

Autoregressive Modeling based ECG Cardiac Arrhythmias' Database System

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Abstract: This article proposes an ECG (electrocardiography) database system based on linear filtering, wavelet transform, PSD analysis, and adaptive AR modeling technologies to distinguish 19 ECG beat types for classification. This paper uses the Savitzky-Golay filter and wavelet transform for noise reduction, and wavelet analysis and AR modeling techniques for feature extraction to design a database system of AR coefficients describing the ECG signals with different arrhythmia types.

In the experimental part of this work, the proposed algorithm performance is evaluated using an ECG dataset containing 19 different types including normal sinus rhythm, atrial premature contraction, ventricular premature contraction, ventricular tachycardia, ventricular fibrillation, supraventricular tachycardia, and other types from the MIT-BIH Arrhythmia Database. The simulation is performed in a MATLAB environment.

Keywords — AR modeling, arrhythmia classification, Discrete Wavelet Transform, ECG noise analysis, power spectral density (PSD).

- 1) Sino-atrial (SA node) is a tiny structure located in the wall of the right atrium and the pacemaker is where the electrical impulse is generated.
- 2) Atria (two upper chambers - left and right atrium).
- 3) Ventricles (lower two chambers- left and right ventricles).
- 4) AV disk "AV node" (fibrous, nonconductive tissue that keeps the ventricles electrically isolated from the atria, the only conduction pathway between the atria and ventricles).

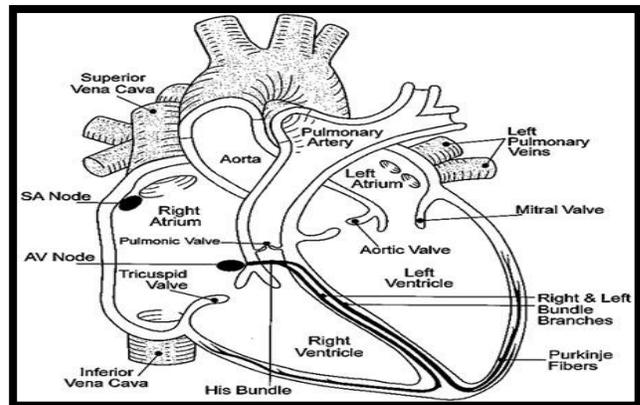


Figure 1. Schematic structure of the human heart

I. INTRODUCTION

This section describes the specific methods and techniques used in this research and an overview of other related scholarly work.

A. The physiological basis of the electrocardiogram

ECG definition: The ECG [1, 2] is one of the most clinically used biological signals that provide useful diagnostic information about the functional status of the heart and is used to estimate the rate and regularity of heartbeats, as well as to identify various heart infections and abnormalities.

The graphic recording of the ECG reflects the contraction and expansion activities of the heart muscle (direction and magnitude). It is obtained using electrodes attached to the skin of the human body over different areas of the heart, these activities are generated by an electrophysiological continuous process of depolarization and repolarization of the heart cells (atria and ventricles).

The heart consists of four chambers as shown in Fig. 1, from an electrical point of view the heart components are:

Components of the ECG waveform: The ECG time series is a well-structured signal, each beat is represented as a series of electrical waves characterized by peaks and valleys (P, QRS, T waves), with QRS being the most significant element.

The representation of a single normal heartbeat in the ECG signal is shown in Figure 2, the ECG is defined by waves, segments, and intervals as follows:

- ✓ The P wave corresponds to the sequential activation (depolarization) of the right and left atria, and indicates the beginning of the atrial contraction that pumps blood into the ventricles – an upright (positive) wave.
- ✓ The QRS complex reflects the depolarization of the ventricles (right and left ventricles are activated simultaneously) and indicates the beginning of the ventricular contraction, which pumps blood to the lungs and the rest of the body.
- ✓ The T wave corresponds to the repolarization of the ventricles - upright (positive) wave after QRS.
- ✓ The U wave represents the repolarization of Purkinje fibers – upright wave after T wave.

- ✓ PR interval: Time interval from the onset of the P wave to the onset of the QRS complex and PR Interval measures the time during which a depolarization wave travels from the atria to the ventricles (ventricular rate).
- ✓ QRS interval: Duration of ventricular muscle depolarization.
- ✓ QT interval: Time from the onset of the QRS to the end of the T wave, representing the duration of ventricular depolarization and repolarization.
- ✓ ST segment: The distance between the S wave and the onset of the T wave measures the time between ventricular depolarization and the beginning of repolarization.

