Automatic heart activity diagnosis based on Gram polynomials and probabilistic neural networks

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Abstract The paper proposes a new approach to heart activity diagnosis based on Gram polynomials and probabilistic neural networks (PNN). Heart disease recognition is based on the analysis of phonocardiogram (PCG) digital sequences. The PNN provides a powerful tool for proper classification of the input data set. The novelty of the proposed approach lies in a powerful feature extraction based on Gram polynomials and the Fourier transform. The proposed system presents good performance obtaining overall sensitivity of 93%, specificity of 91% and accuracy of 94%, using a public database of over 3000 heart beat sound recordings, classified as normal and abnormal heart sounds. Thus, it can be concluded that Gram polynomials and PNN prove to be a very efficient technique using the PCG signal for characterizing heart diseases.

Keywords Heart sounds · Phonocardiogram · Cardiac signal analysis · Gram polynomials · Probabilistic neural network

1 Introduction

Both phonocardiography (PCG) and electrocardiogram (ECG) are the basic investigative methods used in cardiology. It is well known that the ECG has been the major diagnostic tool for cardiologists providing almost all

information about the electrical activity of the heart [1–3]; in particular, the PCG signal, recorded by means of a stethoscope, contains different timings and relative intensities of heart beat sounds [4].

In the future, the introduction of electronic stethoscopes to the market allowing digital recording of heart sounds, together with the development of powerful algorithms for signal analysis [5–7], will enable the development of intelligent monitoring and telemedicine applications in which the patient could independently monitor the occurrence of any heart disease.

The aim of this paper is to focus on the use of Gram polynomials and probabilistic neural networks (PNN) as the PCG classifiers for the recognition of heart diseases [8]. This technique has been successfully applied in the field of cardiac biometry, or for personal identity recognition purposes [9].

Different approaches have been recently presented in the literature showing strong interest in automatic algorithms for heart disease recognition, based on different signal feature extraction such as Discrete Wavelet Transform (DWT) [10, 11], Discrete Sinc Transform (DSNT) [12] and different classification methods such as Support Vector Machine (SVM) [13, 14], Learning Vector Quantization (LVQ) [15, 16], Feed Forward Neural Network (FFN) [17], Convolutional Neural Network (CNN) [18], Generalized Regression Neural Network (GRNN) [19], Back Propagation Neural Network (BPNN) [20] etc. A particular typology of Neural Network, often used in ECG analysis in order to identify and classify various heart diseases is the Probabilistic Neural Network (PNN) [21–23]. In this paper the authors propose a new very robust method for heart disease recognition using a PNN and an innovative feature extraction technique based on Gram polynomials and Fourier Transform.

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The paper is organized as follows: in Sect. 2 the basics of heart sound physiology is described; in Sect. 3 a brief description of Gram Polynomials is presented; in Sect. 4 the use of Gram Polynomials and FFT for the feature extraction is explained; in Sect. 5 the proposed RBPNN is described and the performance of the system is analysed. Finally in Sect. 6 relevant conclusions are drawn.

2 Heart sounds physiology

Heart sounds have an inherent periodicity due to the cardiac activation being periodic in nature. Traditionally heart sounds have been analyzed in one cardiac cycle at a time. Conclusions have been drawn from one beat or from an average of several beats. A cardiac cycle consists of precisely timed electrical and mechanical events that result in rhythmic atrial and ventricular contractions that pump blood into the pulmonary and systemic circulation. The period of ventricular contraction and ejection is called systole, and the period of ventricular relaxation and filling is called diastole (see Fig. 1).

Both the systole and diastole start with periods of isovolumic pressure changes. The systole begins with isovolumic contraction (phase 2) where the ventricles contract against closed valves and hence no blood is ejected and

volume is held constant. This increased ventricular wall tension causes the pressure to increase which eventually opens the aortic and pulmonic valve and the ventricular ejection occurs (phase 3). Blood is ejected through the aorta and the pulmonary artery when the ventricles contract. It is the forced closure against the mitral valve and the sudden rush of blood through the aorta that causes the first heart sound (S1). The total volume of blood ejected by each ventricle is called the stroke volume. Systole is complete when the aortic valve closes due to reduced flow and pressure (phase 4). This aortic and pulmonary closure, and the movement of blood column after their closure, cause the second heart sound (S2).

