertension is blood pressure measurement in clinical settings. Unfortunately, hypertension usually has no warning signs or symptoms and may not be detectable from the simple blood pressure test, so many people do not realize they have it (Rosamond et al. 2008), which leaves many people with undiagnosed hypertension. Since there is evidence that a detectable

decrease in autonomic nervous function (measurable in the HRV signal) precedes the development of clinical hypertension (Schroeder et al. 2003), HRV can also be used for diagnosis (Terathongkum and Pickler 2004). For example, features of the HRV signal in both the time and frequency domain are decreased and potentially more variable among hypertension patients (e.g., Poddar et al. 2014; Puente 2010).

Thus, analysis of longer-term HRV has become an option for situations where hypertension is suspected but not severe enough to show up during a simple blood pressure test as part of a short clinic visit. HRV is typically derived from ECG signals, which have long been a focus of attention in clinical settings due to their high diagnostic value (Poddar et al. 2014). More recently, attempts to monitor ECG signals in the field have proliferated (e.g., Coyle et al. 2010; Farotto et al. 2015), with the goal of monitoring a variety of conditions. After reviewing that work, we discuss HRV analysis approaches that have been used for hypertension, and motivate the need for an alternative approach that can work with noisy field data.

2.1 Monitoring ECG in the field

A number of research groups have focused on effective solutions for sensing ECG signals in the field. Functional textiles have been used to manufacture a garment for physiological monitoring, where ECG signals are successfully recorded using fabric sensing elements (Coyle et al. 2010; Curone et al. 2010; Merritt et al. 2009). Similarly, there exist commercial devices that detect ECG continuously, such as the Zephyr Biopatch, a mobile and wearable chest-worn system (Rubin et al. 2015). These approaches suffer from motion artifacts, which introduce noise in the acquired data.

Another approach for moving from the clinic to the field is to minimize the number of electrodes used for sensing, to reduce motion artifacts and increase wearability. For example, in (Farotto et al. 2015), the authors investigated the feasibility of synthesizing a 3-lead ECG signal from 3 separate wearable and wireless patches. In (Da He et al. 2015), a wearable vital signs monitor uses one electrode placed on the mastoid area, and a second electrode on the posterior upper middle neck. Together, the two electrodes comprise a single-lead ECG. Both systems must be worn on a patient's body, attaching to ECG electrodes or an ECG strap. Separation of the electrodes from the body during normal daily activity is a concern due to its impact on data quality and analysis.

An even less intrusive approach is to piggyback ECG monitoring on other activities, by using coupling capacitance to monitor ECG rather than electrodes. In particular, Sinabro monitors ECG during smart-phone use, by leveraging sensors integrated into the phone (Kwon et al. 2014). Electrodes have also been directly embedded into a bed to continuously sense presence, position, and ECG (e.g., Ito et al. 2013; Lee et al. 2015; Lim et al. 2007), in a bed-sheet (Wu and Zhang 2008), in a chair (e.g., (Kim et al. 2006), in a wheelchair (Chou et al. 2015) and in a toilet seat (Baek et al. 2008). These approaches are relatively difficult to move from home to home or person to person. In addition, because of the high impedance between the signal source (the heart) and the sensor, the signal quality is worse than from contact-based ECG systems.

As described in a recent review article (Acharya et al. 2006), these approaches are sensitive to motion noise, and are difficult to use during sleep when motion is less likely. In one study of such an ECG system being used during sleep (Lee et al. 2015), issues arose with motion artifacts, making it most useful for the relatively simple problem of sleep detection.

2.2 Detecting hypertension

How well existing algorithms will perform in a field setting is still an open question. However, a good starting place is to review algorithms designed for detecting HRV from high-quality clinical data. There are two common approaches for HRV analysis (Al-Tabbaa and Oweis 2014): linear methods that use time-domain and frequency-domain features (e.g., (Lewicke et al. 2008; Long et al. 2012) and nonlinear, entropy-based methods (e.g., Pincus et al. 1991; Lake et al. 2002; Costa et al. 2002). Time-domain analysis considers the R-R interval length but, for example, cannot discriminate between sympathetic and parasympathetic HRV changes. Thus, most previous work has combined it with frequency-domain measures (e.g., Ramirez-Villegas et al. 2011; Poddar et al. 2014). Frequency-domain measures focus more on sympatho-vagal activity. Most previous work calculates the power spectral density in various frequency ranges (e.g., Long et al. 2012; Sun et al. 2012). The power value in each frequency range reflects physiological signals such as vascular mechanisms caused by negative emotions, sympathetic modulation of heart rate, parasympathetic activity, and sympatho-vagal balance. Finally, entropy-based methods have been popular because they were especially designed to deal with noisy time series signals (e.g., Signorini et al. 2006; Ho et al. 2011). Most previous work has used approximate entropy (Pincus et al. 1991), sample entropy (Lake et al. 2002), and multi-scale entropy (Costa et al. 2002).

