Heart-Based Biometrics and Possible Use of Heart Rate Variability in Biometric Recognition Systems

Nazneen Akhter, Sumegh Tharewal, Vijay Kale, Ashish Bhalerao and K.V. Kale

Abstract Heart rate variability (HRV) is an intrinsic property of heart and active research domain of the medical research community since last two decades. But in biometrics it is still in its infancy. This article is intended to present the state of art into heart-based biometrics and also explore the possibility of using HRV in biometric recognition systems. Subsequently, we designed hardware and software for data collection and also developed software for HRV analysis in Matlab, which generates 101 HRV Parameters (Features) using various HRV analysis techniques like statistical, spectral, geometrical, etc., which are commonly used and recommended for HRV analysis. All these features have their relative significance in medical interpretations and analysis, but among these 101 features reliable features that can be useful for biometric recognition were unknown; therefore feature selection becomes a necessary step. We used five different wrapper algorithms for feature selection, and obtained 10 reliable features out of 101. Using the proposed 10 HRV features, we used KNN for classification of subjects. The classification test gave us encouraging results with 82.22 % recognition rate.

Keywords ECG biometrics · PCG biometrics · Heart rate variability · Linear HRV features · Poincare map · Feature selection · Wrapper algorithms · K-NN

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R. Chaki et al. (eds.), *Advanced Computing and Systems for Security*,
Advances in Intelligent Systems and Computing 395,
DOI 10.1007/978-81-322-2650-5_2

1 Introduction

Biometric-based security systems are common nowadays and among all other modalities fingerprints, face, palm print, hand geometry, and voice by now are established and most utilized ones. Fundamental researches into these modalities have reached its pinnacle, yet certain propelled parameters are still being investigated to endeavor their utility to its fullest like in multidimensional space, multi- and hyperspectral space, etc. Similarly, even biosignals like electrocardiography (ECG), electroencephalogram (EEG), and electromyography (EMG), etc., are also being explored for improvising efficiency and robustness of biometric systems. For more than a decade, human heart is being explored as a potential candidate for biometric recognition. ECG being the most reliable clinical practice was the most explored for heart-based biometric purpose. Along with ECG, researchers have also focused on phonocardiogram (PCG) signals of heart (heart sounds) and recently even the heart pulses were studied using photoplethysmogram (PPG) signals.

Heart rate variability (HRV) is an intrinsic property of heart and active research domain of the medical research community since last two decades. But in biometrics it is still in its infancy. There have been several classification attempts for disease pattern identification in HRV data [1–4]. But only two early attempts of recognition using HRV are documented in the literature. Milliani et al. attempted to recognize two different postures, i.e., upright and supine of each individual using HRV [5], but mainly their focus was more on identification of posture and not specifically biometric recognition, while Irvine et al. proposed HRV-based human identification [6] which is the only reported attempt specifically aimed at biometric recognition but its techniques and results are unknown due to lack of information. This article is intended to present two independent parts, one is the state of art into heart-based biometrics and the second is to explore the possibility of using HRV in biometric recognition systems. Due to lack of HRV literature specifically dedicated to biometrics, we mostly had to rely on medical literature and using the techniques suggested by [7, 8]; we generated 101 HRV features (as per medical literature they are called as HRV parameters) which are commonly used and recommended for HRV analysis. All these features have their relative significance in medical interpretations and analysis, but among these 101 features, reliable features that can be useful for biometric recognition are unknown, therefore, feature selection becomes a necessary step, but it cannot be done arbitrarily hence we used five different wrapper algorithms for feature selection.

This article is divided into following sections: Sect. 2 will give a brief introduction to the background of HRV, while Sect. 3 will present state of art into heart-based biometrics, further Sect. 4 will present a much elaborated methodology section including the hardware and software designing as well as an extensive feature sets generation process. And finally, the last sections include the results and discussions along with conclusion and future directions.

