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ESTUDIO COMPARATIVO DE ALGORITMOS PARA LA DETECCIÓN DE LA FIBRILACION AURICULAR

COMPARATIVE STUDY OF ALGORTIHMS FOR ATRIAL FIBRILLATION DETECTION

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Title Comparative Study of Algorithms for Atrial Fibrillation Detection

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Keywords:

Electrocardiogram (ECG), Atrial Fibrillation (AF), RR intervals Irregularity (RRI), Atrial Activity (AA)

Abstract:

Nine algorithms for Atrial Fibrillation (AF) detection were evaluated using the same protocol. The public databases MIT-BIH Arrhythmia and AF from PhysioNet were employed for the evaluation and comparison of these nine algorithms. Their performances were reported not only in terms of sensitivity (Se), specificity (Sp), positive predictive value (PPV), and error rate (Err), but also in terms of window length, input signal length, robustness to noise and computation time. These algorithms are based on the analysis of two characteristics observed in ECGs with AF: RR intervals Irregularity (RRI) and a chaotic atrial activity (AA). This AA can be analyzed in frequency (FA) and/or in time domain (P wave absence, PWA). Five algorithms were based on RRI; one algorithm was based only on AA; and the last three algorithms combined RRI with AA techniques.

Conclusions:

- AF detection algorithms are based on two main characteristic that this arrhythmia shows in an ECG: RR intervals Irregularity (RRI) and atrial activity properties (AA), which are due to the P wave absence
- The techniques based on RRI and RRI - AA combination for AF detection have higher performance than the ones based on AA analysis.
- Addition of AA analysis can improve AF detection, by incrementing Specificity.
- Techniques based on RRI are the most robust against noise.
- An algorithm based on RRI required the shortest signal length (10 seconds) to detect AF.
- RRI based algorithms have the lowest computational complexity.
- RRI+AA combination algorithm is proposed as a future algorithm to obtain better results.

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List of abbreviations

Acronym	Description
AA	Atrial Activity
AE	Approximate entropy
AF	Atrial Fibrillation
AFL	Atrial Flutter
ANN	Artificial Neural Networks
AR	Autoregressive model
bpm	Beats per Minute
BW	Baseline Wander
CCE	Corrected Conditional Entropy
CV	Coefficient of Variation test
DFT	Discrete Fourier Transform
DRR	Difference between successive RR intervals
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
Err	Error
FA	Frequency Analysis
FFT	Fast Fourier Transform
FN	False Negative
FP	False Positive
HMM	Hidden Markov Model
ICA	Independent Component Analysis
KS	Kolmogorov Smirnov test
LA	Left Arm
LL	Left Leg
LPC	Ventricular Premature Beats
MDW	Neural Network
MM	Markov Model
NN	Neural Networks
NPV	Negative Predictive Value
PPV	Positive Predictive Value
PSD	Power Spectrum Density
PVC	Premature Ventricular Contraction

PWA	P wave absence
RA	Right Arm
RRI	RR intervals Irregularity
SDH	Standard Density Histogram
Se	Sensitivity
SNR	Signal Noise Ratio
Sp	Specificity
SWT	Stationary Wavelet Transform
T Acc	Total Accuracy
TH	Threshold
TN	True Negative
TP	True Positive
TPR	Turning Points Ratio
VA	Ventricular Activity
VPB	Ventricular Premature Beats
WN	White Noise

1 Introduction

This chapter contains the description of the problem and the motivation of this work. In addition the structure of the report will be summarized.

1.1 Problem Description and Motivation

Atrial Fibrillation (AF) is the most common sustained arrhythmia. Although it is not a lethal disease, it may be lead to severe complications such as cardiac failure and atrial thrombosis, with the subsequent risk of a stroke [2]. Thus, detection of AF becomes decisive in the prevention of cardiac threats.

Several algorithms for automatic real time of AF detection in ECGs can be found in the literature. However, these techniques are evaluated differently. The database used for training and evaluating, the techniques used in the signal pre-processing and some other specifications are different in each paper.

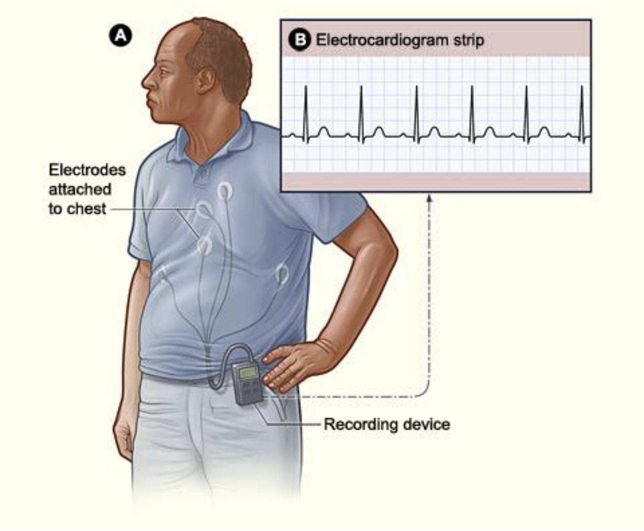


Figure 1- Automatic real time AF detection

Therefore the use of the same evaluation method seems required with the aim to evaluate and compare the different techniques. This study analyzed nine different methods for AF detection using the same evaluation method, which implies the same procedure and database. As a result the strengths and disadvantages of different techniques were determined and the future algorithm proposed.

1.2 Synopsis

The rest of the document is organized as follows:

- Chapter 2 describes AF, and the literature's methods description for AF detection
- Chapter 3 gives the evaluation method description
- Chapter 4 explains the nine tested algorithms
- Chapter 5 presents the results obtained
- Chapter 6 contains a discussion on the results with conclusions, limitations, the future lines of work and a proposed algorithm.

2 Background

This chapter provides a brief description of cardiology and Atrial Fibrillation (AF), and also contains a background about heart and electrocardiograms. Secondly different methods for AF detection and the pre-processing used on those have been described. Finally a brief discussion is made based on the published results.

2.1 Cardiology Basics

2.1.1 Heart

The heart, a hollow muscular organ, is divided in four chambers [3]: the right and left atria, and the right and the left ventricles (*Figure 2*).

The heart has a natural pacemaker - the sinoatrial (SA) node - sends out “regular” electrical impulses from the right atrium causing it to contract and pumps blood into the bottom chamber, the ventricle. The electrical impulse is then conducted to the ventricles through a form of 'junction box' called the AV node. The impulse spreads into the ventricles, causing the muscle to contract and to pump out the blood. The blood from the right ventricle goes to the lungs, and the blood from the left ventricle goes to the body [3].

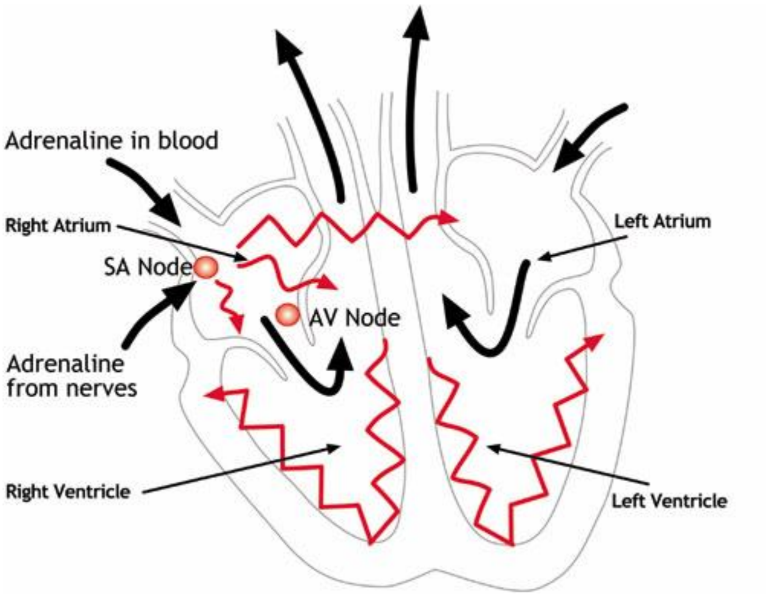


Figure 2 - Anatomy of the heart [4]

2.1.2 Heart rate

Heart rate is the number of heartbeats per unit of time – typically beats per minute (bpm) - which can vary as the body's need to absorb oxygen and excrete carbon dioxide changes, such as during exercise or sleep. The measurement of heart rate is used by medical professionals to assist in the diagnosis and tracking of medical conditions. For an adult, a normal resting heart rate ranges from 60 to 100 beats per minute (bpm) [5]. This rhythm occurs as a result of regular electrical discharges (currents) that travel through the heart and cause the muscle of the heart to contract.

2.1.3 Electrocardiogram (ECG)

2.1.3.1 Definition

An electrocardiogram (ECG) is the noninvasive graphical visualization test that records the electrical activity of the heart [6]. By positioning leads (electrical sensing devices) on the body, usually in standardized locations, ECG collects different waves which are studied and interpreted.

2.1.3.2 ECG waves

A typical clean ECG from a healthy person consists of a P wave, a QRS complex and a T wave as it is shown in Figure 3. The signal amplitude is 0.1 to 1 mV, and frequently contains undesired signals of similar amplitude ranging from very low frequencies (respiration at about 0.2 Hz) to high frequencies (muscle noise up to about 200 Hz).

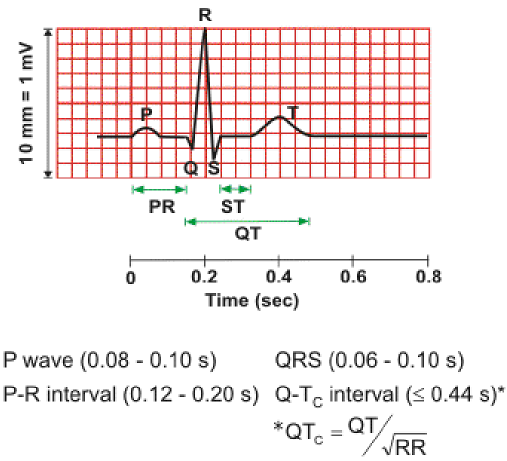


Figure 3 - ECG waves [6]

P wave: represents the initiation of the heartbeat, atrial depolarization that spreads from the SA node towards the AV node.

QRS complex: is the result of the rapid depolarization of the right and left ventricles. The amplitude is higher because of the larger size of ventricles.

T wave: represents the depolarization (or recovery) of the ventricles.

2.1.3.3 Electrodes and ECG leads

The electrical currents generated by the heart are commonly measured by an array of electrodes placed in standardized locations [6]. The system of positioning of leads for performing a 12-lead ECG is universal. It is measured using 10 electrodes. By convention, the first 4 electrodes are placed on each arm and leg, and 6 electrodes are placed at defined locations on the chest. These electrode leads are connected to a device that measures potential differences between selected electrodes to produce the characteristic ECG tracings. It includes three limb leads, three augmented unipolar leads and six chest leads.

- Limb Leads (Bipolar)
- *Lead I:* difference between the two arms. $V_I = \Phi_{LA} - \Phi_{RA}$

The other two limb leads, an electrode on the right leg serves as a reference electrode for recording purposes.

- *Lead II*: positive electrode left leg; the negative electrode right arm. $V_{II} = \Phi_{LL} - \Phi_{RA}$
- *Lead III*: positive electrode left leg; the negative electrode left arm. $V_{III} = \Phi_{LL} - \Phi_{LA}$

These three bipolar limb leads roughly form an equilateral triangle (with the heart at the centre) that is called Einthoven's triangle as shown in Figure 4.

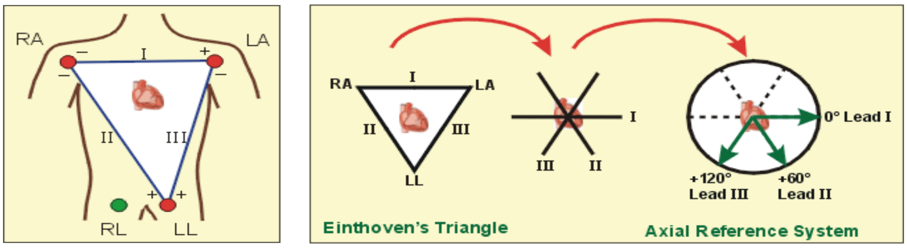
Positions:

RA: On the right arm, avoiding bony prominences

LA: In the same location that RA was placed, but on the left arm this time.

RL: On the right leg, avoiding bony prominences.

LL: In the same location that RL was placed, but on the left leg this time.



- Figure 4- Einthoven's Triangle [6]Augmented Limb Leads (Unipolar)

The three augmented unipolar limb leads are termed unipolar leads because there is a single positive electrode that is referenced against a combination of the other limb electrodes. The positive electrodes for these augmented leads are located on the left arm (aV_L), the right arm (aV_R), and the left leg (aV_F). In practice, these are the same electrodes used for leads I, II, III.

- Chest Leads (Unipolar)

This configuration places six positive electrodes on the surface of the chest over different regions of the heart in order to record electrical activity in a plane perpendicular to the frontal plane *(*Figure 5*)*. These six leads are named V_1 - V_6, and corresponding positions are defined in Table 1.

Table 1: V_1 – V_6 leads position definition

V_1	In the *fourth* intercostal space (between ribs 4 & 5) just to the *right* of the sternum (breastbone).
V_2	In the *fourth* intercostal space (between ribs 4 & 5) just to the *left* of the sternum.
V_3	Between leads V_2 and V_4.
V_4	In the fifth intercostal space (between ribs 5 & 6) in the mid-clavicular line (the imaginary line that extends down from the midpoint of the clavicle (collarbone)).
V_5	Horizontally even with V_4, but in the anterior axillary line. (The anterior axillary line is the imaginary line that runs down from the point midway between the middle of the clavicle and the lateral end of the clavicle; the lateral end of the collarbone is the end closer to the arm.)
V_6	Horizontally even with V_4 and V_5 in the midaxillary line. (The midaxillary line is the imaginary line that extends down from the middle of the patient's armpit.)

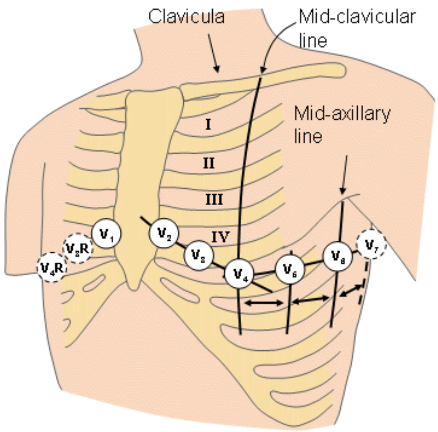


Figure 5 - Chest Leads [7]

2.2 Atrial Fibrillation (AF)

2.2.1 Definition

Atrial fibrillation (AF) [2], like Atrial Flutter (AFL), is the most common, abnormal rhythm of the heart. Electrical discharges in the atrium are irregular and rapid and, as a result, the heart beats become irregular and, usually, rapid.

It can often be identified by taking a pulse and observing that the heartbeats do not occur at regular intervals. However, a stronger indicator of AF is the absence of P waves on an electrocardiogram (ECG), which is a non-invasive cardiac monitoring technique used to detect AF.

In addition, since AF cases can be asymptomatic, medical professionals sometimes have to rely on incidental findings of AF on the ECG or during physical examination. It can be quite impractical for doctors to go through the ECG manually, especially for cases where the occurrence of AF episodes are random and a long term ECG recording is required in order to extract the irregularity or abnormal activity for further evaluation.

This justifies the implementation of automatic AF detection algorithms, which should be good enough to be considered.

2.2.2 Function of the heart during atrial fibrillation

During AF, electrical discharges are not generated solely by the SA node. Instead, electrical discharges come from other parts of the atria. These abnormal discharges are rapid and irregular and may exceed 350 discharges per minute. The rapid and irregular discharges cause ineffective contractions of the atria. In fact, the atria quiver rather than beat as a unit. This reduces the ability of the atria to pump blood into the ventricles [2].

The rapid and irregular electrical discharges from the atria then pass through the AV node and into the ventricles, causing the ventricles to contract irregularly and (usually) rapidly. The contractions of the ventricles may average 150/minute, much slower than the rate in the atria. (The ventricles are unable to contract at 350/minute.) Even at an average rate of 150/minute, the ventricles may not have enough time to fill maximally with blood before the next contraction, particularly without the normal contraction of the atria. Thus, AF decreases the amount of blood pumped by the ventricles because of their rapid rate of contraction and the absence of normal atrial contractions [5].

The rate of ventricular contraction is less than the rate of atrial contraction. The rate of ventricular contraction in AF is determined by the speed of transmission of the atrial electrical discharges through the AV node. In people with normal AV node, the rate of ventricular contraction in untreated AF usually ranges from 80 to 180 beats per minute; the higher the transmission, the higher the heart rate [3; 4].

2.2.3 Consequences

AF is often asymptomatic and is not in itself generally life-threatening, but it may result in palpitations, fainting, chest pain, or congestive heart failure. Heart failure results in the accumulation of fluid in the lower legs (edema) and the lungs (pulmonary edema).

People with AF usually have a significantly increased risk of stroke (up to 7 times that of the general population). Stroke risk increases during AF because blood may pool and form clots in the poorly contracting atria and especially in the left atrial appendage (LAA). One common complication of AF is a blood clot that travels to the brain and causes the sudden onset of one-sided paralysis of the extremities and/or the facial muscles (an embolic stroke). A blood clot that travels to the lungs can cause injury to the lung tissues (pulmonary infarction), and symptoms of chest pain and shortness of breath. When blood clots travel to the body's extremities cold hands, feet, or legs may occur suddenly because of the lack of blood.

2.2.4 Treatment

AF may be treated with medications which either slow the heart rate or revert the heart rhythm back to normal. Synchronized electrical cardioversion may also be used to convert AF to a normal heart rhythm. Surgical and catheter-based therapies may also be used to prevent recurrence of AF in certain individuals. People with AF are often given anticoagulants to protect them from stroke [6].

2.2.5 ECG with AF

Figure 6 represents a normal ECG from a healthy person. The rhythm is regular - each beat is at similar distance from the next beat which means that the time between each beat is similar. The rhythm strip is the long tracing on the bottom of the ECG which shows several continuous seconds of the heart. This allows us to look at the rhythm of the heart, and determine the heart rate. Moreover atrial activity (AA) is also regular and P wave could be distinguished clearly in some leads, such as Lead II in Figure 6.

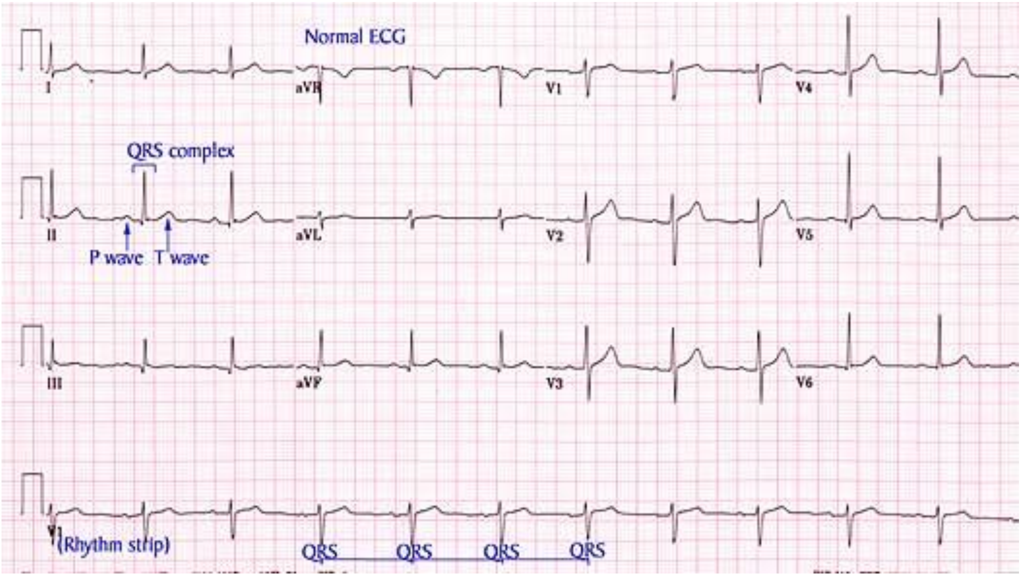


Figure 6 - Normal ECG of a healthy person (P wave is present and heart rhythm is regular) [8]

Figure 7 represents an ECG with Atrial Fibrillation. It reflects many of the changes we have discussed previously that take place in the heart. The most obvious differences are the absence of the P wave (Leads I, II, III and V1 show the classical appearance of AF, the "undulating baseline") and the other major change is that the heart rhythm is no longer regular. The distance between each QRS complex in the rhythm strip is variable meaning that the timing of each beat is irregular. There is no pattern to the irregularity, so the rhythm of AF is called "irregularly irregular".

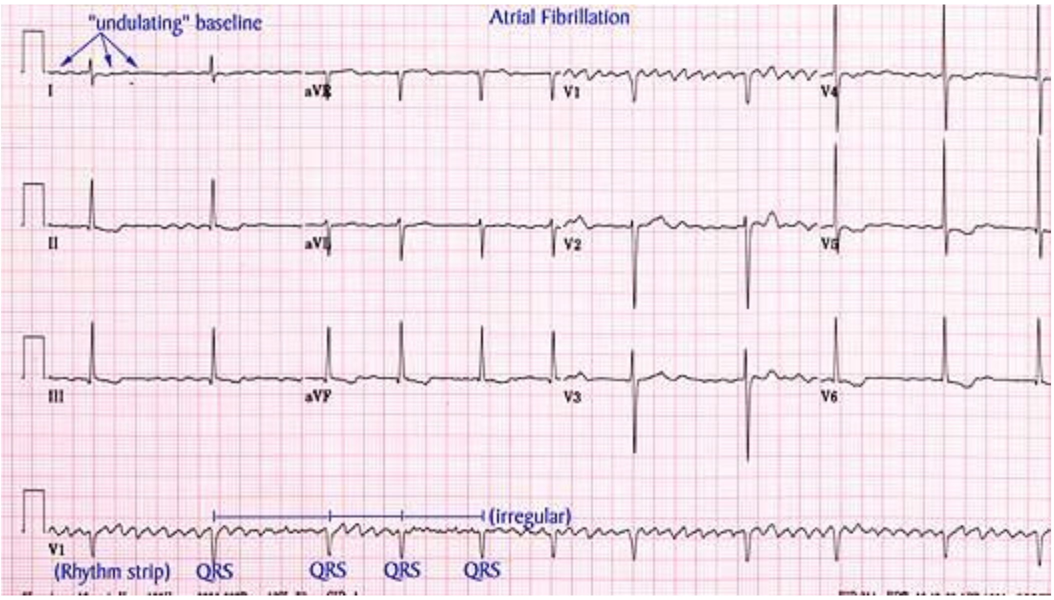


Figure 7 - ECG with AF [8]

2.3 Methods for Atrial Fibrillation Detection

AF detection methods from literature are explained, along with signal pre-processing techniques, and the database and the evaluation method employed for the different methods. Finally a brief conclusion from the literature is included.

2.3.1 Pre-processing the signal

Signal pre-processing is done to avoid some of the inconveniences that the signal presents. It also involves fiducial points (R peak) detection and signal segmentation.

2.3.1.1 Filtering

The ECG usually contains undesired signals like Baseline Wander (BW), muscle noise and power line interferences. They tend to cause false detections and therefore ECG filtering is necessary to improve the algorithms.

Baseline Wander (BW) is a low frequency component due to various sources of recording noise, including patient movement, respiration, and mechanical displacement of the ECG leads. A high pass filter with a cutoff frequency of about 0.5Hz-1Hz to cut off the lower-frequency components are used to remove BW.

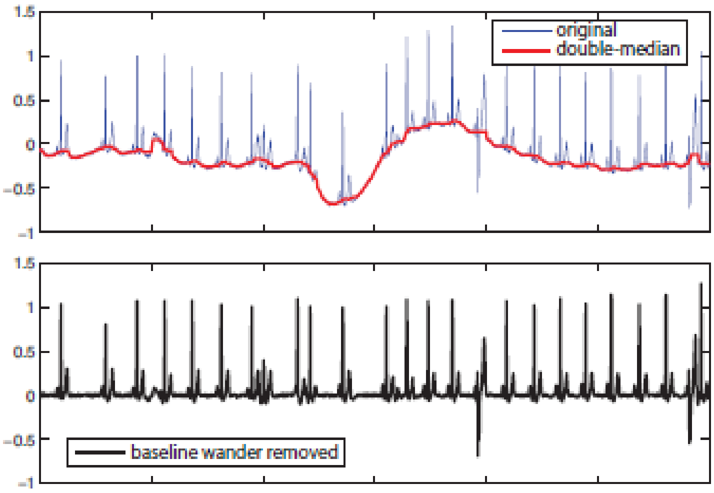


Figure 8 - Baseline Wonder removal

Power line filter: Electromagnetic fields from power lines can cause 50/60 Hz sinusoidal interference, possibly accompanied by some of its harmonics, which is desirable to filter.

Muscle noise filtering: Muscle noise can cause severe problems, and low-amplitude waveforms, such as the P wave, can be masked especially in recordings during exercise. The spectral content of the noise considerably overlaps with that of the ECG signal.

2.3.1.2 Ectopic beat filtering

Premature Ventricular Contractions (PVC) or Ventricular Premature Beats (VPB) during regular sinus rhythm could lead to false detection of AF due to the effect in irregular rhythm. For this reason, numerous methods exclude them from the signal by considering the annotations within an annotated database [8; 9; 10; 11] or by applying an automatic PVC detector [12] .

On the other hand, Tatento et al [13; 14] commented the problem of PVC, but they did not filter them in order to be consistent with real ECGs. Accordingly they assumed that their test sometimes classified rhythms with frequent PVCs as AF.

2.3.1.3 Noise level estimation

If the noise level on the signal is high, the original signal becomes difficult to be distinguished. Therefore, Ying's study [15] identified the noisy parts of the signal in order to exclude them.

2.3.1.4 Fiducial points (R peak) detection

QRS complex, or R peak, is the main characteristic within the ECG to determine and to identify each beat, as it is the larger point of the signal for each beat. Consequently R peak detection is needed to determine Heart Rate or RR intervals as well as to decide and analyze each heart beat interval individually.

Some authors applied automatic methods for beat detection [13-17]. For example, Ying [15] used Pan Tomkins et al [16] beat detection algorithm which consist on analysis of the slope, amplitude, and width of ECG signal. Ita [17] applied a threshold in time in order to detect the peaks (*Figure 9*).

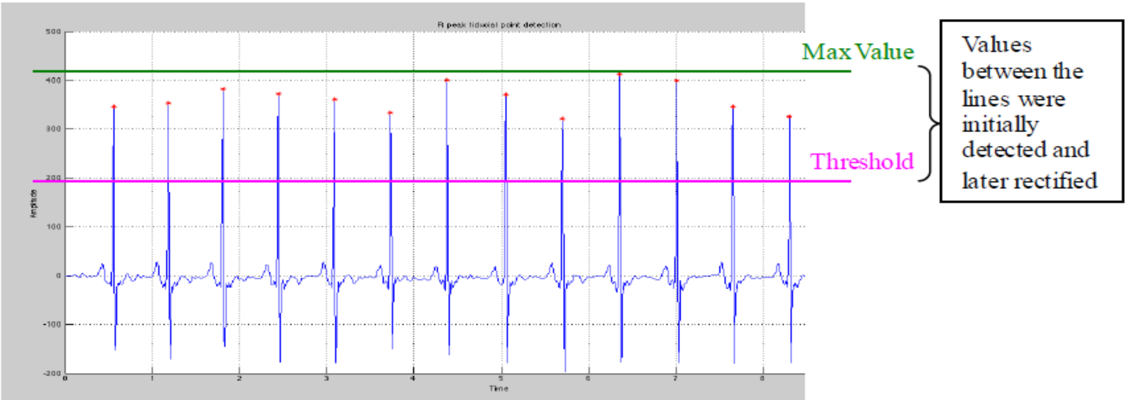


Figure 9 - An example of an ECG, with the R-peak detected as indicated in red [17]

Logan [18] used WQRS technique [19] which provides a morphology independent QRS detector. This allows an accurate detection regardless of the different morphology of the QRS complex. Since, due to the different electrode position on the body, the R-wave can either be upwards or downwards; or can even have both up and down deflections. Figure 10 shows that regardless of morphology the signal can be transformed allowing the detection of the peak.