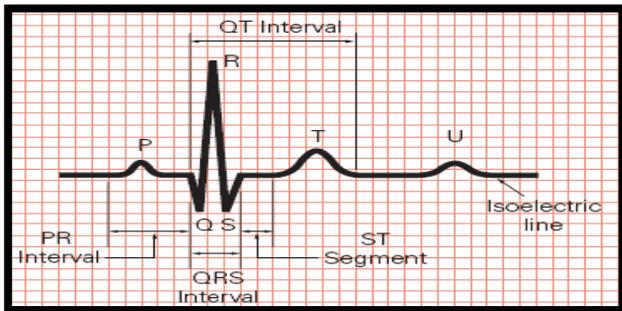


Figure 2. Typical one-cycle ECG recording

Analysis of a rhythm: Heart rate is calculated as the number of heartbeats per minute (bpm), the basic critical values of the heart rate parameter (HR) are the following:

- Normal rhythm (60–100 bpm).
- Tachycardia rhythm (increase in heart rate) - $HR > 150$ bpm.
- Bradycardia rhythm (slowing down of rhythm) - $HR < 60$ bpm.

Classification of cardiac arrhythmias: When the ECG is abnormal, it is called arrhythmia. Arrhythmias can be better understood by classifying them as follows:

- 1) Sinoatrial (SA) node arrhythmias– pacemaker in the Sinoatrial node.
- 2) Atrial arrhythmias– pacemaker in the atria.
- 3) Junctional arrhythmias– pacemaker in A-V junction.
- 4) Ventricular arrhythmias – pacemaker in the bundle branches, Purkinje network, or ventricular myocardium.
- 5) Atrioventricular (AV) blocks– impulse blockage in the A-V junction.
- 6) Bundle Branch Block (BBB) and Fascicular Blocks – impulse blockage in the bundle branches and sub-branches (fascicles).

The detailed classification version is shown in Fig. 3.