HRV signals extracted from high quality data collected in laboratory settings has proven useful for detecting a variety of information including sleep state or quality (Long et al. 2012), mental stress (Sun et al. 2012), and heart and cardiovascular disease (Ramirez-Villegas et al.

2011) including hypertension (Poddar et al. 2014; Melillo et al. 2015). However, when applying such analyses to field data, both linear and nonlinear analyses are not sufficient to describe HRV, due to the additional noise associated with field data (Manis et al. 2005; Nikolic-Popovic and Goubran 2013). Even the use of entropy-based methods cannot address this problem due to noise caused by motion artifacts and sensing errors.

One study made use of home monitoring HRV data (Lewicke et al. 2008) for classifying sleep and awake states of infants. Linear and nonlinear analyses were used to measure HRV, and additionally incorporated sample rejection through reliability in the classification model in order to improve classification performance. Although they rejected unreliable samples (30% of the data) for model training, they achieved only 85–87% correct classification. This result shows that rejection of unreliable data is not sufficient for detecting hypertension and that a richer HRV representation is needed to achieve high accuracy.

2.3 Summary

To summarize, past work has established a set of highly effective features for detecting a variety of conditions from HRV signals. However, most of this work has depended on high-quality clinically collected ECG data. A field-ready solution requires both a sensing solution that is relatively high quality (and easy to use) and an approach to analysis that is robust to noisy data.

3 A waist belt for HRV monitoring in the field

We developed a wearable heart-rate monitoring system based on a waist belt, as seen in Fig. 1. The belt is comprised of three kinds of sensors: three dry electrodes, a 3-axis accelerometer and two pressure sensors with different sensitivities. Data is collected from the sensors and transmitted by a control unit over bluetooth to a nearby computer.

Fig. 1 Our waist-belt HRV monitoring system

Most similar approaches are designed to be worn around the chest. While the waist is non-standard, we believe it will (1) be easier to adjust, requiring no special expertise because the exact positioning is flexible, and (2) minimize motion artifacts (i.e., noise) due to breathing motions.

HRV data is sampled from the electrodes at 200 Hz. Artifacts caused by body motion during sleep are detected by the accelerometer. Breathing and coughing are detected with the pressure sensors. The HRV signal is amplified and filtered through a 40 Hz notch filter, a 0.5 Hz high-pass filter frequency, and a 30 Hz low-pass filter frequency. These filters were chosen empirically, using input from the sensors to remove various artifacts, including motion noise, power frequencies, baseline drift, and loss of electrode contact. To obtain a smooth HRV signal, a second-order (0.5–20 Hz) bandpass filter was applied, before data was transmitted to a nearby computer.

3.1 Data collection

To validate the usefulness of our waist belt monitoring system, we collected ECG data from 28 hypertensive patients (ages ranging from 52 to 71 years, 10 female, 18 male) and 24 non-hypertensive controls (ages ranging from 55 to 73 years, 8 female, 16 male). All the subjects were recruited by the Aero Medical Institute in Beijing, China. The hypertensive patients were from an affiliated hospital of the Institute, and the control subjects were elderly volunteers from the Institute and several universities in Beijing, China.

The control subjects underwent a medical examination to confirm that they had no cardiac disorders or negative cardiac histories. Subjects were given the waist belt device and instructed on how to use it. They were told to turn it on and wear it overnight in their homes, while they were sleeping. All the subjects put the waist belt on by themselves in their home.

3.2 Data preparation

Across our participants, we collected heart rate data for 7–9 h. An author of this study who is a medical expert manually inspected the collected dataset to identify anomalous data (i.e., excessive motion noise, very short sleep times), and excluded those participants from the study. A total of 4 participants (1 female, and 3 male) were excluded from among the hypertensive patients. When we collected the data from them, all of them said they didn't sleep very well during the night, and the female patient have worn the waist-belt for 2 h, and then gave up. Moreover, two of the patients have some other diseases, and their data could be influenced by complex reasons, which is not suitable for further analysis based

on the medical expert viewpoints. After removing these individuals, the patient population consisted of people ranging from 52 to 71 years, 9 female, 15 male. None of the control subjects were excluded.

4 Hypertension recognition approach

Classification of a patient as hypertensive or not based on field data is an open problem. However, as stated in the "Background" section, past work has identified the key types of time-domain, frequency-domain and entropy features for HRV that can be used in laboratory settings for effective classification.

We contribute a novel approach to long-term temporal data analysis, which we call pooled temporal pyramids. A pyramid representation is a multi-scale signal representation used in the computer vision, image processing (Burt and Adelson 1983; Adelson et al. 2003), and signal processing (Mallat 1989; Coifman et al. 1993) communities. It is a predecessor to scale-space representation and multi-resolution analysis. The Discrete Wavelet Transform (Mallat 1989), an example of a pyramid representation, is a powerful method for analyzing time-series signals at multiple resolutions for different frequencies. It is calculated by successively passing a signal through high-pass and low-pass filters, producing approximate and detailed wavelet coefficients. This approach has been applied to signal compression, noise reduction, and signal representation (Adeli et al. 2003; Subasi et al. 2005).