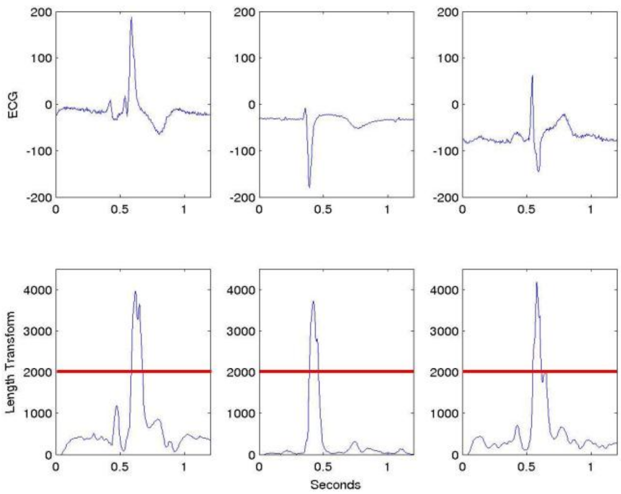


Figure 10 - Demonstration of the effect of the length transform on three ECG morphologies [18]

Some authors used the annotations included within an annotated dataset such as the MIT-BIH Arrhythmia database for fiducial point detection [1].

2.3.2 Methods description

AF detection algorithm usually employs RR intervals Irregularity (RRI) and/or Atrial Activity (AA) analysis as the most important characteristics of AF in ECG signal. The AA analysis is based on the P wave morphology and location, and signals frequency and power spectrum.

2.3.2.1 RR intervals Irregularity (RRI)

Several methods have been reported for AF detection based only on beats interval irregularity, but also combining it with AA analysis. Irregularity was measured by simple techniques, like variance of selected RR intervals and variance of the difference between successive RR intervals (DRR); or by more complex methods such as Markov Models and Hidden Markov Models, Neural Network and different statistical frameworks.

Markov Model (MM)

It is based on the probabilities for transitions between states [20]. For AF detection, a MM is applied characterizing each RR intervals as a representative of one of three states {short (S), long (L), regular (R)} depending how they vary with regards to the RR interval mean value.

Based on the transitions between the states (Ti, i=1, 2 ... 9) a transition matrix, S, is created for a sequence of non-AF rhythm sequence and for AF sequence. The regularity of heart rate is characterized by higher probability of transition in RR (regular to regular), since this transition is more likely to occur when RR intervals present approximately the same length (no-AF sequences). When AF is present, the probability is more distributed between all the transitions and Regular to Regular transition is less common.

Non AF AF

$$S = \begin{pmatrix} SS & SR & SL \\ RS & RR & RL \\ LS & LR & LL \end{pmatrix} \qquad \begin{pmatrix} SS & SR & SL \\ RS & \boldsymbol{RR} & RL \\ LS & LR & LL \end{pmatrix} \qquad \begin{pmatrix} \boldsymbol{SS} & \boldsymbol{SR} & \boldsymbol{SL} \\ \boldsymbol{RS} & RR & \boldsymbol{RL} \\ \boldsymbol{LS} & \boldsymbol{LR} & \boldsymbol{LL} \end{pmatrix}$$

Moody and Mark [9] constructed MM to detect AF. Dividing non-AF rhythm matrix by those of the AF transition matrix, and applying a logarithm, the S_{ij} matrix is defined. This matrix is more likely to contain negative elements when AF is present than otherwise because non-AF transition matrix will contain most of the transitions between regular to regular intervals and AF transition matrix more distributed. Consequently MM suggest that a sequence of n intervals can be classified by simply adding n-1 appropriately chosen elements of S_{ij}, and declaring AF if the sum is negative.

For the purpose of improving the results got from Markov process model, an extension of the method was performed applying interpolation in S matrix (to reduce the quantification error in S matrix) and filtering (to reduce noise in the signal).

Moody et al [9] is a common reference for later works. In Schmidt Patents [21], published on 2008, one of the features, based on RR intervals, directly uses Moody's algorithm to measure the irregularity of the RR intervals. Besides, Ying's [15], Babaeizadeh et al [22] and Kurzweil et al [23] used Markov modeling approach, combined with other features. Artis et al [24] implemented a generalized interval transition matrix, to use as an input to a neural network (NN).

Couceiro et al [25] also, used the fact that probabilistic distribution when AF presents is more disperse in the transition matrix (not too concentrated in regular to regular transitions), applied the entropy of the distribution.

$$D_{KL}\left(P(x,y),\overline{P_{AF}(X,Y)}\right) = \sum_{x=1}^{3}\sum_{y=1}^{3} P(x,y)\log\left(\frac{P(x,y)}{\overline{P_{AF}(x,y)}}\right)$$

With this results and using the ***Kullback–Leibler*** divergence (D_{KL}), the similarity between the distribution $P_{AF}(x, y)$ and the distribution under analysis ($P(x, y)$) was evaluated. Based on this parameter and combining with other features, AF was detected in the signal.

Hidden Markov Model (HMM)

In HMM the states are not directly visible, but the observations are probabilistic functions of the state and can be computed from the training set since the underlying states are known from the reference annotations. For AF detection, RR intervals are classified as one of seven possible observations {very short, short, slightly short, normal, slightly long, long, very long} and a transition matrix created.

In ***Young et al*** [8] the HMM model algorithm was applied and compared with some other statistical methods, finding the best performance for HMM. Besides, in ***Bock's technique*** [26] one of the structures used to determine AF is based on HMM analysis.

Other Statistical methods applied to RR and DRR intervals

- RRvar: $\frac{RR_i - RR_{i-1}}{\overline{RR_\iota}}$.

If $RRvar$ was greater than $\%\overline{RR_\iota}$ (a specific percentage of the average heart rate) the rhythm was considered AF [8].

Ghodrati et al [11] considered $RRvar$ (where $\overline{RR_\iota} = 0.9 * \overline{RR_{\iota-1}} + 0.1 * RR_i$). Based on that, Neyman Pearson (NP) detection approach [27] was used assuming Laplace and Gaussian distribution functions for the data, and these values were compared with a threshold to determine the presence of AF.

Gaussian: $L_1(x) = \sum_{i=1}^{N} x_i^2 > \varphi_1$ Laplace: $L_2(x) = \sum_{i=1}^{N} |x_i| > \varphi_2$ where xi=RRvar

- RRnorm variance: $\mathrm{Var(RRnorm)\ where\ RRnorm} = \frac{RR}{\overline{RR_n}}$

$\overline{RR_n} = 0.75 * \overline{RR_{n-1}} + 0.25 * RR$ (where RR is the current R-R interval).

Logan et al [18] algorithm presented three variants: $RRvar$, $Var(RRnorm)$, and $Smoothed\ Var(RRnorm)$. $Var(RRnorm)$ incorporated beat normalization to the first test and $Smoothed\ Var(RRnorm)$ used a simple majority voting scheme over 600 beat windows applied to the previous result of RRnorm variance.

- Normalized Absolute Deviation (NADev) (M intervals): $NADev = \sum_{i=1}^{M} \frac{|RR_i - \overline{RR}|}{M * \overline{RR}}$
- Normalized Absolute Difference (NADiff) (M intervals): $NADiff = \sum_{i=2}^{M} \frac{|RR_i - RR_{i-1}|}{(M-1) * \overline{RR}}$

NADev and *NADiff* were used in ***Ghodrati et al*** [10]. To identify AF, two thresholds were defined which were called THR_{dev} and THR_{diff} respectively.

- RR100 algorithm:

This is an up/down counter which depends of RR interval differences that exceed 100 milliseconds and it is also used by ***Young et al*** [8] . When the counter exceeded 6, the rhythm was considered AF.

$$RR_i - RR_{i-1} > 100ms \rightarrow count = count + 1$$
$$RR_i - RR_{i-1} < 100ms \rightarrow count = count - 1$$

- Contextual analysis:

The contextual analysis, which was used in *Bock's* [26], determines a percent similarity between consecutive RR intervals in a buffer. If all the intervals are within the acceptable difference between them, less than a determined Threshold, then the rhythm is considered not irregular enough for AF.

- Median of medians

Linker's technique [28] determined RR_i intervals, within consecutive segments (J-1, J, J+1...) separately. The mean value of each segment was subtracted from each RR interval of the same segment, obtaining "absolute deviation from mean" (Di= $|RR_i$-m(J)|). The median of absolute deviation for each segment was determined, and finally the median of absolute deviation of segment J, together with the adjacent segments, J-1 and J+1. If the median of medians of all the segments was greater than a threshold, then the existence of AF was probable. Otherwise, AF was unlikely to exist during the determined segment J.

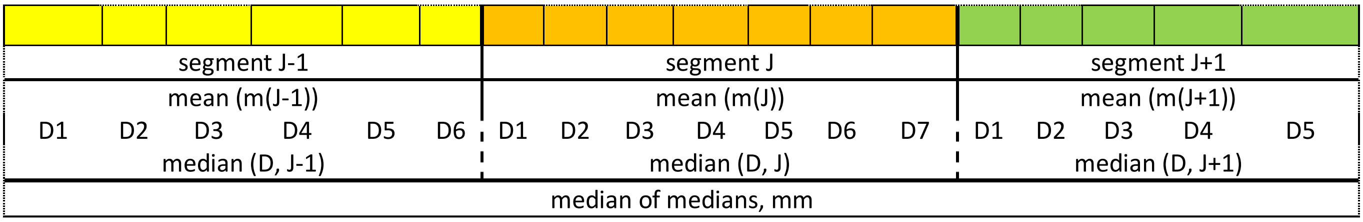


Figure 11 - Example of three segments of RR intervals and how the method is applied

- Kolmogorov Smirnov test (KS)

KS test can be used to test whether two probability distributions differ. For RRI the difference between the actual density histogram and the standard density histogram defined previously is determined and a p value is returned.

Tatento et al [13; 14] used KS test in distributions created from RR intervals and DRR intervals. Firstly different standard density histograms for RR and DRR intervals were created depending on the mean value of RR intervals of the signal segment, collected during AF periods, and classify in different classes represented by its mean (350-399 ms, 400-449ms etc).

To test if AF was present in a signal segment, firstly the mean value of the RR intervals of the segment was calculated and determined to which class correspond. Subsequently RR and DRR intervals distributions of this segment were compared by Kolmogorov Smirnov test with the respective standard density histograms of the class that belongs.

If p value (from KS) was greater than certain value (Pc), then it was said that the distributions are not significantly different. In this case, since the standard density histograms represented AF, if p>Pc, the hypothesis that the test distribution was not AF failed and was associated with a positive identification of AF.

The standard density histograms were determined taking each 100 successive beats block of Atrial Fibrillation and depending on the mean value of those, they were compiled in 9 different classes for the standard density histogram of RR and DRR [13].

The parameters of the KS test were optimized by defining the standard density histograms for 50 successive beats during AF and classify in 16 different classes [14].

- Coefficients of variation (CV test):

CV= $\frac{\sigma}{\mu}$, where σ is the standard deviation $= \sqrt{\frac{\sum_{i=1}^{N}(xi-\mu)^2}{N}}$ and μ is the mean.

CV test was applied in ***Tatento et al*** [14] and the results were compared with KS test. CV of both RR and DRR intervals were approximately constant during AF. Therefore CV of RR and DRR in a test record were compared with the standard coefficients of variation, obtained from the standard density histogram, and if the CV was within the standard coefficient of variation $\pm R_{cv}$% (acceptable range of CV), the rhythm was labeled as AF.

- Main distribution width (MDW)

MDW is used to discriminate between non-AF and AF distributions, similar to KS test, which was used by ***Petrucci et al*** [29], and in this work it was applied for two different types of histograms:

DRR histogram: To characterize the histogram the first empty beans on the right and on the left of the modal value from the histogram were taken. The difference between these two beans was a representative value for Main Distribution Width (MDW) and used to discriminate between non-AF and AF.

RR Prematurity histogram (P): To characterize P histogram, the following parameters were considered: number of non empty bins (NEB), MDW, difference between mean and median and geometric test of bimodality. Different decision rules and thresholds were defined for indentifying AF onset or offset.

$$P(i) = \frac{RR(i) - RR_{mean}}{RR_{mean}} \times 100$$

- Linear Predictive Coding (LPC)

It is a method used to predict the future outputs using past samples. The coefficients used for LPC are derived from parametric spectral estimation obtained with maximum entropy method (MEM) [30]. Once the calculation is done, the predictor error is taken as an indicator of AF. If the rhythm, obtained from RR intervals in a segment, is abnormally irregular, such as AF, the prediction error will be high and the segment of the signal would be considered AF [8].

- Approximate entropy (AE)

It is a measure of signal randomness. To compute AE, segments of the signal containing several RR intervals are compared with themselves. For this, correlation sum is computed and this measurement is then converted into a probabilistic value which is the AE measurement. AF will yield significantly higher AE values than other values, and based on it AF will be declared [8].

- Turning Points Ratio (TPR)

On the other hand ***Dash et al*** [12] described a robust algorithm based on the randomness, variability and complexity of RR intervals employing a new statistic, TPR. TPR tested the randomness of the time series, and combininig it with other tests, as the Root Mean Square of Successive RR Differences (RMSSD) and Shannon Entropy, AF arrhythmia is characterized. The condition for AF classification was given if certain conditions based on thresholds and simple logical “AND” were fulfilled.

Artificial Neural Networks (ANN)

ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. ANN training requires appropriate data, pre-processing and post-processing algorithms, an appropriate network topology, and a training algorithm, to be able to classify AF and non-AF subset [24].

Artis et al [24] employed interval transition matrixes, similar to that discussed by Moody [9], as input to an ANN. Sliding window of intervals until the end of the data was used, obtaining different interval transition matrixes, in order to improve the performance.

A Neural Network (NN) was created with 9 possible transitions between the states {short, regular, long}. The output layer consisted of one unit which was trained to represent AF as 1.0 and 0.0 otherwise (*Figure 12*).

For the analysis, 30 RR interval moving segments were considered and an output value obtained for each segment. Once 30 outputs from ANN were collected the average was calculated. This number was compared with two thresholds, T1 and T2. If the number exceeds the higher threshold the given interval was labeled as AF. If the number was lower than the low threshold then the beat label was left unchanged from its original value. And if it was between the two thresholds, the assigned label was the same as the previous assigned label *Figure 12*.

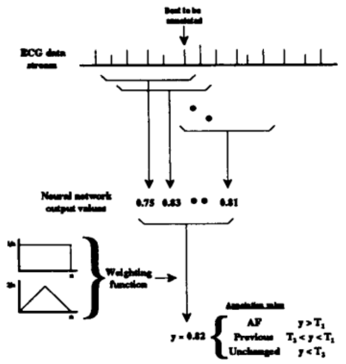


Figure 12- Post-processing ANN output data using a 6-point moving average [24]

Spectral analysis based on RR intervals

In AF the ventricular response to the irregular activation of the atria produces a **pseudo white-noise** (WN) pattern in the RR series and a **wide-band spectrum**.

Cerutti et al [31] proposed a time-variant identification of a linear Autoregressive (AR) Modeling Parameter and non linear Corrected Conditional Entropy (CCE) methods based on WN property.

Two parameters were extracted from AR modeling: percentage of power (P) which may be predicted by the model in order to assess the characteristics of predictivity; and the maximum modulus among the model poles (M). The closer the pole was to the origin of the z-plane (M tends to zero), the wider was the peak which models the presence of the wide band oscillation on the series, and so RR irregularity and AF presence.

$$P = \left(1 - \frac{\sigma_e^2}{\sigma_{rr}^2}\right) * 100 \qquad\qquad M = \max\{|z_k|\}$$

Conditional Entropy (CE) measured the regularity of a time series and values of CE close to zero mean high regularity, while CE increased in presence of WN.

Time-Frequency analysis of RR intervals

Wavelet Transform of Heart Rate Intervals was used by ***Duverney et al*** [32]. The identification of AF required the use of a cascade of two sequential complementary analyses of RR intervals: Discrete Wavelet Transform (DWT), identifying periods of high RR intervals Irregularity (RRI) coefficient, and Fractal Analysis, classifying these high variability periods into sinus rhythm or AF rhythms.

2.3.2.2 Atrial Activity (AA) analysis

There are several methods that use AA study based on P wave location measurement, P wave morphology, and AA spectrum and power to detect AF.

P wave absence (PWA)

AF detection based on P wave is based on the idea that ECG should have no P wave and it displays a chaotic baseline instead. When the noise is high, a detector could be tricked into extracting noise instead of a P wave.

- P wave morphology

- P wave template matching

Template-Based Matching algorithm analyzes the similarities between the actual ECG with a template created. Based on AF characteristic (absence of the P-wave or a chaotic shape), template matching was mainly focused on the P wave, and PR section of a cardiac cycle.

The methods used for template creation are different. K-means clustering method was applied for a representative P wave in Wild test [33]. In Suzana's [17] several templates were obtained from PR. Couceiro et al [25] extracted a P wave model by averaging all annotated P waves found in QT database from Physionet [1], and Bock's [26] extracted the "favourite" template from the signal as well. Furthermore the templates were manually selected in some studies [34].

Once the templates were created, the methods used to detect AF, are the following:

In ***Wild's*** [33] the comparison between the templates and the actual P wave was performed using a statistical procedure of *One-Way analysis of variance (ANOVA)*. The obtained value was compared with a given threshold and in the case that in a sliding window the majority of the P waves ware marked as AF, then the current P wave was labeled as AF and the window shifted.

Dotsinsky's method [34] applied the convolution equation outside QT interval, taking the odd samples only from the optimal length of 120ms as a template.

$$C(t+7) = \frac{\sum_{k=0}^{14} S(t+k) * Te(k)}{0.3 * \sum_{k=0}^{14} [|S(t+k) - Te(k)] + 0.001} \quad t = 1, 2...$$

This equation was applied twice to improve the P wave detection. First template was shifted to locate the first term Te(1) closely to the corresponding samples of the signal S(t). Then, such shifting is done toward the middle template term Te (8). And finally the results for both convolutions were summed.

$$C_{sum}(t+7) = C_{fst}(t+7) + C_{mid}(t+7)$$

P wave occurrence was marked when the current summary convolution exceeded an adaptive threshold and the decision rule for AF recognition was applied on a window of four RR intervals, which was shifted, and associated with AF segment.

Ita [17] considered samples from a short interval after the previous beat (after T wave) to the point before the R peak. When the ECG was within the maximum and the minimum threshold, determined by the templates, they flagged it as "1" (*Figure 13*) and the similarity percentage was calculated by counting the total number of samples that fell within the threshold range against the total number of samples extracted. If the percentage match was above 70%, it would be flagged as a positive match. AF was considered if consecutive cycles match positively with the same template.

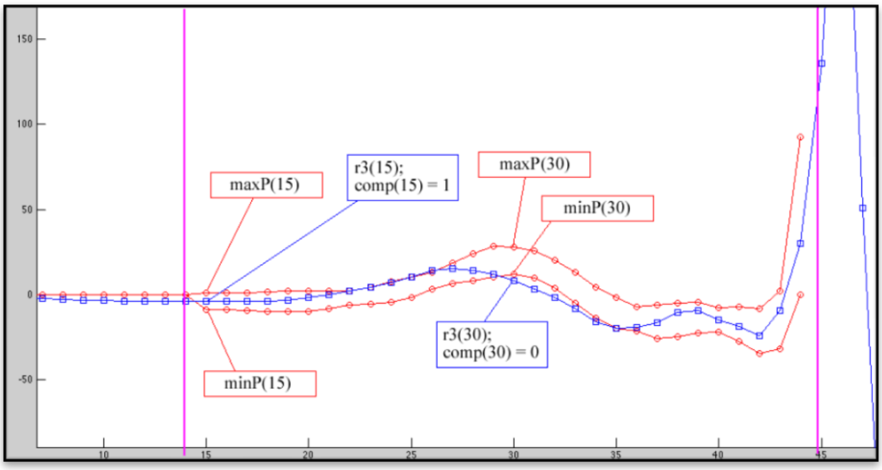


Figure 13 - View of the thresholds (in red) and ECG (in blue) [17]

Also ***Babezaideh et al*** [22] studied the similarity measure between 2 consecutive P waves. In sinus rhythm, the P waves usually match well when the signal is not noisy, and in AF, the match is usually poor.

- P wave location:

In AF, due to the absence of P wave and irregular heart rate, P wave location, i.e. P-R interval, is too long or not measurable. In a normal sinus rhythm P-R is around 0.12-0.20 seconds long. Based on that, P-R interval variation and T-P segments are analyzed to detect AF.

P-R is defined as the time between the onset of P wave to onset of QRS, and it is related with AF when it is large or non measurable. ***Babaeizadeh et al*** [22], after combining RR interval Markov score with P wave morphology and this P wave location measurement, included a corrector and hysteresis counter. A final decision tree statistical approach was used to classify these groups as either AF or non-AF.

T-P interval was defined by ***Christov et al*** [35; 36] from T_{offset} to P_{onset} using a "flatness" criterion according to Daskalov et al [37]. PQ and QT intervals also were measured using the following formulas:

$$QT = 0.4\sqrt{RR} \qquad\qquad PQ = \frac{RR - \frac{RR*90}{100}}{0.4}$$

AF and AFL detection was done based on three different tests: P wave test to verify the lack of P wave, arrhythmia test based on RR intervals variation, and AA test, which measures the residual atrial activity in TP interval.

P wave lack was considered by the ratio AFF_{PQ}/AFF_{TP}, where AFF_{PQ} is the quantitative AA index in the P_{onset} - QRS_{onset} interval, and AFF_{TP} is AA index in the TP interval. The condition of AFF_{PQ} being twice the value of AFF_{TP} was considered as a threshold value for the P wave test; and P wave absence was considered in case that $AFF_{PQ} < 2*AFF_{TP}$.

Kurzweil et al [23] employed P wave detection at a specific time within TQ interval. Then, using also RR variation measure, an indicator of an AF condition was produced.

Frequency and spectrum analysis (FA)

The spectrum of the QRST overlaps the spectrum of the atrial activity. Therefore, QRST cancelation is required to suppress the ventricular activity before Fast Fourier Transform (FFT) or Discrete Fourier Transform (DFT) is applied in the following algorithms. This process usually involves demarcation of QRS complex and T-wave boundaries, which may become difficult if the measured signal is noisy and the waveform is masked.

Frequency and power spectrum density (PSD) in the remainder AA segment of the ECG is also one of the most common analysis to detect AF. That is because AF has a higher energy concentrated in the 4-9Hz band than regular rhythms. In *Slocum el al* [38] it was reported that the percentage power of the peak in the 5-9Hz was greater than or equal to 32% of the total power in the group of rhythms with AF. While in the other group (no AF) around 14% of the total power was generally concentrated in this range of frequencies. *Chang et al* [39] studied that if the number of peaks in PS diagram was only one in the 3.5-9Hz band, the input signal was considered AF; if there was not peak or a PS diagram had more than one peak itself, the case was classified as non-AF.

- Power study based in frequency bands analysis

In Slocum et al [38] , the power ratio in each 8 Hz band between 2 and 57 Hz to the total power was calculated. The frequency with the largest amplitude was located in the 2-57 Hz range of the power spectrum. All the frequencies containing less than 10% of the maximum power were set to zero (to suppress noise) and total power was recalculated. The point with the maximum amplitude in 5-9Hz region was noted and the amount of power in the 2Hz wide band around this maximum was evaluated.

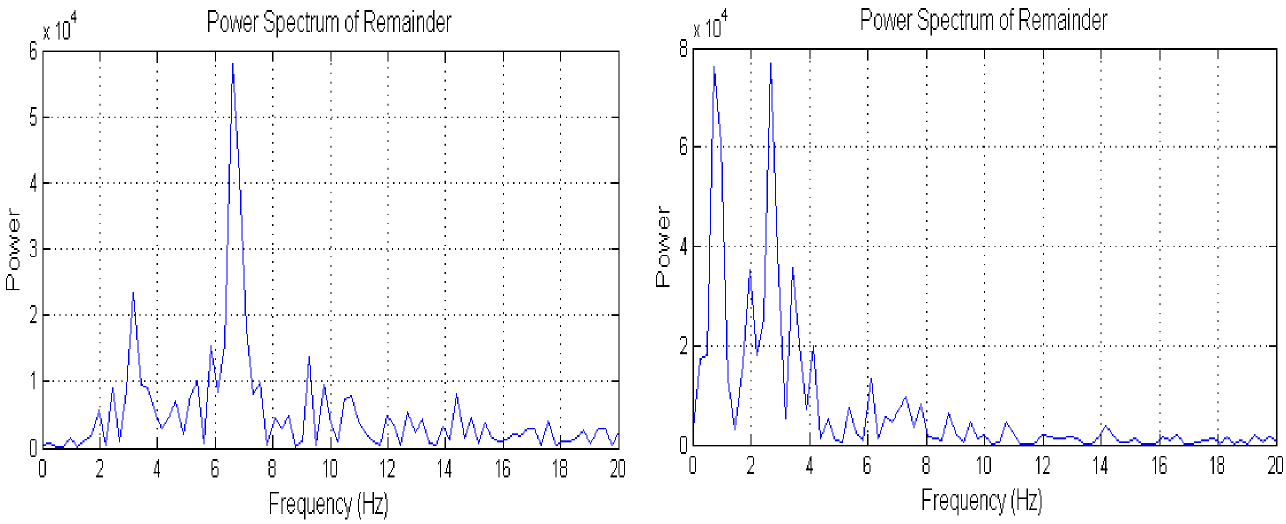
The first step in Slocum et al was to test in each rhythm the presence of the P wave. If P waves were detected, the rhythm was considered non AF and no further test was done. If the rhythm did not have P waves, taking into consideration that the power in the 5-9 Hz range was significantly different in the group of AF (higher), the rhythm was considered AF if power percentage of the 2Hz wide band was greater than or equal to 32% of the total.

Chou et al [40] calculated 10 Hz bins summing components (between 0 and 10 Hz, 10 and 20 Hz, and so on) and computed the power by taking the log of these sums, and normalizing them. Frequencies above 200 Hz reflected noise in the signals and were considered not representative.

In the detection, to classify sections of a 30-minute record, a test window which slides through the record was considered. From each window 10 features were extracted, combining Fourier Transforms, wavelet transforms, and RR interval analysis, and a linear discriminant applied (Gaussian discriminant). The windows output was 1 for AF detection (0 otherwise) and when the normalized cumulative sum of all outputs of the test window was greater than 0.5 the positive alarm for arrhythmia was considered.

In Ying's [15], the power spectrum (PS) was computed per blocks. In the case of AF ECGs the absolute power was concentrated in the frequency band 4-10Hz, exhibiting a narrow and great power component in this frequency band. From this information power ratio, percentage of the absolute power in the 5-10Hz band (and 4-10 HZ band) to the total power from 0-125Hz was estimated. Also peak ratio (the total ratio of the number of the number of heart beats exhibiting maximal power in the 4-10Hz frequency band to the amount of beats in the ECG block) was calculated (Figure 14).

Finally, the different features from three groups (RR interval, P wave morphology and frequency properties) were combined in different ways and AF was determined using several classifiers.



(a) AF *(b) Non-AF*

Figure 14 - Frequency spectra from the signals in (a) AF case and (b) non- AF case

Chang et al [39] classified the signal as AF if it was only one peak in the 3.5-9Hz band of PS diagram. Otherwise, if there was not peak or a PS diagram had more than one peak itself, the input was classified as non-AF. But before applying PSD analysis, different steps were followed. Firstly, 12 lead data was needed. In a multichannel signal process such 12 lead ECG data, Independent Component Analysis (ICA) was made with the objective to separate AA from ventricular activity (VA). For all the data applied by ICA, the result was resorted by Kurtosis measurement, and finally Second-Order Blind Identification (SOBI) algorithm. SOBI can separate the mixed uncorrelated sources and PSD analyzed the transformed sources from SOBI to determine is AF is present.

Schmidt's method [21] extracted some features based on frequency domain properties applying absolute bands of PSD spectrum extending from 10, 20, 30, 40, 60, 80Hz and 125 Hz:

$$P(F) = \frac{\sum_{f=F}^{125} PSD}{\sum_{f=0}^{F} PSD}$$

The results were combined with other features. At least two of the methods were used: RR interval measure (using Moody's algorithm [9]), frequency domain properties, and presence or absence of P waves. In order to reduce the dimension of the feature space it was possible to use a decision tree algorithm or various different classifiers.

- Power study based on the main peak

Couceiro et al [25] studied the level of concentration around the main peak and its position in the 4-10 Hz interval. The concentration of each spectrum is assessed by calculating the entropy of each normalized ECG window spectrum. Based on the spectrum from MIT-BIH AF database, a specific spectrum model was extracted, Q(x), and the similarity between it and the spectrum under analysis P(x), was related with the likelihood of being an AF episode.

P wave absence, RRI and frequency properties in AA were combined for the final measurement (*Figure 15)*. The proposed classifier consists of a three layer feed-forward neural network [41].