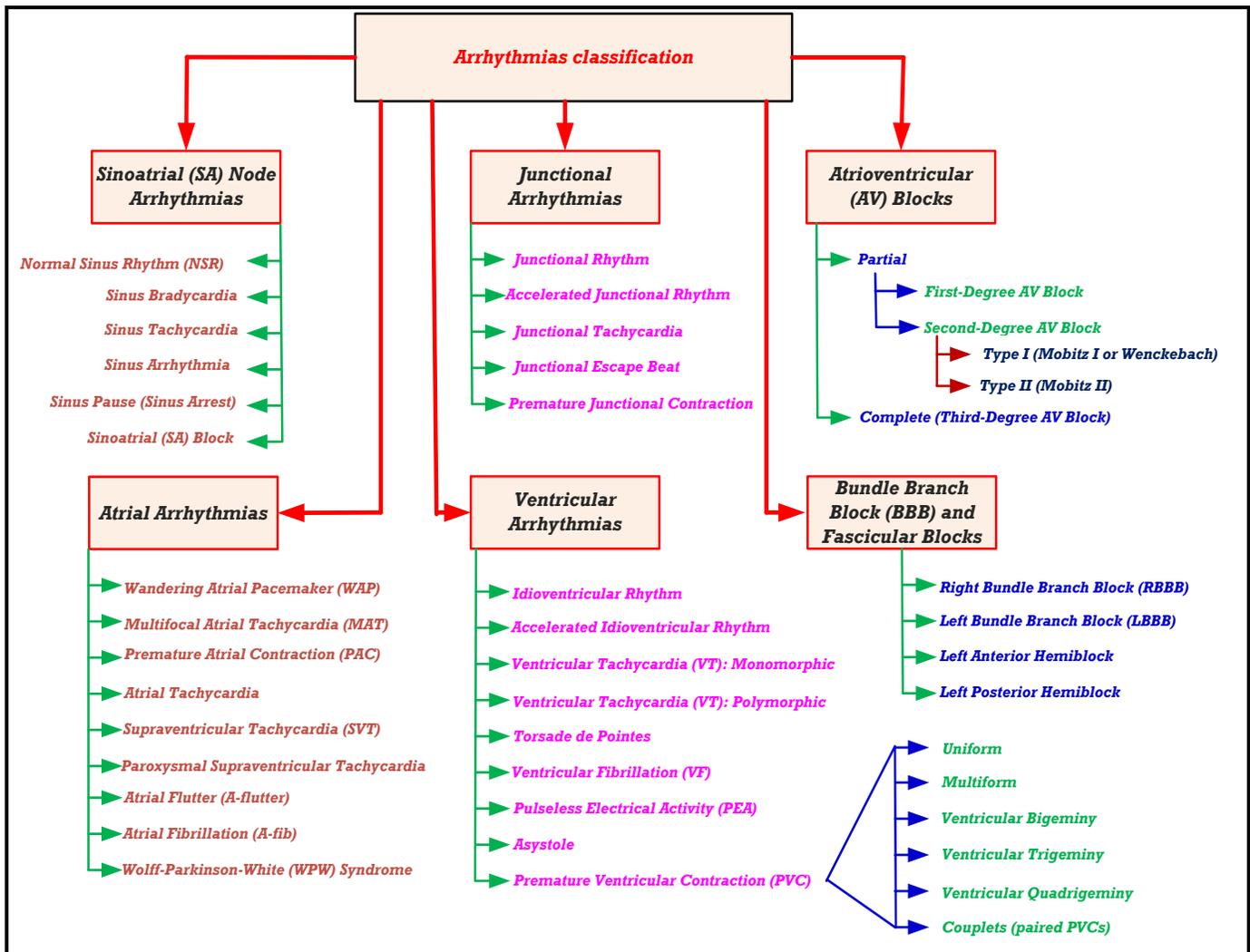


Figure 3. Classification of cardiac arrhythmias

B. MIT-BIH Arrhythmia Database

To analyze ECG signals with different beat types, several standard ECG databases are available to evaluate the research results as shown in Table 1; Most of these databases contain clinical manual annotation files.

Table 1. Standard ECG databases			
Ñ	Database Name	Sampling Frequency/Hz	Records
1)	European ST-T	250	90
2)	QT		100
3)	AHA database		80
4)	MIT-BIH (Used in research)	360	48
5)	CSE	500	1000
6)	TWA		100
7)	MEDSET	1000	----

In this work, the ECG signals from the PhysioBank database (MIT-BIH Arrhythmia Database [3, 4]) were chosen for analysis for the following reasons:

- PhysioBank databases are large and well-characterized digital physiological signals used by many researchers and referred to as a benchmark database by the biomedical research community.
- PhysioBank databases contain signals of considerably long duration (30-minute signals).
- PhysioBank databases contain recordings of different beat types (Normal, PVC, APC, LBBB, RBBB, etc.) with different QRS and ST-T morphologies and also contain low and high SNR ratio signals.
- Several tools and software support are available to analyze, view, convert from one format to another, and manipulate PhysioBank data.
- PhysioNet provides free web access to large collections of recorded physiological signals (www.physionet.org).

C. Theory of Discrete Wavelet Analysis

The wavelet transform (WT) represents an alternative to conventional spectral analysis, such as the Fast Fourier Transform (FFT) or the Gabor transform. The discrete wavelet analysis [5] is an effective and powerful analysis tool for a time-scale analysis of non-stationary Signals that can be found in the fields of medicine and biosignal processing. The WT

uses sub-band coding to decompose (project) a signal into two sub-signal parts using a set of wavelet basis functions, detail signal (cD) and approximation signal (cA). The detail signal contains the upper half of the frequency components (low scale) and the approximation signal contains the lower half (high scale).

The wavelet function, ψ , called the mother wavelet [5, 6], has:

- ✓ Zero mean value.
- ✓ Integrable and limited to a finite region (small wave):

$$\int_{-\infty}^{\infty} \psi(t) dt = 0.$$
- ✓ Total energy finite: $\int_{-\infty}^{\infty} |(\psi(t))^2| dt < \infty.$

In general, the mathematical expressions needed to obtain the discrete wavelet transform (DWT) coefficients of discrete time series $x(n)$, can be written as

$$W_{\varphi}(j_0, k) = \frac{1}{\sqrt{M}} \sum_n x(n) \varphi_{j_0, k}(n) \quad 1$$

$$W_{\psi}(j, k) = \frac{1}{\sqrt{M}} \sum_n x(n) \psi_{j, k}(n) \quad 2$$

Where $j \geq j_0$ and $x(n)$, $\varphi_{j_0, k}(n)$ and $\psi_{j, k}(n)$ are functions of discrete variables $n = 0, 1, \dots, M - 1$.

Equation (1) calculates the approximation coefficients and Equation (2) calculates the detail coefficients. The corresponding inverse discrete wavelet transform (IDWT) used to express the discrete signal in terms of the wavelet coefficients can be written as

$$x(n) = \frac{1}{\sqrt{M}} \sum_k W_{\varphi}(j_0, k) \varphi_{j_0, k}(n) + \sum_{j=0}^{\infty} \sum_K W_{\psi}(j, k) \psi_{j, k}(n) \quad 3$$

In general, several types of wavelet basis functions are available with different properties, e.g. B. Morlet, Mexican Hat, Coiflet, Symmlet, Meyer, BiorSplines, ReverseBior, Frequency B-Spline, Gaussian, Shannon, Haar, Daubechies, etc.

Motivation for using wavelets

- ✓ Simple, fast implementation with the reduction in computation time using the Mallats filter bank algorithm (linear complexity- $O(N)$).
- ✓ Optimally adjustable (varying) window size (wide for low frequencies and narrow for high frequencies, this can be a good solution to overcome the resolution problems present in Short-Time Fourier Transform (STFT)).
- ✓ Ability to fully reconstruct the signal from the wavelet decompositions.
- ✓ WT has good energy concentration properties: most DWT coefficient values are usually of very small value (referred to as a sparse representation of the signal) and can be discarded without a significant error in the reconstruction phase, which is useful for compression techniques.
- ✓ Decorrelated coefficients: The correlation of wavelet coefficients is much smaller than the correlation of the corresponding temporal process.
- ✓ Multi-Scale decomposition.
- ✓ Joint time-frequency localization.
- ✓ Features extracted from WT coefficients can efficiently represent the properties of the original signal at varying levels of detail.