The S2 consists of two components, i.e. the aortic component (A2) and the pulmonic component (P2). Both the S1 and S2 are audible sounds with a bandwidth of 15–90 Hz. During the first part of diastole (phase 5), the ventricles relax and the aortic and pulmonary valves close. The ventricular pressure falls and when it drops below the corresponding atrial pressures the tricuspid and mitral valves open. This is followed by diastolic ventricular filling. The early diastolic filling (phase 6) is passive and in a stiff heart, as in a heart failure, results in the third heart sound (S3). During the late diastole (phase 1), when the atrium contracts against a stiff ventricle, the fourth heart sound is heard (S4). When present in adults, the S3 and S4 are indications of pathologic conditions of the heart. Both these sounds are low frequency sounds with a bandwidth of 5–25 Hz.

Heart sounds have been studied and used for many pathologic conditions of the heart including the deterioration of systolic performance, murmurs and increasing pressure. Historically, the S1 heart sound intensity has been associated with the force of blood ejected from the heart. Time frequency transforms have been thoroughly applied in the context of heart sounds.

2.1 Common applications of heart sounds

One of the most widespread applications of heart sounds analysis has been for murmur detection. Stethoscopes have been commonly used to listen murmurs, and several researchers have attempted to automate both murmur detection and classification. Cardiac sounds are by definition non-stationary signals, and are located within the low frequency range, approximately between 10 and 750 Hz. Since cardiac murmurs are high frequency sounds localized in certain parts of the cardiac cycle, time frequency transforms have been used to analyze them.

Time frequency techniques are used to improve heart sound signal quality. Moreover, time frequency transforms have also been used to understand the genesis of heart sounds. Whatever the approach, one of the first phases in the analysis of heart sounds is segmentation.

Fig. 1 The cardiac cycle showing left sided pressures and events. AP aortic pressure, LVP left ventricular pressure, LAP left atrial pressure, LVEDV LV end diastolic volume, LVESV LV end systolic volume

Fig. 2 Heart sound: **a** S1 and S2, **b** S3, **c** S4

Heart sound segmentation process divides the PCG signal into four parts: S1 (first heart sound), systole, S2 (second heart sound) and diastole (see Fig. 2a). First, S1 and S2 are located, then systole is represented by the interval S1 to S2 and diastole by the interval S2 to S1. In general, S3 and S4 are unusual sounds, similar in quality to S1 and S2, but smaller in magnitude. Both sounds are rare, and more often heard in the hearts of children. If S3 is present (Fig. 2b), it occurs between S2 and S1 (in diastole), usually right after S2. If S4 is present (Fig. 2c), it precedes S1 by approximately one hundred milliseconds.

3 Gram polynomials

Let us consider the finite energy signal space $(L^2(a, b))$ where a, b is a not necessarily limited interval of a real function which corresponds to $w: (a, b) \rightarrow \mathbb{R}$ if we define the scalar product and the rule as follows:

$$\langle g, h \rangle_{2,w} = \int_a^b f(x) \cdot g(x) \cdot w(x) dx \quad (1)$$

and

$$\|g\|_{2,w} = \langle g, g \rangle_{2,w}^{\frac{1}{2}} \quad (2)$$

It is indicated that the present Euclidean space $(L^2(a, b))$ endowed with the scalar product and the rule outlined in (1) e (2) is an Hilbert space with scalar product.

In particular, it is considered that w is a nonnegative function, thus:

$$\int_a^b |x|^n \cdot w(x) dx < +\infty \quad \forall n \in \mathbb{N} \quad (3)$$

$$\int_a^b g(x) \cdot w(x) dx = 0 \iff g(x) \equiv 0 \quad \forall x \in (a, b) \quad (4)$$

It can be proved that

Theorem 1 The vector space $(L_w^2(a, b))$ includes the polynomial space $\mathcal{P}_n$ of all polynomials of degree n ($n \in \mathbb{N}$)

3.1 Least squares approximation

Knowing that $f \in (L_w^2(a, b))$ and $n \in \mathbb{N}$, the least squares problem lies in the estimation of $\Phi_n(x) = \sum_{k=0}^n \beta_k \phi_k(x)$, so that

$$\|f - \Phi_n\|_{2,w} = \min \quad (5)$$

where $\{\phi_k\}_{k=0}^n$ is an orthonormal basis of $\mathcal{P}_n$, compared to the above indicated scalar product.