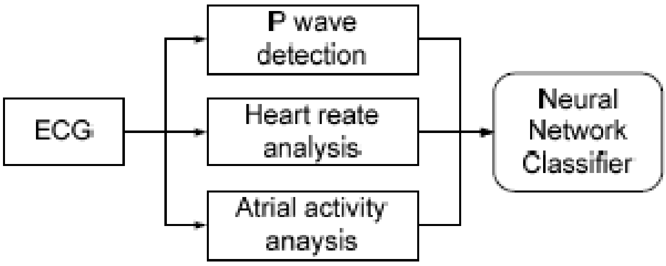


Figure 15 - Architecture of Couceiro's algorithm [25]

In order to preserve both time and frequency resolution ***Weng et al*** [42] used Stationary Wavelet Transform (SWT) analysis to extract features form ECG without the QRST cancellation step *Figure 16*.

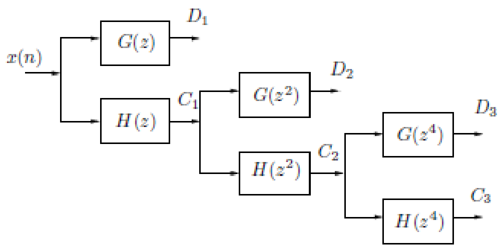


Figure 16 - Three level stationary wavelet transform [42]

The frequency content of SWT wavelet coefficients gave a way to quantify the AF fibrillatory waveform. In AF 4-9 Hz range was frequency range of interest, so peak-to-average power ratio (PAR) was linked with the power distribution profile in the AF frequency band. The spectral characteristics which were of wavelet coefficients were extracted as features, and they were selected using Fisher's Discriminant Ration (FDR). A linear classifier was applied thereafter to determine AF detection.

$$\zeta_{i[c]} = \frac{P_{\mathrm{peak},i[c]}}{P_{\mathrm{avg},i[c]}} \qquad P_{\mathrm{peak}} = \max_{f \in F_{af}} S(f)$$

$$\zeta_{i[d]} = \frac{P_{\mathrm{peak},i[d]}}{P_{\mathrm{avg},i[d]}}, \qquad P_{\mathrm{avg}} = \frac{1}{F_{\max} - F_{\min}} \int_{F_{\min}}^{F_{\max}} S(f)df.$$

Kurzweil et al [23] suggested various methods to detect AF combining the spectral measures and/or the time domain models, such as RR variability measure (Markov Model) and AA measure (presence or absence of P waves). But also the approach applied spectral analysis to TQ interval in order to determine primary atrial frequency from peak and signal to noise measure for peak. If the peak to noise quality was high, and the magnitude of the detected AA surpassed a threshold, then the frequency of the peak was used to determine an indication of AF.

2.3.3 Database

The databases used to evaluate the different algorithms in literature are often not the same. Also in some algorithms more than one database is used. Therefore the results of the same algorithm could be different depending on the database used.

On the other hand, the methods which need a training set or development set before the evaluation might change the design depending on this database used and the accuracy of AF detection is compromised (Markov [9], HMM [8], KS [10; 11], ANN [24] or the methods which need a P template). They are dependent on the quality of the training data. For example if the characteristics that define AF, like RR interval length, are different from those learned in the training data, the accuracy of AF detection is compromised.

The main database, used for most of the algorithms, is MIT-BIH AF Database. MIT-BIH Arrhythmia Database also is a common database, which was often utilized for development or training set. Some of the algorithms used only part of the data based on their own judgment [9; 11; 12].

Various algorithms employed a database from other resources, their own database or a combination of several databases. Sofia Medical Faculty Hospitals ECG records [36; 35], Schiller database [34], Draeger database [11] and Belt database (Philips) [15] are the databases used for some of the algorithms studied. They are not public and they are used in specific algorithms, so they will not be considered in this study.

- Excluded signals

Premature Ventricular Contractions (PVC) that some signals contain, were not considered in some of the algorithms due to the fact that PVC can be indentify as AF. It is caused by the RR irregularity that PVC also present. Consequently, although some algorithms possess high sensitivity, they can have a low positive predictive value (PPV) when a database that contains lot of PVC is evaluated [14].

In Ying's test [15], noise level in the signal was estimated to exclude the high noisy part before the evaluation, and as a result it is expected to get better performance.

- Signal window length or number of beats

Finally, the number of beats or the window length of the signal required for the method to identify AF plays a decisive role, since determine the algorithms resolution and the time of response.

Depending on the type of process used to determine if AF the following effects were distinguish. If the detection was made for each beat (or P wave, depending of the method) short term fluctuations and false-positive alarms could happen. To reduce the number of short false-positive episodes a hysteresis counter may be used [9; 22]; or a sliding window classification method, which consider the previous beats, or a segment of several beats, to determine the state of one beat [33].

Detecting AF based in a large segment involves a loss of resolution. Both false negatives and false positives could occur due to the fact that inside the segment both AF and non AF episodes could be present. In the case where the segment is declared as AF, the non AF episodes of the segment will be erroneously determined, resulting in false positives. Also when non AF is considered for whole segment false negatives will occur in the beats inside this segment that are AF. Nevertheless the identification of AF by sequences is more robust against noise.

Therefore it is interesting to evaluate the algorithms depending on the length that it is introduced. Tatento et al [14] studies how the length of the segment affects detection and determines the most suitable segment length.

2.3.4 Evaluation Method

The performance of the algorithms is evaluated by calculating sensitivity (Se), specificity (Sp), positive predictive accuracy (PPV), and error rate (Err) values. These values are standard statistics used to measure the performance of ECG arrhythmia analysis algorithms. But also Negative Predictive Value (NPV), False Positive Rate (FPR) and Total Accuracy (T. Accu) were evaluated in some of the algorithms. They were determined by comparing the annotations of the database used as an input with the results obtained. From this comparison "true Positives" (TP), "true Negatives" (TN), "false Positives"(FP) and "false Negatives" (FN) were extracted.

- Sensitivity (Se) = TP / (TP + FN)
- Specificity (Sp) = TN / (TN + FP)
- Positive Predictive Accuracy or Value (PPV) = TP / (TP + FP)
- Negative Predictive Accuracy or Value (NPV) = TN / (TN + FN)
- Error Rate (Err) = (FP + FN) / (TP + TN + FP + FN)
- False Positive Rate (FPR) = FP / (TP + FP)
- Total Accuracy (T. Accu) = (TP + TN) / (TP + TN + FP + FN)

TP (true positive) = count of all beats in AF which are correctly called by the algorithm as being in AF
TN (true negative) = count of all beats NOT in AF which are correctly called by the algorithm as NOT being in AF
FP (false positive) = count of all beats in NOT AF which are incorrectly called by the algorithm as being in AF
FN (false negative) = count of all beats in AF which are incorrectly called by the algorithm as NOT being in AF

Sensitivity is a measure of how well the algorithm can identify periods of AF; specificity is a measure of how well the algorithm identifies periods of the signal NOT in AF, and positive predictive accuracy measures how often the algorithm is correct when it calls a time period AF. These are all performance measures that have important meanings to clinicians relying on these algorithms to help them manage patient care. The error rate is a value which is useful as a single value summary of the overall percentage of mistakes made by the algorithm.

2.3.5 Conclusions from the literature study

As described from the electrocardiographic viewpoint, AF is characterized by absence of P waves, irregularly fluctuating baseline and widely irregular QRS timing. Based on these characteristics the methods studied analyze RR intervals irregularity, P wave absence and AA spectrum, but each study presents some advantages and disadvantages.

More than half of the algorithms studied are focused on RR intervals analysis (appendix A.2). The basic idea is that, in well defined conditions, the totally irregular RR sequence of AF could be translated in a typical pattern of RR distribution, and that simple rules could be used to differentiate AF from other, non-AF rhythms. Besides, QRS complex is the most prominent feature of an ECG and the easiest to detect in presence of noise.

The major problems with the method based on RR irregularity occur when in fact AF occurs in the presence of a regular ventricular rate. This causes false negatives. In any case, that is not the most common problem, and therefore the methods based on ventricular irregularity as a criterion have higher values regarding to sensitivity (Appendix A.2).

The second criterion for classifying a rhythm as AF is based on lack of the P wave in all ECG recordings. AA properties could be masked by high amplitude QRS and T waves and is relatively well observable only in T-Q segments. So AA characteristic used to be analyzed with the remaining signal obtained after QRST wave or ventricular activity is removed from the ECG.

The inconvenience of such methods is that not every signal could be successfully classified using P wave detection algorithm solely. Especially the performance on noisy signals is poor, where P waves are totally masked in the noise because of the small amplitude. The chaotic nature and a small size of AA in the signal comparing with ventricular activity are also reasons for the difficulty in detecting AF. Therefore this algorithm should not be used alone, but only in conjunction with other methods to achieve better results. *Christov et al* for example, improved the detection algorithm by applying RR interval variation test (Sensitivity (Se) was improved from a 79.10% to 95.70%) [36; 35]. The same problem occurs for power spectra or frequency analysis, since it is based in the AA spectrum as well [40]. Consequently the methods based only on AA cannot detect some AF presences.

In clinical setting, false-negative detection is more problematic than a false positive one, because of the fact that it is possible to miss an AF episode when a severe or critical condition occurs.

In some circumstances some algorithms can have a better response, but in general is shown in [Appendix A.2] that the combination of these three features, or at least two of them, improves the performance. This is shown in Babaizadeh et al [22], where some methods are compared.

Hence, RR interval irregularity, being the most accessible ECG characteristic for AF detection, could be considered in first place. But analysis of AA leads could improve performance, particularly in specificity and positive predictivity.

3 Methods

This chapter describes the method used for evaluation of the AF detection algorithms. The database employed and the different tests made to evaluate the algorithms for this study are described.

3.1 Database

Two databases were used through this study: MIT-BIH Arrhythmia Database and MIT-BIH AF Database [1]. These are public databases published by PhysioNet [1] and also well known databases used by most of the authors. Therefore, the results can be compared in a more objective way with the ones published. Also it can be considered a fairly large database to evaluate the different algorithms.

MIT-BIH Arrhythmia Database was used on a previous development or training step of the algorithms which required it. MIT-BIH Arrhythmia Database signals contained a relatively small sample size as compared to MIT-BIH AF database. For this reason, most of the algorithms firstly used MIT-BIH Arrhythmia Database for training or development steps of the method, while a much larger database, MIT-BIH AF Database, was used for AF detector evaluation.

3.1.1 MIT-BIH Arrhythmia Database

It is a collection of 48 fully annotated half-hour two-channel ambulatory ECG signals sampled at 360 samples per second with 11-bit resolution over a range of ±10 mV. Two or more cardiologists independently annotated each record. Of these, 23 are in the 100 series and the rest in the 200 series. The recordings in the 100 series contain sinus rhythms and arrhythmias but not AF episodes. The 200 series contains AF, various arrhythmias and sinus rhythm. 15 different rhythms annotations are shown. Among these, (AF (Atrial Fibrillation), (AFL (Atrial Flutter), (NOD (AV junctional rhythm), and (N (used to indicate all other rhythms). Also each beat is included in the annotations.

3.1.2 MIT-BIH AF Database

It includes 23 available records of approximately ten-hour of duration. They contain two ECG channels each, but with not lead specification. Each signal was sampled at 250 samples per second with 12-bit resolution over a range of ±10 mV obtained from Holter tapes. The rhythm annotation files were prepared manually; these contain rhythm annotations of types (AFIB (atrial fibrillation), (AFL (atrial flutter), (J (AV junctional rhythm), and (N (used to indicate all other rhythms). Beats were annotated using an automated detector and were not corrected manually. Therefore, the beat annotations for this database in this study were acquired using Romero et al's QRS complex detection algorithm [43] and they were included to the annotations of each signal.

3.1.3 ECG lead Configuration

The placement of the electrodes affects notoriously on the output signal obtained, and accordingly in the AF detection algorithms. Therefore, the ECG lead that could have the best performance for each algorithm has to be considered and determined. Normal QRS complexes are usually prominent in lead II. On the other hand, lead V1 is used in most of the algorithms based on AA due to the fact that is in this lead where AA is more clear and shows higher accuracy for this type of algorithms [36; 38].

Both MIT-BIH databases contain recordings of two ECG channels. MIT-BIH Arrhythmia database has annotated the lead which corresponds to the signal. In most of the records, the upper signal (ecg1) is a modified limb lead II (MLII) and the lower signal (ecg2) a modified lead V1 (occasionally V2, V5 or V4).

MIT-BIH Atrial Fibrillation database has no information about the lead that corresponds to the signals. Therefore, in order to get higher performance, and use the appropriate lead for the algorithm to test, the channels of each signal were checked visually and assigned as ecg1 or ecg2. They were divided in these two groups, trying to assign the actual lead to the most similar lead (ecg1 and ecg2 to lead II and V1 respectively). Nevertheless in some of the records only one channel was related or similar to one of this leads, or none of them. Consequently the performance obtained from these signals could be lower if the algorithms are dependent on the lead used, which is common in AA analysis based techniques.

3.2 Evaluation Method Design

3.2.1 Performance criteria

The performance of the algorithms was reported in terms of sensitivity (Se), specificity (Sp), positive predictive accuracy or value (PPV), and error rate (Err).

Also, the computation time of each algorithm (*TComp)* was calculated. TComp measured the duration (seconds) that the algorithm needs to compute 1 hour of the current signal.

3.2.2 Evaluation

3.2.2.1 Window Length Test

The resolution or signal segment length used to determine if AF is present, affects in the performance. That is due to the fact that a short segment could not be accurate enough and more vulnerable with noise. But also longer segments can cause false positives and negatives. Thus “Window Length Test” can determine which is the resolution, or window length, required to get the best performance for each algorithm.

3.2.2.2 Input Signal length

Some algorithms require memory to set up some parameters, such as the mean value of RR intervals in Logan et al [18]. The variables stored in the memory are consistent after some time, which means some initial input signal length. Therefore “Input Signal length” test was done in the methods that require of memory to determine the required initial length of the input signal to get the expected performance of the algorithm to evaluate.

3.2.2.3 Results

The results were obtained based on the window length that offered the “best” performance for each algorithm.

It is possible to notice a significant difference on the results depending on the percentage of AF that the signal contains (Figure 17). The most remarkable parameter that shows that is the Positive Predictive Value (PPV). PPV is defined as TP / (TP + FP). Therefore in the signals where the AF rate is low, the number of FPs are more probable, and PPV is low. This factor was noticed by Ying [15] and only eighteen signals were included in his test, excluding the ones that had low AF episodes. This relation between the percentage of AF in the signal and the PPV is shown on every method (A.1*)* where PPV is significantly lower in those signals, being PPV 0 in some cases.

Also Specificity (Sp) value, defined as TN/ (TN+FP), present a significant low value in two of the signals (07162, 7859) for some tests. These are AF in more than 99.99% of the signal, leading in a no representative Sp value. Sp value is expected to be very high or low with values of 100% or 0%, which could vary also depending on the resolution (window length value).

To avoid this confusion, for FP values lower than 0.01% percentage of the total number of samples due to the signals which corresponds mostly to AF episodes, Sp was considered as 100%, instead of 0%.

In general, not to have misunderstanding due to the Se, Sp and PPV values that can be obtained for the characteristics of each signal, the Error could be a better representative performance value.

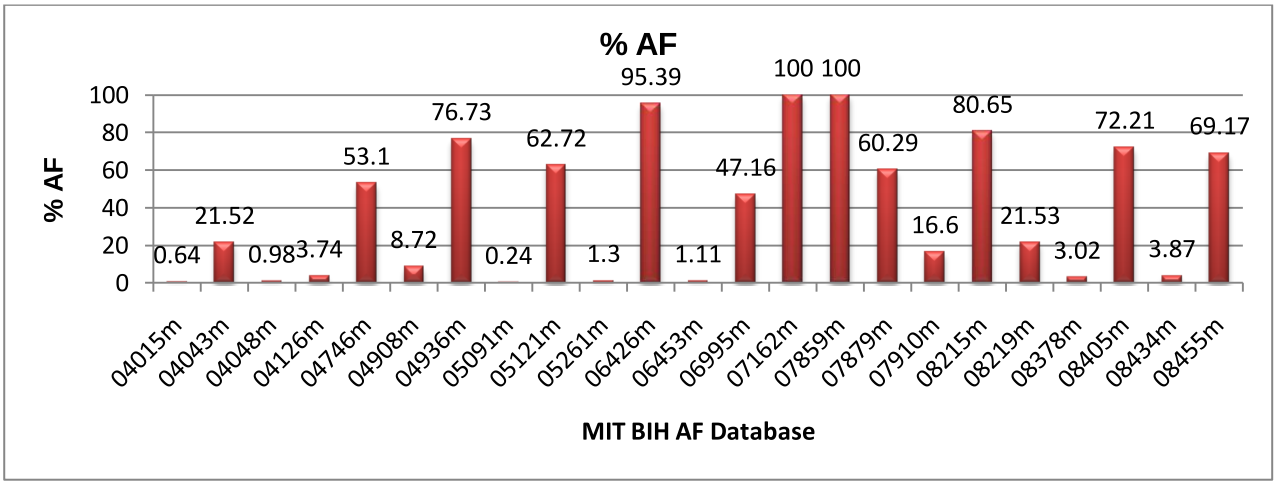


Figure 17- Percentage of AF of each signal from MIT-BIH AF Database

3.2.2.4 Noise

The robustness of each algorithm to noise was evaluated using a graphic of the response (%)-SNR (Signal Noise Ratio). A dataset was generated by combining clean ECG signals with different levels of noise.

The clean ECG signals used for SNR test were obtained from 2 channel MIT-BIH AF database. 10 arbitrary signals where cut to 1 hour length (07162, 07859, 07879, 07910, 08215, 08219, 08378, 08405, 08434, 08455), containing AF and normal sinus rhythm.

Noise recordings were got by placing 9 electrodes in the back of 5 healthy subjects at the height of the lumbar curve where ECG signals were negligible, with a sampling frequency (fs) of 1000 Hz. Then, the subjects were asked to move randomly. For each subject, 2 minutes while standing and 2 minutes while seated were recorded, obtaining 10 noisy episodes in total to add to clear ECGs [44]. The first 2 channels from the 12 recorded noisy leads were selected and resampled to have the same sampling frequency as the clean signals (fs=250 Hz) and repeated until having the same length of 1 hour duration.

Clean ECG and noise signals were then combined to acquire signals with a specific SNR value. This was done by multiplying each 2-lead noise signal by a gain factor and adding it to each 2-lead clean ECG. SNR values ranging from 30 to -30 dB were considered.

QRS complexes, or R-peaks, were detected after the noise was added to the signal. Otherwise the algorithms based on RRI would not be influenced by the noise. In RRI based algorithms, R peak detection algorithm is the one which would influence the performance.

It may be noted that once the SNR becomes too small (smaller that SNR=-10 dB), the Se and Sp is less meaningful, and the Sp or Se could become even better with more noise. Since that R peaks are erroneously detected and AA is significantly affected by noise, the algorithms, which are based on RRI and AA analysis, will work erroneously and in some cases the segment to evaluate can be consider as AF just for the noise influence; or NSR when AF is present. That could increase Se, decreasing Sp; or increase Sp while Se decrease. That is a characteristic shown in several algorithms [20; 27; 30; 37].

3.2.2.5 Computation time (C. Time)

The study also includes the computation time that each algorithm requires to evaluate one hour of data. It was measured for the whole length of each signal and for the mean value of the 23 signals from MIT-BIH AF database.

Nevertheless it was proved that the same algorithm could vary the C. Time due to the fact that a computer server shared by various users was used for the calculations and the computational load could be different at different times.

The computer used for evaluating the algorithms had the following specifications: Each processor has two cores: 2x Dual-Core AMD Opteron (tm) Processor 8220, 2.8 GHz, and 1M cache. The machine has 64GB of main memory.

4 Evaluation of Algorithms

This chapter will cover the nine algorithms implementation issues and comparison with the author's description. They are divided in three groups: based on RR intervals Irregularity (RRI), based on Atrial Activity (AA) analysis and finally the ones which combined RRI and AA.

4.1 RR intervals Irregularity (RRI)

4.1.1 B Moody and RG Mark

Moody et al [9] is one of the most famous and referenced paper, that makes it a significant method to be evaluated in the study. It is based on Markov process models of the RR interval sequence.

There are slight differences between the current evaluation method used in the study when compared to the one used in Moody's paper. Even though the databases employed for the learning and evaluating process are the same, not all the signals from the database were considered in Moody et al. Intervals bounded by PVC were ignored, and also only 12 records from the 48 records available from MIT-BIH Arrhythmia database were selected for the learning process [9], which are the ones containing AF episodes.

Moody's algorithm works reasonably well for real-time monitors, as mentioned in the paper. The published results are considered for n=20 RR intervals. In the study, a window length of 20 second, gave a reasonably good performance of Se=91.08%, Sp=86.63%, PPV=81.92% and Err=11.56%.

Interpolation of the transition matrix of Markov process (2.3.2.1) and signal first order filtering were done for reduction of the quantization error and noise in the signal respectively. But in contrast to the results published in Moody et al, not much improvement was got.

Table 2: Moddy et al's methods results from the study and publication

METHOD		**Window**	**RESULTS**				
	SubMethod	**(sec)**	**Se (%)**	**Sp (%)**	**PPV (%)**	**Err (%)**	**C. Time (sec)**
Moody et al (Study)	*RR*	*90*	*87.54*	*95.14*	*92.29*	*7.88*	0.55
	RR + Interpolation	*90*	*85.29*	*95.44*	*92.55*	*8.6*	0.63
	RR + Filtering	*140*	*87.81*	*95.23*	*92.44*	*7.72*	2.23
	RR + Interpolation + Filtering	*120*	*85.48*	*95.82*	*93.14*	*8.3*	2.29
Moody et al (Published)	*RR*	*20 RR*	*99.59*	-	*65.97*	-	-
	2a. (1) + Interpolation + Filtering	*20 RR*	*93.58*	-	*85.92*	-	-
	2b. (2a) + PVC-bounded intervals	*20 RR*	*90.65*	-	*82.38*	-	-
	3. RR predictor array	*20 RR*	*75.79*	-	*91.93*	-	-

4.1.2 BT Logan and J Healey

Logan et al's work [18] is based on the measurements of the RRI variance. The author suggested three different variants of the algorithm as explained in section 2.3.2.1: $RRvar$ [M1], $Var(RRnorm)$ [M2], and $Smoothed\ Var(RRnorm)$ [M3].

In order to improve the performance, RR intervals are normalized according to the following equation and the variance is then studied:

$\mathrm{RRnorm} = \frac{RR}{\overline{RR_n}}$; $\overline{RR_n} = 0.75 * \overline{RR_{n-1}} + 0.25 * RR$ (*RR*= current RR interval).

This implies that the mean value of the signal suffers certain modifications on time, and consequently also the output. Therefore input signal length test (section 3.2.2.2) was applied to determine the minimum input signal length required to establish the mean value and get the expected performance. *Figure 18* shows how from input signals above 1000 seconds the algorithm shows on stationary performance.

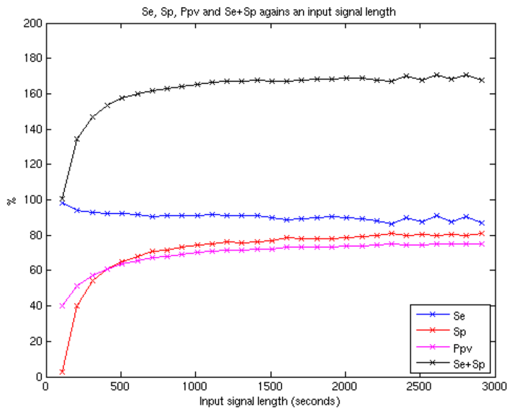


Figure 18 - Input signal Test for Logan et al's second method (M2)

With "full algorithm" [M3], "Smoothed % RR Mean Var", that considers the simple majority voting scheme over a window applied to the previous result of RRnorm variance, the outcome got was not as good as in the paper. The best performance was got for a window of 260 seconds applied to a 10 second resolution of Var(RRnorm): Se=87.30%, Sp=90.31% and Err=10.89% . However the publication shows 96% of Se and 89% of Sp for a 600 beat window set to 10 second of sliding windows, which means that each 10 second window was used to evaluate each beat, and sliding the window the next beat was evaluate, and so on until the end.

The higher performance published in the paper may be due to the use of sliding windows to evaluate each beat and moreover, the signals used from the MIT-BIH database were not specified.

Table 3: Logan et al's methods results from the study and publication

METHOD		***Window***			***RESULTS***		
	SubMethod	***(sec)***	***Se (%)***	***Sp (%)***	***PPV (%)***	***Err (%)***	***C. Time (sec)***
Logan et al (Study)	*M1*	*10*	*92.36*	*75.06*	*71.18*	*18.02*	*2.88*
	M2	*110*	*91.40*	*93.02*	*78.19*	*13.62*	*0.45*
	M3	*260*	*87.30*	*90.31*	*85.72*	*10.86*	*2.90*
Logan et al (Published)	*M3*	*600 beats*	*96.00*	*89.00*	*65.97*	*-*	*-*

4.1.3 DT Linker

Linker's algorithm [28] is based on Absolute Deviation of a number of RR intervals segments.

The only result published was from an example and the database used was not mentioned. Also, in this study, the evaluation method was designed for windows of a specific number of seconds in contrast with the paper, where the segments were defined as specific number of RR intervals. Consequently the number of RR intervals evaluated in each segment could not be the same for a fixed time window.

The only mention about the performance was for 19RR intervals, for which the paper reports a Se of 98.00% and Sp of 98.70%, without any threshold value specification.

Table 4: Linker's algorithm results from the study and publication

METHOD	Window	RESULTS				
	(sec)	Se (%)	Sp (%)	PPV (%)	Err (%)	C. Time (sec)
Linker (Study)	10	97.64	85.55	81.81	9.61	5.06
Linker (Published)	19 beats	98.00	98.70	-	-	-

4.1.4 K Tatento and L Glass

Tatento et al [14] described a method based on the sequence of RR intervals and the difference between two successive RR intervals, DRR, using Kolmogorov Smirnov (KS) and Coefficient of Variation (CV) tests.

For these tests, preprocessing was required to prepare the Standard Density Histograms (SDH) for RR and DRR intervals. The similarities between the density histograms of the test data and the SDH were estimated using KS and CV tests.

The main problem found in this process is the creation of SDH. In this method 16 different classes of distributions were required for SDH based on the mean value of the RR intervals of segments of 50 beats with AF. To create these histograms using MIT-BIH Arrhythmia data was not possible because only 8 different distributions could be obtained. Moreover, they were not representative because of the low number of AF episodes in the database.

So as an alternative the MIT-BIH AF database was divided in two groups: the first 13 signals were used for the evaluation, and the last 10 signals to create SDH. These last 10 signals contained enough AF episodes to create a representative SDH. In the Appendix section A.1.4 and in *Figure 19* the differences in the performance obtained using the entire database is shown, and since part of the data was used for SDH, the performance was higher.

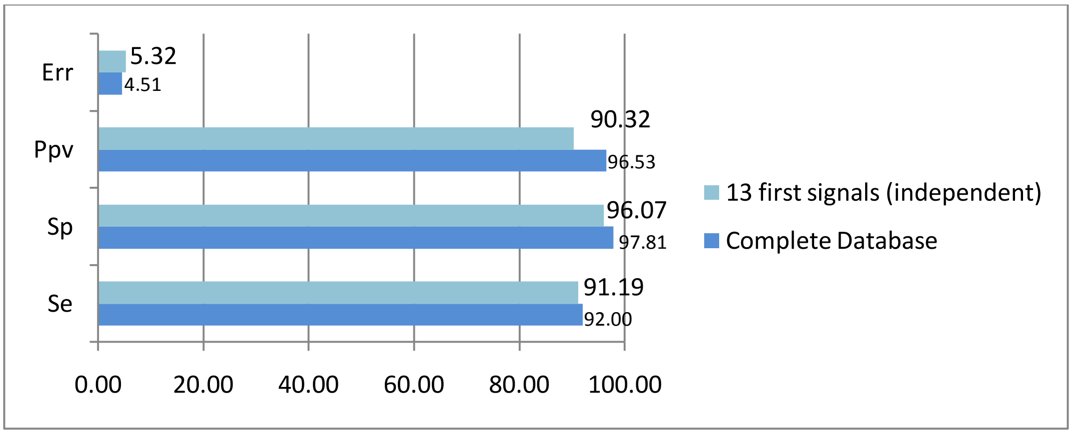


Figure 19 - Tatento et al's method (KS DRR) comparison depending on the signals used for the evaluation

Tatento et al used the whole MIT-BIH AF database to both create SDH and for evaluation. Moreover the segments considered in the study to build the histograms were based on time windows (seconds) being consistent with the evaluation method. But Tatento et al considered segments of a specific number of RR intervals.

