POINCARE GEOMETRY-CHARACTERIZED ARRHYTHMIA IDENTIFICATION SCHEME IN GRID

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ABSTRACT:

In this paper, we propose a new scheme of Poincare geometry-characterized ECG analysis for cardiac disease identification. Based on reliable P-wave detection we created P-P Poincare plot applying P-P intervals of ECG signal. By the new geometric Poincare plot analysis, which combines R-R intervals and P-P intervals, we identified geometric differences of normal and arrhythmia ECG databases at PhysioBank in Physionet.

Poincare descriptors show that the analysis scheme can classify two ECG signals reliably. Furthermore, we discuss a cardiac disease estimation system that may be applicable to estimate the occurrence of arrhythmia in healthy person.

KEYWORDS: Geometry, Poincare, ECG, Arrhythmia Identification, Grid.

1. INTRODUCTION:

Electrocardiography (ECG or EKG) signal analysis is one of typical methods to detect cardiovascular diseases. Various attempts have been made to analyze typical arrhythmia syndromes from the analysis of QRS complex and HRV (Heart Rate Variability) using long-term ECG signals. Those approaches are utilizing time-domain threshold, spectrum analysis, principal component analysis, fuzzy logic, and artificial neural network. However, there are some limitations to identify arrhythmia as early as possible using ECG analysis. Every analysis procedure can be processed to get diagnosis outcome and sometimes the diagnosis outcomes need more processing for advanced diagnosis. It is known that arrhythmia showing abnormal range of heart beat rates can occur with some specific syndromes; low blood pressure, hypersensitivity, congestion, depression and others. We consider a service to help diagnosis of arrhythmia not only through web interface, such as a Physio-Grid system we developed [1][2] but also in mobile device since a collaborative environment is needed for medical doctors and patients for future e-Healthcare services.

In this paper, we propose a new scheme of arrhythmia identification applicable for patient-care services. From ECG database, we used Poincare plot descriptors such as mean square and standard deviation that are useful to identify arrhythmia identification. Poincare descriptors are evaluated using two kinds of ECG databases from PhysioBank in Physionet [3]. We detected that the descriptors calculated from arrhythmia ECG database are different to the descriptors calculated from a long-term ECG database. Using this experimental result, we propose a new ECG analysis based on Poincare-geometry descriptors for cardiac disease identification that will be implemented on the advanced Physio-Grid [reference] that also provides a collaborative environment for advanced diagnosis of physiological diseases.

P wave Detection and Poincare geometry descriptors

Despite qualitatively new diagnostic techniques in cardiology such as cardiac mapping and echocardiography that provide different imaging modalities, the standard ECG recording still remains the main diagnostic tool that cardiologists use first for examining cardiac state. Few recording electrodes are sufficient for identifying regions of ischemia or detecting heart attack. Furthermore, computer-based signal processing and analysis techniques enable inspection of subtle electrocardiogram features that are “invisible” to human sensory perception but have been recognized as important markers for serious heart illnesses [3]. By geometric Poincare plot analysis, which is a combination of R-R intervals and P-P intervals tested on two different ECG databases from PhysioBank, quantitative differences of geometry were found. Geometrical median positions of RR or PP Poincare plot were calculated and compared according to different ECG databases.

In general, when the statistics on standard deviation and variance of R-R interval are given, the Poincare descriptor can be easily represented with equations (1) and (2).

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$$SD1^2 = Var(\frac{1}{\sqrt{2}} RR_n - \frac{1}{\sqrt{2}} RR_{n+1}) \quad (1)$$

$$SD1^2 = Var(\frac{1}{\sqrt{2}} RR_n + \frac{1}{\sqrt{2}} RR_{n+1}) \quad (2)$$

where SD is standard deviation; Var(*) is variance; RR is an R-R interval.

