

To use an Efficient Linearly proportional Band Pass Filters Institution, a High Blood Pressure Prognosis Indicator was established for the unequal Treatment of Rising High Blood Pressure

Abstract

Hypertension (HT) is a high blood pressure that can lead to heart attack, kidney disease, and stroke. At its earliest stages, HT does not cause any symptoms but can result in a variety of cardiovascular diseases. Therefore, it is essential to identify it early on. Due to their small bandwidth and low amplitude, electrocardiogram (ECG) signals are difficult to visually analyse. As a result, an automated ECG-based system is developed to prevent human error in the diagnosis of HT patients. Using ECG signals and an optimal orthogonal wavelet filter bank (OWFB) system, the computerized segregation of low-risk hypertension (LRHT) and high-risk hypertension (HRHT) is proposed in this paper. Patients with syncope, myocardial infarction, and stroke are included in the HRHT class. The physionet smart health ECG event (SHAREE) database, which contains recordings from 139 subjects, is used to obtain the ECG data for risk assessment. ECG signals are first segmented into five-minute epochs. OWFB is used to split the segmented epochs into six wavelet sub-bands (WSBs). From each of the six WSBs, we extract the log-energy (LOGE) and signal fractional dimension (SFD) features. We select the WSBs of LOGE and SFD features with the highest ranking based on Student's t-test ranking. Using two features—SFD and LOGE—we create a novel hypertension diagnosis index (HDI) that uses a single numerical value to distinguish between the LRHT and HRHT classes. We believe that our developed system can be used in intensive care units to monitor the sudden rise in blood pressure while screening the ECG signals, provided that this is tested with an extensive independent database. The performance of our developed system is found to be encouraging.

Keywords: ECG • Wavelets • Optimization • Semi definite programme • Filter design

Introduction

Patients with hypertension (HT), also known as high blood pressure, do not initially exhibit any symptoms. This may make it worse for hypertensive patients and increase their risk of cardiovascular disease because of a lack of awareness and proper treatment. The number of deaths in today's world as a result of hypertension has increased. According to global data from 2005, 20.6% of males and 20.9% of females in India had high blood pressure. This pattern is expected to rise to 22.6 percent for women and 22.9 percent for men. According to the most recent survey, hypertension affects 25% of rural and 10% of urban Indians. After receiving treatment, only 25% of people with hypertension are able to control their blood pressure (BP). The blood's pressure on the arteries' walls is known as the BP [1, 2]. The heart's activity and blood vessel obstruction both contribute to the pressure. Reduced physical activity, a sedentary lifestyle, smoking, stress, kidney disease, and a family history of hypertension are all potential causes. As a result, raising awareness, providing medical care and providing treatment for hypertension are crucial issues. Hypertension can be classified clinically as mild, moderate, or severe. The determination of hypertension's severity is more crucial[3].

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Therefore, HRV signals derived from ECG were used in all of the aforementioned studies. In contrast to HRV, the proposed work makes use of optimal wavelet-based features extracted from ECG signals. The proposed study made use of the optimal orthogonal wavelets that are created by optimizing spectral localization (SL) [4, 5]. Wavelets are thought to be the best methods for analysing non-stationary signals, such as the electrocardiogram (ECG). As a result, we developed an automated method for determining LRHT and HRHT by utilizing wavelet-based ECG features. The reasons for using the SL-optimized wavelet filter are as follows. The majority of studies were carried out using conventional techniques, which consisted of precisely defining the edge frequencies and maximizing the stop-band and pass-band energies. That might not be immediately clear in every application. In this case, we made use of the orthogonal wavelet filter, which was created with its frequency spread minimized. If a filter's spectral localization is minimized, ripples and the filter's transition band can both be addressed. The SL optimized filter produces significantly less roll-off and ripples [6].

We used the SL optimal OWFB in our study. We optimized the filter coefficients using a semi-definite program (SDP) technique, and the interior point algorithm provided the best possible solutions. In order to distinguish LRHT patients from HRHT patients, we tested the optimized OWFBs for analysing ECG signals. We extracted log energy (LOGE) and spectral fractal dimension (SFD) features from the OWFB-provided ECG signal sub-bands (SBS). All extracted features and the most significant SBS of SFD and LOGE features were ranked using the Student's t-test [7, 8].