2 HRV Background

The time interval (duration/gap) between two adjacent R–R peaks of QRS complex of a heartbeat is known as R–R interval as shown in Fig. 1. This R–R interval varies in every adjacent pair of beat as shown in Fig. 2. The variance in RRI, i.e., beat-to-beat variation is popularly known as heart rate variability (HRV). HRV analysis is the ability to assess the overall cardiac health and the state of the autonomic nervous system (ANS) responsible for regulating cardiac activity [8]. HRV is a useful signal for understanding the status of the ANS. The balancing action of the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) branches of the ANS controls the HR. Increased SNS or diminished PNS activity results in cardioacceleration. Conversely, a low SNS activity or a high PNS activity causes cardio-deceleration. The past decades have witnessed the

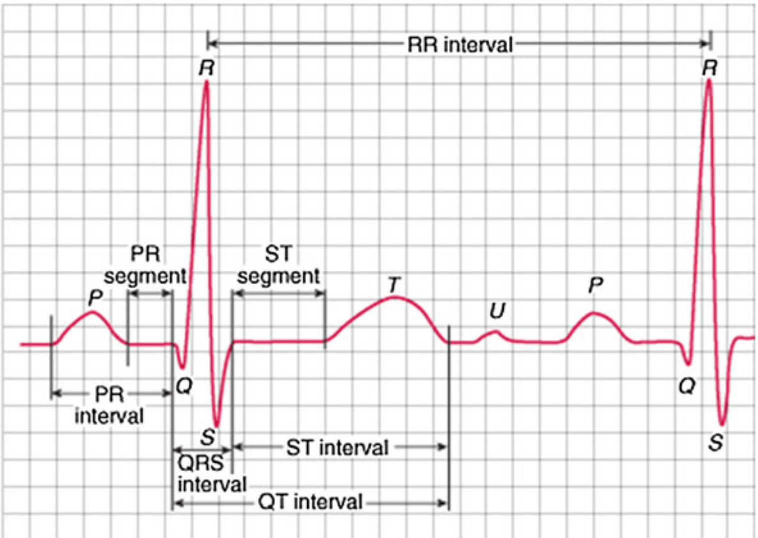

Fig. 1 Schematic of an ECG *strip* showing major components

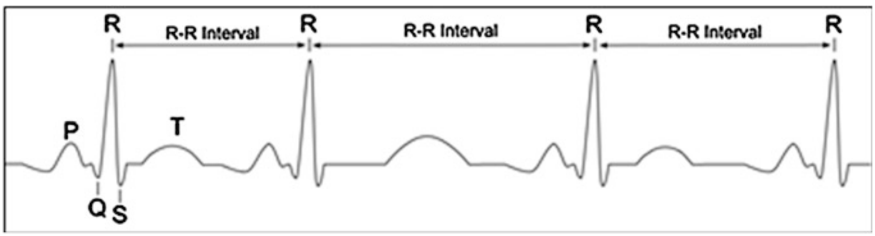

Fig. 2 Schematic of ECG indicating the R–R interval variation

recognition of the significant relationship between ANS (automatic nervous system) and cardiovascular mortality, including sudden death due to cardiac arrest [7]. In 1996, a task force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology developed and published standards for the measurement, physiological interpretation, and clinical use of HRV analysis [8].

Heart rate (HR) or the beat interval is a nonstationary signal; its variation may contain indicators of current disease, or warnings about impending cardiac diseases. The indicators may be present at all times or may occur at random during certain intervals of the day. It is strenuous and time consuming to study and pinpoint abnormalities in volumes data collected over several hours. Therefore, the HRV signal parameters, extracted and analyzed using computers, are highly useful in diagnostics. Computer-based analytical tools for in-depth study of data over day-long intervals can be very useful in diagnosis. Analysis of HRV consists of a series of measurements of successive R–R interval variations of sinus origin, which provide information about autonomic tone [9]. Different physiological factors may influence HRV such as gender, age, circadian rhythm, respiration, and body position [10]. Hence, HR variation analysis has become a popular noninvasive tool for assessing the activities of the autonomic nervous system.