Inspired by the success of pyramid representation in prior work, we take a similar approach for representing HRV from ECG signals. Our method does not apply frequency filtering for the decomposition of the input signal like in a wavelet transform, but instead we decompose the signal into sub-signals using multi-scale temporal resolutions. By building a pyramid at several levels of temporal resolution for HRV representations, we can more effectively recognize whether the input signal is from a subject with hypertension or not. Building such a pyramid at different levels with multi-scale time resolutions lets us consider different information while also being more robust to noise, as variances are reduced.

To avoid feature explosion, we combine this approach with feature pooling methods. The pooling approach has been used to aggregate feature statistics in the spatial domain (Boureau et al. 2010; Lowe 2004) and in the temporal domain (Lemieux et al. 2011). It combines the features over a local neighborhood using a statistical method in order to create a joint feature representation. It is invariant to small transformations, is robust to noise, and has a compact representation.

4.1 Data preprocessing

Given a digitized ECG signal, we first perform noise filtering using Savitzky-Golay filtering (Savitzky and Golay 1964). This is a method of data smoothing based on local least-squares polynomial approximation. Based on the previous work (Awal et al. 2011) and empirical results, we set the parameters of the filtering to use a polynomial of degree 7 and frame size of 21.

Next, we detect R peaks by applying a threshold algorithm on 1-min segments extracted from the entire signal. We first split the entire signal into multiple short-term signals with a specific time duration, and then detect peaks by finding the local maximum and thresholding peaks for each short-term signal. Rather than applying this to the whole long-term signal, this approach allows us to reduce erroneous peak detection caused from sensing or motion noise, by setting an appropriate threshold constrained to the short-term signal. We use 1-min duration and 0.5 mV as a threshold, determined empirically. In order to remove additional erroneous peaks, peaks that are very close to each other are ignored. The acceptable number of samples for separations between two neighboring R peaks was established as 120 by considering the lower bound of a resting heart rate for adults (60 BPM) and our belt's sampling frequency (200 Hz).

The R-R interval is extracted by calculating the time difference between adjacent R peaks. First, we again filter out erroneous R-R interval values as those errors can affect HRV analysis and the final recognition task. For filtering, we perform a thresholding by considering the distribution of R-R interval values as following in Eq. (1):

$$RR_{mean} - \alpha RR_{std} \leqslant \widetilde{RR} \leqslant RR_{mean} + \alpha RR_{std} \quad (1)$$

where $\widetilde{RR}$ is the filtered sequence of R-R intervals, $RR_{mean}$and RR_{std}indicate the mean and standard deviation values of R-R intervals, while α controls which R-R interval values can be included in the filtered R-R intervals. Too large of an α value may include erroneous R-R intervals, while too small of an α value may miss valid R-R intervals. In our dataset, the average amount of data filtered out are 18.395, 3.611, 1.196, and 0.646% for $\alpha = 1$, 2, 3 and 4, respectively. We select α to be 3, based on the normal range of heart rate R-R intervals.

4.2 Feature extraction

Given a set of filtered R-R intervals, we extract linear (time-domain and frequency-domain) and nonlinear (entropy-based) features that have been commonly used for describing HRV [Al-Tabbaa and Oweis 2014].

Time-domain features

- RR_{MEAN}, RR_{MEDIAN}, RR_{MIN}, RR_{MAX}: Mean, Median, Minimum, Maximum of R-R intervals.
- RR_{SDANN}: Standard deviation of the averages of R-R intervals in all 5-min segments of the entire signal.
- $RR_{SDNN\ index}$: Mean of the standard deviations of all R-R intervals for all 5-min segments of the entire signal.
- RR_{RMSSD}: Root mean square of differences between successive R-R intervals.
- RR_{pNN50}: Percentage of differences between successive R-R intervals over entire signal that are greater than 50 ms.

Frequency-domain features

- P_{VLF}: Power in very low frequency ranging from 0 to 0.04 Hz, which reflects vascular mechanisms caused by negative emotions.
- P_{LF}: Power in low frequency ranging from 0.04 to 0.15 Hz, which reflects sympathetic modulation of heart rate.
- P_{HF}: Power in high frequency ranging from 0.15 to 0.4 Hz, which reflects parasympathetic activity.
- P_{Total}: Power in total frequency ranging from 0 to 0.4 Hz.
- $P_{LF/HF}$: Ratio of power in the LF and HF, which corresponds to sympatho-vagal balance.