D. AR modeling techniques

Autoregressive modeling (AR) [28, 29] has been used in various practical applications to analyze and synthesize the systems, including the classification of physiological signals such as ECG, EEG, heart rate, etc.

A general AR model of order p can be expressed as

$$x_n = \sum_{k=1}^p a_k x_{n-k} + e_n \quad 4$$

Using this formula, the AR model (parametric-based linear forward prediction model) can also be treated as an attempt to predict the current signal sample, x_n , based on p past values, x_{n-k} , of the signal weighted by constant autoregression coefficients, a_k , e_n the noise term. It is a crucial issue to determine the model order, which best fits the data when constructing an AR model.

The advantage of AR modeling is

- ✓ AR models are popular due to the linear form of the system.
- ✓ Suitable for real-time classification in the ICU or ambulatory monitoring.
- ✓ Suitable for spectra with sharp peaks but not deep valleys.

The AR methods used to compute the AR coefficients are:

- Burg method: AR by minimizing linear prediction errors (forward and backward errors); always produces stable models.
- Yule-Walker equations: spectral estimation of a time series from its estimated autocorrelation function; always produces stable models.
- Covariance method: AR by minimizing forward prediction errors; can produce unstable models.
- Modified covariance: AR by minimizing the forward and backward prediction errors; can produce unstable models.
- Linear Predictor Coefficient LPC (Levinson-Durbin recursion).

Measures of selecting the AR model order:

Different model orders were preselected to estimate the model order. To evaluate the order of the AR model, the information-theoretic measures used in this investigation to get the right order of the process were evaluated by:

- Finding the minimum of the Akaike Information Criterion (AIC), which is a function of the model order p :

$$AIC(p) = \frac{2p}{N} + \log V \quad 5$$

Where p is the model order, N - number of signal samples used for estimating the model parameters, V - residual noise variance.

- Minimize the root mean square error (RMSE) between the model-predicted signal samples and the actually measured signal samples.

This article proposes the AR modeling technique to classify 19 types of cardiac arrhythmias, namely: The algorithm aims to detect the following types of arrhythmias:

Normal, Left bundle branch block, Right bundle branch block, Bundle branch block (unspecified), Atrial premature, Aberrated atrial premature, Nodal (junctional) premature, Supraventricular premature or ectopic (atrial or nodal), Premature ventricular contraction, R-on-T premature ventricular contraction, Fusion of ventricular and normal,

Atrial escape, Nodal (junctional) escape, Supraventricular escape (atrial or nodal), Ventricular escape, Paced, Fusion of paced and normal, Unclassifiable, and Beat not classified during learning.

E. Pre-Processing of ECG

With real-time acquisition and transmission of the ECG signal, the ECG may contain noise signals superimposed thereon.

Because the ECG signal is very weak, the range between $110 \mu V - 4V$, it is easily affected by the various noises when collecting and recording, in some cases the strength of the noise will be greater than the strength of the signal, so the pre-processing of ECG signals will help us to remove unwanted components, reduce the noise present in the ECG and improve the signal-to-noise ratio (SNR) for more accurate analysis, it becomes an essential part of the right analysis process and is still a very important area of research.

Usually, the raw ECG signals are corrupted by various types of artifacts and noises, either physiological (other signals generated by different systems of the human body) or non-physiological (technical artifacts) in origin, which greatly affect the ECG signal analysis and can mask some important features of the ECG signal, examples of typical main noise sources are:

Technical artifacts such as:

- Electrical interference from power lines adding narrowband noise centered around the 60 (or 50 Hz) fundamental frequency of the power line, with a bandwidth less than 1 Hz and harmonics (120 Hz and 180 Hz, etc.) modeled as periodic sine waves and combination of sinusoids, this noise is the most dominant artifact.
- Impedance changes at the skin/electrode interface where the electrodes are not firmly connected to the patient, leading to some distortion.
- Quantization or aliasing errors.
- Noise produced by instruments or electronic devices used in signal processing circuits for data acquisition.
- Electrosurgical unit (ESU) interference generated by other medical equipment in the patient care environment when radio frequency signals (100 KHz-1 MHz) from the ESU used by surgeons during surgery interfere with the ECG.
- Poor channel conditions during ECG transmission.

Biological artifacts such as:

- Muscle contraction signals and muscle activity can generate low-amplitude, high-frequency electromyographic (EMG) noise that interferes with the ECG; This noise is extremely difficult to remove as it is in the same region as the actual signal, this noise is also one of the most annoying sources of noise.
- ECG waveform baseline drift is a low frequency component typically present in the range (0.1-2.5 Hz) in the ECG system. This is caused by the patient's breathing where the baseline begins to drift up and down in a sinusoidal pattern.
- Motion artifact is a low-frequency component generated due to patient movement.
- Bowel sounds contaminating the heart sounds (PCG).