Table 5: Tatento et al's methods results from the study and publication

METHOD		***Window***	***RESULTS***				
	SubMethod	***(sec)***	***Se (%)***	***Sp (%)***	***PPV (%)***	***Err (%)***	***C. Time (sec)***
Tatento et al (Study)	*KS RR*	*60*	*90.03*	*95.53*	*89.00*	*6.04*	*1.61*
	KS DRR	*40*	*91.19*	*96.07*	*90.32*	*5.32*	*2.31*
	CV RR	*60*	*91.64*	*85.57*	*71.95*	*12.68*	*1.04*
	CV DRR	*20*	*91.80*	*68.76*	*54.80*	*24.50*	*2.63*
Tatento et al (Published)	*KS RR*	*100 beats*	*66.30*	*99.00*	*98.00*	-	-
	KS DRR	*100 beats*	*94.40*	*97.20*	*96.10*	-	-
	CV RR	*100 beats*	*86.60*	*84.30*	*79.80*	-	-
	CV DRR	*100 beats*	*83.90*	*83.70*	*78.70*	-	-

4.1.5 S Cerutti et al

Cerutti et al [31] investigated AF detection using parameters extracted through a time-variant identification of an autoregressive (AR) model and non-linear measurements based on the Corrected Conditional Entropy (CCE).

Since AR model was proved to work better, this study was focused on this technique. Two parameters were extracted from AR modelling: percentage of power (P) which may be predicted by the model in order to assess the characteristics of predictivity; and the maximum modulus among the model poles (M).

A relationship between poles from the AR model, and the pseudo white noise (WN) pattern in the RR series was found. During normal rhythm the RR spectrum shows a more concentrated spectrum, while in AF the spectral pattern is more wide-band like *(Figure 20)*.

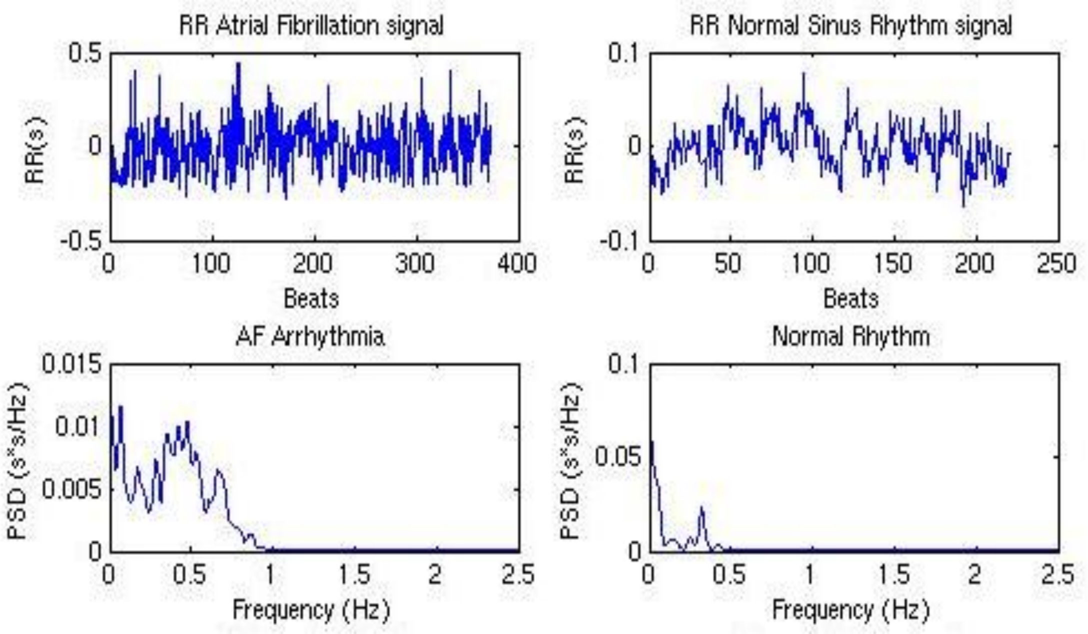


Figure 20 - RR interval tachogram, its spectrum and the correspondent spectrum in dB (logarithmical scale) for atrial fibrillation and for normal sinus rhythm.

The thresholds defined for the tests were, TH_P=12 for percentage of power and TH_M=0.65 for maximum poles modulus. These values were consistent because the mean values and the range of the parameters (P and M) of the test were reported in the paper and the THs defined are in the range between AF and Normal Sinus Rhythm (NSR).

Table 6: Mean ± SD of the different indexes considered for the study

	NSR	*AF*
Mean RR (ms)	*780.96 ± 200.96*	*690.30 ± 260.15*
P	*43.71 ± 22.34*	*5.05 ± 2.59*
M	*0.7393 ± 0.1424*	*0.5568 ± 0.1031*
L	*3.4666 ± 0.9904*	*3.3157 ± 1.1081*
MCCE	*1.1094 ± 0.1988*	*1.3129 ± 0.1593*

The database used by Cerutti et al was 13 episodes from MIT-BIH AF database, and 7 from another source. The resolution window length was also not the same since the authors used RR series. Therefore the results obtained in this study were different from those reported in the paper.

In both the study and Cerutti et al's paper, the higher performance was obtained with the P parameter.

Table 7: Cerutti et al's methods results from the study and publication

METHOD		Window	RESULTS				
	SubMethod	(sec)	Se (%)	Sp (%)	PPV (%)	Err (%)	C. Time (sec)
Cerutti et al (Study)	P	110	88.06	79.83	74.53	16.87	0.60
	M	290	87.19	58.75	58.87	29.79	0.36
Cerutti et al (Published)	P	-	93.30	-	94.40	-	-
	M	-	93.30	-	78.90	-	-

4.2 Atrial Activity (AA) Analysis

4.2.1 J Slocum et al

Slocum et al's [38] algorithm was based only on the AA analysis to identify AF. Ventricular activity cancellation was done first and the remainder ECG studied.

First analysis was for "Non-coupled P wave" detection. Autocorrelation function was used to identify the presence of P waves. If P waves were detected, the rhythm was considered non-atrial fibrillation and no further test was done. Otherwise Power Spectrum Analysis was done, and if the power in the range of 4-9 Hz was greater than or equal to 32% of the total power, the rhythm was considered AF.

a. b.

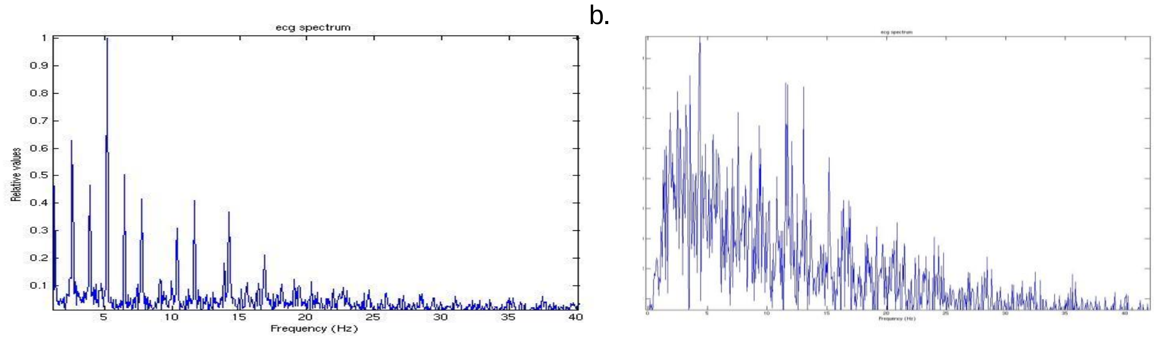


Figure 21 - Power Spectrum of the remainder ECG after QRST removal for (a) AF and (b) NSR

Slocum et al used a specific database of 221 rhythms provided with standard 12 lead ECGs, and the data was filtered. The signals were classified in different groups depending on the rhythms (AF, control group, and sinus rhythm), and divided into a training set and test set. The training set was used to define some parameters to determine when AF was present. The results were shown for the training set and for the test set.

In the present study MIT-BIH Arrhythmia database was used for training and MIT-BIH AF database for the evaluation, and specific groups were not defined for the analysis. Ventricular activity cancellation was executed with QRST cancellation algorithm described in Romero et al's [45].

Table 8: Slocum et al's methods results from the study and publication

METHOD		***Window***			***RESULTS***		
	SubMethod	***(sec)***	***Se (%)***	***Sp (%)***	***PPV (%)***	***Err (%)***	***C. Time (sec)***
Slocum et al (Study)	*Original*	*250*	*62.80*	*77.46*	*64.90*	*28.39*	*1.62*
	Proposed	*30*	*92.43*	*83.76*	*79.06*	*12.78*	*2.43*
Slocum et al (Published)		*-*	*98.60*	*84.00*	*84.90*	*-*	

4.3 RRI and AA analysis combination

4.3.1 R Schmidt et al

This work presented a combination of the three main AF detection characteristics: RR interval sequences irregularity, ECG spectrum analysis after QRS cancellation, and P wave's presence or absence.

Schmidt et al's paper [21] is not too detailed. Therefore several assumptions were made for its implementation.

For the first analysis of RR intervals, a method defined by Moody et al [9] was used. The second feature group was tested for the P wave detection using correlation coefficient. As the template for the P wave was not defined, an autocorrelation function of the signal was made and a TH was applied to consider the existence of P wave.

The third feature group, which consisted of the frequency domain properties of ECG signal after QRST cancellation, had some inconveniences. Firstly the QRST cancellation algorithm [45] was executed. Secondly frequency bands of PSD spectrum extending from 10, 20, 30, 40, 60, 80 to 125Hz were estimated and the ratios of high frequency to low frequency calculated as a percentage:

$P(F) = \frac{\sum_{f=F}^{125} P}{\sum_{f=0}^{F} P}$ where F is the reference frequency (10,20,30,40,60 and 80)

A large percentage of total power can be seen around 5-9Hz when AF is present [38]. Since, using all band percentages as features leads to inaccurate results, the first band was determined as a main feature to solve the problem. First ratio, which is the PSD of 10 to 125 Hz band divided by 0 to 10 Hz band, is expected to be lower for AF than for a NSR.

The features were extracted in windows of 30 seconds, instead of using a sliding window of 30 beats, as explained in the paper.

To analyze the resulting performance, linear classifier and decision tree were used, as mentioned in the paper. In general, linear classifier had higher performance, and it was used for the final results. Also noticeable is the low performance of the combination of P wave and frequency features which is listed Table 9.

There are not published results in this publication [21].

Table 9: Schmidt et al's methods results from the study and publication

METHOD		Window	RESULTS				
	SubMethod	(sec)	Se (%)	Sp (%)	PPV (%)	Err (%)	C. Time
Schmidt et al (Study)	RR+P wave	70	89.14	93.98	90.78	7.94	2.64
	RR+Freq	70	89.20	94.58	91.62	7.57	1.80
	P wave+Fre	30	78.73	87.69	80.95	15.88	2.83
Schmidt et al (Published)	-	-	-	-	-	-	-

4.3.2 S Babaezaideh et al

Babaezaideh et al [22] used Markov Modelling (MM) approach, but also added AA analysis, P wave location and morphology, and a final hysteresis counter to reduce the number of short false alarms caused by variety of reasons, such as short segments of RR irregularity, noise, and difficulties in P wave detection.

RR interval analysis, based on MM, was similar to the work done by Moody et al [9]. They introduced a modification since the sequence was assumed to be controlled by a transition probability matrix. So the probability matrix was got from each segment and multiplied with the defined transition matrix (S_0) from learning set, where the lower elements are relatively more likely to occur in AF than in non-AF.

$$S_0 = k * log\ (p_{ij,NoAF}/p_{ij,AF})$$

P location was based on PR interval, assuming that for normal sinus rhythm, PR interval is relatively small. In AF, due to the absence of P wave, PR is either not measurable or very large due to false P wave detection. The main problem emerged in the implementation of P wave onset detection, which was not specified by the author.

The criterion used to get the performance of the feature based only on P wave location was P onset - R peak interval length. A new measurement was also implemented based on the variance of these PR interval lengths.

P wave morphology measurement was defined as the similarity between 2 consecutive P wave test, but no further specification was mentioned by the authors. Therefore the similarity was simulated as the mean of the differences between the samples of two adjacent P waves. Lastly the variance of the differences of these values for a segment with multiple P waves was acquired, and this value was considered the feature for P wave morphology analysis. A correlation was also tried, but it gave poor results.

Once these different features were obtained, a classifier system was applied. The training dataset used in this study, MIT-BIH Arrhythmia database, was not as representative as the one used by Babaezaideh et al. Contrasting with the author, who extracted the features for each RR interval, the features of the training set were extracted in 30 seconds segments in the study.

Moreover, Babaezaideh et al's paper uses a technique to eliminate very short AF episodes using a hysteresis counter. Since the evaluation method is based in the resolution determined in time windows, the signal was evaluated by segments and the number of short false alarms were avoided with it.

Table 10: Babaezaideh et al's methods results from the study and publication

METHOD		Window	RESULTS				
	SubMethod	(sec)	Se (%)	Sp (%)	PPV (%)	Err (%)	C. Time
Babaezaideh et al (Study)	RR	70	97.18	85.44	81.69	9.85	2.64
	RR+P	160	87.27	95.47	92.75	7.80	1.80
Babaezaideh et al (Published)	RR+P	-	91.00	96.00	89.00	-	-

4.3.3 R Couceiro et al

Couceiro et al [25] combined the three main physiological characteristics of AF: RR irregularity, P wave absence, and spectrum properties from AA analysis.

RR irregularity was studied following the algorithm proposed by Moody et al [9], as a three-state Markov process, adding *Kullback–Leibler* divergence (D_{KL}), to study the similarity between the distribution $P_{AF}(x, y)$ and the distribution under analysis ($P(x, y)$).

$$D_{KL}\left(P(x,y), \overline{P_{AF}(X,Y)}\right) = \sum_{x=1}^{3}\sum_{y=1}^{3} P(x,y)\log\left(\frac{P(x,y)}{\overline{P_{AF}(x,y)}}\right)$$

Couceiro et al used QT Database for Physionet to extract a template of the P wave. However, in this study all P waves from the data were extracted and P wave was assessed using the correlation coefficient between the P wave to analyze and the template.

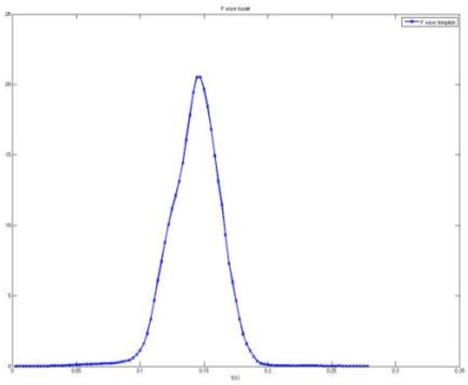


Figure 22 - P wave model

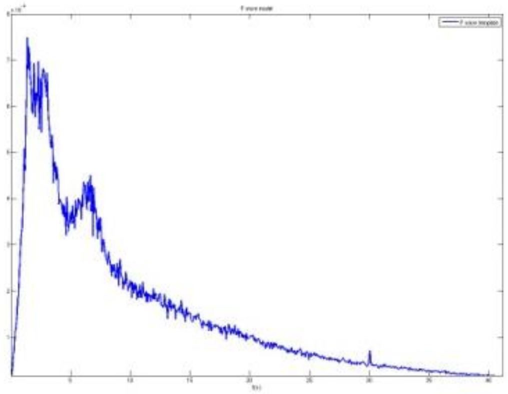


Figure 23 - AA Spectrum model for AF episode

For the last feature, AA analysis based on the spectrum, *Kullback–Leibler* divergence was also applied. This compared the spectrum of the template acquired from MIT-BIH Arrhythmia Database AF signals spectrum with the spectrum of the segment to analyze.

The author also uses a Neural Network classifier for which several parameters have to be defined. The study has followed the properties proposed by Couceiro et al: three layer feed-forward neural network with seigmoid activation functions, trained with Levenberg- Marquardt algorithm. The number of neurons considered was 20 since it was not specified by the author.

The main difference between this study and the paper is that the features were extracted for a time window in this study. However, Couceiro et al needed 100 beats segment to classify each beat, and therefore they reported that this technique would not be adequate in real time detection of AF episodes.

There are not available results in Couceiro et al's publication.

Table 11: Couceiro et al's methods results from the study and publication

METHOD		Window	RESULTS				
	SubMethod	(sec)	Se (%)	Sp (%)	PPV (%)	Err (%)	C. Time
Couceiro et al (Study)	Linear Classifier	410	96.65	79.70	76.04	13.51	11.35
	Neural Networks	220	96.58	82.66	78.76	11.77	2.77
Couceiro et al (Published)	Neural Networks	100 beats	-	-	-	-	-

5 Algorithms Comparison

The evaluation of the nine algorithms is reported in a comparative way in this chapter. The results got for different tests used on the evaluation method, as Window Length test, Computation Time test and also the robustness against noise are included.

5.1 Methods and variations

Authors usually proposed several variations of their techniques and evaluated them to show the improvement. In this study, the different variations of the techniques reported in each paper were also implemented.

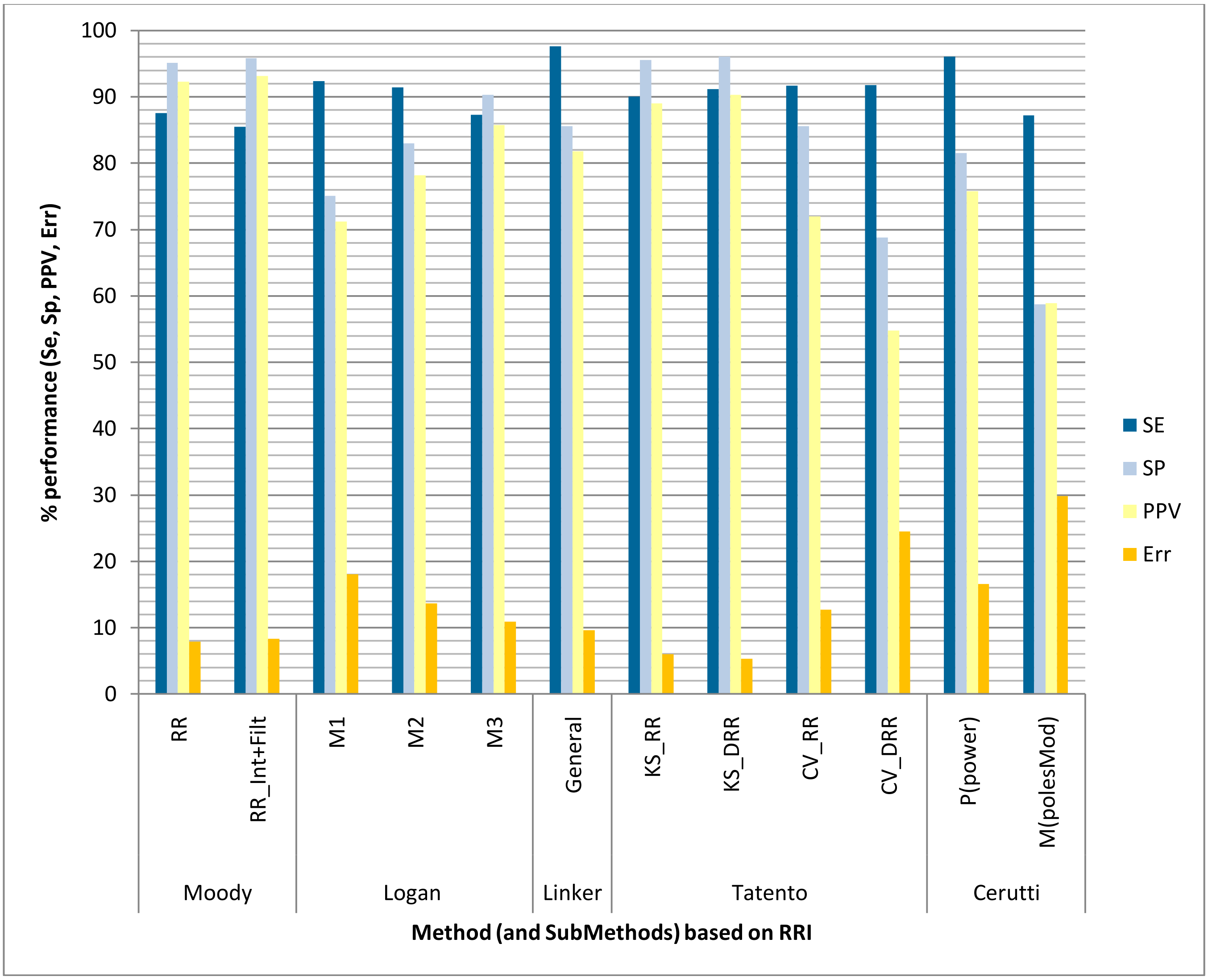


Figure 24 - The performance of the Methods and SubMethods Implemented based on RRI techniques

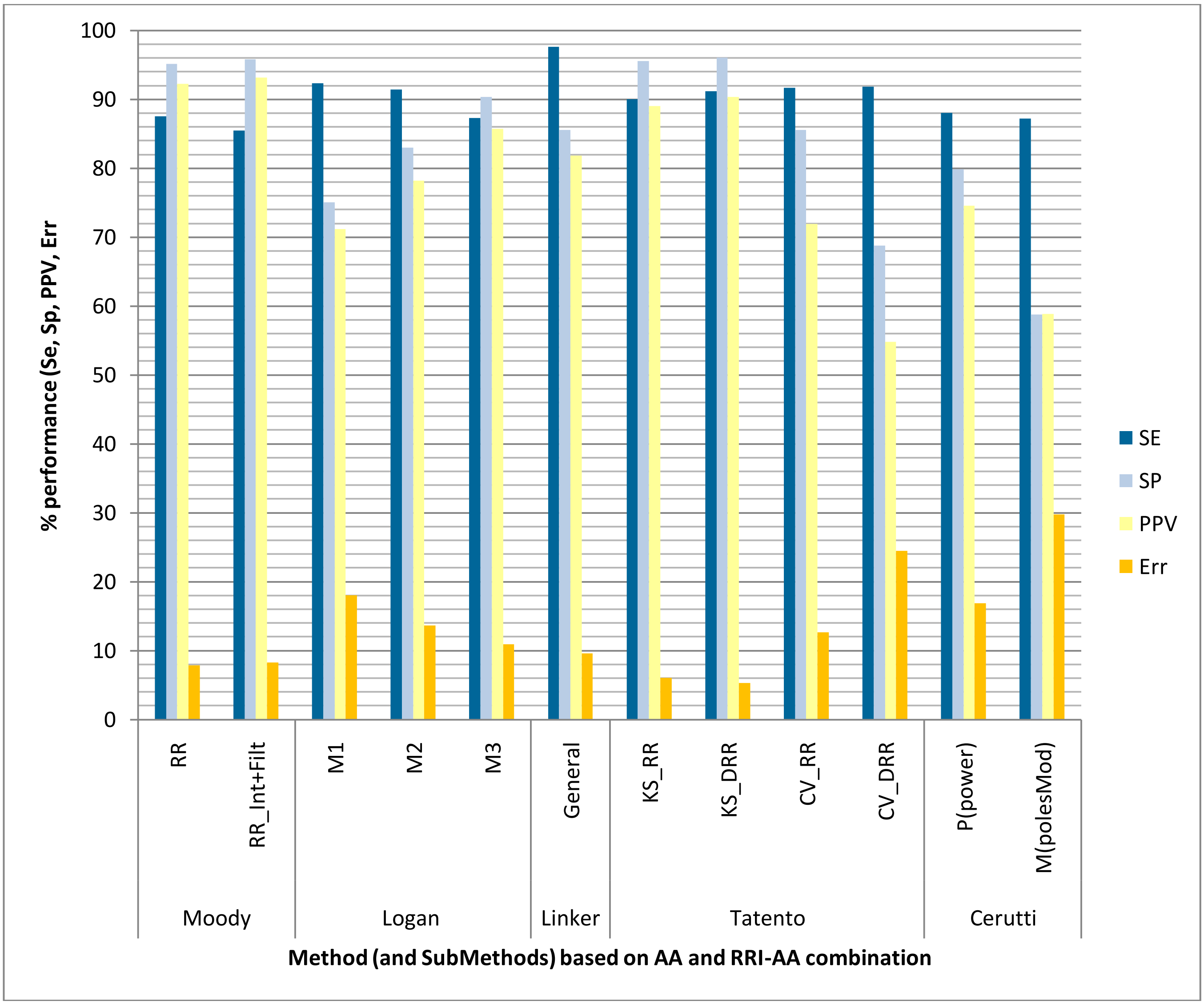
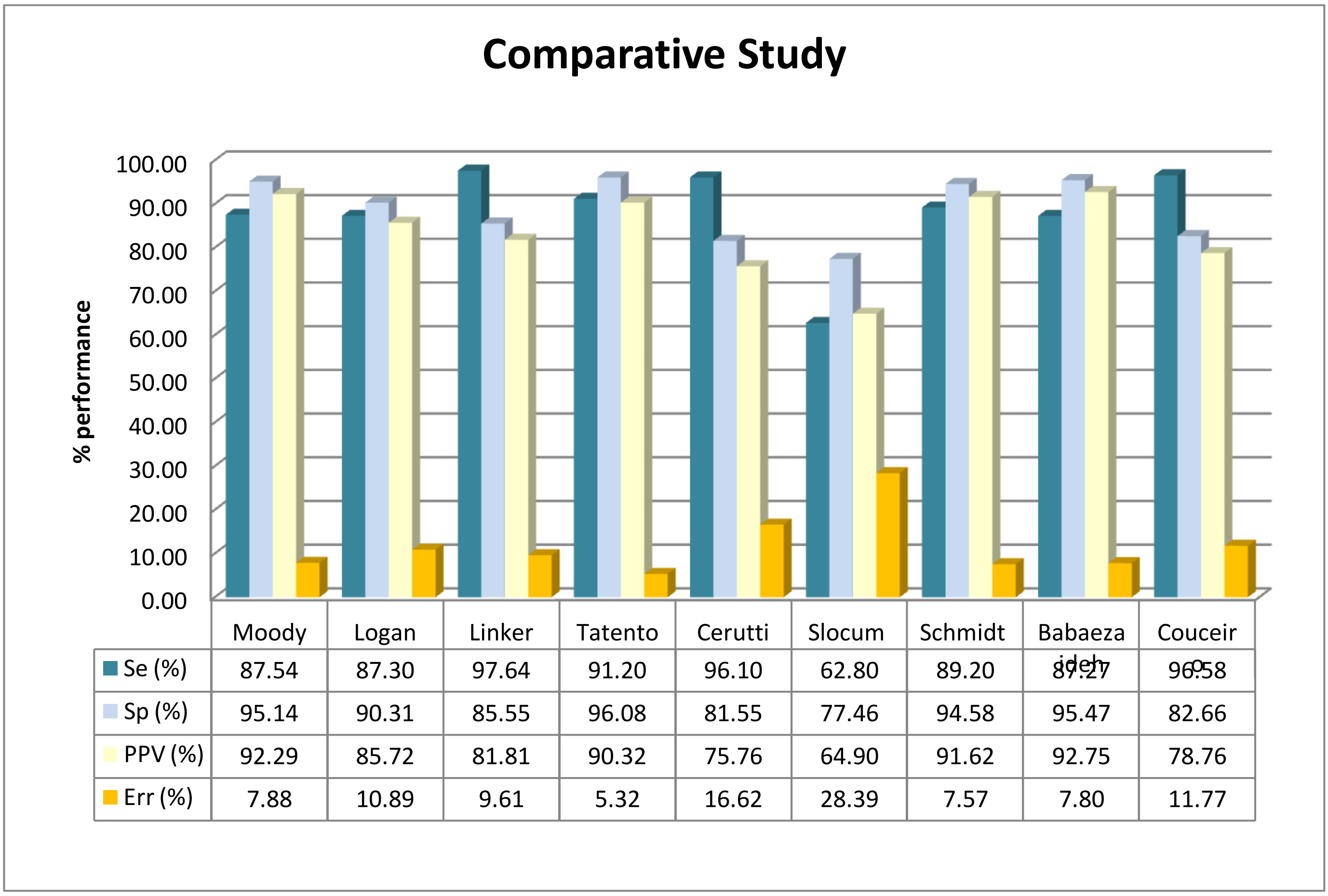


Figure 25 - The performance of the Methods and SubMethods Implemented based on AA techniques and RRI and AA combinations

Slocum et al is the only method based on AA analysis. The rest of the algorithms showed RRI to the AA analysis (Figure 25). Babaezaideh et al used at first only RRI, and then, evaluated how the performance improved when adding P wave analysis.