3 State-of-the-Art Heart-Based Biometrics

Biometric research community is exploring every physiological and behavioral aspect of humans that can be employed in biometric recognition systems. Human heart has caught the attention since more than a decade. Heart-based biometric research activities up till now are mainly focused on two very specific aspects of heart, one is the sound produced by heart, i.e., lub, dub sound and the electrical signal generate from every beat of heart, i.e., electrocardiogram (ECG) and recently even PPG signals were also examined. Heart sounds are one of the most important human physiological signals, which contain information about the atrium, ventricle, great vessels, cardiovascular, and valvular function [11]. Most of the initial literature available on heart sound-based biometric recognition is contribution of Beritelli et al. [11–15]. In 2007 Beritelli et al. [12] first time proposed the frequency analysis of heart sounds for the identity purpose. And in 2009 Beritelli et al. applied MFCC technique on heart sounds [13] and reported a 10 % reduction in the EER rate from their previous work. By the year 2010, few more researchers Huy Dat et al. [16], Ye-wei [17], Al-Shamma et al. [18], Jasper [19] and even Beritelli [12] extended the work. Tao et al. attempted to extract features using wavelet and used CPSD for recognition purpose, while Huy Dt. et al. attempted fusion of features. Al-Shamma et al. used energy percent in wavelet coefficients. And Beritelli et al. applied statistical approaches. Then in 2011, Zhidong Zhao and Jia Wang proposed MFCC with vector quantization. In 2013 Gautam and Kumar [20], proposed feature set based on Daubechies wavelet with second-level decomposition and did classification using Back Propagation Multilayer Perceptron Artificial Neural Network

(BP-MLP-ANN) classifier. And recently in 2014, Abo-Zahhad et al. [21] also attempted feature fusion, but applied canonical correlation analysis.

The pioneering work on ECG-based biometrics recognition is credited to Biel et al. [22] who in 2001 not only proposed that the ECG of a person contains sufficiently detailed information which is highly personalized, but also that single channel ECG is sufficient for biometric purpose. Use of single channel ECG is the simplest hence most studied. However, some researchers have documented improved results by incorporating 2, 3, and even 12 channels [23–26]. Traditional clinical grade ECG devices, though may be too advance, but are too complex for biometrics systems with poor user acceptability, there have been a dart of specifically designed standard ECG database for biometrics research; so far what researchers have been using is either physionet [27] a central repository having huge collection of ECG records of healthy subjects and even with pathological conditions, or MIT-BIH [28] which has also served the research community in their ECG-based research endeavors but all records coming from clinical settings. Both these databases are not designed specifically keeping biometrics in mind. Most of researchers face a common problem of lack of larger databases to test their hypothesis. And this is the special case with ECG-based biometrics is being studied. Hugo et al. in [29] made some efforts in resolving the database shortage issue hovering over the ECG-based biometric research by creating the CYBHi ECG database particularly for biometric research. Also Lourenco et al. in [30] proposed that ECG collected at finger tips are sufficiently enough for biometric recognition. Hugo Silva et al. in [31] presented a very simple approach toward ECG biometrics by subjecting the ECG strips to segmentation and creating mean and median waves and using them as templates in authentication systems.

R–R intervals are the duration between two consecutive heart beats as in Fig. 1, this duration represents the variability property of heart rate. Only R–R interval is required for HRV analysis and it is traditionally measured from ECG signals. Researchers have documented evidences in favor of PPG to surrogate ECG for HRV analysis [32–34]. While the ECG monitors the electrical activity, PPG monitors the mechanical activity of the same event, i.e., a heartbeat. ECG from the chest is the clearest, but rarely used outside hospital [35] and if it has to be employed in biometric applications it faces the challenge of poor user cooperation. If heart signals are to be used in biometric recognition systems, then other methods need to be explored. PPG sensors being low cost and comfortable in data collection are one of the instant choices for ECG alternative. While Gu et al. [36] proposed a novel biometric approach for human verification using PPG signals, Resit et al. [37] proposed a novel feature ranking algorithm for time domain features from first- and second-order derivatives of PPG signals for biometric recognition.

Israel et al. in [38] gave an extensive performance analysis of three different sensing methods of heart, i.e., ECG, pulse oximetry, and blood pressure, which documented the latter two methods to be on the lower side. da Silva et al. in [39] has presented the usability and performance study of heart signals from fingertips and also in [40] da Silva et al. proposed CYBHi (Check Your Biosignals Here initiative) ECG dataset which was collected at fingertips of the subjects.