De-noising ECG algorithms and techniques

On the other hand, technical artefacts can be eliminated by designing suitable measurement methods; Resolving biological artifacts is much more difficult and requires special signal analysis techniques. Researchers have worked to eliminate all of the above sounds and preserve the useful information needed for further analysis; Many DSP methods have been proposed as follows:

- ✓ Applying digital filtering methods:
 - Low-pass filter with a cut-off frequency of 45 Hz to remove unwanted high frequencies in the ECG signal.
 - Remove baseline drift [9]: To suppress it, the following solutions can be used:
 - Rectangular window-based digital filter: FIR or IIR high pass filter (Butterworth, Kaiser, Rectangular, Bartlet, Hamming, etc.) [13, 15, 16, 17].
 - A median filter can be applied to extract the baseline wander of the processed ECG signal, and then subtract it from the processed ECG signal.
 - High-pass filter with a cut-off frequency of 0.3 Hz can be applied.
 - Removing power line noise, for rejecting this noise the following solutions can be used [10, 17]:
 - Digital IIR notch filter [14].
 - Digital smoothing polynomial: Savitsky-Golay filter.
 - Band reject filter of cut-off frequencies 50 (or 60) Hz.
- ✓ Nonlinear adaptive methods [12].
- ✓ Polynomial fitting: third-order approximation where the baseline is estimated by polynomial approximation and then subtracted from the original raw ECG signal.
- ✓ Short Time Fourier Transform (STFT).
- ✓ DWT methods and techniques are used to eliminate the baseline shift and other broadband noise [18, 19, 20, 21, 23, 24, 25]: To remove the noise, specific wavelet details coefficients corresponding to the noise components were selected and discarded, and all other details were retained to reconstruct the signal without these components; This method removes low and high frequencies, a wavelet-based approach is better as this approach introduces no latency and less distortion and has different versions that can be used successfully like:
 - Wavelet coefficients threshold-based hyper shrinkage function [22].
 - Wavelet packets method [26].
- ✓ Signal averaging [7, 14, 24].
- ✓ Neural network.
- ✓ Genetic algorithms.
- ✓ Hilbert transform [8].
- ✓ Other methods [11, 27].

II. PROPOSED WORK - MAIN ALGORITHM AND DISCUSSION

The block diagram shown in Fig. 4 shows the actual implementation of the procedure proposed in this document, which consists of the following phases:

Stage 1: ECG data acquisition (raw time-varying biomedical signal): Different ECG signals have to be used for the analysis, for this case study the ECG signals from the

MIT-BIH database were selected

Stage 2: Savitzky-Golay Filtering (S-G Filter): Also known as polynomial smoothing or least-squares smoothing filters, these are generalizations of the FIR averaging filter that can better preserve the high-frequency content of the desired signal.

At this stage, an S-G filter can be used to solve the ECG signal noise problem associated with the mains interference. The following measures must be taken:

- ✓ Resampling conversion process to change the sample rate of ECG data sampled at 420 with a rational factor equal to 7/6 (interpolation in sample rate).
- ✓ Filter the newly created 420 Hz with Savitzky-Golay filter with appropriate polynomial order smaller than frame size to get 60 Hz filtered ECG signal.
- ✓ Using the resampling process (decimation of the sample rate) to get the original ECG signal without any interference from the power line.

Stage 3: removing other noises using wavelet decomposition process: filtering unnecessary data of the received ECG signal (passband 0.08-90 Hz) using wavelet technology. In this step, the following actions must be taken to improve the signal-to-noise ratio of the signal and to extract the features from the pre-processed signal:

- ✓ A 12-level DWT decomposition of the input ECG signal is performed using the Daubechies db6 type mother wavelet function, the frequency band associated with each scale is shown in Figure 5 and the decomposition level is assumed to be a high value, to ensure the existence of some low-frequency components of the original signal. In general, the figure shows the following:
 - A frequency above 100 Hz has no useful information (corresponding wavelet coefficients are changed to zeros).
 - Power line Interference lies in CD2.
 - QRS Complex lies in the frequency range between 10-50 Hz (CD2, CD3, CD4, and CD5).
 - T and P waves lie in the frequency range between 1-7 Hz (CD6 and CD7).
 - Baseline wander lies in the frequency range between 0.1-2.5 Hz (CD8, CD9, CD10, and CD11).
 - Low frequency noise (CA12 and CD12).
- ✓ As a result of the DWT decomposition, a set of wavelet subband signals (coarse approximation and details information) is obtained. Proper accumulation of selective reconstruction coefficients (approximation coefficients: CA12, details coefficients: CD1, CD8, CD9, CD10, CD11, and CD12 are discarded, changing to zeros) of the ECG signal must be performed to isolate the ECG signal from various noises.