In order to compare the 9 different methods, the best variation of each algorithm was chosen.

5.2 Performance on the MIT-BIH AF database



	Moody	Logan	Linker	Tatento	Cerutti	Slocum	Schmidt	Babaeza ideh	Couceir o
Se (%)	87.54	87.30	97.64	91.20	96.10	62.80	89.20	87.27	96.58
Sp (%)	95.14	90.31	85.55	96.08	81.55	77.46	94.58	95.47	82.66
PPV (%)	92.29	85.72	81.81	90.32	75.76	64.90	91.62	92.75	78.76
Err (%)	7.88	10.89	9.61	5.32	16.62	28.39	7.57	7.80	11.77

Figure 26 - Comparative Study of the best methods for the nine algorithms studied

The methods based on RRI and on RRI with AA had the highest performance. Linker et al (RRI) had the highest Se=97.64%. Tatento et al (RRI) algorithm tested with Kolmogorov Smirnov test for DRR study contain the highest Sp=96.08% and the lowest error, Err= 5.32%. Babaezaideh et al (RRI+AA) had the highest PPV=92.75.

On the other hand, AF detection depending only on AA analysis (Slocum et al [38]) showed the lowest performance: Se=62.80%, Sp=77.46% and the highest error values of 28.39%.

It is important to note that although Tatento et al's shows the best performance, this is probably due to the fact that the data used for the evaluation is not the complete MIT-BIH AF database, in contrast with the rest of the algorithms tested.

5.3 Window lengths

The window length was other of the parameters studied. The window length was evaluated in seconds in all algorithms. It defines the resolution of the output.

Although short segments can cause false alarms due to short segments of RR irregularity, noise, and difficulties in P wave detection [46], too long segments also cause a decrement in the performance since some AF segments could be masked from the NSR and also NSR masked from AF episodes. This is shown in Table 13 and Table 14 (e.g. Tatento et al and Cerutti et al)

In most of the algorithms a short segment (10 seconds) does not show a good performance. In the other hand, some algorithms require a minimum signal length to be analyzed correctly, such as algorithms that require QRST complex removal.

In general, the methods analyzed used to show a good performance from window length of 1 minute and more. Beyond that, the performance become constant for a several minutes in some of them, in others it could slightly increase or decrease. In the Appendix section (A.1) window length variation graphs are represented for each algorithm and this effect could be observed.

Table 12: Window Length where the algorithm has the higher performance or starts to settle for some time

METHOD	*Window length (seconds)*
Moody et al	*60*
Logan et al	*120*
Linker et al	*10*
Tatento et al	*50*
Cerutti et al	*90*
Slocum et al	*180*
Schmidt et al	*60*
Babaezaideh et al	*40*
Couceiro et al	*60*

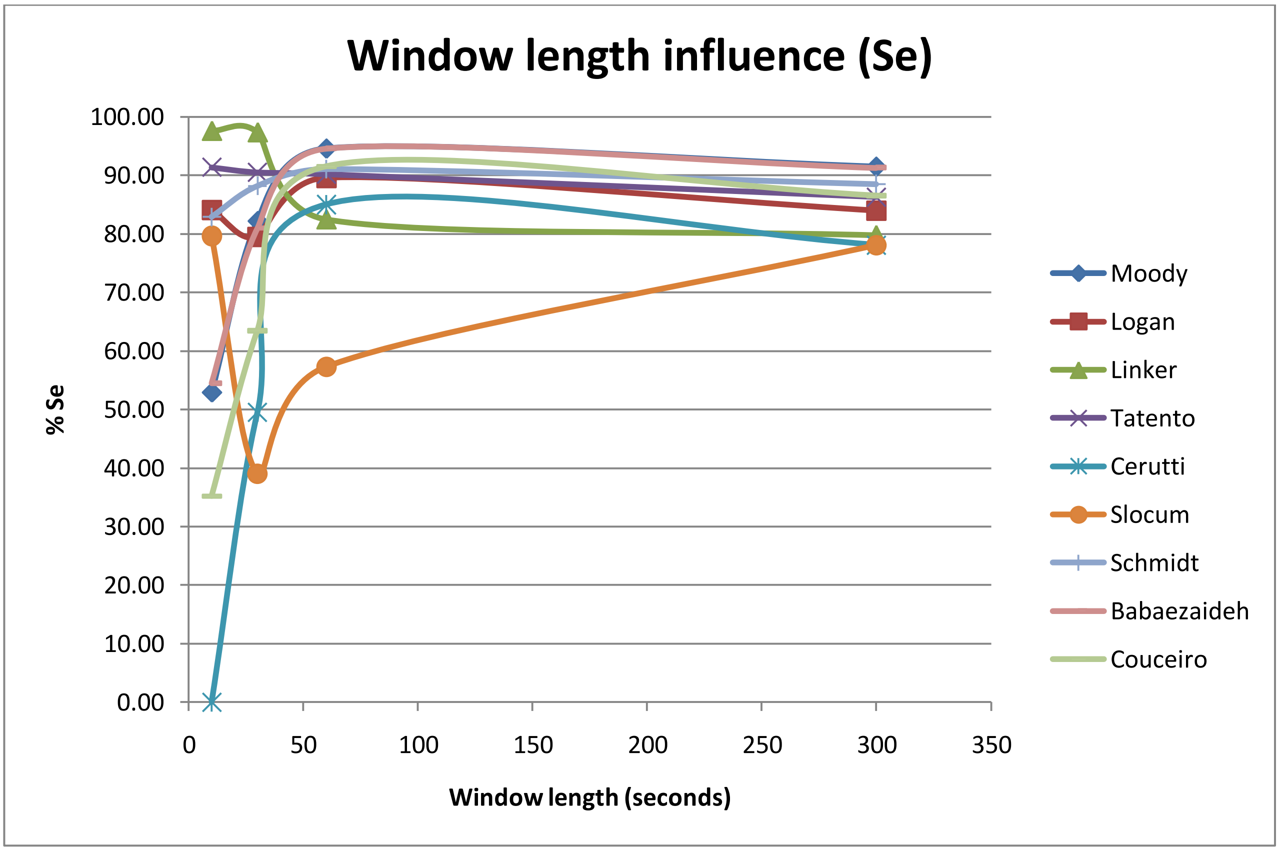


Table 13: Window length influence in the Se for the methods compared

	Se (%)			
Window length	10 seconds	30 seconds	60 seconds	300 seconds
Moody	52.88	82.20	94.60	91.50
Logan	84.04	79.50	89.60	84.00
Linker	97.65	97.40	82.50	79.80
Tatento	91.36	90.50	90.20	86.30
Cerutti	0.00	49.50	85.00	78.10
Slocum	79.65	39.00	57.30	78.10
Schmidt	82.90	88.20	91.10	88.50
Babaezaideh	54.51	81.00	94.60	91.30
Couceiro	35.20	63.50	91.50	86.50

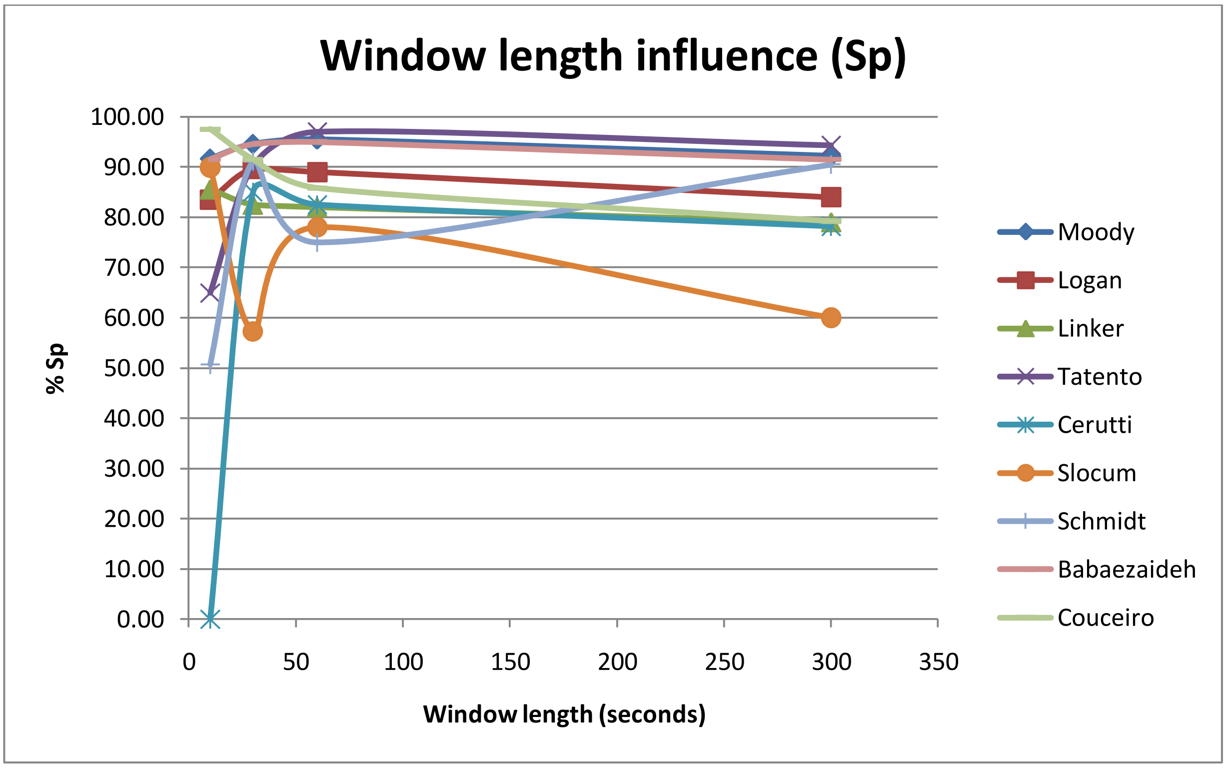


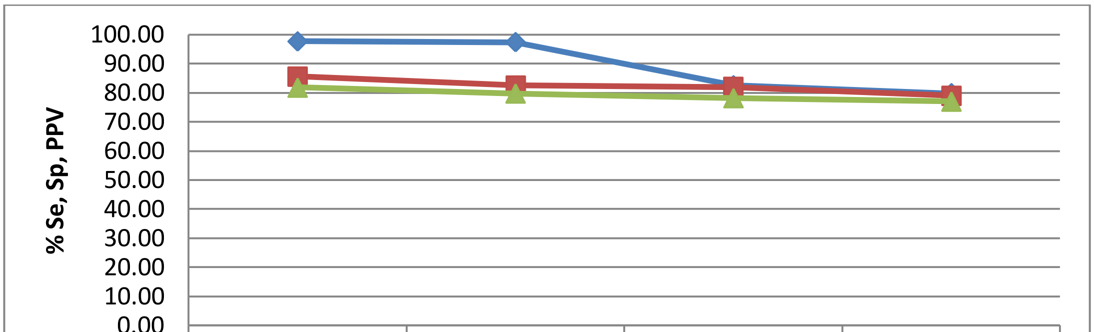
Table 14: Window length influence in the Sp for the methods compared

	Sp (%)			
Window length	10 seconds	30 seconds	60 seconds	300 seconds
Moody	91.68	94.60	95.50	92.20
Logan	83.47	89.60	89.00	84.00
Linker	85.56	82.50	82.00	79.00
Tatento	64.91	90.20	97.00	94.30
Cerutti	0.00	85.00	82.50	78.20
Slocum	89.91	57.30	78.00	60.00
Schmidt	50.66	91.10	75.00	90.50
Babaezaideh	91.61	94.60	95.00	91.50
Couceiro	97.50	91.50	85.79	79.20

5.3.1.1 Short window length effect (10 sec)

Linker's algorithm responds gave the highest performance for a window length of 10 seconds. Although the resolution is for a window length of 10 seconds, the algorithm requires the adjacent two segments to determine AF or NSR in the present segment. Therefore although the resolution is equal to 10 seconds, the signal length required is equal to 30 seconds.

Table 15: Windows length influence in Linker's algorithm performance



	10 seconds	30 seconds	60 seconds	300 seconds
Se	97.65	97.40	82.50	79.80
Sp	85.56	82.50	82.00	79.00
PPV	81.81	79.80	78.20	77.00

5.4 Computation time

Computation Time (C. Time) was defined as the time required to evaluate an hour of data. This was done by calculating the C. Time per signal and divided by the number of hours. The measurement was done considering the complete MIT-BIH AF Database. Every signal C. Time was measured for the specific window length defined for each algorithm and the mean value of the entire database was considered as the C. Time for the algorithm under study.

Cerutti et al got the lowest C. Time, which is the algorithm tested with the longest window length segment, and it is based only in RRI. The algorithms which combine several techniques, and also those that use a classifier are expected to have higher computation time, as shown in Couceiro et al.

Nevertheless C. Time could change for the same algorithm due to the fact that computer server used for the calculations was shared by various users and the computational load could be different at different times.

Table 16: Computation Time required evaluating an hour of data

Methods	*SubMethods*	*Window Length(sec)*	*Comp. Time (sec/hour of data)*
Moody et al	*RRI*	*90*	*0.55*
Cerutti et al	*RRI*	*290*	*0.36*
Couceiro et	*RRI/PWA/FA (QRS removal)*	*40*	*11.35*

5.5 Noise

In order to evaluate the robustness against noise for the different methods, a database was generated by combining clean ECG signals with different levels of noise (section 3.2.2.4). Clean ECG and noise signals were combined multiplying each 2-lead noise signal by a gain factor and adding it to each 2-lead clean ECG. SNR values ranging from 30 to -30 dB were considered [44].

The algorithms that demonstrated highest robustness were the ones based on RRI: Cerutti et al, Se=82.52 and Sp=40.47 for SNR=-5bB; and Tatento et al, Se=85.79% and Sp=81.90% for SNR=0dB.

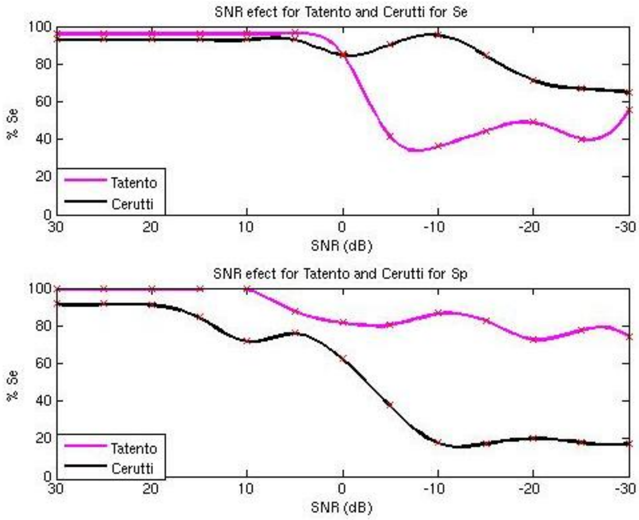


Figure 27 - Noise Effect in Tatento et al and Cerutti et al algorithms

The higher robustness of RRI based algorithms is due to QRS complexes, or R-peaks, were detected after the noise was added to the signal. Since the R peak is the more prominent and accessible feature in the ECG, even with noise, the influence of the noise was only dependant on the QRS detection algorithm [45]. Figure 28 shows that even though noise is present in the signal, R peaks are detected correctly.

In the other hand AA is more vulnerable to noise, and the algorithms which employed AA analysis were more influenced and the performance went down for lower levels of noise. It is observable in Figure 28 that the AA is highly influenced by noise.

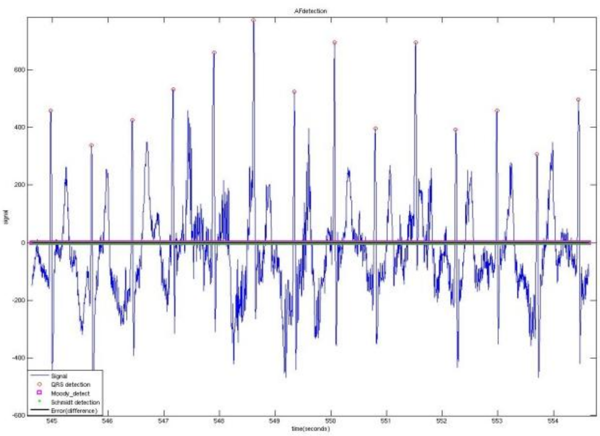


Figure 28 - Noise in ECG with detected R peaks

5.5.1 Se increment with Noise

As can be observed in Figure 29 (upper graph), Se increased with higher levels of noise in several algorithms. This is because noise can show a chaotic baseline similar to AF, which is detected as AF, and thus resulting in an increment in Se, however Sp decreases (Figure 29, lower graph)

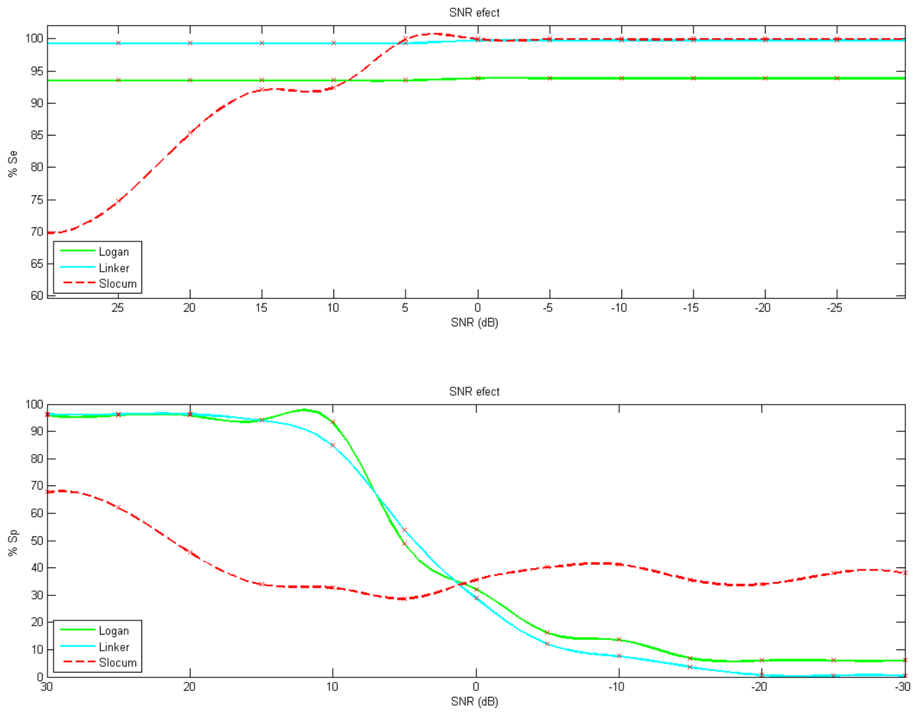


Figure 29 - Se increment with noise for Logan et al, Linker et al and Slocum et al

5.5.2 Sp and PPV increment with Noise

Interestingly the opposite effect could occur with high levels of noise. AF cannot be detected thus Sp increases while Se becomes lower. Couceiro et al's algorithm showed such behaviour. The reason is not clear, but the neural networks used in Couceiro et al's algorithm might not confound noise with AF's chaotic nature. For values lower than 0dB of SNR the Se decreases until becoming 0 after -20dB. Moreover the Sp increases after 5dB Figure 30, as well as the PPV, which start increasing after -20dB.

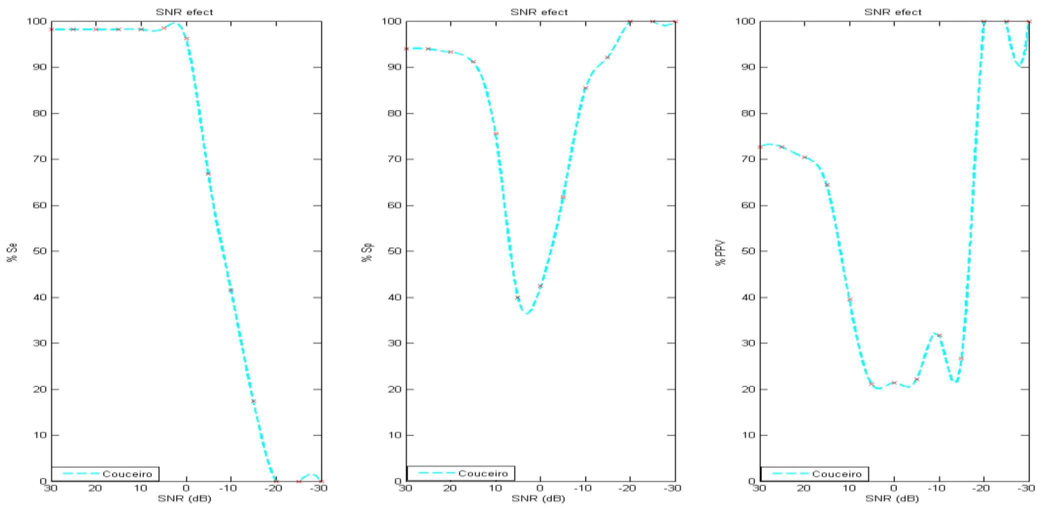


Figure 30: Sp increment with noise for Couceiro et al

5.5.3 Performance decrement

The most common and expected effect for high levels of noise is to have random detections, having as a result a general decrement on Se, Sp and Ppv, which is the common effect with noise, as it is shown in the Figure 31. Even though, as explained before, Se and Sp could also increment, while decreasing Sp and Se respectively.

In the case of PPV, the decrement of the performance becomes consistent for all the algorithms, with the only exception of Couceiro et al. Increment in the PPV when SNR decreased in Couciero et al is due to the fact that in presence of noise the number of false positives decreases as explained in section 5.5.2. The noise is not confounded with AF chaotic nature and AF is not detected even in the segments where it is present, therefore false positives will not occur. However, the number of false negatives increased, decreasing sensitivity.

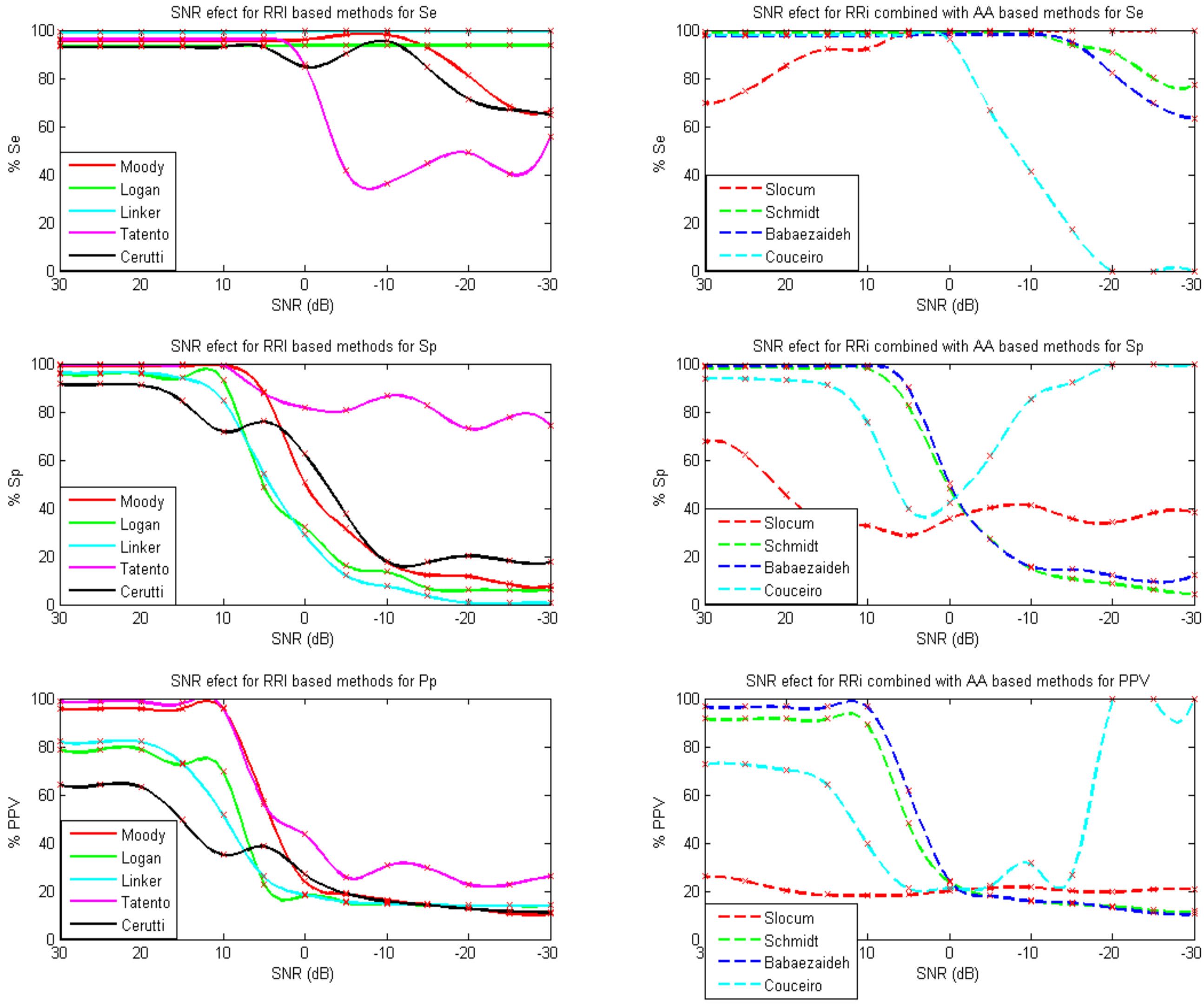


Figure 31 - Se and Sp values for all the Methods compared with a SNR variation from 30dB to -30 dB.

6 Conclusions

The main aim of this work is to analyze nine algorithms with a common evaluation method. Each algorithm was evaluated and compared based on the tests made. A discussion of the algorithms performance, the limitations, and future lines of work are included in this chapter.

6.1 Performance on MIT-BIH AF database

The results were calculated with the window length that gave the highest Se+Sp values for each algorithm, and the variation of each algorithm reported by the author. As can be observed in Figure 26 the techniques based on RRI and RRI-AA combination gave the best performance.

Tatento et al algorithm, based on RRI analysis, gave the highest specificity and the lowest error values, Sp=96.08% and Err= 5.32% respectively. Moreover, the Sensitivity and Positive Predictive Value are high (above 90%).

Babaezaideh et al (RRI+AA), which combined RRI study with P wave location and morphology analysis, had the highest PPV=92.75%. It also showed low error value, Err=7.80%, and high Sp=95.47%.

Schmidt et al (RR+AA) had similar performance to Babaezaideh et al, with PPV=91.62% and Err=7.57%. The author proposed a combination of at least two of the following three techniques: RRI, PWA and FA. Although RRI combined with PWA and with FA had similar performance (Figure 25), RRI combined with FA showed lower error and was used for the comparison. In the other hand, PWA combined with FA gave a low performance and it was excluded from the study.

Linker et al (RRI), which was based only in RRI, contained the best sensitivity value, Se=97.64%, with a window length of just 10 seconds. Couceiro et al gave a high Se, by combination of RRI and AA (Se=96.58%).

Table 17: Algorithms with the best performance

METHOD		***Window***	***RESULTS***			
	Analysis	***(sec)***	***Se (%)***	***Sp (%)***	***PPV (%)***	***Err (%)***
Linker	*RRI*	*10*	*97.64*	*85.55*	*81.81*	*9.61*
Tatento	*RRI*	*40*	*91.20*	*96.08*	*90.32*	*5.32*
Schmidt	*RRI/FA*	*70*	*89.20*	*94.58*	*91.62*	*7.57*
Babaezaideh	*RRI/PWA*	*160*	*87.27*	*95.47*	*92.75*	*7.80*
Couceiro	*RRI/PWA/FA*	*220*	*96.58*	*82.66*	*78.76*	*11.77*

6.2 Window length

For a real time AF detection the Window Length is important to be considered since the optimal performance is also determined by the time required to have a detection. Linker's algorithm is the one which need shorter signal length, giving Se=97.64%, Sp=85.55%, PPV=81.81% and Err=9.61% with a 10 seconds window length.

6.3 Noise

The algorithms that were more robust against noise were the ones based on RRI (section 5.5): Cerutti et al, Se=82.52% and Sp=40.47% for SNR=-5bB; and Tatento et al, Se=85.79% and Sp=81.90% for SNR=0dB. In the remaining cases the Se or/and Sp were lower for this values of SNR (SNR=0dB and SNR=-5dB). Therefore in case that the ECG to analyse contains high levels of noise Cerutti et al's algorithm is recommended if high sensitivity values are required. Otherwise, for high Sp values Tatento et al's algorithm will be the best for AF analysis in a noisy signal.