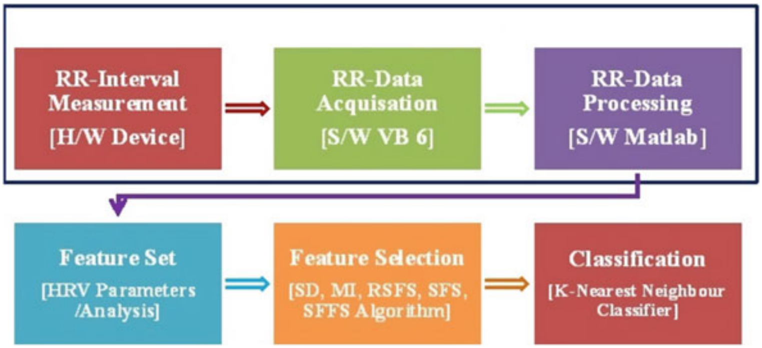

Fig. 3 Workflow of proposed HRV biometric system

4 Proposed System

In the proposed system, as seen in Fig. 3, initially the biometric data of subjects is collected in this case it is the raw HRV time series data, i.e., the R–R interval sequence. For data acquisition, we designed and developed a R–R interval measurement hardware that is equipped with a pulse sensor to detect the heartbeats. This gave us the freedom to generate our own KVKHRV database, as there is no such specific standard HRV database available for biometric purpose.

4.1 Block Diagram

The first step in the process is the detection of the R–R interval. The detector hardware based on a light sources and a detector employing the signal conditioning electronics senses the heartbeat and produce pulses in synchronism with the heartbeats. The interval between two consecutive beats, i.e., the R–R interval is implemented using a microcontroller-based circuit that measures the time interval between two consecutive beats (R–R interval) in milliseconds and sends it to serial port using RS232 protocol that can be received by any standard device like a computer. This R–R interval is received by a computer to which the hardware is interfaced, the computer side controlling program is developed in visual basic. This data acquisition software (shown is second block) unscrambles the incoming data and performs the necessary processing and saves it in standard text files for further use and processing. In the next block, the files from data acquisition system are further processed in programs specifically developed in Matlab12 for this purpose. This software allows for selecting parameters required for implementation of different algorithms like statistical, spectral, time-frequency, and nonlinear techniques, for the purpose of extraction of features for use in the authentication system. In the next step, feature selection takes place using five different algorithms and finally the last block, i.e., classification is done using KNN classifier.

4.2 R–R Interval Acquisition

Basically, the detection hardware detects the heart beats and the associated microcontroller-based system through its firmware polls for the arrival of a pulse and computes the time in milliseconds elapsed between the arrivals of two consecutive pulses. This R–R interval is sent through the serial port to a computer interfaced to the acquisition system via a serial to USB bridge. The computer side controlling program receives this RR data via USB port in the form of two bytes and performs some preprocessing like combining two bytes and saves the results in text files for further use.

The data acquisition system of Fig. 4 is the computer side program written in visual basic 6 that collects the R–R Intervals and stores in text files for further processing. This is developed in Visual Basic with GUI support for ease of operation in a user friendly manner and displays the real time R–R interval received in a graphic panel. Screenshot in Fig. 4 shows a typical data collection for 512 intervals of a subject. The GUI consists of four modes of collecting R–R intervals, i.e., for 1, 2, 5, and 10 min; in the first mode, 64 R–R intervals are measured for 128 intervals, similarly 128, 256, and 512, respectively. The computer side program

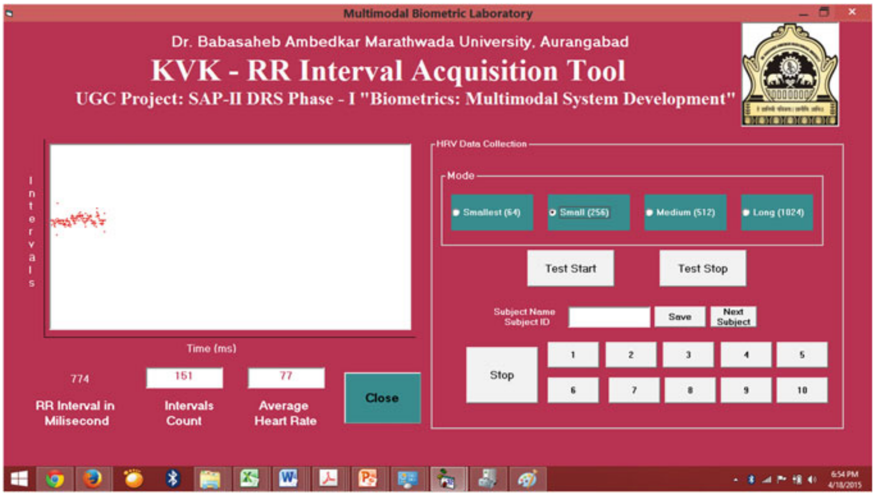

Fig. 4 GUI for R–R interval acquisition system

has provision for recording data from different subjects recorded under different conditions in the appropriate folders for further analysis. It also has the capability to auto detect and remove ectopic beats, i.e., noise from the HRV data.