Stage 4: Features extraction and selection:

Stage 4.1: Wavelet analysis.

- ✓ Sub-band decomposition with 6-level DWT: decomposition of the ECG signal into elementary building blocks (sub-bands with uniform frequency bandwidth: approximation A6 and details D1-D6).
- ✓ The reconstruction of each frequency sub-band can be performed separately to obtain sub-band signals

(A6_ECG from A6, D1_ECG-D6_ECG from the respective coefficients D1-D6). Features extracted from frequency subbands and their reconstructed signals can efficiently represent the properties and behavior of the original ECG signal [30, 31].

Stage 4.2: Building Blocks' PSD Estimation.

In this step, the PSD of all building blocks is calculated and estimated via the Thomson Multitaper Method (MTM), where the PSD is the distribution of power per unit frequency, as data windows, the discrete prolate spheroidal sequences or Slepian sequences (multiple orthogonal tapers).) are used, the outputs of this step are:

- PSD of the original ECG signal: ECG_PSD.
- PSD of wavelet approximation and details coefficients: A6_PSD, D1_PSD-D6_PSD.
- PSD of sub bands signals: A6_ECG_PSD, D1_ECG_PSD-D6_ECG_PSD.

Stage 4.3: Features extraction and selection process (choose the relevant information from the building blocks).

In this work, during this stage, AR modeling was performed on ECG data (30 building blocks) for normal ECG, as well as for various arrhythmias, the AR parameters were computed using the following model-based techniques [28, 29]: Burg method, Yule-Walker equations, Covariance method, Modified Covariance, and Linear Predictor Coefficient LPC.

In this stage, transformation techniques are used to generate the smallest set of features from a set of measurements that allows an acceptable classification rate to be achieved.

Two sub steps are required:

- ✓ Features extraction block (or features generation block).
- ✓ Features selection block (or dimensionality reduction block).

In the features extraction block, the following are performed:

- ✓ AR parameters (AR vectors) for 30 building blocks are calculated using the AR models and methods mentioned above with adaptive AR order (4, 6, 8, and 10).
- ✓ $N - T \times P$ matrixes are generated, and the dimension of the generated data for each ECG signal (Totally 48 ECG signals) is defined by the following formula:

$$ECG_{Matrixes_Dimension} = N \times T \times P \quad 6$$

Where N : number of building blocks (in our case, 30).

T : AR model types (5 types).

P : AR order (4,6,8 and 10- can be extended).

$$AR_{MAT} = T \times P \quad 7$$

Where AR_{MAT} is an $T \times P$ matrix whose columns contain the data vectors (AR model types).

The feature selection block uses techniques to select a subset of features from a larger pool of available features, reducing and discarding the less informative ones. The following is executed:

- ❖ Select the best AR values: the best AR values (vector: one column from each $T \times P$ matrix) for each building block using the following features minimization algorithm (see sub algorithm in Fig. 4).

Features minimization algorithm:

The procedure for selecting the best combination of features is demonstrated as follows:

- A. Construct the ECG signals using the contents of the AR matrix (different ECG signals depending on the AR type) with adaptive initial values needed for AR models (depending on the AR order) from the data itself and using the AR model equation.
- B. Calculate the mean square error of prediction (RMSE) according to the following equation:

$$RMSE = \sqrt{\text{mean}((ECG_{Data} - AR_{signal})^2)} \quad 8$$

Where ECG_{Data} the original ECG data, and AR_{signal} is the ECG signal created by using AR coefficients for each method and build RMSE vector contains the RMSE for all methods.

Remarks: There is no direct way to determine the correct model order; since as the order of the model increases, the RMS mean square error generally decreases rapidly to some order and then remains constant more slowly, so the RMSE is used for selection will be the correct order.

- C. Find the smallest RMSE (the indices of the minimum values in the RMSE vector).
- D. Assign the best solution to the smallest RMSE and store the AR coefficients for that solution.
- ❖ Construct the features vectors (for one ECG signal, one AR matrix for the given order).
- ❖ Normalize the AR matrix, as feature sets can vary quite a bit and a normalization process is necessary to standardize all features within predetermined ranges. This step is

performed to prepare the data for the clustering or classification process, in this step the range (minimum and maximum values) of each attribute (column in the AR matrix) is calculated and then the data is normalized according to the following equation:

$$Normalized_{data}(r, c) = \frac{Original_{Data}(r,c) - MinMax_{range}(1,c)}{MinMax_{range}(2,c) - MinMax_{range}(1,c)} \quad 9$$

Where

r is the row number,

c is the column number, and

$MinMax_{range}$ is the matrix that contains the minimum and the maximum values (the columns of the matrix) for each attribute (AR coefficients different bands).

❖ Building an ECG Database System.