Entropy features

- $E_{Approximate}$: This is used to quantify the regularity and unpredictability of fluctuation by observing repetitive patterns of fluctuation in the heart rate time series (Pincus et al. 1991). A signal containing many repetitive patterns has a relatively small value, while more complex and less predictable data has a higher value. For parameter values, 2 and 0.2 of standard deviation of input were used for embedded dimension (m) and tolerance level (r), respectively.
- E_{Sample}: This is a modification of $E_{Approximate}$ that is independent of data length and relatively consistent over a broad range of possible parameter values [Lake et al. 2002]. The same parameters were used as $E_{Approximate}$.
- $E2_{Multi\text{-}scale}$, $E3_{Multi\text{-}scale}$, $E4_{Multi\text{-}scale}$, $E5_{Multi\text{-}scale}$, $E6_{Multi\text{-}scale}$: This set of five features is an extension of Sample entropy that uses a multi-scale analysis (Costa et al. 2002). This computes Sample entropy over a range of scales and can investigate complexity in signals that have correlations at multiple scales. We use five types of scales ranging from 2 to 6.

4.3 Temporal pyramid representation for describing HRV

Most previous recognition tasks based on an HRV analysis have used a combination of linear and nonlinear features, as described in the related work. Although this has worked well when applied to clean short-term data obtained from controlled clinical settings as is common in the previous work, noisy data such as that collected in the field can cause performance to decrease (Nikolic-Popovic and Goubran 2014; Manis et al. 2005). To address this, we present a temporal pyramid representation for boosting hypertension classification performance, which is a more powerful method than using traditional linear and nonlinear features.

The pyramid is built by subdividing the entire signal at L different levels of temporal resolution (Fig. 2). The number of levels may vary depending on the signal parameter (e.g., sampling frequency) or goal of the recognition task. Level 0 starts with the entire signal, and higher levels are built from smaller temporal resolutions, such that level l has 2^l temporal segments. All d features are calculated for each segment at level l. Therefore, level 0 produces the single combined feature vector that consists of time-domain, frequency-domain, and entropy features for each input signal. Level 0 represents the typical non-pyramidal approach. Level 1 produces two combined feature vectors because its number of sub-signals is two using a 4-h temporal resolution, and level 2 produces four combined feature vectors from 4 sub-signals with a 2-h temporal resolution. These are recursively combined with feature vectors from the previous level. Thus there are $d*2^l + d*2^{(l-1)} + d*2^{(l-2)} + \ldots + d*2^0$ features total at level l, where d indicates the dimensionality of the three types of features (temporal, frequency, and entropy).

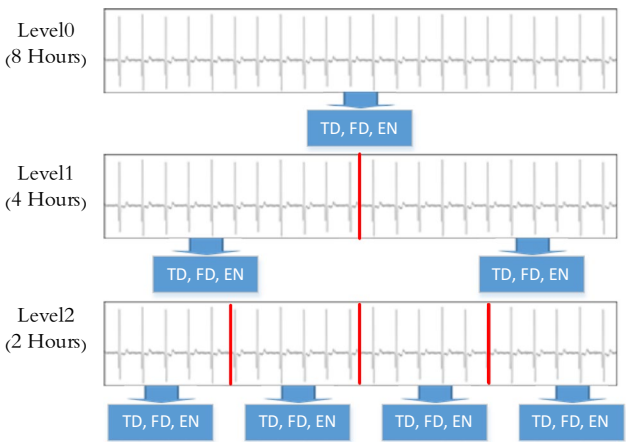

Fig. 2 Example of constructing a pyramid at three-levels of temporal resolution. At each level, Time domain, Frequency domain, and Entropy features are calculated. Time periods at each level are twice as many (half as long) as the previous level

4.4 Feature pooling

Once a pyramid is obtained by the method described in the previous section, we take a pooling approach (Boureau et al. 2010) for aggregating multiple feature vectors within levels into a single feature vector to describe HRV at each pyramid level. This allows the dimensionality of the pyramid representation to be reduced to d*L, where L is the number of levels. To limit the number of features, we also pool across levels, with a resulting final dimensionality of d.

We used four types of pooling methods within levels: average, maximum, minimum, and magnitude (the root of the sum of squares of each feature). Average and magnitude combine information from all sub-regions in a level. Maximum picks one value from the sub-regions. For each feature, we averaged its value across levels.

4.5 Classification

The pooled features derived from the temporal pyramid representation are normalized and then used as an input to a classifier. Since our dataset is small (48 subjects), the classifier should be carefully determined because noise/outliers can have greater impact and there is a higher risk for over-fitting than if using a large dataset. This means that complex nonlinear models are not a good choice because a small dataset cannot fit models with many degrees of freedom. Therefore, we used linear classifiers in order to avoid those problems. We use two linear classifiers to recognize hypertensive and non-hypertensive subjects: L_1-regularized logistic regression and linear support vector machine (SVM).

Logistic regression is a simple and efficient classification method; however over-fitting may occur with a small dataset. In order to overcome this problem, L_1 regularization was enforced by an L_1 norm constraint on the parameter vector. The SVM is popular for recognition tasks because it usually achieves good performance. We use a linear SVM with parameter C = 1.

5 Experimental analysis

We divided our data into two groups. Data from 18 participants (the optimization set, containing 9 hypertension patients and 9 control subjects) was used to select a variety of parameters and the remaining data (the test set, containing 15 hypertension patients and 15 control subjects) was used as a validation dataset to assess the performance of our method based on the selected optimal parameters.