The reason of obtaining better result against noise in RRI based techniques is due to the fact that is based only on the QRS detection and depends only on the beat detection.

6.4 Computation Time

Computation Time (C. Time) is measured as the computing time per hour of signal. Usually the algorithms tested required around 1 second C.Time per hour of data.

Therefore it does not limit that much the real time AF detection.

When computing resources are limited, as in ambulatory devices, a simple algorithm is required. Consequently in this case RRI based algorithms required less processing techniques, and in particular Logan et al's first method, which is based on the variance of RR intervals, is expected to be the fastest with Se= 92.36% and Sp= 75.06% for a 10 second window length. Also Linker et al's technique does not require much processing requirements, and the performance obtained is also good.

6.5 Recommendations on the algorithm to use

The best AF detection algorithm to use will depend on the application.

For analyzing a long ECG recording that can also be visually inspected by an expert, it is preferred to use an algorithm which gives high Sensitivity. Specificity is less important as False Positives could be rejected by visual inspection. In this scenario it would be recommended to use Linker et al's algorithm that gives a Se of 97.64% and a Sp of 85.55%. In addition, this algorithm has high resolution with a window length of 10 seconds.

When both Se and Sp are important, such as for automatic ambulatory AF detectors, the algorithm preferred would be the one that combines high performance in both parameters. In this case Tatento et al could be a good choice with a Se of 91.20% and Sp of 96.08%.

In case that we are going to monitored patient with short periods of AF (paroxysmal AF) low window length or high resolution is required. Therefore, Linker's et al algorithm, which has high performance for a window length of 10 seconds, could be the best choice.

When robustness to noise is needed, such as for ambulatory AF detection devices, then the algorithm preferred would be Tatento el al's, which gives Se=85.79% and Sp=81.90% for SNR=0dB; or Cerutti et al's, Se=82.52% and Sp=40.47% for SNR=-5dB.

Considering computational complexity, Logan et al algorithm's had a low computing time of 0.45 seconds with Se=91.40% and Sp=93.02%. This algorithm could be the best choice when computational resources are limited.

6.6 Limitations

6.6.1 Training dataset

MIT-BIH Arrhythmia database was used as a training set. The number of AF episodes that it includes is low, but the performance obtained with the algorithms that require a training process was good enough.

However, depending on the training dataset used, the results could vary. Therefore the algorithms which required a training dataset are dependent on the robustness of it and the accuracy of AF detection is compromised if the characteristics of AF are different from those learned in the training data.

In Tatento et al the problem found was that the MIT-BIH Arrhythmia Database had not enough AF episodes to build Standard Density Histograms required for the test. Consequently the data used for training was extended with the last 10 signals from MIT-BIH AF database (section 4.1.4).

6.6.2 Tested data

As shown in section 3.1.3, ECG lead configuration for MIT-BIH AF database was done manually due to the not specified lead (lead II or V1) of the two channels that each record contains. Therefore the algorithms that depend on the used lead, such as algorithms based on AA analysis, could have a different performance.

6.6.3 QRST complex removal and P wave detection

In AA analysis, frequency spectrum analysis and P wave absence detection were studied. For both studies waves detection are determinant.

For frequency spectrum analysis, and also for some of P wave detection techniques, QRST complex should be removed. The procedure used in this study was the subtraction of a QRST template got from the current window to analyze [45].

For P wave absence analysis the P-onset and P-offset detection techniques also could be improved. In the current study P-wave peak was determined as the maximum value in an “expected” range before R-peak. Based on that, P-onset and P-offset were measured.

The techniques for QRST complex removal [45] and P wave detection were simple and a better technique could lead to higher algorithm performance.

In this study, for QRST complex removal, R peak detection was done firstly. Once the R peak was detected a window to the left and right was applied. P wave peak was assumed to be the maximum value of the window length of around 0.2 seconds before the R peak. On the other hand, the maximum value in the range of 0.3 seconds to the right of the R peak, T wave peak was declared.

However in some algorithms more sophisticated methods were described, as in Christov et al [35], where more than two ECG leads were required for QRS, T and P wave detection. In this study the database used contained only two leads. So, even though the performance obtained could be improved, the currently implemented algorithm worked suitably.

6.7 Future lines of work

QRST complex removal, and also P wave detection techniques (P-onset, P-offset) could be improved to obtain a higher performance on algorithms based on AA analysis.

High levels of noise could induce to erroneous detections in ECG signals for AF detection. Both additive noise, due to sources such as power line inferences, respiration, electromyography (EMG) signals and motion artifacts; and multiplicative noise, such as respiration noise, are the main problems.

When there is low level of noise in the ECG, detection could be done without a previous noise removal technique.

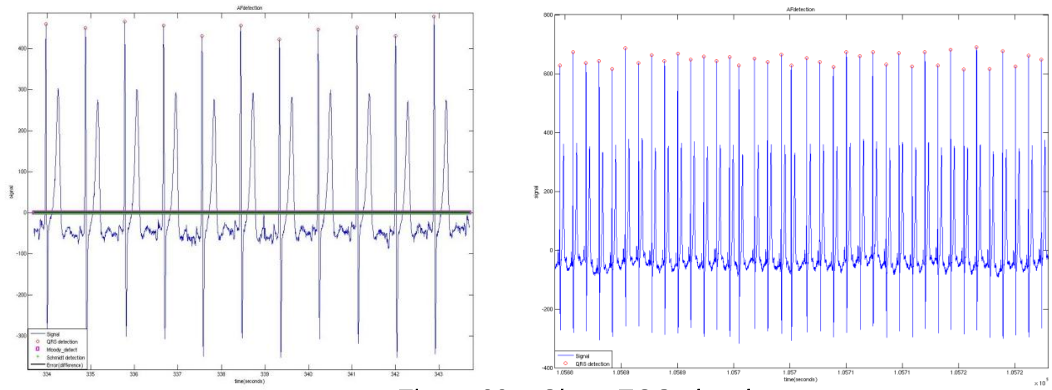


Figure 32 – Clean ECG signal

When the level of noise is reasonably small, due to moderate motion artifacts, signal pre-processing methods such as filtering or more sophisticated ones, such as PCA and ICA applied to ECG denoising [44], are suggested before applying AF detection.

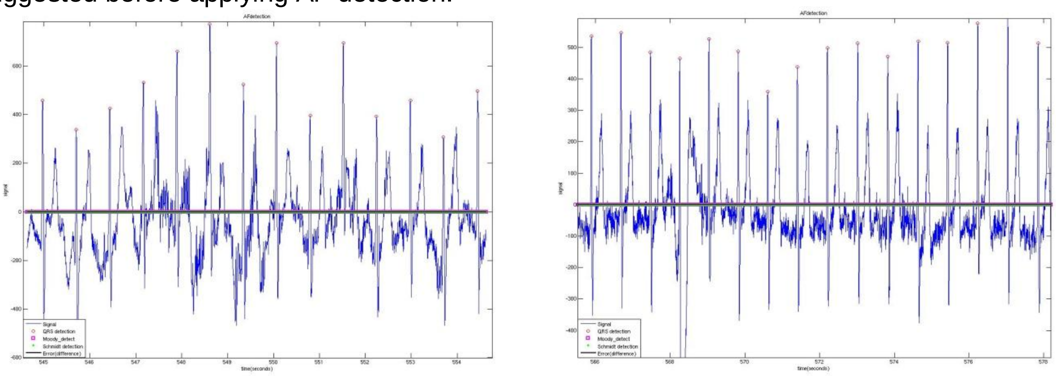


Figure 33 – ECG signal with moderate motion artifact noise

For the signals with high level of noise due to high amplitude motion artifacts or electrode removal, the detection could be stopped and ignored due to the inappropriate working mode in order to avoid false alarms.

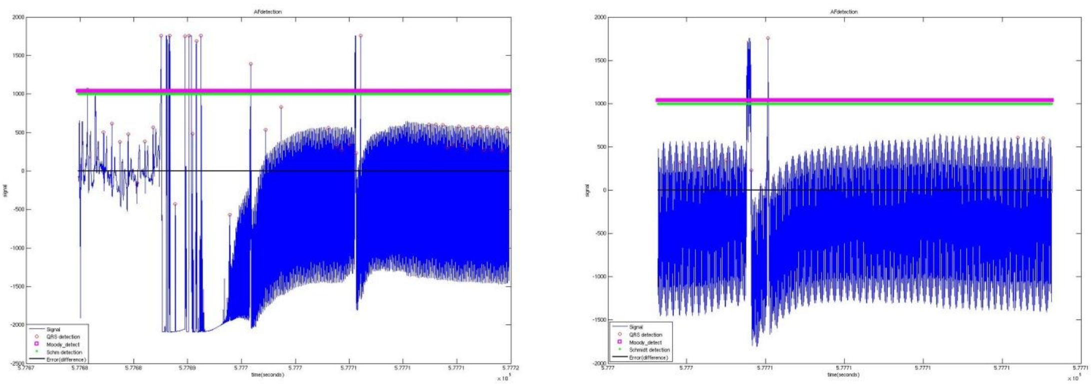


Figure 34 – High level noise

6.8 Proposed algorithm

The combination of an algorithm based on RRI such as Linker et al's, which offer high Se=97.64, with a method based on AA with high Sp, could lead into a better algorithm for AF detection.

In case of Babaezaideh et al and Schmidt et al Moody et al's method was combined with AA techniques, but the resulting performance was not as good since the Se was less than 90%. Despite of it, the Sp values were high (Sp=95.47% and Sp=94.58% respectively).

Considering that Moody et al's algorithm had not the best Se values, instead of using it combined with AA techniques, a combination of Linker's algorithm with AA is suggested in order to increase the Se. Also Cerutti et al's method, which had high Se could be a good choice to be combined with AA techniques of FA and PA to obtain a better algorithm.

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A Appendix Heading

A.1 Evaluation of each algorithm

A.1.1 Moody et al

A.1.1.1 RR

ATRIAL FIBRILLATION DETECTION

Contents

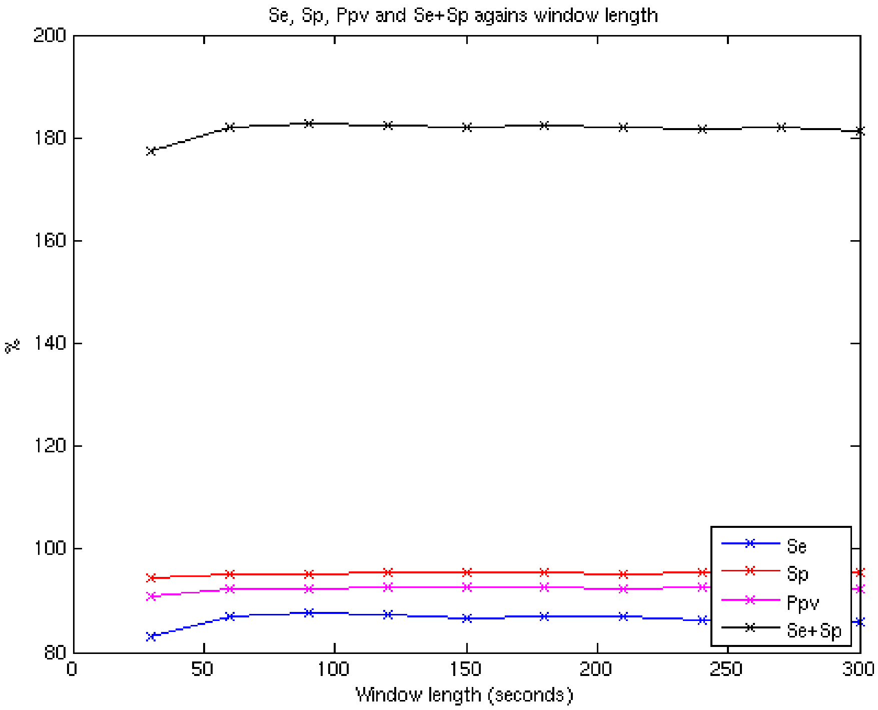
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 90 seconds,
giving Se=87.547%, Sp=95.1466% and Ppv=92.29%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 90, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

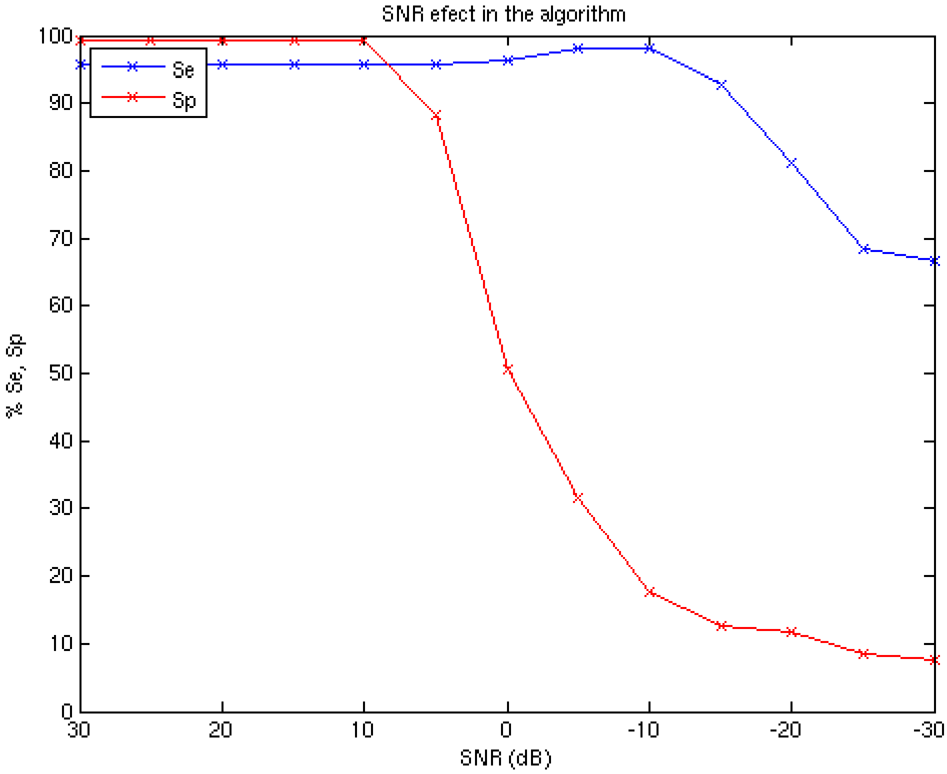
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	84.22668	91.93616	6.343293	8.113507	0.5654972
MIT_BIH_AF_04043m	56.29473	97.36441	85.40708	11.46863	0.6501672
MIT_BIH_AF_04048m	63.18159	94.45435	10.13079	5.852043	0.5033656
MIT_BIH_AF_04126m	95.17029	97.35188	58.28409	2.729758	0.518751
MIT_BIH_AF_04746m	99.22966	99.78214	99.80646	0.5112234	0.6396604
MIT_BIH_AF_04908m	89.25023	94.3829	59.55238	6.052374	0.7037891
MIT_BIH_AF_04936m	84.84534	93.32854	97.05149	12.79045	0.5839779
MIT_BIH_AF_05091m	49.04112	99.62583	23.63895	0.493365	0.454252
MIT_BIH_AF_05121m	96.78457	93.01091	95.97448	4.601956	0.5426863
MIT_BIH_AF_05261m	83.09461	94.9052	17.70759	5.248594	0.4925864
MIT_BIH_AF_06426m	99.3844	52.96791	97.8218	2.701483	0.5572557
MIT_BIH_AF_06453m	24.24154	99.72667	50	1.114955	0.4213883
MIT_BIH_AF_06995m	96.98673	84.81888	85.08522	9.441241	0.5627088
MIT_BIH_AF_07162m	98.74257	100	99.9981	1.259288	0.4515562
MIT_BIH_AF_07859m	28.10773	100	99.99838	71.8924	0.6511291
MIT_BIH_AF_07879m	92.39291	100	100	4.58816	0.6085432
MIT_BIH_AF_07910m	97.71888	99.33876	96.55422	0.9194352	0.4782003
MIT_BIH_AF_08215m	98.8746	100	100	0.9069105	0.4945664
MIT_BIH_AF_08219m	95.30483	79.17009	55.74378	17.34697	0.5873603
MIT_BIH_AF_08378m	73.84322	97.88733	90.2333	7.139454	0.5831195
MIT_BIH_AF_08405m	99.85134	100	100	0.1073458	0.7064312
MIT_BIH_AF_08434m	93.67888	95.12337	43.58582	4.932477	0.4879974
MIT_BIH_AF_08455m	99.28931	100	100	0.4915944	0.621911
DATABASE_TOTAL	87.54704	95.14658	92.29005	7.88484	0.5594305

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 90, has this robustness against the noise
SNR        Se           Sp            PPV
 30       95.8217       99.3388       95.9389
 25       95.8217       99.3388       95.9389
 20       95.8217       99.3388       95.9389
 15       95.8217       99.3388       95.9389
 10       95.8217       99.3388       95.9389
  5       95.8217       88.2898       57.1547
  0       96.1895       50.5513       24.0767
 -5       98.2166        31.692       18.9891
-10       98.2166       17.7359       16.2925
-15       92.6907       12.4736       14.7225
-20       81.1509       11.7553       13.0373
-25       68.4906       8.52849       10.8787
-30        66.707       7.65626       10.5357
```



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A.1.1.2 RRI & Filtering

ATRIAL FIBRILLATION DETECTION

Contents

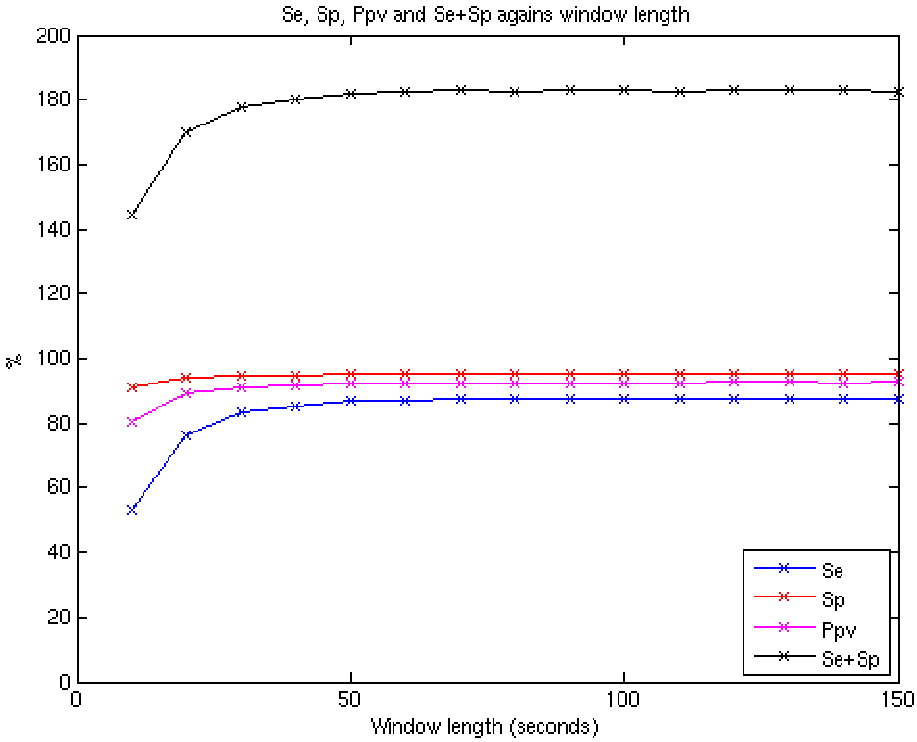
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 140 seconds,
giving Se=87.8162%, Sp=95.2318% and Ppv=92.4427%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 140, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

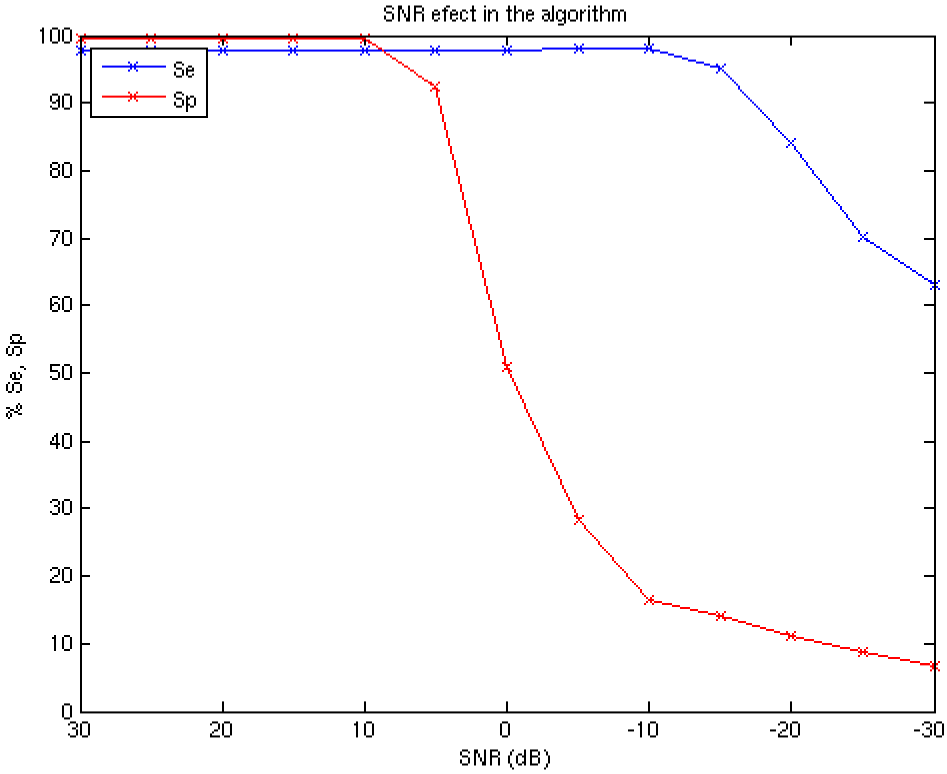
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	92.22982	7.702418	7.720123	2.030858
MIT_BIH_AF_04043m	39.36794	98.19314	85.65291	14.45868	2.522968
MIT_BIH_AF_04048m	63.25254	94.48248	10.18745	5.823495	2.19801
MIT_BIH_AF_04126m	92.93571	97.68823	60.98124	2.489615	2.286417
MIT_BIH_AF_04746m	99.67203	99.35655	99.43304	0.4759303	2.166523
MIT_BIH_AF_04908m	94.02868	93.72562	58.03111	6.248783	2.478538
MIT_BIH_AF_04936m	86.7238	91.38737	96.31807	11.98002	2.196303
MIT_BIH_AF_05091m	0	99.61889	0	0.6158427	1.895377
MIT_BIH_AF_05121m	96.90194	92.0873	95.4819	4.864465	2.15236
MIT_BIH_AF_05261m	79.6251	96.81312	24.79163	3.410691	1.914115
MIT_BIH_AF_06426m	99.12536	34.1631	97.13644	3.635463	2.13518
MIT_BIH_AF_06453m	0	100	100	1.114955	1.576007
MIT_BIH_AF_06995m	97.50485	86.30978	86.41271	8.409224	2.410718
MIT_BIH_AF_07162m	99.99176	100	99.99812	0.0101241	2.095269
MIT_BIH_AF_07859m	26.99402	100	99.99831	73.00611	2.702661
MIT_BIH_AF_07879m	95.55296	99.60218	99.7268	2.840081	2.454449
MIT_BIH_AF_07910m	98.29872	99.64256	98.11837	0.5716312	1.854412
MIT_BIH_AF_08215m	99.38029	100	100	0.5002412	2.181163
MIT_BIH_AF_08219m	96.14697	78.467	55.14103	17.71649	2.939233
MIT_BIH_AF_08378m	80.69902	97.7768	90.56128	5.793568	2.246635
MIT_BIH_AF_08405m	99.92235	99.6959	99.88301	0.1405859	2.652145
MIT_BIH_AF_08434m	94.48549	95.09935	43.67582	4.924384	1.861989
MIT_BIH_AF_08455m	99.4856	100	100	0.3558207	2.483852
DATABASE_TOTAL	87.81623	95.2318	92.44271	7.727783	2.236312

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 140, has this robustness against the noise
SNR       Se           Sp            PPV
 30       97.7085       99.6464       97.8282
 25       97.7085       99.6464       97.8282
 20       97.7085       99.6464       97.8282
 15       97.7085       99.6464       97.8282
 10       97.7085       99.6464       97.8282
  5       97.7085       92.4096       67.7268
  0       97.8429       50.8211       24.4906
 -5       98.0184       28.2355       18.2113
-10       98.0184        16.476        16.059
-15       95.2441       14.2146       15.3258
-20       84.1467       11.0485       13.3612
-25        70.326       8.79544       11.1667
-30       62.9416       6.68711       9.90687
```



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A.1.1.3 RRI & Interpolation

ATRIAL FIBRILLATION DETECTION

Contents

PARAMETERS:

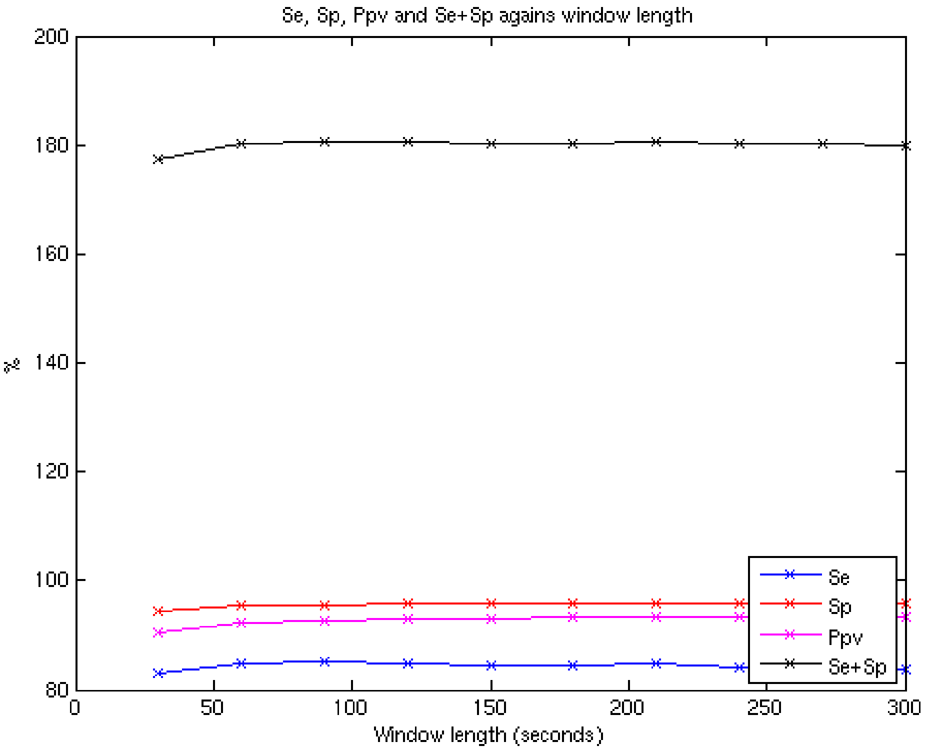
The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
This test evaluates the performance of the algorithm under study for
different window length and determines which window length obtains the
best performance.
```

```
The optimal window length is: 90 seconds,
giving Se=85.2979%, Sp=95.4441% and Ppv=92.5503%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 90, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