Create a database containing text files with contents of AR matrices (general and normalized) for each ECG signal with the best AR order of (4, 6, 8, and 10). This database can be used as templates (reference ECG signals) to compare or match against a newly calculated AR matrix for an unknown ECG signal to determine the most appropriate pattern that class of ECG signal defined.

As examples of the best matrix contents, part of the AR matrix and the normalized AR matrix are shown in Tables 2 and 3.

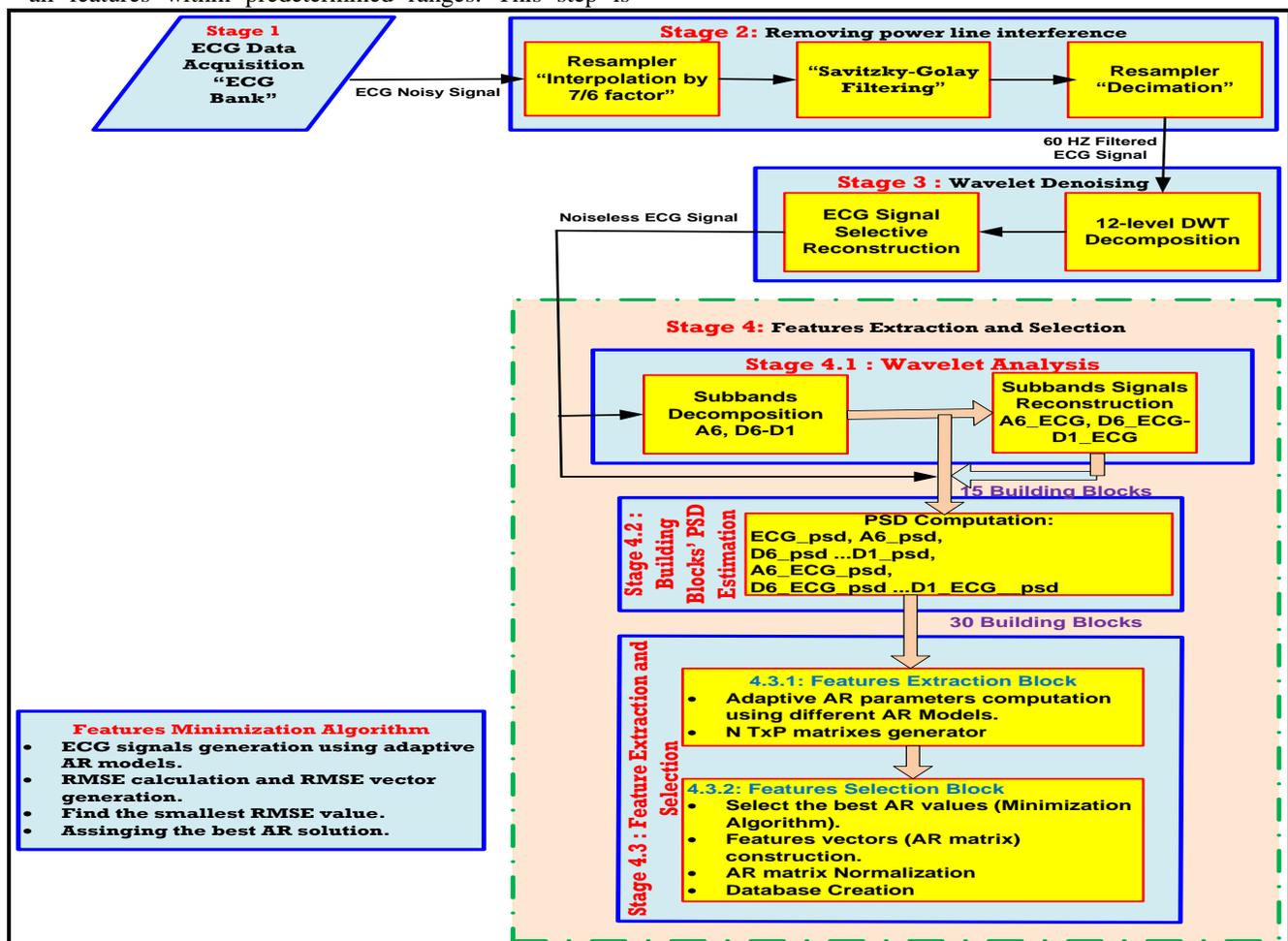


Figure 4. Schematic representation of the proposed method

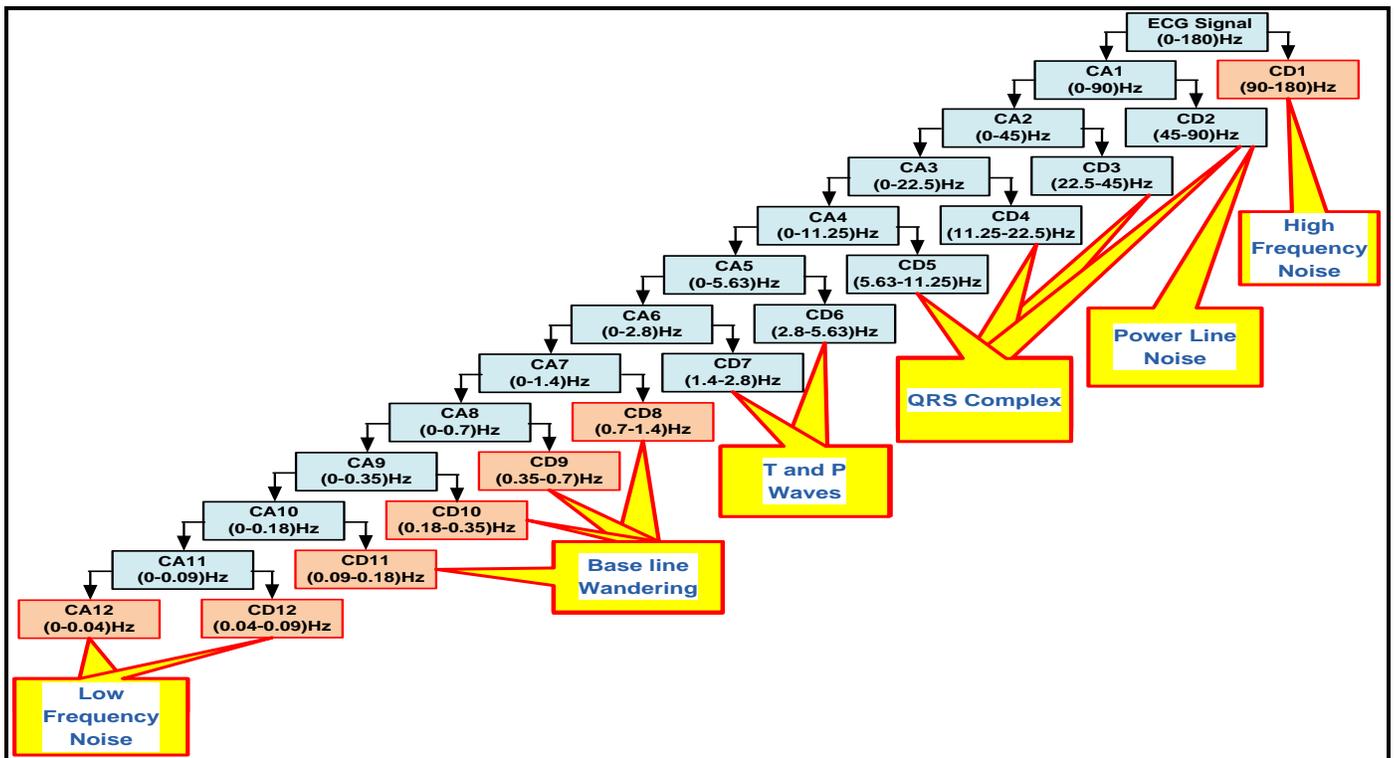


Figure 5. ECG signal's 12-level DWT decomposition

Table 2. AR matrix for MIT BIH (103 ECG signal with order 4)

Table 3. Normalized AR matrix (103 ECG signal with order 4)

-2.72	2.80	-1.26	0.20
0.77	0.01	-0.12	0.01
1.14	0.93	0.38	0.05
1.12	0.59	0.21	0.05
0.22	0.05	0.01	-0.00

0.057	0.892	0.292	0.649
0.910	0.249	0.785	0.431
1.000	0.459	1.000	0.478
0.995	0.382	0.926	0.474
0.776	0.257	0.842	0.414

III. CONCLUSIONS AND FUTURE IMPROVEMENTS

This article proposed an ECG beat database system based on linear filtering, wavelet transform, PSD analysis, and adaptive AR modeling technologies implemented in a MATLAB environment to detect different types of cardiac arrhythmias.

To evaluate the performance of the proposed algorithm, a dataset with different types of ECG signals from the MIT-BIH standard database was used, and the RMSE was used as criteria to evaluate the performance of the AR model to find the best AR representation for the given ECG signal to be obtained; The order of the AR model was chosen adaptively to extract the features.

The following results can be recorded:

- The experimental results demonstrate that appearance-based features extracted from wavelet coefficients, their reconstructed sub-signals, the PSD of wavelet

coefficients, and their reconstructed sub-signals can successfully capture the properties of ECG signals of different beat types and are suitable for their classification.

- The combination of different signal processing techniques applied to ECG signals: linear filtering, wavelet analysis, AR modeling, and PSD analysis are particularly well suited to study ECG analysis.
- The database of ARMA representation of wavelet coefficients can be used as a compact method for ECG interpretation and this result can be used for deep learning ECG classification.

Future work will address feature selection and classification as follows.

- Minimize the feature vectors using the PCA algorithm.
- Classify unknown ECG signals based on AR parameters with ANN neural networks.

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