Using our optimization set, we explored: (1) *validity of data* whether there was a difference between the hypertensive and healthy participants, (2) *feature selection* which features were most predictive of hypertension, (3) *impact of the use of overnight data* showing why long-term data should be used, (4) *pyramid depth* how many levels to use in the pooled temporal pyramid, (5) *pooling operator* what pooling operator was best to pool temporal pyramid for HRV.

5.1 Metrics

For each dataset, a leave-one-subject-out cross validation procedure is conducted. We use three evaluation metrics: Sensitivity (also known as recall), specificity, and accuracy, defined as

$$\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100 \tag{2}$$

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100 \tag{3}$$

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FN + TN + FP} \times 100 \tag{4}$$

where *TP, TN, FP* and *FN* indicate true positive, true negative, false positive, and false negative, respectively. Sensitivity (or recall) measures how good the classifier is at detecting the true positives, that is the proportion of hypertension patients from the correctly recognized results. Specificity measures how good the classifier is at avoiding false positives, that is the proportion of control subjects from the correctly recognized results.

Based on criteria such as disease type, its severity, or prevalence, an appropriate model and its parameter can be determined. A high sensitivity value indicates that fewer cases of hypertension are missed, while a high specificity value indicates that fewer cases of control subjects receive an unnecessary diagnosis of hypertension. The ideal case is to have both high sensitivity and high specificity values; however there is typically a trade-off. This is a common tradeoff in for medical diagnosis and it should be addressed by considering some other physiological parameters and symptoms.

5.2 Validity of dataset

According to (Virtanen et al. 2003), hypertensive patients have decreased HRV values when compared with non-hypertensive subjects. We can validate that our dataset has been correctly collected from the waist-belt body-worn sensor, by checking that the hypertensive patients have lower feature values for HRV than the control subjects.

Table 1 shows the comparison of features that are calculated from signals for the hypertension patients and control subjects. Overall, all of the features for the hypertension

Table 1 Comparison of HRV features for hypertensive patients and control subjects

Type	Feature	Control (mean ± SD)	Hypertensive (mean ± SD)
Time-domain	RR_{MEAN}	0.8977 ± 0.1034	0.9010 ± 0.1301
	RR_{MEDIAN}	0.8860 ± 0.1311	0.9102 ± 0.1405
	RR_{MIN}	0.6800 ± 0.1296	0.7206 ± 0.1152
	RR_{MAX}	1.1704 ± 0.1596	1.0767 ± 0.1804
	RR_{SDANN}	0.0619 ± 0.0248	0.0572 ± 0.0336
	$RR_{SDNN\ index}$	0.1034 ± 0.0594	0.0539 ± 0.0401
	RR_{RMSSD}	0.1351 ± 0.0854	0.0698 ± 0.0628
	RR_{pNN50}	0.9496 ± 0.0331	0.8689 ± 0.0845
Frequency-domain	P_{VLF} (ms^2)	5.7261 ± 4.0433	3.6910 ± 3.6003
	P_{LF} (ms^2)	3.3063 ± 3.2327	1.1621 ± 1.7799
	P_{HF} (ms^2)	6.0722 ± 6.3137	1.9928 ± 3.7635
	P_{Total} (ms^2)	15.1046 ± 12.9242	6.8459 ± 8.1397
	$P_{LF/HF}$	0.6995 ± 0.3277	0.9367 ± 0.6504
Entropy	$E_{Approximate}$	1.7599 ± 0.2015	1.2948 ± 0.3590
	E_{Sample}	1.4784 ± 0.2685	0.9879 ± 0.3747
	$E2_{Multi\text{-}scale}$	1.6924 ± 0.3042	1.3291 ± 0.4648
	$E3_{Multi\text{-}scale}$	1.6045 ± 0.2368	1.1535 ± 0.2946
	$E4_{Multi\text{-}scale}$	1.4956 ± 0.2360	1.1293 ± 0.2669
	$E5_{Multi\text{-}scale}$	1.4604 ± 0.2216	1.1300 ± 0.2521
	$E6_{Multi\text{-}scale}$	1.4683 ± 0.2109	1.2036 ± 0.2678

patients have lower mean values than those of the control subjects except for RR_{MEAN}, RR_{MEDIAN}, RR_{MIN} and $P_{LF/HF}$. Most researchers consider the RR statistics to be less meaningful time-domain features for classifying hypertension and do not use them (e.g., Poddar et al. 2014). For the LF/HF ratio, previous work (Singh et al. 1998) has shown that this value varies for those with hypertension. Therefore, we use these results to demonstrate the validity of our waist belt collected dataset.

5.3 Feature selection

From the entire feature set (20 features) including time-domain, frequency-domain, and entropy features, We selected a subset in order to reduce the risk of over-fitting, and used a linear SVM weight for feature ranking for the reason that SVM yielded the most rapid convergence to the best performance on the given dataset. We used information gain as a feature selection metric and 7 top ranked features were selected because 7th ($E3_{Multi\text{-}scale}$) and 8th (RR_{MAX}) features have large gap on the average rank (6.3 ± 2.33 and 8.6 ± 2.06).