The coefficients β_k reduce the (5) if normal equations are formed:

$$\sum_{k=0}^n \langle \phi_i, \phi_k \rangle_{2,w} \beta_k^* = \langle \phi_i, f \rangle_{2,w} \quad i = 0, \dots, n. \quad (6)$$

Let us consider the group of polynomials $\bar{\phi}(x)_k = x^k$ $k = 0, \dots, n$ e $w(x) = 1$, $x \in [-1, 1]$ (Legendre weight). It can be proved that the above mentioned accounts for a nonorthogonal basis of $\mathcal{P}_n$.

In case of discrete time signals in $\bar{\phi}(x)_k = x^k$ $k = 0, \dots, n$ orthonormal basis can be obtained (compared to the scalar product with Legendre weight) with the following iterative formulae [24] with $1 < n < m$, where m stands for the length of signal:

$$\phi_n(x) = 2\alpha_{n-1}\phi_{n-1}(x) - \frac{\alpha_{n-1}}{\alpha_{n-2}}\phi_{n-2}(x) \quad (7)$$

$$\alpha_{n-1} = \frac{m}{n} \left(\frac{n^2 - \frac{1}{4}}{m^2 - n^2} \right)^{\frac{1}{2}} \quad (8)$$

with $\phi_0(x) = 1$, $\phi_{-1}(x) = 0$ and $\alpha_1 = 1$.

For a good approximation of f by means of *Gram polynomials* it is necessary to find out the optimal value of n [25]. In fact, a well-known difficulty arises: when n increases, the approximant Φ_n may oscillate with large amplitude near the endpoints of $[-1, 1]$. This phenomenon is called the *Gibbs phenomenon* [26]. Thus, the optimal value of n is the one reducing (1) and avoiding the *Gibbs phenomenon*.

4 The use of Gram polynomials and FFT in the novel proposed feature extraction

For practical applications, the original input variables are typically preprocessed to transform them into some new space of variables where, it is hoped, the pattern recognition problem will be easier to solve. This preprocessing stage is called *feature extraction* [27].

Preprocessing is performed in order to speed up computation and improve the classifications performances. Instead, the aim is to find useful features that are fast to compute, and that have good properties of discrimination.

A feature set suitable for the classification should possess two important properties:

- Should be insensitive to significant translations.
- Should have a very low correlation (both inter-class that intra-class).

The justification for the use of Gram polynomials for the feature extraction is due to the fact that this involves a simple and mild computational burden and also determines a strong reduction of dimensionality while preserving useful discriminatory information.

Looking at the top of Fig. 4 it can see the great power of discrimination of the coefficients of the expansion (7), where $\Phi_n(x)$ is the PCG trace in exam. Infact, it can be notice that there is a marked difference between different pathologies.

On the other hand, such a coefficient set does not have a sufficiently low inter-class correlation as shown in Fig. 3

Fig. 3 Covariance matrix related to: **a** the Gram polynomial coefficients, **b** the FFT amplitudes, **c** the FFT phases, **d** the absolute FFT spectrum

Fig. 4 An example of a normal heartbeat in comparison with two pathologies (*left to right*). From the *top* to the *bottom*: the Gram coefficients, the related FFT amplitude spectrum and the FFT phases

(for low inter-class correlation the covariance matrix should be diagonally dominant).

In order to provide a better discrimination among different kind of pathologies, we have applied to the Gram coefficients space the Fast Fourier Transform (FFT) so as to obtain the FFT Amplitudes and Phases as separated information. The reasons underlying this decision regard the covariance matrix of the computed coefficients (see Fig. 3b, c): while the amplitudes were able to correctly discriminate among different signals, the phases were suitable in order to make the correct associations among similar kind of pathologies. It is considered that such a behaviour would be lost using the absolute FFT spectrum (see Fig. 3d). Therefore, the input vector $\mathbf{u}$ for the neural network was composed as a set of 64 features

$$\begin{cases} \mathbf{u} &= [f_1, f_2, \dots, f_{32}, \phi_1, \phi_2, \dots, \phi_{32}] \\ \mathbf{f} &\triangleq \Re[\mathcal{F}(\psi)] \\ \phi &\triangleq \Im[\mathcal{F}(\psi)] \end{cases} \quad (9)$$

where $\hat{F}$ is the FFT of the Gram polynomial projection ψ , therefore $\Re[\mathcal{F}(\psi)]$ represents the FFT amplitudes, while $\Im[\mathcal{F}(\psi)]$ represents the FFT phases.