Since P-wave is strongly related with arrhythmia syndrome, it is important to detect signal and identify the distortion with normal signal pattern. Therefore, based on reliable P-wave detection within the two types of tested ECG databases, we created P-P Poincare plot applying P-P intervals of ECG waveform. By geometric Poincare plot analysis, which is a combination of R-R intervals and P-P intervals tested on two different ECG databases from PhysioBank, quantitative differences of geometry were found. Geometrical median positions of RR or PP Poincare plot were calculated and compared according to different ECG databases.

(i) Extraction of P-P Poincare Descriptor

Automatic P wave detection is still a difficult problem in surface ECG analysis. The difficulties in P wave detection are due to low amplitudes, widely varying shapes, low signal-t-noise ratios, and adjacent QRS complexes or T waves. Mostly, P wave detection is based on local measurements like derivatives, amplitude, or spatial velocity. Even though these quantities allow an efficient measurement of signal activities connected to the presence of P waves, they are likely to fail in the presence of noise or small amplitudes, because they do not take into account the signal energy of the P wave as a whole. However, several methods were developed recently to solve the problem of detection and localization of signal structure. One of these methods is the Gabor wavelet transform as represented in equation (3) [5][6].

$$g_{\sigma,t_o}(t) = e^{ic\frac{(t-t_o)}{\sigma}} e^{-\frac{1}{2}\frac{(t-t_o)^2}{\sigma^2}} \quad (3)$$

Here 'c' is a fixed constant which gives the number of oscillations. The parameters σ and t indicates the scale and the shift in the time domain of the function g. The projection on such a set of functions with varying u and to is called a wavelet transform. As we tune the scale using the value of sigma, we can see the filtering results as shown in figure 1. Determination of the value of sigma depends on experimental trials. We use a wavelet transform of the ECG signal for proposal of Poincare geometry model. The mother wavelet of our transform is a complex Gabor function with considerably fewer oscillations than those used in most other applications. This means that at coarse scales, where the size of the wavelet is approximately the size of a P wave, the wavelet transform is rather a template matching for P waves than a local frequency analysis of the signal. At the small scales, it is qualitatively a real and imaginary part given by derivatives of the signal. These derivatives are used to localize the onset and offset of the P wave in sample databases. The detection of patterns in non-stationary signals is closely connected to local frequency analysis. This implies that a filter should have a good localization in the time domain as well as in the frequency domain.

Gabor wavelet implementation result in Matlab

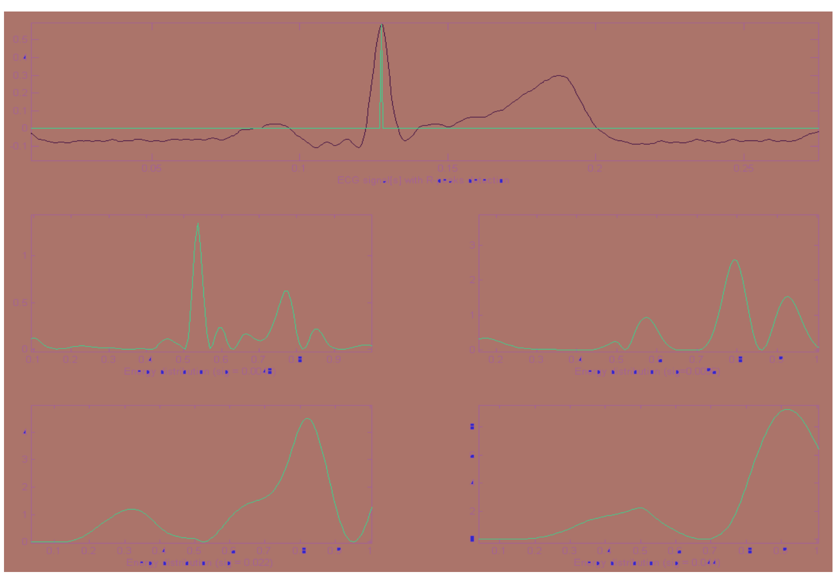

Figure 1 Results of Gabor wavelet in different sigma values

P-wave detection ratio is defined by (Number of detected P-wave) / (Number of true P-wave). Each signal is ECG record of five-minute long. P wave detection ratio was approximately 97% in average of 15 ECG signal sets (Figure 2).