Table 2 shows the selected top-7 features in the order of the information gain score. The information gains were calculated for training set in each validation under a leave-one-subject-out cross validation for optimization set. The average and standard deviation on information gain were calculated. Overall, E_{Sample} was ranked as the most relevant feature for our task, and the remaining multi-scale entropy features and entropy features were highly ranked as well. The frequency-domain feature P_{VLF} was also determined as an important feature.

Table 2 The selected feature set

Average rank	Feature	Score average ± STD
1.1 ± 0.24	E_{Sample}	0.467 ± 0.054
2.2 ± 0.53	$E_{Approximate}$	0.460 ± 0.046
4.1 ± 1.54	$E5_{Multi\text{-}scale}$	0.105 ± 0.183
5.3 ± 0.75	$E6_{Multi\text{-}scale}$	0 ± 0
5.7 ± 2.59	P_{VLF}	0 ± 0
6 ± 1.22	$E4_{Multi\text{-}scale}$	0.028 ± 0.109
6.3 ± 2.33	$E3_{Multi\text{-}scale}$	0.134 ± 0.199

5.4 Impact of the use of overnight data

Unlike the short resting ECG test in clinical settings, we have used overnight ECG data that is collected while sleeping for recognizing hypertension. Although the short resting data collected in clinical settings could be enough for a diagnosis, our data collected from a wearable device in real-world settings could include erroneous data in due to motion noise or sensing errors. Therefore, analyzing short-term data collected from a wearable device does not provide acceptable and stable performance because performance depends on the data quality. In order to overcome

the problem of short-term data analysis, we have used long-term data for the recognition task.

In this section, we show the impact of the use of long-term data (as compared to the short in-clinic blood pressure measurement) by providing comparisons for different durations of data. We created data segments by splitting the overnight data into 1/2, 1/4, 1/8, 1/16 and 1/32 size of the entire data in order to show the performance of short-term data analysis. Figure 3 shows the average accuracy for different durations of data using two classifiers. The average sizes of each data segment for different splitting sizes were 4.28 h (1/2), 2.14 h (1/4), 1.07 h (1/8), 32 min (1/16) and 16 min (1/32), respectively. We can see that shorter amounts of data tend to produce lower performance for both classifiers.

To show the impact of our temporal pyramid representation, we provide comparisons for different numbers of levels as well as a comparison between a typical feature vector ($L=1$, level 0) and our temporal pyramid representation feature ($L>1$) in Fig. 4. We used a maximum L of 6 (with the 6th level having a maximum of 32 segments of size 16 min on average). A greater number of levels would produce segments that are too small to appropriately examine HRV. An L of 1 calculates features over the entire data set for each participant. As described earliear, we use four different pooling operators (Max, Min, Average, and Magnitude) to generate a feature value for each feature at each level.

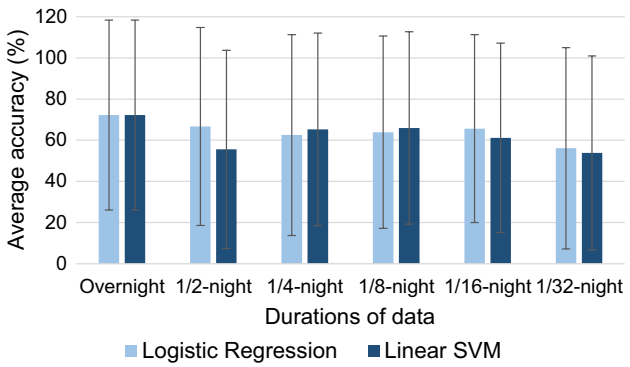

Fig. 3 Average accuracy for different durations of data. **a** Logistic Regression. **b** Linear SVM

Figure 4 shows that the magnitude pooling operator tends to perform better than the average and max pooling operators. Average and max pooling methods are known to perform well for visual recognition tasks (Boureau et al. 2010). However, max ignores most elements obtained from the multi-scale analysis, and it can lead to non-representative feature aggregation, while average considers all elements evenly, which can diminish or remove characteristics of multi-level elements. The magnitude pooling method takes the scale of each element into account, which is well-suited to our task.