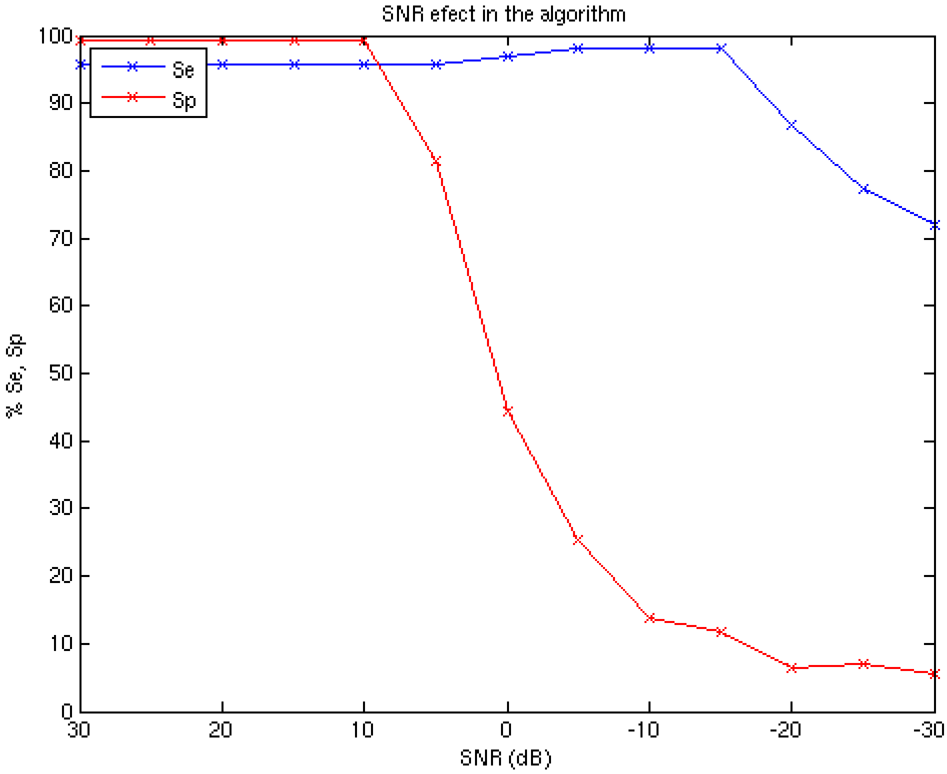
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	84.22668	91.93616	6.343293	8.113507	0.6153577
MIT_BIH_AF_04043m	50.53027	97.96464	87.18365	12.23729	0.7213335
MIT_BIH_AF_04048m	63.18159	94.45435	10.13079	5.852043	0.5952306
MIT_BIH_AF_04126m	95.17029	96.59012	52.03932	3.463017	0.5437913
MIT_BIH_AF_04746m	98.7694	99.78214	99.80556	0.7556247	0.627108
MIT_BIH_AF_04908m	83.97059	94.91972	60.34829	6.00347	0.7038153
MIT_BIH_AF_04936m	86.20068	93.32854	97.09651	11.81283	0.7167192
MIT_BIH_AF_05091m	49.04112	99.62583	23.63895	0.493365	0.5470708
MIT_BIH_AF_05121m	93.90677	94.04296	96.44638	6.043195	0.6827695
MIT_BIH_AF_05261m	83.09461	95.15282	18.44535	5.004193	0.6069735
MIT_BIH_AF_06426m	99.44913	54.34357	97.88551	2.577843	0.6424833
MIT_BIH_AF_06453m	24.24154	99.72667	50	1.114955	0.517165
MIT_BIH_AF_06995m	95.9505	88.05761	87.76667	8.219115	0.641449
MIT_BIH_AF_07162m	98.74257	100	99.9981	1.259288	0.5585191
MIT_BIH_AF_07859m	17.84262	100	100	82.15701	0.7345163
MIT_BIH_AF_07879m	85.90934	100	100	8.498679	0.6949569
MIT_BIH_AF_07910m	97.71888	99.33876	96.55422	0.9194352	0.5726847
MIT_BIH_AF_08215m	98.57131	100	100	1.151312	0.5798052
MIT_BIH_AF_08219m	93.06189	81.66958	58.29225	15.8712	0.6812788
MIT_BIH_AF_08378m	62.15238	97.88733	88.60552	9.583598	0.5482262
MIT_BIH_AF_08405m	99.51288	100	100	0.3517472	0.7269712
MIT_BIH_AF_08434m	93.67888	94.6149	41.16446	5.421291	0.5839918
MIT_BIH_AF_08455m	99.64264	100	100	0.2471931	0.7599377
DATABASE_TOTAL	85.29787	95.44415	92.5503	8.60294	0.6348763

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 90, has this robustness against the noise
SNR       Se           Sp            PPV
 30       95.8217      99.3388       95.9389
 25       95.8217      99.3388       95.9389
 20       95.8217      99.3388       95.9389
 15       95.8217      99.3388       95.9389
 10       95.8217      99.3388       95.9389
  5       95.8217      81.6023       45.9191
  0       96.9736      44.2826       22.1023
 -5       98.2166      25.2956       17.6502
-10       98.2166      13.6654       15.6445
-15       98.2166        11.63       15.3394
-20       86.8693        6.291       13.1284
-25       77.4084      7.07477       11.9564
-30       72.0577      5.62098        11.069
```



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A.1.1.4 RR & Filtering & interpolation

ATRIAL FIBRILLATION DETECTION

Contents

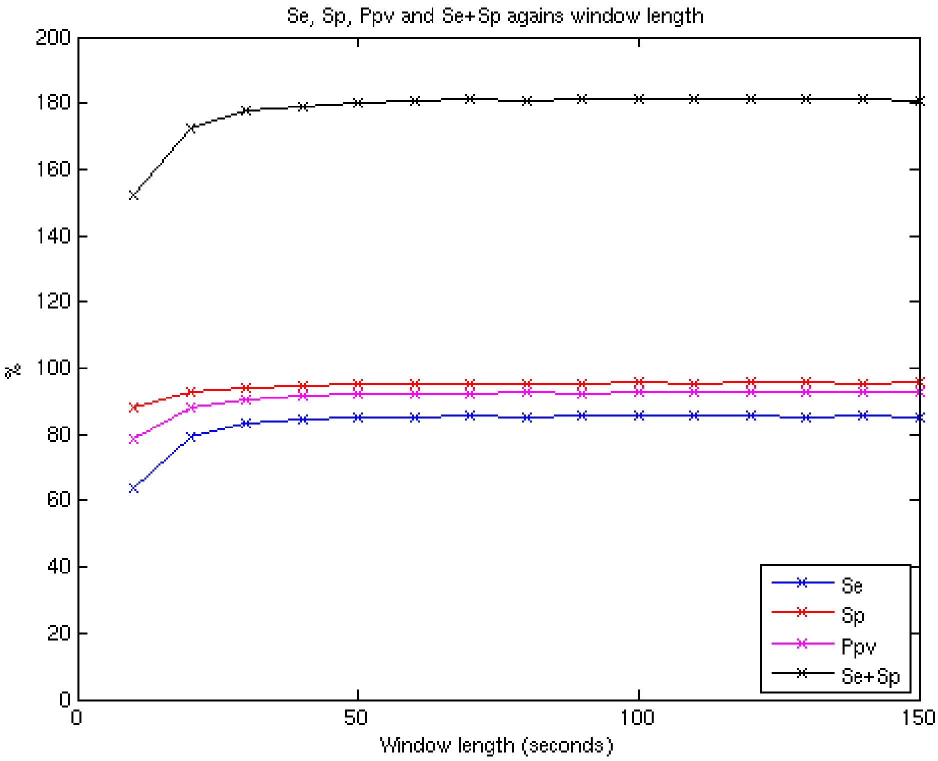
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 120 seconds,
giving Se=85.4852%, Sp=95.824% and Ppv=93.1476%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 120, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

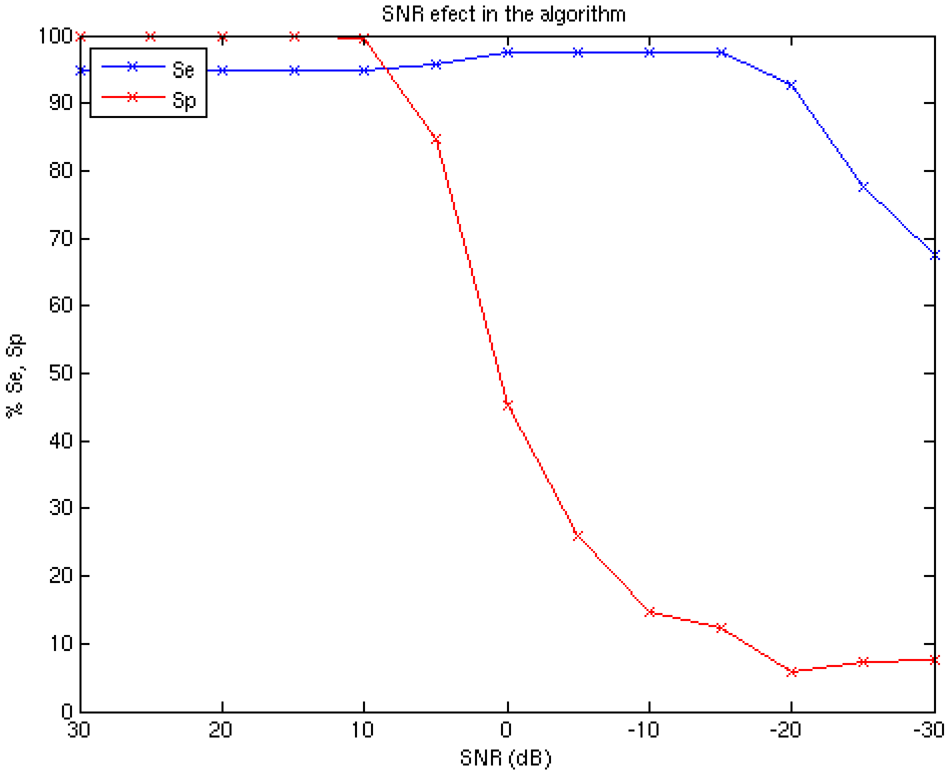
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	71.58104	91.60819	5.241189	8.520839	2.183516
MIT_BIH_AF_04043m	33.97425	98.51436	86.23744	15.36659	2.874158
MIT_BIH_AF_04048m	57.47722	94.64474	9.600132	5.719408	1.922571
MIT_BIH_AF_04126m	93.12874	97.18791	56.28367	2.963992	1.968982
MIT_BIH_AF_04746m	99.16582	99.70986	99.74224	0.5790288	2.257096
MIT_BIH_AF_04908m	88.57441	95.71954	65.64423	4.884453	2.718799
MIT_BIH_AF_04936m	86.31888	95.38889	97.97775	11.15336	2.403857
MIT_BIH_AF_05091m	0	99.67334	0	0.5615289	1.813508
MIT_BIH_AF_05121m	96.8822	93.03566	96.05698	4.515934	2.377844
MIT_BIH_AF_05261m	79.6251	96.75807	24.47366	3.465026	2.265628
MIT_BIH_AF_06426m	98.9096	40.05452	97.15414	3.803836	2.527324
MIT_BIH_AF_06453m	0	99.63556	0	1.475327	1.802107
MIT_BIH_AF_06995m	93.70534	89.29144	88.65415	8.626414	2.267535
MIT_BIH_AF_07162m	99.3943	100	99.99811	0.6075653	1.934527
MIT_BIH_AF_07859m	20.53057	100	99.99778	79.46953	2.473009
MIT_BIH_AF_07879m	86.47623	100	100	8.154243	2.450368
MIT_BIH_AF_07910m	95.74649	99.93398	99.63766	0.7334647	1.693827
MIT_BIH_AF_08215m	98.84596	99.73477	99.93596	0.9826891	1.902994
MIT_BIH_AF_08219m	91.7342	83.27828	60.16312	14.89637	2.922275
MIT_BIH_AF_08378m	70.63601	98.06969	90.63014	7.665733	2.531425
MIT_BIH_AF_08405m	99.09497	99.50046	99.80636	0.7923409	2.767366
MIT_BIH_AF_08434m	100	94.86916	43.94225	4.932455	2.109243
MIT_BIH_AF_08455m	99.40158	99.98767	99.99447	0.4177385	2.590599
DATABASE_TOTAL	85.48521	95.82396	93.14758	8.301782	2.29385

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 120, has this robustness against the noise
SNR       Se          Sp           PPV
 30       94.7166       99.934     99.5743
 25       94.7166       99.934     99.5743
 20       94.7166       99.934     99.5743
 15       94.7166       99.934     99.5743
 10       94.7166      99.5463     97.1455
  5       95.8133      84.6055     50.3632
  0       97.3353      45.3109     22.4895
 -5        97.622      25.9741     17.6946
-10        97.622      14.7315     15.7286
-15        97.622      12.4054     15.3751
-20       92.8661      5.81495     13.8481
-25       77.6357      7.20878     12.0025
-30       67.4769      7.49107     10.6273
```



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A.1.2 Logan et al

A.1.2.1 RR var (M1)

ATRIAL FIBRILLATION DETECTION

Contents

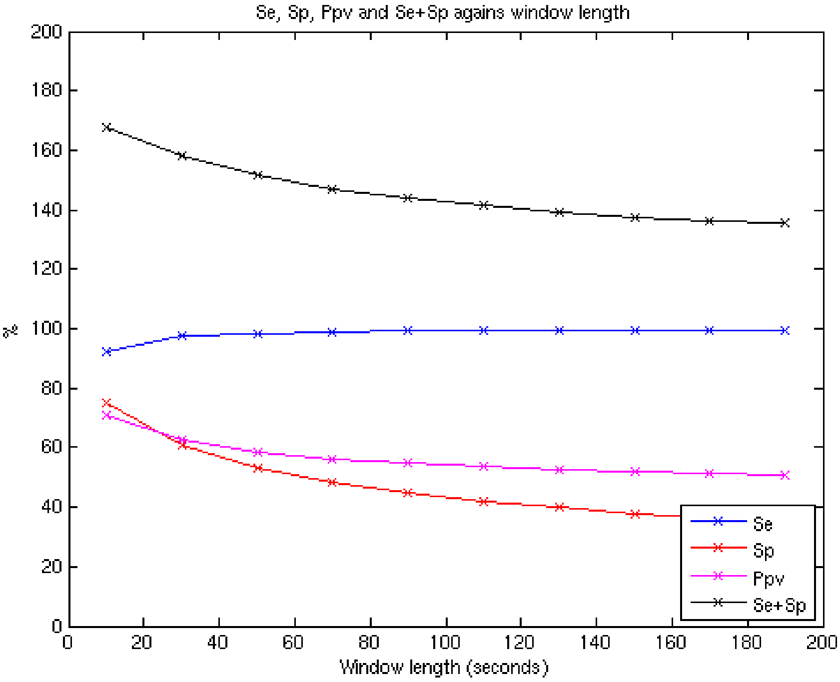
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 10 seconds,
giving Se=92.366%, Sp=75.0577% and Ppv=71.1819%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 10, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

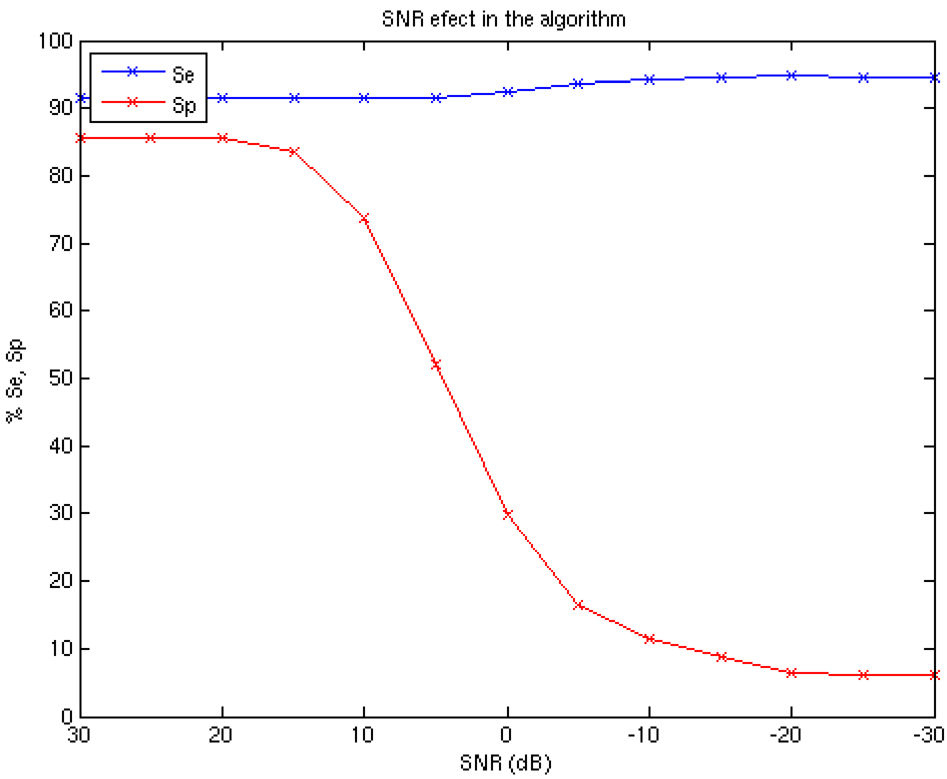
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	95.7308	81.2484	3.20432	18.6583	2.50395
MIT_BIH_AF_04043m	91.8891	91.0326	73.7753	8.78288	3.47567
MIT_BIH_AF_04048m	95.1771	82.7645	5.18081	17.1139	2.48279
MIT_BIH_AF_04126m	95.7195	43.3598	6.16489	54.6809	2.56099
MIT_BIH_AF_04746m	93.262	84.8263	87.4353	10.6944	2.78824
MIT_BIH_AF_04908m	94.5356	86.9627	40.1227	12.3967	3.7144
MIT_BIH_AF_04936m	89.4539	91.901	96.8715	9.90268	3.18191
MIT_BIH_AF_05091m	92.5226	88.6401	1.8874	11.3507	2.29013
MIT_BIH_AF_05121m	91.7031	64.4613	81.7833	18.2397	2.9353
MIT_BIH_AF_05261m	94.7953	63.9283	3.35098	35.6698	2.67574
MIT_BIH_AF_06426m	93.1259	55.732	97.9045	8.48531	3.10609
MIT_BIH_AF_06453m	83.566	83.2806	5.3349	16.7162	2.0361
MIT_BIH_AF_06995m	93.3673	28.5021	53.8325	40.9002	3.31875
MIT_BIH_AF_07162m	90.2582	5.78035	99.998	9.74338	2.52082
MIT_BIH_AF_07859m	93.1371	4.7619	99.9995	6.86334	3.68371
MIT_BIH_AF_07879m	93.7192	82.6912	89.1646	10.6573	3.25117
MIT_BIH_AF_07910m	92.0447	86.28	57.2116	12.762	2.2161
MIT_BIH_AF_08215m	90.9494	82.0589	95.4777	10.772	2.46096
MIT_BIH_AF_08219m	93.3929	26.4058	25.8904	59.1339	3.34464
MIT_BIH_AF_08378m	92.3092	86.4972	64.4565	12.2843	2.5691
MIT_BIH_AF_08405m	93.8048	89.6829	95.9389	7.34074	3.41062
MIT_BIH_AF_08434m	93.6682	85.8738	21.0539	13.8248	2.31569
MIT_BIH_AF_08455m	93.9717	89.879	95.4197	7.29006	3.45325
DATABASE_TOTAL	92.366	75.0577	71.1819	18.0169	2.88244

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 10, has this robustness against the noise
SNR       Se           Sp            PPV
 30        91.656       85.6118       50.9442
 25        91.656       85.6118       50.9442
 20        91.656       85.5576       50.8502
 15       91.6556        83.448       47.4439
 10       91.6551       73.6682       36.2019
  5       91.6551        52.024       23.7482
  0       92.4202       29.7929       17.6685
 -5       93.6686       16.5991       15.4758
-10       94.2962       11.5291       14.8035
-15        94.573       8.82803       14.4644
-20       94.7159        6.5058       14.1744
-25       94.6463       6.13776       14.1177
-30       94.3929       6.14101       14.0857
```



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A.1.2.2 Var (RRnorm) (M2)

ATRIAL FIBRILLATION DETECTION

Contents

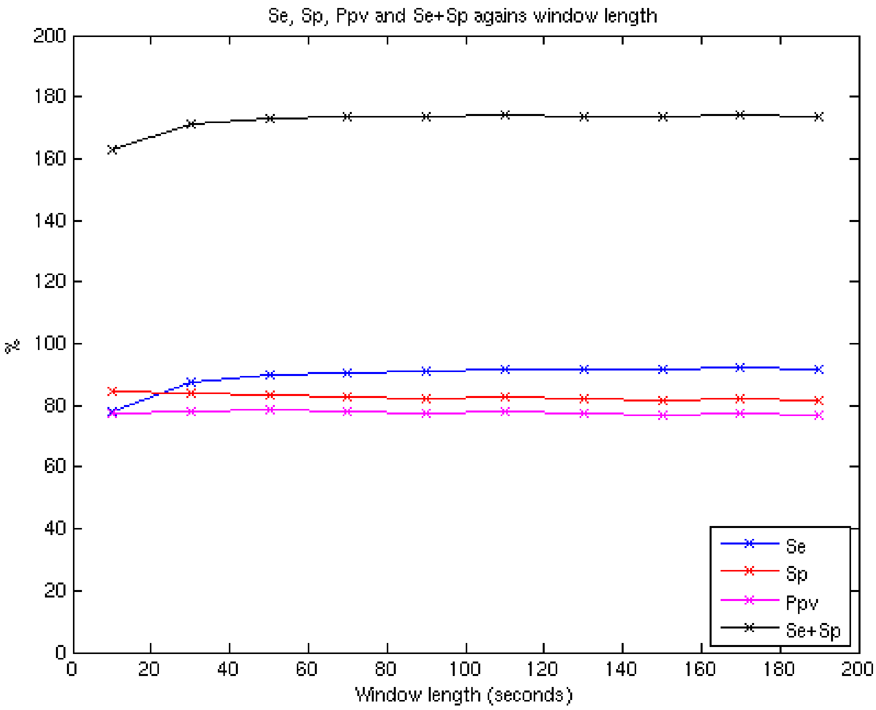
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

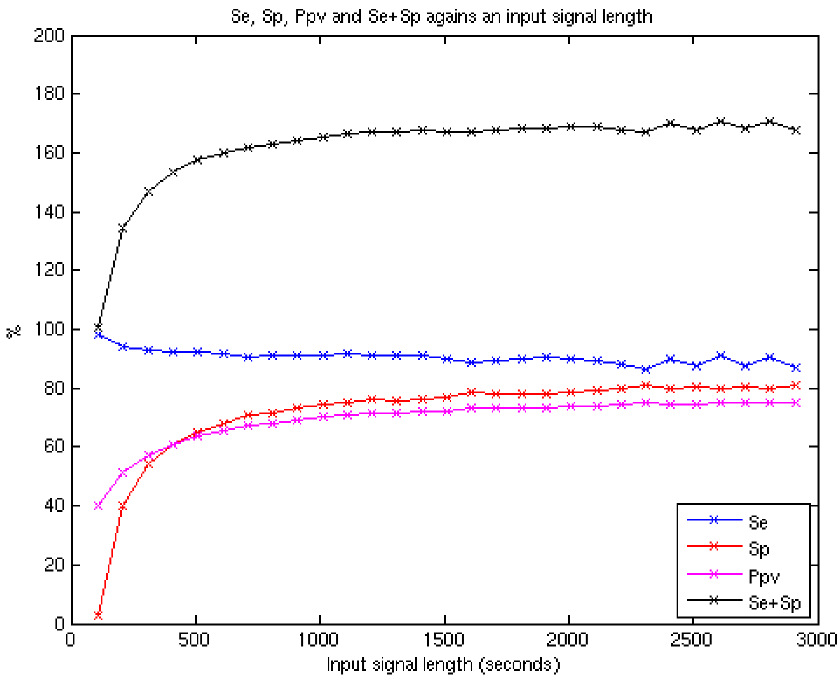
```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 110 seconds,
giving Se=91.4051%, Sp=83.0249% and Ppv=78.1904%.
```



INPUT SIGNAL LENGTH TEST

Description:

This test evaluates the performance of the algorithm under study for different input signal window lengths and determines which window length obtains the best performance.
The optimal segment length is: 2610 seconds, for a window length of 110 giving Se=90.9157%, Sp=79.8109% and Ppv=74.9084%.



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 110, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

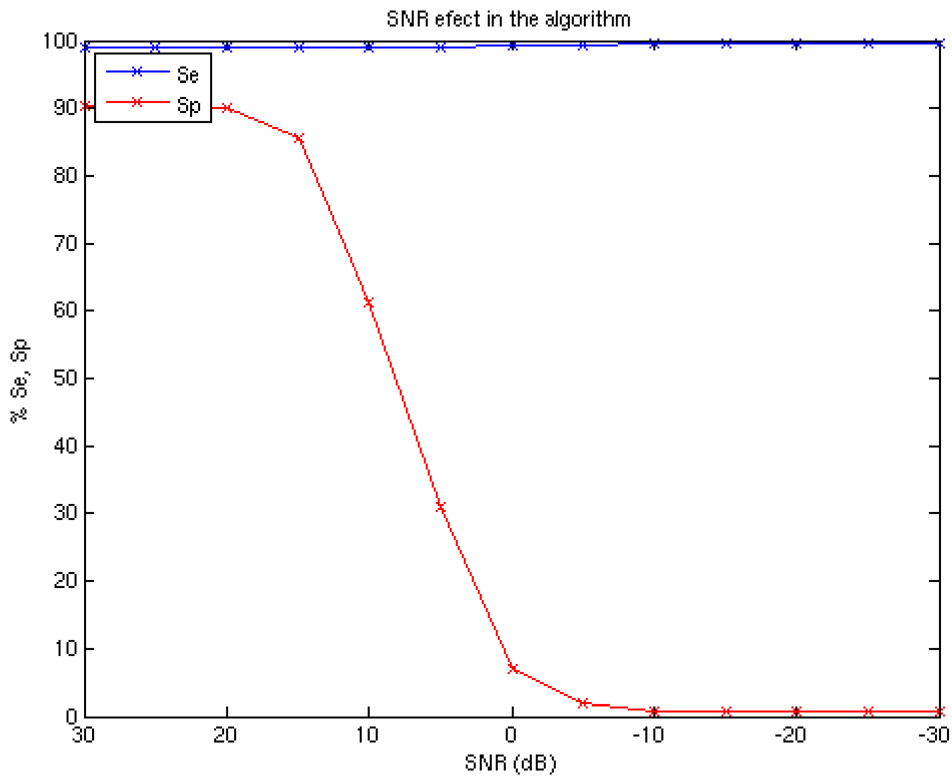
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	99.4149	76.1761	2.63458	23.6742	0.425491
MIT_BIH_AF_04043m	74.0831	90.3983	67.8883	13.1107	0.510293
MIT_BIH_AF_04048m	99.7661	84.5807	6.01674	15.2706	0.417196
MIT_BIH_AF_04126m	99.6894	64.8578	9.9328	33.8387	0.422117
MIT_BIH_AF_04746m	99.2318	95.8943	96.4745	2.33346	0.446573
MIT_BIH_AF_04908m	92.082	89.6667	45.1215	10.1292	0.51702
MIT_BIH_AF_04936m	93.1496	81.1211	92.8443	10.1644	0.478716
MIT_BIH_AF_05091m	92.9698	84.7843	1.42263	15.1964	0.38676
MIT_BIH_AF_05121m	97.9672	70.0979	85.1558	12.1636	0.468385
MIT_BIH_AF_05261m	98.4217	66.1304	3.69228	33.4492	0.438127
MIT_BIH_AF_06426m	98.9825	28.3433	97.0164	3.89601	0.481221
MIT_BIH_AF_06453m	50.0119	95.0378	10.2042	5.46423	0.371962
MIT_BIH_AF_06995m	96.6332	93.1045	92.6002	5.23092	0.477315
MIT_BIH_AF_07162m	99.0957	5.78035	99.9982	0.90602	0.384152
MIT_BIH_AF_07859m	52.5092	4.7619	99.9992	47.491	0.500115
MIT_BIH_AF_07879m	95.9515	93.8536	95.9556	4.88107	0.520563
MIT_BIH_AF_07910m	99.0735	94.6491	78.729	4.61381	0.38902
MIT_BIH_AF_08215m	98.9642	96.14	99.0691	1.58412	0.436105
MIT_BIH_AF_08219m	98.9247	53.4591	36.9144	36.7264	0.499489
MIT_BIH_AF_08378m	55.0767	94.297	71.8527	13.9026	0.424575
MIT_BIH_AF_08405m	99.4467	92.4942	97.1772	2.48547	0.498377
MIT_BIH_AF_08434m	91.783	84.8774	19.6207	14.8556	0.397984
MIT_BIH_AF_08455m	99.299	97.5498	98.9122	1.24027	0.508824
DATABASE_TOTAL	91.4051	83.0249	78.1904	13.6256	0.45219

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 110, has this robustness against the noise
SNR       Se          Sp            PPV
 30         98.93      90.4958       62.9208
 25         98.93      90.4958       62.9208
 20         98.93      90.1439       62.0685
 15         98.93      85.6682       52.9484
 10       99.0644      61.1465       29.3615
  5       99.0648      30.9075       18.9458
  0       99.2607      7.10019       14.8346
 -5       99.3881       1.8234       14.1656
-10       99.4626     0.718593       14.0392
-15       99.4464     0.673145       14.0317
-20        99.461     0.662458       14.0322
-25       99.4681      0.63355       14.0295
-30       99.4597     0.636613       14.0289
```



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A.1.2.3 Smoothed Var (RRnorm) (M3)