4.3 Database Specification

At present, our in house-generated database consists of sequence of R–R intervals of 81 subjects (47 males and 34 Females) whose 512 R–R intervals were measured continuously for 10–12 min approximately in session one, while 64 R–R intervals were measured continuously for 1–1.5 min approximately in sessions two and three with time interval of 3 months between each session. The age of the individuals varied from 18 to 69 years, with mean and standard deviation of 31 and 11, respectively. As it would be natural in any physiological-based biometric recognition system, some subjects would have health issues; we too have few samples of this sort around 11 % of subjects reported hypertension and other diseased conditions. Any biosignals-based biometric system is susceptible to the effects of mental, physical, physiological, and even emotional state of the subject. Hence, subjects were relaxed first and data was collected in sitting relaxed position for all the sessions.

4.4 Feature Set Generation

Experimenting HRV for biometric recognition we generated the HRV parameters suggested in [4] with a few more additions identified from the literature survey. HRV parameters are actually the results of applying various linear methods like statistical and spectral techniques and nonlinear like Poincare and auto regression and also some time-frequency methods like wavelets on RR data. These HRV parameters can serve as a feature vector for biometric classification. In all we obtained 101 features, each has some significance or the other in HRV analysis for diagnostic or prognostic purpose, but which one would really prove suitable for uniquely identifying an individual that is yet to be established. The initial feature set of 101 features includes 9 statistical features 39 frequency domain features obtained by applying three different techniques, namely Welch, auto regression, and Lomb–Scargle; and in nonlinear methods, 2 features from a Poincare map and 4 features from sample entropy while 42 time-frequency analysis features from Welch, auto regression and wavelet power spectrum density analysis (Fig. 5).

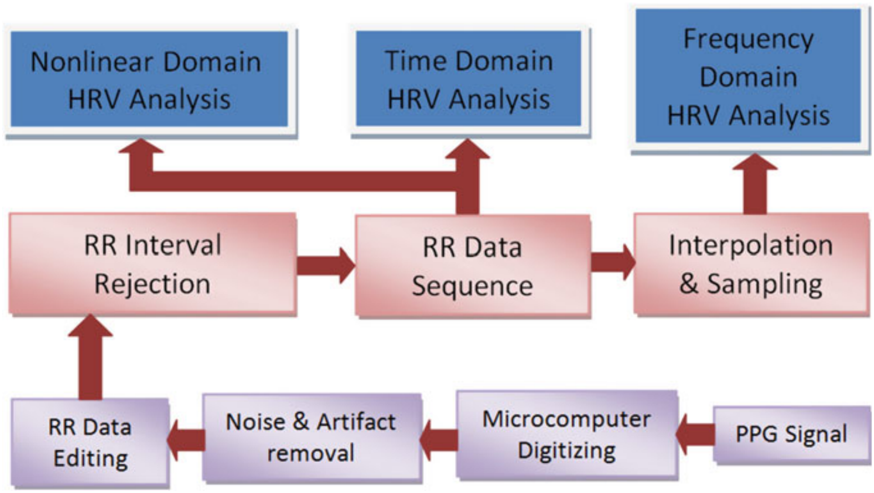

Fig. 5 R–R interval processing for HRV features set generation

4.5 Feature Selection Algorithms

Biometric applications inherently are pattern-recognition problems. And in any pattern recognition system, each pattern is represented by a set of features or measurements and is viewed as a point in the dimensional feature space [19] called as feature vectors. As HRV-based biometrics recognition is being explored for the first time we are not sure whether all or subsets of features will give best classification. Apparently, feature selection becomes a very critical and major step before the classification. Actually, as a matter of fact feature selection is an important problem for pattern classification systems [20], which aims at selecting features that allow us to discriminate between patterns belonging to different classes and in biometrics it aims at discriminating or recognizing different humans. The feature set with 101 HRV features generated by HRV analysis naturally must contain irrelevant or redundant features which would degrade the performance of classification. In general, it is desirable to keep the number of features as small as possible to reduce the computational cost of training a classifier as well as its complexity [19] in addition of getting a better classification rate. According to Jain et al. [21], feature extraction methods create new features based on transformations or combinations of the original feature set, whereas feature selection refers to methods that select the best subset of the original feature set. Feature selection algorithms can be classified into filters and wrappers [22]. Filter methods select subset of features as a preprocessing step, independent of the induction (learning) algorithm. Wrappers utilize the classifier (learning machine) performance to evaluate the goodness of feature subsets [19]. As Wrapper methods are widely recognized as superior alternative in supervised learning problems [23], we choose five wrapper methods, namely statistical dependency (SD) which estimates the statistical dependency between features and associated class labels using a quantized feature space [19, 23], mutual information (MI) measures arbitrary dependencies between random variables [19, 24], random subset feature selection (RSFS) aims to discover a set of features that perform better than an average feature of the available feature set [19], sequential forward selection (SFS) works in the opposite direction, initially starting from an empty set, the feature set is iteratively updated by including the feature which results in maximal score in each step [19], and sequential floating forward selection (SFFS) is improvisation over SFS algorithm, it uses SFS as baseline method [19] and further extends by iteratively finding the least significant features and eliminates it; this process continues till a desired number of features are not obtained. The obtained features are discussed in detail in the results and discussion section.