P-wave detection ratio

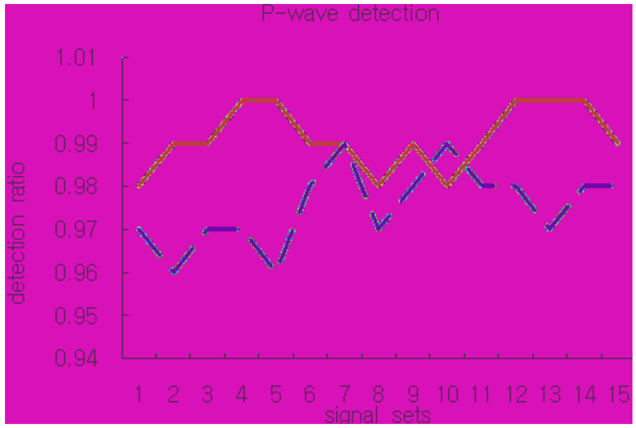

Figure 2 Solid line indicates the result from normal ECG records; broken line represents the result from arrhythmia ECG records.

(ii) Performance Analysis Results

Poincare plot of R-R intervals of ECG signal has been considered as a non-linear expression of HRV. Each axis of X-axis and Y-axis represents R-R intervals. In the shape, that perhaps contains some clues for detecting cardiac diseases. Relationships between cardiac diseases and shapes of Poincare plot of R-R intervals of ECG signal have been reported by several researches. The output shows the results of fitting a multiple linear regression model to describe the relationship.

The P-P Poincare plots are analyzed as same as R-R Poincare plots and those two different analysis results are evaluated using two different ECG signal database: 1) MIT-BIH Normal Sinus Rhythm database, and 2) MIT-BIH Arrhythmia ECG database. The first database includes 18 long-term ECG recordings of subjects who were found to have had no significant arrhythmias; they include 5 men, aged 26 to 45, and 13 women, aged 20 to 50. The second database is a set of over 4000 long-term Holter recordings [8].

Table 1 Analysis Result of Poincare Geometry Descriptor

		Normal Sinus Rhythm ECG DB (Mean ± S.E.) [s]	Arrhythmia ECG DB (Mean ± S.E.) [s]
RR Poincare	SD1	$7.15 \times 10^{-9} \pm 1.5 \times 10^{-9}$	$6.71 \times 10^{-9} \pm 2.04 \times 10^{-9}$
	SD2	$1.74 \times 10^{-8} \pm 9.12 \times 10^{-9}$	$1.28 \times 10^{-8} \pm 8.21 \times 10^{-9}$
PP Poincare	SD1	$1.35 \times 10^{-9} \pm 1.14 \times 10^{-9}$	$7.55 \times 10^{-9} \pm 2.75 \times 10^{-9}$
	SD2	$4.40 \times 10^{-8} \pm 4.57 \times 10^{-9}$	$1.66 \times 10^{-8} \pm 5.54 \times 10^{-9}$