We can also see from Fig. 4 that the temporal pyramid approach usually performs better than a standard single level algorithm only if an appropriate pooling operator is used. Past studies [Melillo et al. 2015, Poddar et al. 2014] correspond to an L of 1 (a temporal resolution is the entire signal). As we can see in Figs. 4, 2 ~5 levels usually performs better than 1 level. However, using too many levels does not provide an improvement due to the instability of signal in the short-term time segments. Two classifiers, Logistic Regression and linear SVM, produce the similar performance on the most of the levels. The average accuracies seem to converge from level 2 for both classifiers. The proposed pyramid feature representation produces 83.33% average accuracy on level 2, while using a typical feature vector (# of level = 1) produces 72.22% average accuracy. For each level, the sensitivity and specificity were 66.67%/77.78% (level 1) and 77.78%/88.89% (level 2, 3 and 4). When using a typical feature vector, three hypertensive patients were recognized incorrectly

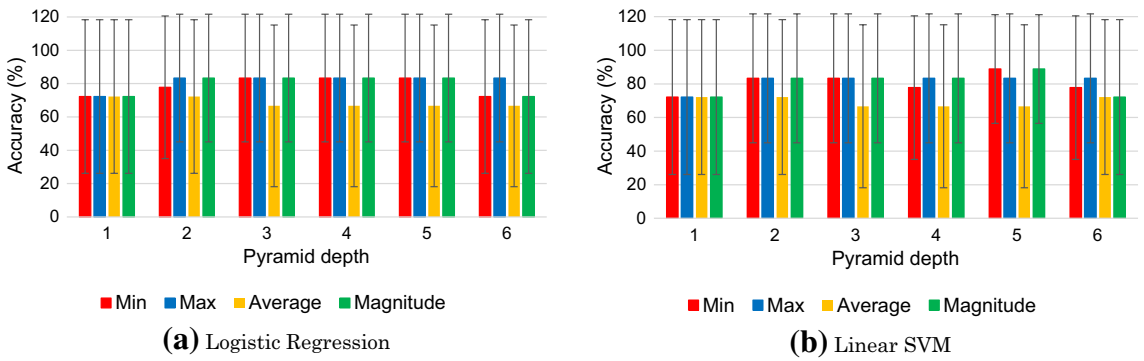

Fig. 4 Performance of different classifiers as the number of levels in the pyramid is increased. For each classifier, three types of pooling methods are evaluated. Magnitude (*Green bars*) performs most consistently for both Logistic Regression (**a**) and Linear SVM (**b**)

as control subjects, while two control subjects were recognized incorrectly as having hypertension. The proposed pyramid feature representation outperformed the typical feature vector approach, especially for detecting hypertensive patients. When using the proposed representation (level 2), two hypertensive patients were recognized incorrectly as control subjects, while one control subjects were recognized incorrectly as having hypertension. We conducted a Wilcoxon signed-rank test to check if there is performance difference between typical feature and proposed pyramid feature representation. The value of h was 0 which indicates that the test does not reject the null hypothesis and there is certainly the mean difference between two performances.

5.5 Impact of different data length with pyramid representation

To show how much our pyramid representation improves the performance for various durations of data, we provide comparisons for different lengths of data with different numbers of levels in the pyramid representation in Fig. 5. We used 4 types of data lengths from the full overnight signal to 1/8 size of the overnight signal as an input signal. Also, we applied different numbers of levels in the pyramid to determine whether using our pyramid representation on the shorter signal results in better performance than using the typical feature representation on the longer signal. Similar to Figs. 3, 5 first shows that using a longer signal usually gives better performance than using a shorter signal. Second, a shorter signal with pyramid representation outperforms the longer signal with typical feature representation, e.g., 72.22% (overnight 1-level) vs. 75.00% (1/2-night 2-level). Our pyramid representation provides a chance to use a shorter signal that gives similar or higher performance than using a longer signal.

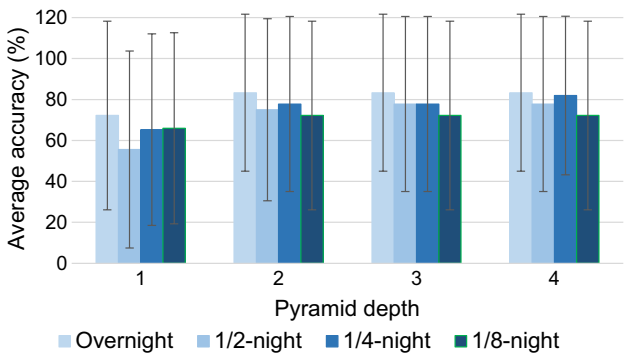

Fig. 5 Comparison of different lengths of data on different pyramid depths using an SVM classifier and magnitude pooling operator

5.6 Result in the validation set

Based on the results from the previous sections, we selected several parameters to evaluate the performance on the validation dataset. First, 7 features obtained by our feature selection were used. Second, the magnitude pooling method was selected for building our feature representation because it performed the best for all classifiers. Third, the linear SVM classifier was selected because it yielded the most rapid convergence to the best performance between the two classifiers. Lastly, the number of levels selected to build the pyramid feature representation was 2 because accuracy converged starting from the 2-level feature representation amongst the three classifiers, as shown in Fig. 4. This configuration was tested using leave-one-out cross validation on the 32 participants who were not in the optimization set.