5 Results and Discussions

From the raw data files of R–R interval sequence, feature set generation was implemented using statistical, spectral, time-frequency, and nonlinear techniques like Poincare map and sample entropy. In all 101 features were generated out of which 14 from statistical techniques, 39 from three different spectral techniques, and 42 from three different time-frequency techniques and remaining from nonlinear techniques.

It was observed that not all the features from all the techniques are very much relevant and these features also depend on the nature of the raw data used. Many features are proposed from different considerations and point of view, and for different applications which may not prove to be effective in the present context of biometric recognition. All features described above are obtained from HRV analysis used in diagnostics, and therefore the main concern is which of these features are going to be effective in biometric recognition. Extensive efforts have been put in for arriving at a rationale to select features that have relative significance and are promising in biometric recognition. With this in view, we subjected the complete feature set to five different tests based on SD, MI, RSFS, SFS, and SFFS algorithms.

From the entire set of features, the first two tests suggested a list of 10 best features while the third one gave 23 and the fourth and fifth one gave 10 sensitive features each. The fives lists of selected features suggested by above algorithms partly overlapped as seen in Table 1. We categorized the features appearing in all the five groups described above as strong, those appearing in three to four groups were considered as moderately well, those found in two groups as weak and features suggested by only one test were considered as poor and were set aside. Features appearing in all 5 and 3, 4 groups are listed in the Table 2. It was found that the range of values covered by the features is large enough, some of the features have values in fractions whereas others are in thousands. This broad range of values resulted in poorer comparison that was evident from the performance in

Table 1 List of features suggested by five wrapper algorithms (for names and descriptions of features, please see Appendix A)

S. no.	Algorithm	No. of features in proposed features list	Features proposed in features list of wrapper algorithms
1	Statistical dependency (SD)	10	max, mean, median, RMSSD, meanHR, aHF (welch), aHF(Burg), SD1, aHF (lomb), aHF(wavelet)
2	Mutual information (MI)	10	max, min, mean, median, RMSSD, meanHR, aHF (welch), SD1, aHF (lomb), aHF(wavelet)
3	Random subset feature selection (RSFS)	23	max, min, mean, median, SDNN, RMSSD, meanHR, sdHR, aTotal Welch), aHF(Burg), aTotal (Burg), peakHF(lomb-Scargle), SD1, SD2, aHF (Burg), aTotal (Burg), peakHF (Burg), aHF (lomb), aTotal (lomb), peakHF (lomb), aLF (Wavelet), aHF(wavelet), aTotal (Wavelet)
4	Sequential forward selection (SFS)	11	mean, RMSSD, meanHR, sdHR, HRVTi, SD1, SD2, aHF (Burg), pHF (Burg), LFHF (lomb), LFHF (Wavelet)
5	Sequential floating forward selection (SFFS)	11	mean, RMSSD, meanHR, sdHR, HRVTi, SD1, SD2, aHF (Burg), pHF (Burg), LFHF (lomb), LFHF (Wavelet)

Table 2 List of features appearing in 3 or more groups

S. no.	Feature(s) name	Technique name
1	Max, mean, median, RMSSD, meanHR, sdHR	Statistical technique
2	SD1, SD2	Poincare chart
3	aHF	Spectral (Lomb)
4	aHF	Time-frequency (Wavelet)

the classification test. This suggested a comparison of features on a similar scale by way of normalization, when normalized the features gave a better performance in the classification test. Details are shown in Table 3.