SD: Standard deviation, S.E.: Standard error

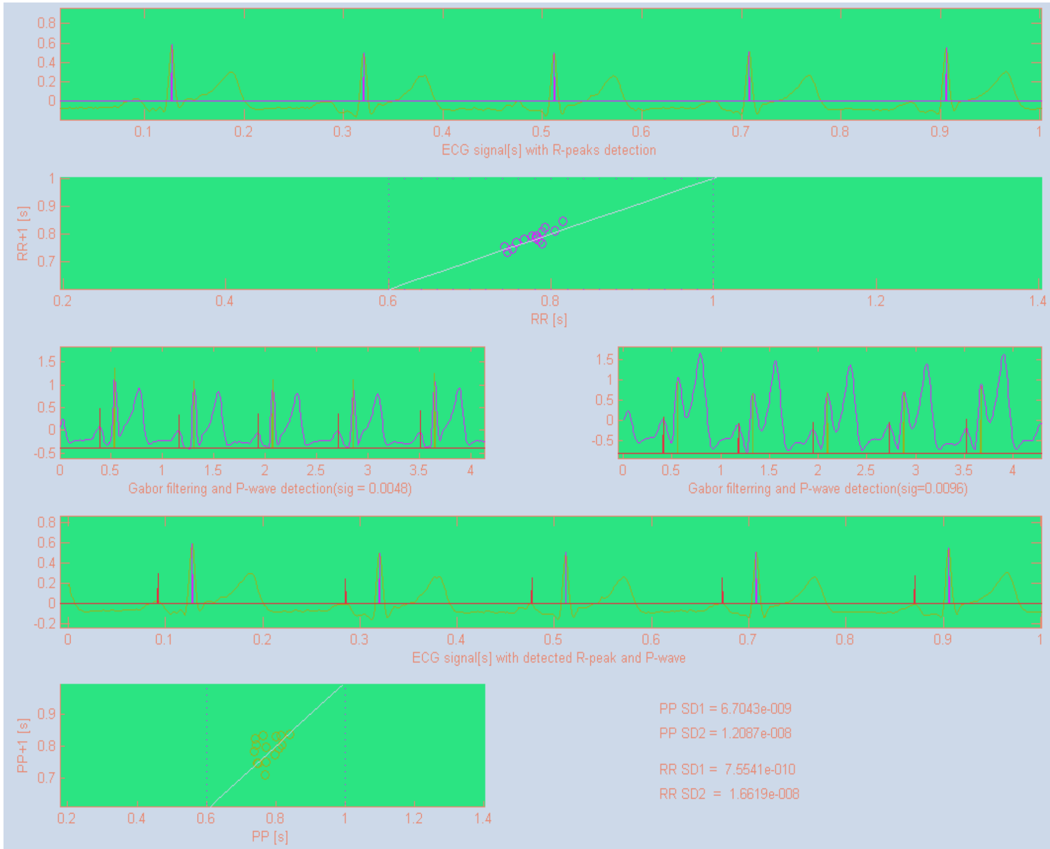

Figure 3 Result of P-wave detection and Poincare plotting

The database contains 23 records chosen at random from this set and 25 records selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small random sample of Holter recordings. Each of the 48 records is slightly over 30 minutes long. The first group is intended to serve as a representative sample of the variety of waveforms and artifact that an arrhythmia detector might encounter in routine clinical use. A table of random numbers was used to select records and then to select half-hour segments of them. Segments selected in this way were excluded only if neither of the two ECG signals was of adequate quality for analysis by human experts. Records in the second group were chosen to include complex ventricular, junctional, and supraventricular arrhythmias and conduction abnormalities. Several of these records were selected because features of the rhythm, QRS morphology variation, or signal quality may be expected to present significant difficulty to arrhythmia detectors; these records have gained considerable notoriety among database users. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years

(iii) Geometry Poincare-Characterized Arrhythmia Identification Scheme

To provide high quality of medical service related with heart disease, we can consider not only information from ECG signal but also emotional status of each person. Recently, a Stress Response Inventory (SRI) questionnaire has been devised to score physical mental, and emotional symptoms related to mental stress [1][7]. The causes of arrhythmia can be expressed by more than 30 reasons. To verifying the relationships between arrhythmia and causes in quantitative analysis require deep understanding of its characteristic. Owing to above reason, we have studied on structure of ‘Questionnaire for Arrhythmia’ which is suitable for mobile system and a Poincare descriptor was applied to identify an accurate arrhythmia syndrome.