The creation of the hypertension diagnosis index (HDI) based on OWFB-based SFD and a LOGE feature is this study's primary contribution. HDI distinguishes between LRHT and HRHT using a single numerical value. HDI is simpler and simpler to use for disease diagnosis in a clinical setting.

Discussion

There were 3614 ECG epochs in the dataset, with LRHT ECG signals accounting for 87% and HRHT ECG signals for 13%. One of the limitations of our work is the dataset's imbalance. LRHT data typically outnumber HRHT data. Synthetic balancing data are required to alleviate

this imbalance issue. The selection of the best number of ZMs and filter length is another limitation of our research. We cannot a priori predict the estimated order and ZM in order to accurately identify HRHT.

In recent studies, deep learning techniques were frequently utilized for classification issues. Convolutional neural networks (CNN) are one type of deep learning technique we can employ. The handcrafted features need not be extracted, selected, or categorized when using techniques based on deep learning. However, the computational complexity is enormous due to extensive data processing. As a result, graphics processing units (GPUs) and fast processing workstations are required.

The non-stationary characteristics of the ECG signal were investigated with the help of the spectral localization method. Our proposed work was different from other research because we used spectral localized OWFB.

We used fewer features to make the computation faster and better. The ECG signal lasted for 5 minutes. As a result, it was less computationally demanding and took less time to diagnose.

Melillo and Izzo used multiple machine learning algorithms—SVM, decision tree (DT), and convolution neural network (CNN)—with the same database, achieving the highest accuracy with HRV signals of 87.8%. Using heart rate variability (HRV) signals, Ni and Wang recently achieved an accuracy of 95%.

Techniques based on HRV have been used to detect hypertension in numerous studies; we utilized ECG-derived wavelet-based features directly. In contrast to HRV-based methods, our method was simple to implement in a clinical setting.

We anticipate that the system can be used in intensive care units to monitor the sudden rise in blood pressure while screening the ECG signals if it is tested with an extensive independent database. The system's performance was found to be promising [9].

For sub-band decomposition of ECG signals, we developed the ideal WFBs. Five levels of decomposition were used. We were able to precisely identify each ECG epoch's six SBS thanks to the five-level wavelet decomposition. We were able to extract the desired frequencies from the ECG signal using this method. As a result, this approach was used to perform the five-level wavelet decomposition of the ECG signal.

There were five detailed SBs (SB1–SB5) and one approximate SB among the six. The best-designed OWFB was used to automatically separate LRHT and HRHT. Wavelet decomposition was used to create six different sub-bands (SBs). For ECG signals, five SBs were used for detail, and one SB was used for approximation. Features were extracted from each SB following the wavelet decomposition into the log energy (LOGE) and signal fractional dimensions (SFD) of six SBs. As a result, each ECG epoch yielded a total of 12 features, including six LOGE and six SFD. The development of the HDI, which can distinguish between LRHT and HRHT ECG signals, is the novelty of this work. The in depth description of the automated high-risk hypertension detection system that is being proposed [10].

Conclusion

An index (HDI) was used in this study to automatically distinguish between LRHT and HRHT ECG signals using the best non-linear features based on OWFB. Six (SBs) were produced by optimal OWFB's five-level wavelet decomposition of ECG signals. For each of the six SBs, the LOGE and SFD features were extracted. Using features (LOGE and SFD), our proposed OWFB-based method was sufficient to accurately distinguish the HT ECG signals by a single numerical value. HDI was developed to evaluate the performance of the best wavelet filter bank. It uses the proposed index to divide the LRHT and HRHT groups. Our findings demonstrate that the developed model is suitable for testing with a large database and outperforms the other systems currently in use. Using the same database and a number of machine learning-based methods, we intend to test the efficacy of our method for determining the severity of hypertension. In addition, we plan to classify LRHT and HRHT ECG signals using deep learning-based techniques in our future work.

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None

Conflict of Interest

None

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