Linear combination of the features will not often suffice to discriminate the classes and then we must use non-linear discriminant functions. For the estimate of discriminant functions, Gaussian neural networks have been found to be powerful scheme, in particular the Radial Basis Probabilistic Neural Networks (RBPNN) has been proved useful for classification and clustering problems.

5 The selected RBPNN

The proposed RBPNN (Fig. 5) is an implementation of a statistical algorithm called kernel discriminant analysis [28] in which operations are organized into a multilayered feedforward network with four layers:

- Input layer
- Pattern layer

Fig. 5 RBPNN model: N_F —the number of features, N_S —the number of samples and N_G —the desired number pathology groups

- Summation layer
- Output layer

When an input is present, the first layer estimates the distance from the input vector to the training input vectors associated with the input layer, each of which represents a particular class (for the purpose of the present paper, has to distinguish between two classes: the normal and the abnormal heart sounds). The interval of values is standardized by subtracting the median and dividing by the interquartile range. As a result, a vector is produced whose elements indicate how close the input is to single classes in terms of Mahalanobis distance. By using this vector, the second layer applies a probability vector to indicate various possibilities of a match between the input vector and a particular class. Finally, the output layer defines the belonging of an input vector to a particular class by selecting the maximum value of the probability vector to predict the target class [29].

More specifically, the k -th network output has the form

$$y_k(x(t)) = \sum_{j=1}^M w_{k,j} \Phi_j(x(t)) \quad (10)$$

where

$$\Phi_j(x(t)) = \exp \left\{ -\frac{1}{2\sigma_j} (x(t) - \mu_j)^T \Sigma_j^{-1} (x(t) - \mu_j) \right\} \quad (11)$$

μ_j and Σ_j are the function center (mean vector) and covariance matrix of the j -th basis function respectively and σ_j is a smoothing parameter controlling the spread of the j -th basis function.

We restricts Σ to two global smoothing parameter σ_1 and σ_2 , where σ_1 is used in those basis functions that have centers coming from the normal heart sounds while σ_2 for the abnormal heart sounds. The determination of the smoothing parameters is done by calculating the spreads of the training data set belonging to the reference classes for σ_1 and σ_2 respectively.

The third layer (summation layer) performs an weighted average of the outputs from the second layer for each class. The fourth layer (output layer) performs a vote, selecting

the largest value (the target values are: 0 for the abnormal heart sounds and 1 for the normal heart sounds).

Adding and removing training samples simply involves adding or removing neurons in the pattern layer and a minimal retraining required.

For the training of the neural network simply note that the centers and spreads are predetermined then only the weights w_{ij} is required to find. The calculation can be performed by using the method of least squares.

6 Experimental setup and results

6.1 The PGC database

In order to evaluate the performance of the proposed method we have analyzed the public database provided at Physionet Challenge 2016. The assembled database consists of nine different databases collected independently by seven research teams from different countries with different data quality, patient types and hardware used to record the heart sound [30]. The training set consists of 3126 heart sound recordings, lasting between 5 and 120 seconds and is divided into two categories: normal and abnormal heart sound. No other information on the pathology type is provided. The validation set contains a copy of 300 recordings from the training set and will be used to evaluate the performance of the proposed method. Heart sounds were collected from different locations on the body (e.g. aortic area, pulmonic area, tricuspid area, mitral area, etc.), the involved subjects include both children and adults and each subject may have contributed between one and six recordings. All recordings have been resampled to 2 KHz and have been provided in a .wav format [31].

6.2 Performance evaluation

The performance of the proposed methods is evaluated using benchmark metrics such as Accuracy (Acc), Sensitivity (Se) and Specificity (Sp), which are defined as follows:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

$$Se = \frac{TP}{TP + FN} \quad (13)$$

$$Sp = \frac{TN}{TN + FP} \quad (14)$$

where TP, FP, TN and FN represents true positive, false positive, true negative and false negative, respectively. Sensitivity, specificity and accuracy are statistical parameters able to evaluate the performance of a binary classifier

Fig. 6 Architecture of the proposed PNN classifier

and are commonly used in medical contexts. The sensitivity parameter measures the ability of the classifier to identify and recognize patients with heart disease; specificity, instead, measures the ability to correctly recognize subjects without heart disease.