Table 2 HR AND SIGNIFICANT SUBSETS OF SRI SCORES BY MULTIPLE LINEAR REGRESSION ($P < 0.1$)

Ages	Multiple Linear Regression Model (MLRM)	p-value
20s	HR = 73.66 + 2.45 ·score 4 – 1.61 ·score 10	0.057
30s	HR = 72.69 + 2.46 ·score 1 +1.98·score 3 - 1.90 ·score 18	0.009
40s	HR = 73.27 + 3.63 ·score 4 – 8.50 ·score 21	0.002
50 ~60s	HR = 68.31+3.15 ·score 9 + 4.23 ·score 11 – 2.65 ·score 1	0.001

HR: Heart rates (bpm)

Figure 4 shows the scenario of e-Health application service on mobile device. It mainly contains two methods to provide diagnosis service: one is R-R peak detection method from raw ECG data and another is simplified questionnaire service. Based on these two methods, application can provide useful information to user and medical doctor. Subjects who had internal treatment history and psychopathic treatment history were excluded in the experiment. 369 people in total participated in experiment. The experiments were administered in the quiet room. Heart rates were acquired using a photoplethysmography sensor (Freeze-Framer®, HeartMath LLC, Boulder Creek, CA). Three minute heart rate recordings were performed during the resting as baseline stage. Mean heart rates were calculated from three minute recordings to be used in the data analysis. Multiple linear regression analysis was performed to evaluate the relation between a set of SRI scores (independent variables) and heart rates (dependent variable) at 90% significant level ($p < 0.1$). P-value means a significance of the result relationship between heart rates and SRI scores. Statistically, at the 90% significant level we can reject the null hypothesis that there is no relationship between heart rates and SRI scores, because the p-value of the experiment result is less than 0.10.

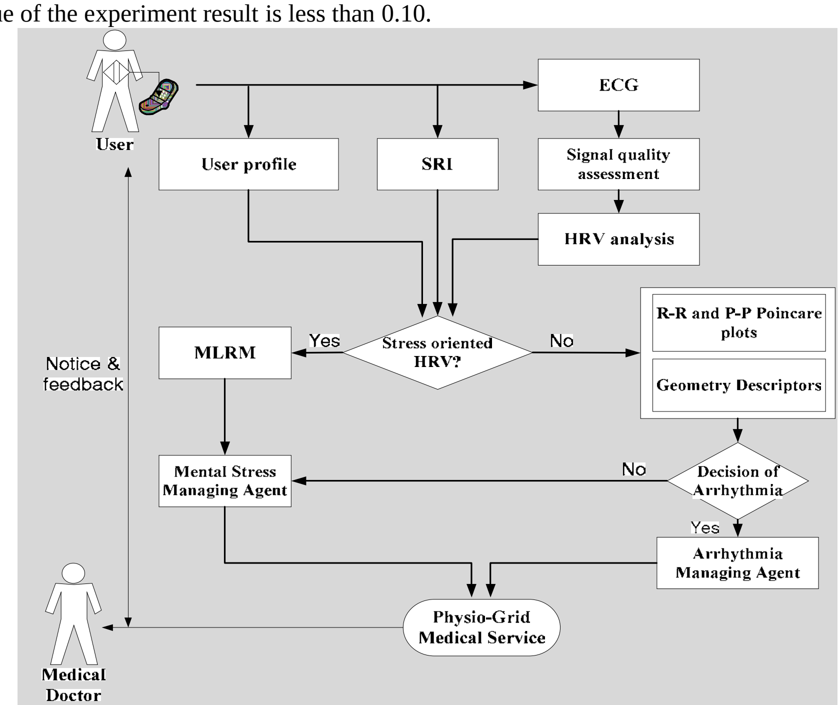

Figure 4 Poincare geometry-Characterized Arrhythmia Identification Scheme

From the detected multiple linear regression models (MLRMs), we estimate heart rate from two or three SRI scores. If MLRMs of service clients are discovered constantly, a medical doctor may identify which stress factor affects heart rate changes simply. We assume that when a medical doctor knows MLRM of service clients, medical doctor needed to ask only the SRI questions involved in the MLRM to find heart rate related stress factors when high heart rate (HR>110 [BPM]) or low heart rate (HR<60 [BPM]) detected.