Our feature representation obtained 93.33% average accuracy with 93.33% sensitivity and 93.33% specificity, while using a typical feature vector ($L=1$) produces 86.67% average accuracy with 80.00% sensitivity and 93.33% specificity. When using a typical feature vector, three hypertension patients were recognized incorrectly as control subjects, while one control subject was recognized incorrectly as having hypertension. Our approach had good performance for our recognition task when compared to typical feature-based recognition. Note that the feature dimensions are the same between our feature representation and the typical feature vector. By aggregating HRV features at multiple scales, our pyramid feature representation outperformed the typical feature vector.

6 Discussion

The main contribution of the paper is to provide a non-intrusive approach for determining whether a patient has hypertension based on overnight continuous HRV monitoring.

Our proposed waist belt based heart-rate monitoring system proved to be a promising alternative for detecting hypertension in common home settings. Overnight sleep monitoring provides a non-invasive and valuable opportunity to sense and assess HRV continuously. Daytime monitoring in the field is likely to be highly error-prone due to external and internal noise (such as activities and emotions). In contrast, sleep is an ideal 'window' in which to investigate inherent HRV in the body, when people will be in a resting calm state that generates minimal noise artifacts.

In addition, the waist belt has several advantages over the existing typical field methods for ECG monitoring: (1) Compared to a chest-worn band, the waist-worn belt

is not as affected by breathing motions, (2) The waist-worn belt is less likely to move around during sleep than appendages such as the arm (which would affect wrist-worn sensors), (3) The waist-worn belt is less intrusive and suitable for relatively long-term monitoring and (4) Unlike clinic-quality ECG monitors, it is easily set up and used by end users. Such a system could be applied for daily health care or assistive screening for clinic diagnosis.

Our results verify that it is possible to detect hypertension with a high degree of accuracy based on overnight data collected with our monitor. Past work has identified three kinds of features of HRV that are predictive: time-domain, frequency domain and entropy features. However, making highly accurate predictions is difficult.

We present a new method for analyzing long-term time series data, the multi-scale temporal pyramid representation. Using this method, we were able to raise our accuracy from 86.67 to 93.33%. These enhanced results were obtained using the same features but collecting them over a multi-scale time window. Our intuition is that this radical improvement is caused by the fact that hypertension is not continually present in the data. Thus, summing over multiple time intervals allows us to capture hypertensive HRV signals that are short in duration or occur only occasionally. These HRV signals are indicative of hypertension, even when hypertensive events occur only 8 or 10 times over the course of a night. In contrast, a flat, non-pyramidal approach will not capture those events because they are essentially drowned in much more prevalent non-hypertensive data.

A limitation of this work is the small number of participants (48 total). Since collecting long physiological data from people in the field (especially patients with disease) is challenging, we were able to apply our method in the small number of participants. If we can use large number of participants so that we can apply more complex nonlinear classifier, we expect that our approach is able to improve performance. We were careful to optimize our approach set on a small separate subset of participants, which helps to increase confidence in our results. Nonetheless our algorithm is unlikely to operate at 93.33% accuracy on other datasets from the field, and further testing on a larger data set is warranted. In addition, HRV can be affected by various factors, including drinking alcohol, smoking, exercising and stress. Training against examples of people without hypertension who exhibit behaviors that affect HRV would help to improve the robustness of our results.

As for the subjects' feedback, participants with hypertension from our data collection group were generally positive about the belt, its ease of use, and their ability to know whether hypertension was developing. Furthermore, they requested a timely reminding of their health status. Control participants were intrigued but less likely to wear the belt, as they did not perceive any benefit.

As for our future work, there are two aspects we would like to investigate: on one hand, our machine learning results should be revisited by a medical expert who could help to interpret features and results, and define or identify some clinical diagnostic rules to guide a more nuanced interpretation of the data. For example, how should longer or more frequent periods of abnormal (hypertensive) HRV be interpreted? Can we come up with a measure of hypertension severity? We would also like to apply this work to predicting HRV for patients who are very early on in the disease, even pre-clinical. Finally, we would also like to investigate how hypertension plays out over longer time periods, such as over multiple nights or even months.

7 Conclusion

Hypertension is a cause of chronic health problems globally. HRV can be used as an early indicator for hypertension. Early detection is important for better prognosis and preventing the progression of the disease.

In our work, we discriminate patients with hypertension from normal healthy subjects using a waist belt based non-intrusive heart rate monitoring system that was used in the field while sleeping overnight. Based on the long-term ECG data of 48 hypertensive and normal subjects, a multi-scale segmented HRV analysis was investigated. Our analysis showed that R-R intervals, as described by time, frequency, and entropy features, have decreased values in hypertensive patients over normal healthy subjects. Our multi-scale temporal pyramid approach was able to achieve very high accuracy for the task of classifying hypertension.

Hypertension is a complex chronic disease, caused by various risk factors, such as age, sex, weight, family history and lifestyle. Our approach may complement diagnostic methods in distinguishing hypertensive patients and normal subjects, and could potentially aid in early and automatic detection of hypertension risk. However, further studies with a larger number of participants are necessary to investigate the long-term diagnostic significance of our approach.

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