6.3 Results

The database was divided into three groups: 2000 recordings for the training set, 826 recordings for the validation set and 300 recordings for the test set. The training set is used to find the model parameters in the used RBPNN network. These parameters are the number of neuron for each class (the abnormal heart sounds and the normal heart sounds), the smoothing parameter σ_1 and σ_2 , and the weights value.

To find the optimal number of neurons we proceed as follows:

1. We use the data points of the training set as the centres of the network's neurons, so obtaining a network with 2000 neurons split up into two classes (1000 neurons represent the abnormal heart sounds and 1000 represent the normal heart sounds).
2. We calculate the network's weights by using the training set.
3. We eliminate the neuron with a minimum weight and recalculate the network's weights by using the training set. The procedure ends when the performance, in

terms of correct classification on the validation set, falls down of the 2% with respect to the previous step.

The resulting network after the training phase is shown in Fig. 6. It consists of 73 neurons (38 of them represent the abnormal heart sounds and 35 represent the normal heart sounds). Once the optimal parameters are found the trained PNN classifier is applied to classify the data points in the test set into one of the two classes.

A comparison of different classification techniques for heart sound classification based on the same database is summarized in Table 1. The reported results in terms of sensitivity and specificity refer to the public training and validation set provided in [31]; the test set used in Physionet Challenge 2016 is unavailable to the public.

Table 2 shows the proposed method performance in terms of accuracy, sensitivity and specificity, according to Eqs. (12), (13), (14).

The proposed technique of heart activity diagnosis based on Gram polynomials and probabilistic neural networks (PNN) is very robust and can recognize any abnormalities of the cardiac system to identify a specific disease. The diagnosis performance of this study shows the advantage of this system: it is rapid, easy to operate, noninvasive, and inexpensive. These technical and performance features of the proposed automatic classification algorithms point out the possibility of designing advanced assistance diagnosis systems.

Table 1 Comparison of different classification approaches on the same database

Methods	Features	Classifiers	Sensitivity (%)	Specificity (%)
Vernekar et al. [32]	Markov	Combination of XGBOOST and ANN	79.2	84.3
Grzegorzczak et al. [33]	Multidomain	Neural network	83	62
Tang et al. [34]	Multidomain	BPNN	81	86
Zabihi et al. [35]	Multidomain	20 Feed forwarding ANN	94.23	88.76
Goda et al. [36]	S1 width, DFT, DWT	SVM	82.7	91.7
Homsy et al. [37]	Multidomain	CSC, LB, RF	86	94.2
Langley et al. [38]	Wavelet analysis	Wavelet entropy threshold	95	60
Nilanon et al. [39]	Spectrograms, MFCC	Logistic regression (LR)	71	68.8
		SVM	82.6	83.2
		Random forest (RF)	68.7	68.5
		CNN	81	96
Rubin et al. [40]	MFCC	CNN	75	100
Potes et al. [41]	Multidomain	Combination of CNN and AdaBoost	94.24	77.81
Munia et al. [42]	Multidomain	SVM	76	88
The proposed method	Gram polynomials and FFT	RBPNN	93	91

BPNN back propagation neural network, *DFT* discrete Fourier transform, *DWT* discrete wavelet transform, *RF* random forest, *CSC* cost sensitive classifier, *LB* LogitBoost, *CNN* convolutional neural network, *ANN* artificial neural network

Table 2 Classification results of the proposed method

Accuracy (%)	Sensitivity (%)	Specificity (%)
94	93	91

7 Conclusion

In this study, we developed an expert diagnostic system for the interpretation of the PCG signals using Gram polynomials and probabilistic neural networks (PNN). The diagnosis performance of this method was demonstrated on a database of over 3000 heart beat sound recordings.

The stated results show that the proposed method can make an efficient interpretation with an accuracy, sensitivity and specificity of 94, 93 and 91%, respectively. Thus, it can be concluded that Gram polynomials and probabilistic neural networks (PNN) prove to be a very efficient technique using the PCG signal for characterizing heart diseases.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest.

Ethical standard This paper does not contain any studies with human participants or animals performed by any of the authors. On this matter we would also like to point out that our experiments, concerning data analysis and classification, has not directly been performed on human beings, but were concerning the off-line analysis of the signals obtained by a public database (see <https://physionet.org/challenge/2016/>) in order to grant more transparency and to use a safe data source also in terms of ethical approval.

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