Poincare plot of R-R intervals of ECG signal has been considered as a non-linear expression of HRV. Each axis of X-axis and Y-axis represents R-R intervals. In the shape, that perhaps contains some clues for detecting cardiac diseases. Relationships between cardiac diseases and shapes of Poincare plot of R-R intervals of ECG signal have been reported by several researches. However, Poincare plot of P-P intervals of ECG signal have not been studied as far as we have surveyed. Since P-wave detection is also an important issue in ECG analysis, several researches have suggested well developed P-wave detection schemes with high quality ECG signals. Based on reliable P-wave detection within the two types of tested ECG databases (i.e. higher than 97 % accuracy over every five minute), we created P-P Poincare plot applying P-P intervals of ECG waveform.

Fig. 5 represents a prototype of Physio-Grid system that has Poincare geometry analysis functions for advanced arrhythmia identification. The system will provide collaborative care of cardiac disease management through e-Health services at home.

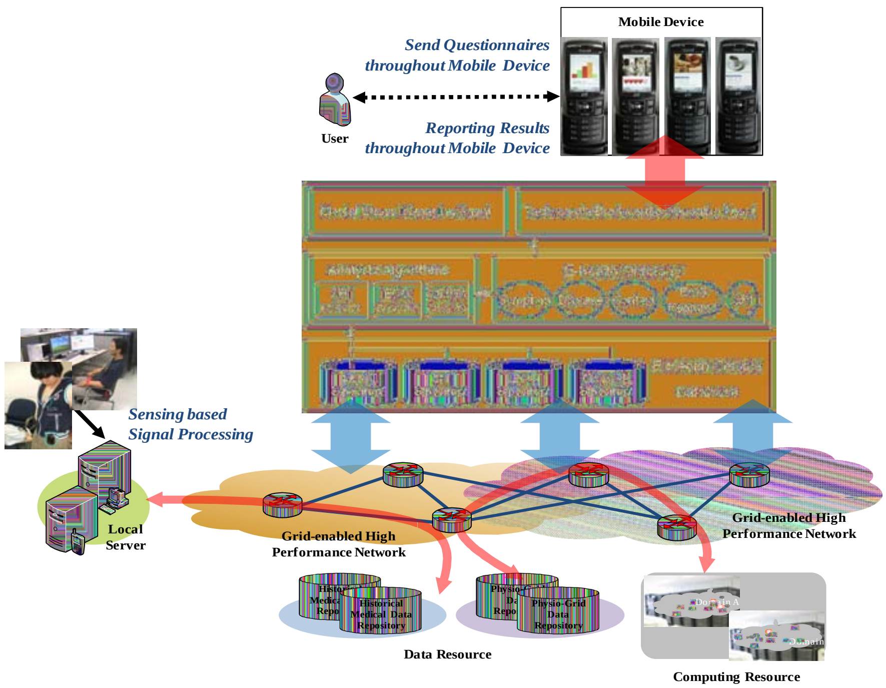

Figure 5 Physio-Grid system with advanced arrhythmia management functions

Conclusions and Discussion

By geometric Poincare plot analysis, which is a combination of R-R intervals and P-P intervals tested on two different ECG databases from PhysioBank, quantitative differences of geometry were found. In addition, the Poincare descriptors are evaluated using two kinds of ECG signal from PhysioBank. We detected that the descriptors calculated from arrhythmia ECG database are different to the descriptors calculated from long-term ECG database. Based on the experiment result from Poincare plot analysis, geometry Poincare-characterized identification scheme was proposed for Physio-Grid. Furthermore, the Physio-Grid system was implemented in laboratory environment.

Advances in patient care monitoring have allowed physicians to track a patient’s physiological state more closely and with greater accuracy. Modern handheld healthcare systems can take information from multiple data sources and store them in a healthcare server. We are developing Physio-Grid system for advanced medical service system. The Physio-Grid system had been designed to support advanced physiological disease identification with data integration of distributed medical database in which ECG signals, and analysis results of virtual heart simulator (VHS) stored.

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