Using the criterion discussed above, selecting ten features (occurrence 3–5 times in the suggested feature list) KNN classifier was tested on the feature set of 27 subjects. It was found that the results significantly improved to 82.22 % of the testing set.

Table 3 List of features appearing in 3 or more groups

S. no.	Algorithm	Recognition rate (%)	
		Without normalization	With normalization
1	SD	60.37	66.30
2	MI	59.26	68.89
3	RSFS	49.63	65.93
4	SFS	63.70	68.89
5	SFFS	63.70	64.63

6 Conclusions and Future Directions

Heart being a vital organ containing characteristic properties for each individual proves to be a potential candidate for biometric recognition. Different approaches have been proposed utilizing different properties like its sound and its electrical activity. One of the important characteristic of the heart is its heart rate variability (HRV) that has been used for different applications including diagnosis and prognosis. We attempted feature generation using different techniques like statistical, spectral, time-frequency, and nonlinear like Poincare and sample entropy used in HRV analysis. In all 101 features have been obtained and to pinpoint the features that are promising in terms of biometric identification we used SD, MI, RSFS, SFS, and SFFS feature selection techniques. After identification of the features, ten prominent features were selected that were common to more than two selection algorithms.

Initial work showed that the range of values of different features extracted is very large, there are features with fractional values, whereas others are in thousands. This suggested that the features are to be compared on similar scale, for this the features were normalized and the normalization resulted in improved results as shown in Table 2. The recognition rate with the ten features found in more than two groups using KNN classifier gave 82.22 % for the testing set.

Looking at the performance of the selected features, it appears that HRV-based biometric recognition is promising research area which needs more prospective studies with larger databases and context aware data conditions. Performance of KNN is seen in the present work, but more classifiers can also be experimented to improve the results further. HRV data can also be used in liveness detection hence attempts in those directions would yield interesting results. HRV can also be experimented in multimodal system and is expected to add much needed robustness and efficiency. With little modification in hardware and data acquisition software, the same setup can also be used for continuous authentication. Due to a simple user friendly device we designed, all these research dimensions look achievable.

Acknowledgments This work was carried out in Multimodal System Development laboratory established under UGC's SAP scheme, SAP (II) DRS Phase-I F. No. 3-42/2009 & SAP (II) DRS Phase-II F. No.4-15/2015. This work was also supported by UGC under One Time Research Grant F. No. 4-10/2010 (BSR) & 19-132/2014 (BSR). The authors also acknowledge UGC for providing BSR fellowship.

Appendix A

Poincare map features		
1 2	• SD1 • SD2	• Standard deviations of the distances of the R–R (I) to the lines • Y = x and y = –x + 2R–Rm, where R–Rm is the mean of all R–R (I) • SD1 related to the • Fast beat-to-beat variability in the data, while SD2 • Describes the long-term variability of R–R (I)

Statistical features		
No.	Name	Description
1	SDNN	Standard deviation of all normal–normal intervals
2	RMSSD	Root mean square of successive differences
3	NN50	It's a count of the number of adjacent pairs differing by more than 50 ms
4	pNN50	(%) NN50 count divided by total intervals
5	MeanRRI	Mean of normal–normal interval
6	MeanHR	Mean heart rate
7	Max	Maximum interval duration in a particular RRI
8	Min	Minimum interval duration
9	Mean	Mean of the whole RRI sequence
10	Median	Median of the RRI sequence
11	SDHR	Standard deviation of heart rate

Spectral features		
No.	Name	Description
1	aVLF	Absolute value in very low-frequency spectrum
2	aLF	Absolute value in low-frequency Spectrum
3	aHF	Absolute value in high-frequency Spectrum
4	aTotal	Total absolute value
5	pVLF	Power % of very low frequency in PSD
6	pLF	Power % of low frequency in PSD
7	pHF	Power % of high Frequency in PSD
8	nLF	Low frequency in normalized Unit
9	nHF	High frequency in normalized Unit
10	LFHF	LF to HF Ratio
11	peakVLF	Peak value in very low frequency
12	peakLF	Peak value in low frequency
13	peakHF	Peak value in high frequency

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Advanced Computing and Systems for Security
Volume 1
Chaki, R.; Cortesi, A.; Saeed, K.; Chaki, N. (Eds.)
2016, X, 278 p. 85 illus. in color., Softcover
ISBN: 978-81-322-2648-2