ATRIAL FIBRILLATION DETECTION

Contents

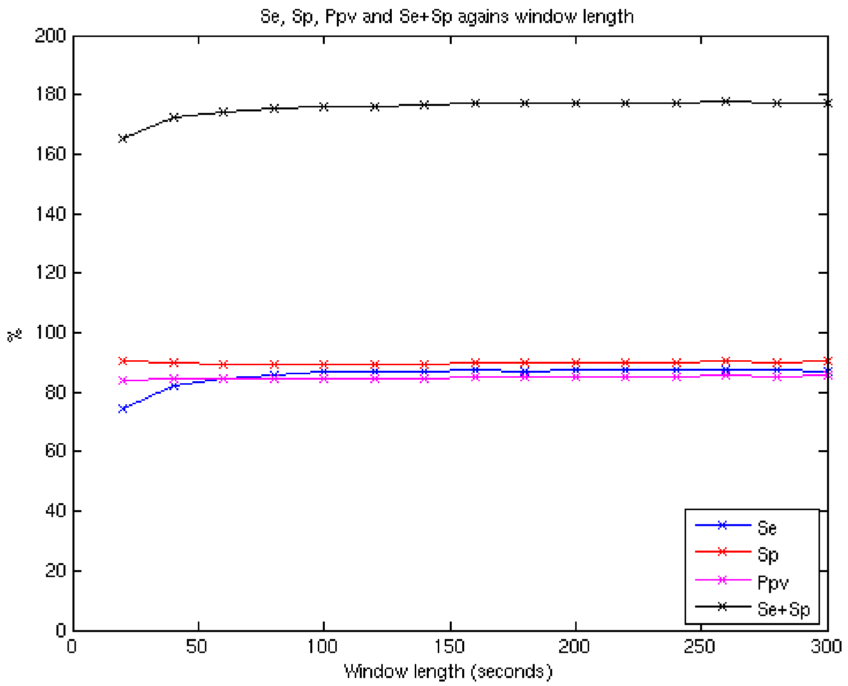
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

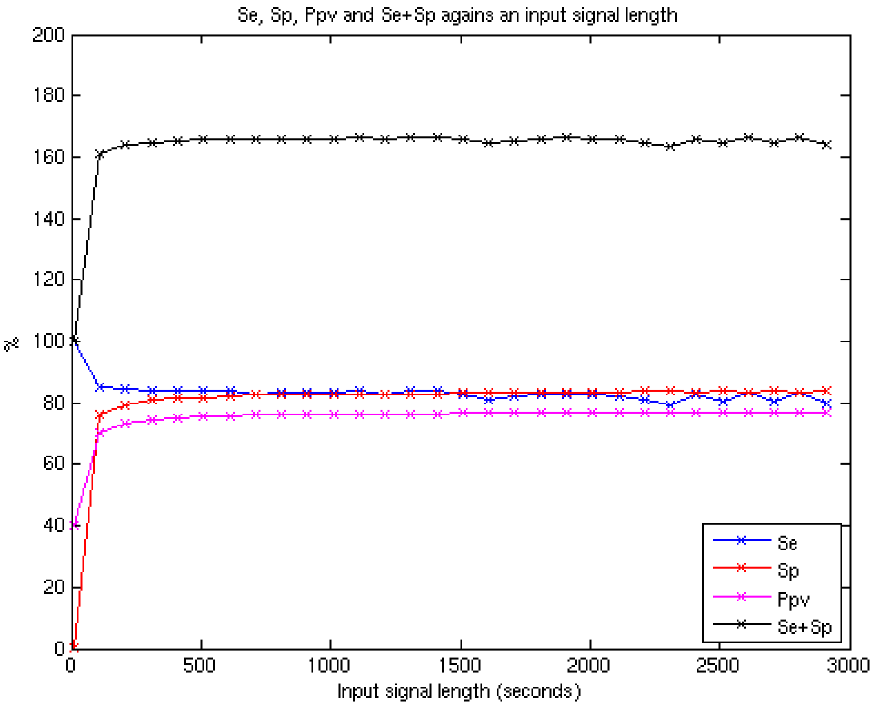
```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 260 seconds,
giving Se=87.3017%, Sp=90.3113% and Ppv=85.7217%.
```



INPUT SIGNAL LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different input signal window lengths and determines which window length
obtains the
 best performance.
The optimal segment length is: 2810 seconds, for a window length of 10
giving Se=83.4407%, Sp=83.3028% and Ppv=76.8141%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 260, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

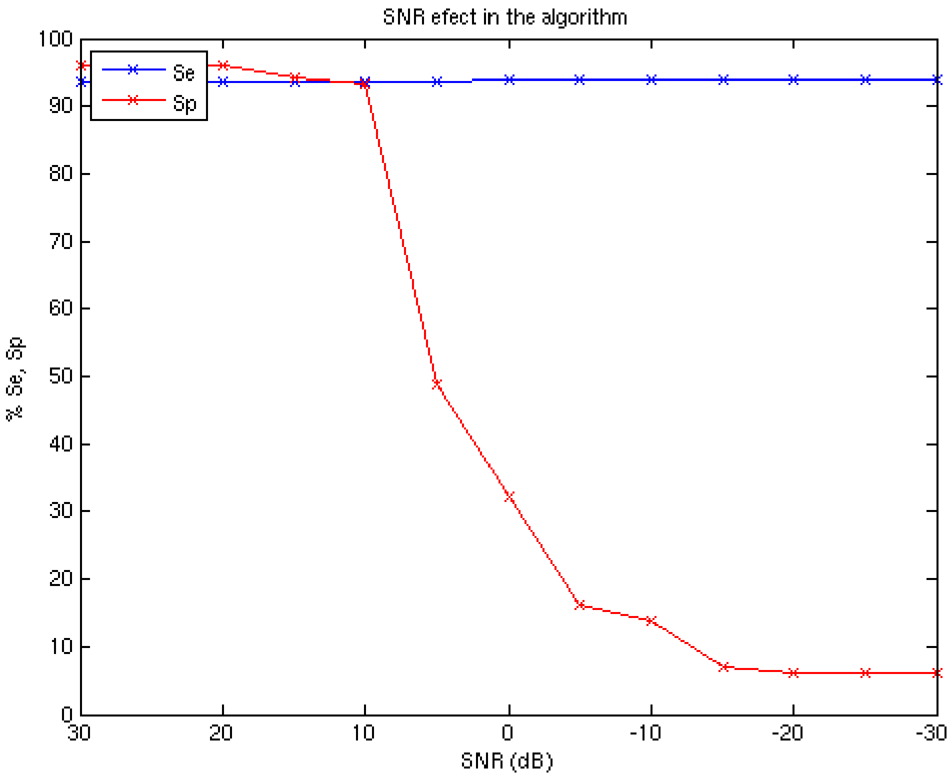
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	89.98851	6.082943	9.94699	2.632223
MIT_BIH_AF_04043m	43.21965	94.75086	69.28821	16.3322	3.622683
MIT_BIH_AF_04048m	47.68166	94.05416	7.351415	6.400178	2.587967
MIT_BIH_AF_04126m	97.19762	80.30556	16.09791	19.06232	2.560799
MIT_BIH_AF_04746m	99.36517	99.58817	99.63526	0.5302441	2.794858
MIT_BIH_AF_04908m	79.40919	92.84971	51.32291	8.315663	3.606189
MIT_BIH_AF_04936m	90.49377	81.61761	92.82066	11.95395	3.162324
MIT_BIH_AF_05091m	9.395169	97.19118	0.7838401	3.015699	2.265426
MIT_BIH_AF_05121m	96.67222	84.74838	91.7355	7.661833	2.964648
MIT_BIH_AF_05261m	77.79567	80.2798	4.947239	19.75255	2.663795
MIT_BIH_AF_06426m	99.17429	8.760768	96.24162	4.507298	3.193844
MIT_BIH_AF_06453m	47.5975	98.16791	22.65629	2.395928	2.054935
MIT_BIH_AF_06995m	92.0934	96.69413	96.13534	5.476148	3.264888
MIT_BIH_AF_07162m	99.55724	100	99.99811	0.4446347	2.393234
MIT_BIH_AF_07859m	28.24312	100	99.99838	71.75701	3.601392
MIT_BIH_AF_07879m	98.16439	99.73904	99.82538	1.210699	3.224382
MIT_BIH_AF_07910m	95.77811	97.06364	86.66199	3.149897	2.280183
MIT_BIH_AF_08215m	99.4515	98.88956	99.73405	0.6568279	2.54335
MIT_BIH_AF_08219m	97.94426	57.6279	38.88825	33.66916	3.415337
MIT_BIH_AF_08378m	49.07805	96.96269	81.12249	13.09687	2.616677
MIT_BIH_AF_08405m	99.38684	96.54554	98.67994	1.402785	3.515959
MIT_BIH_AF_08434m	98.08532	91.45876	31.59437	8.28503	2.351615
MIT_BIH_AF_08455m	99.01447	100	100	0.6817036	3.541624
DATABASE_TOTAL	87.30166	90.31135	85.72171	10.89211	2.906884

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 260, has this robustness against the noise
SNR       Se           Sp            PPV
 30       93.5841       95.9372       78.9701
 25       93.5841       95.9372       78.9701
 20       93.5841       95.9372       78.9701
 15       93.5841       94.2573       72.6525
 10       93.5841       93.4173       69.8582
  5       93.5841       48.8993       22.9913
  0       93.9293       32.1563       18.4143
 -5       93.9293       16.1971       15.4493
-10       93.9293       13.6772       15.0662
-15       93.9293       6.95751       14.1319
-20       93.9293       6.11757       14.0232
-25       93.9293       6.11757       14.0232
-30       93.9293       6.11757       14.0232
```



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A.1.3 Linker et al

ATRIAL FIBRILLATION DETECTION

Contents

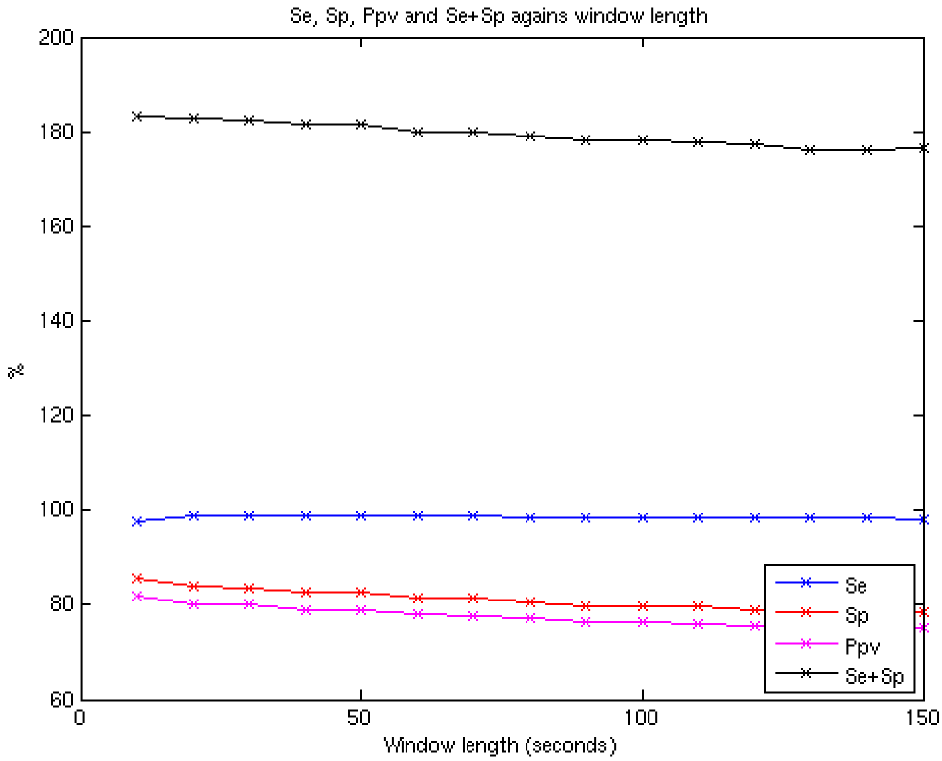
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 10 seconds,
giving Se=97.6473%, Sp=85.5576% and Ppv=81.8142%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 10, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

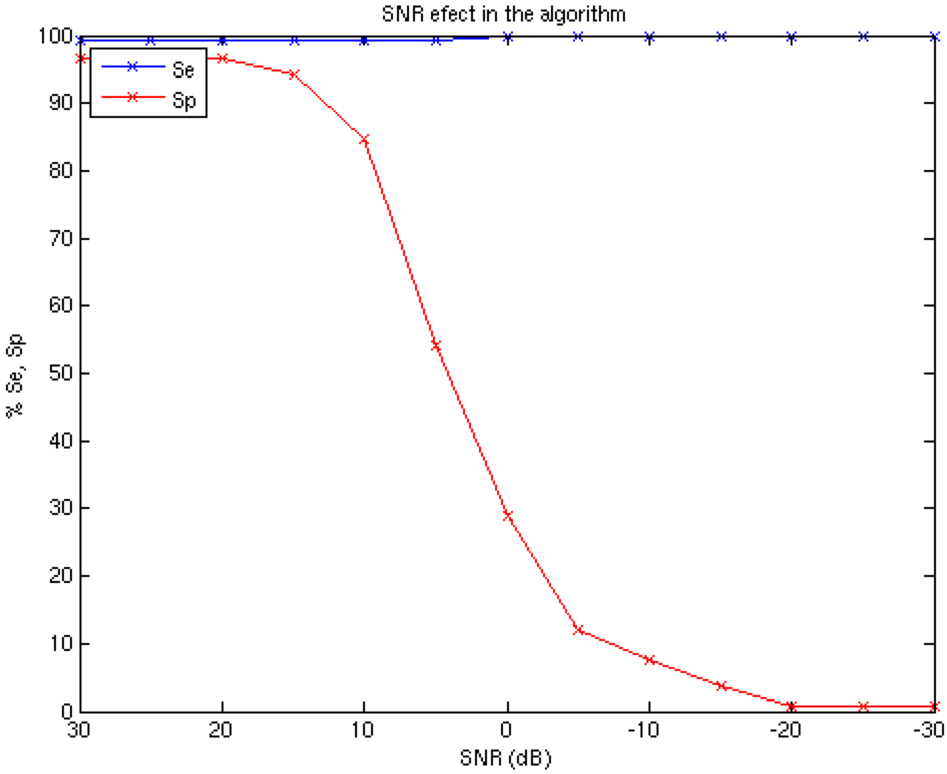
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	84.98564	4.139984	14.91763	3.720919
MIT_BIH_AF_04043m	85.24457	93.54143	78.34743	8.243741	5.675893
MIT_BIH_AF_04048m	98.70501	89.89598	8.813888	10.01772	3.313213
MIT_BIH_AF_04126m	97.07135	57.95337	8.236008	40.58278	3.286669
MIT_BIH_AF_04746m	99.79496	92.54616	93.81121	3.604732	3.962425
MIT_BIH_AF_04908m	96.46366	92.68362	54.9145	6.996706	4.898117
MIT_BIH_AF_04936m	94.69247	93.04467	97.31236	5.757808	5.402236
MIT_BIH_AF_05091m	81.07597	91.5343	2.21197	8.490347	3.940665
MIT_BIH_AF_05121m	97.71728	75.71193	87.51143	10.30888	8.814333
MIT_BIH_AF_05261m	94.14797	83.3558	6.944548	16.50367	4.783247
MIT_BIH_AF_06426m	99.84699	59.1979	98.09455	1.997554	7.773396
MIT_BIH_AF_06453m	99.15535	95.40826	19.58063	4.549958	4.287528
MIT_BIH_AF_06995m	98.53048	57.14903	67.24786	23.33031	6.434243
MIT_BIH_AF_07162m	99.91216	100	100	0.08783631	4.548947
MIT_BIH_AF_07859m	92.09098	100	100	7.908983	9.17417
MIT_BIH_AF_07879m	98.02975	90.08992	93.76315	5.121228	8.525004
MIT_BIH_AF_07910m	99.12808	96.94904	86.6168	2.689001	4.110192
MIT_BIH_AF_08215m	99.86271	97.21154	99.33384	0.6507122	3.701704
MIT_BIH_AF_08219m	97.71112	58.80816	39.50472	32.794	5.052302
MIT_BIH_AF_08378m	93.82537	95.88961	85.78256	4.54195	3.627191
MIT_BIH_AF_08405m	99.72537	96.34995	98.61091	1.212697	4.53707
MIT_BIH_AF_08434m	100	89.92516	28.53087	9.685306	2.851764
MIT_BIH_AF_08455m	99.81942	98.45839	99.31639	0.6001677	3.994567
DATABASE_TOTAL	97.64731	85.5576	81.81416	9.612088	5.061556

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 10, has this robustness against the noise
SNR       Se          Sp            PPV
 30        99.377      96.4612       82.0725
 25        99.377      96.4612       82.0725
 20        99.377      96.4612       82.0724
 15        99.377      94.1025       73.3125
 10        99.377      84.8618       51.6953
  5        99.377      54.0414       26.0632
  0       99.8019      29.0093       18.6453
 -5       99.8019      12.1463       15.6256
-10       99.8019      7.65583       14.9796
-15       99.8019      3.74691       14.4593
-20       99.8019     0.775194       14.0872
-25       99.8019     0.613701       14.0675
-30       99.8019     0.613701       14.0675
```



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A.1.4 Tatento et al

A.1.4.1 Kolmogorov Smirnov Test (RR intervals) for the first 13 independent signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

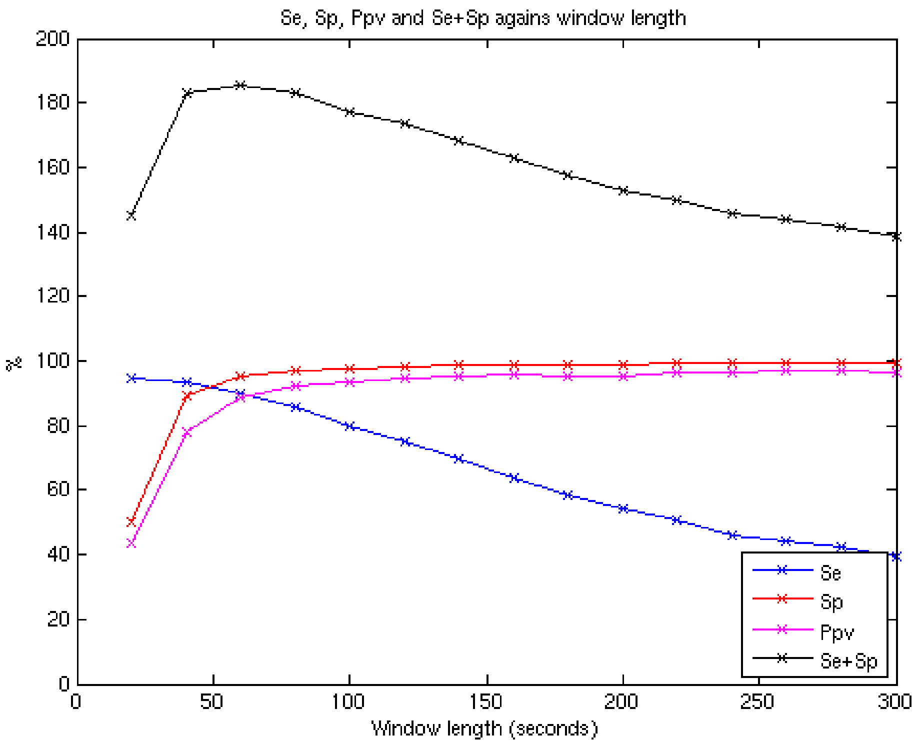
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 60 seconds,
giving Se=90.0344%, Sp=95.533% and Ppv=89.0014%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 60, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

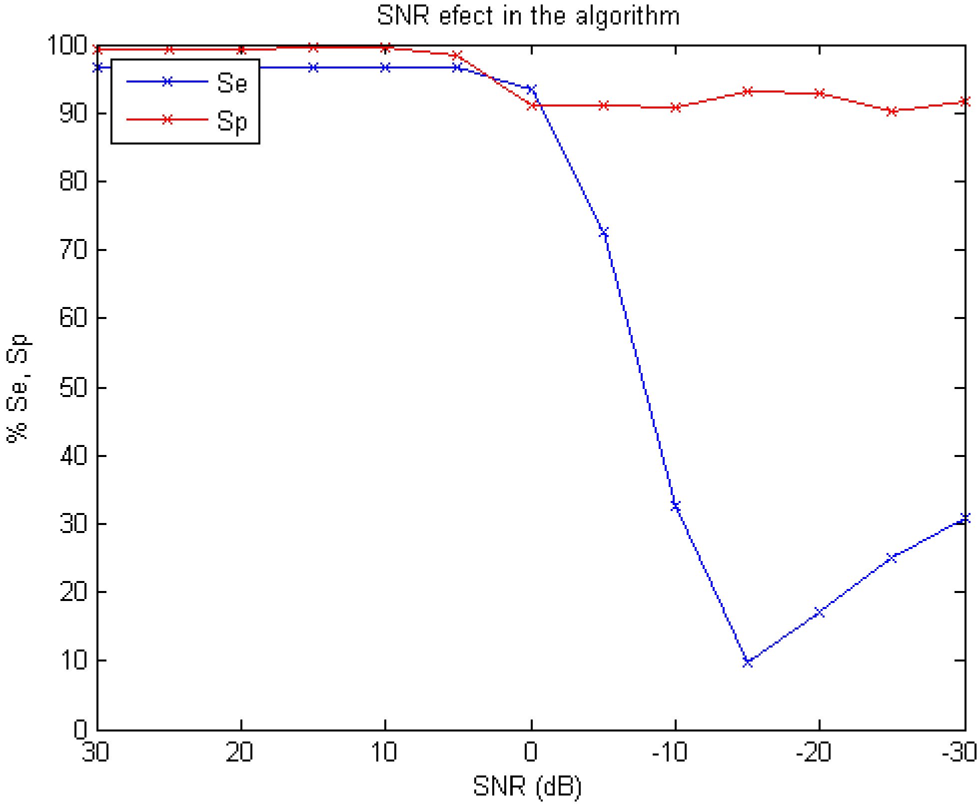
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	78.1349	97.0999	14.872	3.02231	1.23314
MIT_BIH_AF_04043m	71.1438	93.1975	74.1315	11.5457	2.82278
MIT_BIH_AF_04048m	14.5586	99.8205	44.5179	1.01489	1.23353
MIT_BIH_AF_04126m	12.9588	91.6718	5.70411	11.2738	1.27657
MIT_BIH_AF_04746m	96.4773	96.7142	97.0797	3.41162	1.53773
MIT_BIH_AF_04908m	88.6348	99.2108	91.2085	1.68349	2.78308
MIT_BIH_AF_04936m	80.6104	93.3826	97.0212	15.9129	1.5361
MIT_BIH_AF_05091m	49.0411	99.9547	71.8784	0.165288	1.06599
MIT_BIH_AF_05121m	94.9698	92.0869	95.3971	6.08738	1.44668
MIT_BIH_AF_05261m	20.4149	92.6195	3.52087	8.32071	1.26322
MIT_BIH_AF_06426m	97.0089	59.4609	98.048	4.69856	1.9388
MIT_BIH_AF_06453m	81.5255	99.6617	73.0989	0.540492	0.974738
MIT_BIH_AF_06995m	95.6035	84.3495	84.4892	10.3456	1.83959
DATABASE_TOTAL	90.0344	95.533	89.0014	6.04224	1.61169

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 50, has this robustness against the noise
SNR       Se           Sp            PPV
 30       96.6027        99.397      96.3121
 25       96.6027        99.397      96.3121
 20       96.6027        99.397      96.3121
 15       96.6026        99.554      97.2459
 10       96.5979        99.554      97.2457
  5       96.7563       98.4723      91.1698
  0       93.5638       90.9479      62.7564
 -5       72.7783       91.1806      57.3611
-10       32.6317       90.6537      36.2725
-15       9.80218       93.1384      18.8897
-20       17.1407       92.7568      27.8389
-25       24.8793        90.226      29.3271
-30       30.7344       91.6726      37.5654
```



Published with MATLAB® 7.10

Published with MATLAB® 7.8

A.1.4.2 Kolmogorov Smirnov Test (RR intervals) for all signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

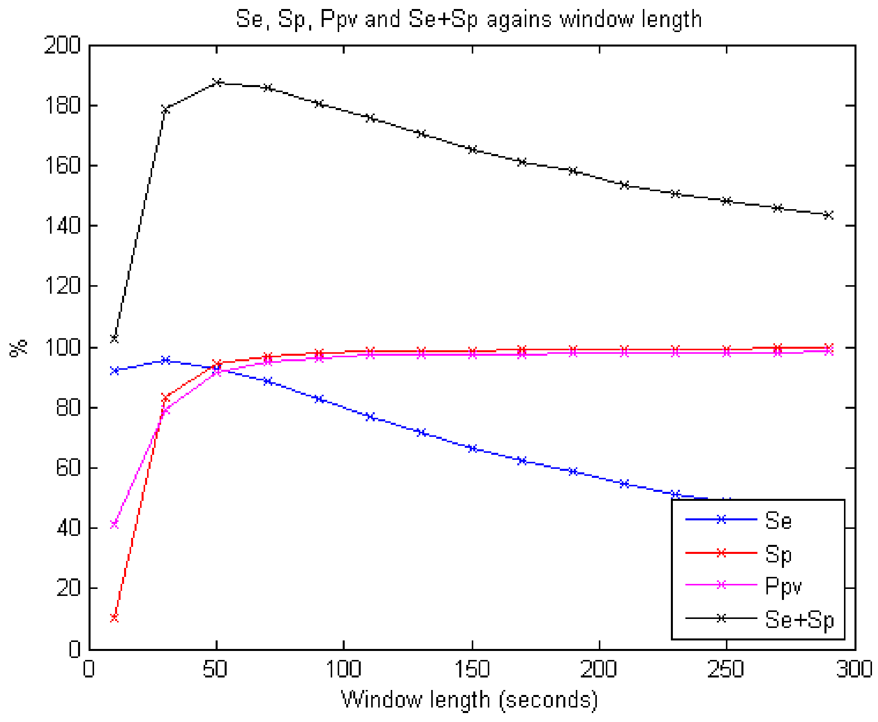
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different beat segment (Nseg) and determines which Nseg obtains the
 best performance.
The optimal window length is: 50 seconds,
giving Se=92.9294%, Sp=94.4255% and Ppv=91.7228%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 50, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	82.03814	96.08545	11.96367	4.005047	0.8299499
MIT_BIH_AF_04043m	79.90521	92.39676	74.26405	10.29423	2.029763
MIT_BIH_AF_04048m	13.66942	99.86561	50.16071	0.978898	0.8496408
MIT_BIH_AF_04126m	24.28496	85.99323	6.314739	16.31598	0.8584943
MIT_BIH_AF_04746m	98.02664	91.53577	92.91395	5.017587	1.022069
MIT_BIH_AF_04908m	87.61948	99.02508	89.26968	1.941263	2.065811
MIT_BIH_AF_04936m	83.09113	89.72234	95.59521	15.10907	1.064082
MIT_BIH_AF_05091m	47.49216	99.97843	83.87202	0.145246	0.6907343
MIT_BIH_AF_05121m	95.70979	90.35833	94.51617	6.245959	0.9919085
MIT_BIH_AF_05261m	71.18617	89.98145	8.570952	10.26329	0.8669804
MIT_BIH_AF_06426m	97.79257	49.10418	97.59085	4.41227	1.352824
MIT_BIH_AF_06453m	91.57725	98.944	49.43874	1.138138	0.6799442
MIT_BIH_AF_06995m	97.24091	72.32663	75.83217	15.92068	1.253367
MIT_BIH_AF_07162m	97.60185	69.36416	99.99941	2.398683	0.7187282
MIT_BIH_AF_07859m	88.03111	100	100	11.96883	1.860949
MIT_BIH_AF_07879m	95.56594	94.29513	96.21775	4.938625	1.239235
MIT_BIH_AF_07910m	97.44457	99.58227	97.78912	0.7584599	0.6265048
MIT_BIH_AF_08215m	97.95723	100	100	1.646958	0.820153
MIT_BIH_AF_08219m	93.69967	88.00971	68.26716	10.76202	1.63381
MIT_BIH_AF_08378m	86.7159	99.41822	97.52468	3.237386	0.8846112
MIT_BIH_AF_08405m	90.91253	99.09302	99.61751	6.814027	1.513727
MIT_BIH_AF_08434m	95.06903	98.40122	70.51526	1.727614	0.7829271
MIT_BIH_AF_08455m	92.15554	99.97984	99.99025	5.432338	1.403778
DATABASE_TOTAL	92.92942	94.42545	91.72279	6.171923	1.132173

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A.1.4.3 Kolmogorov Smirnov Test (DRR intervals) for the first 13 independent signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

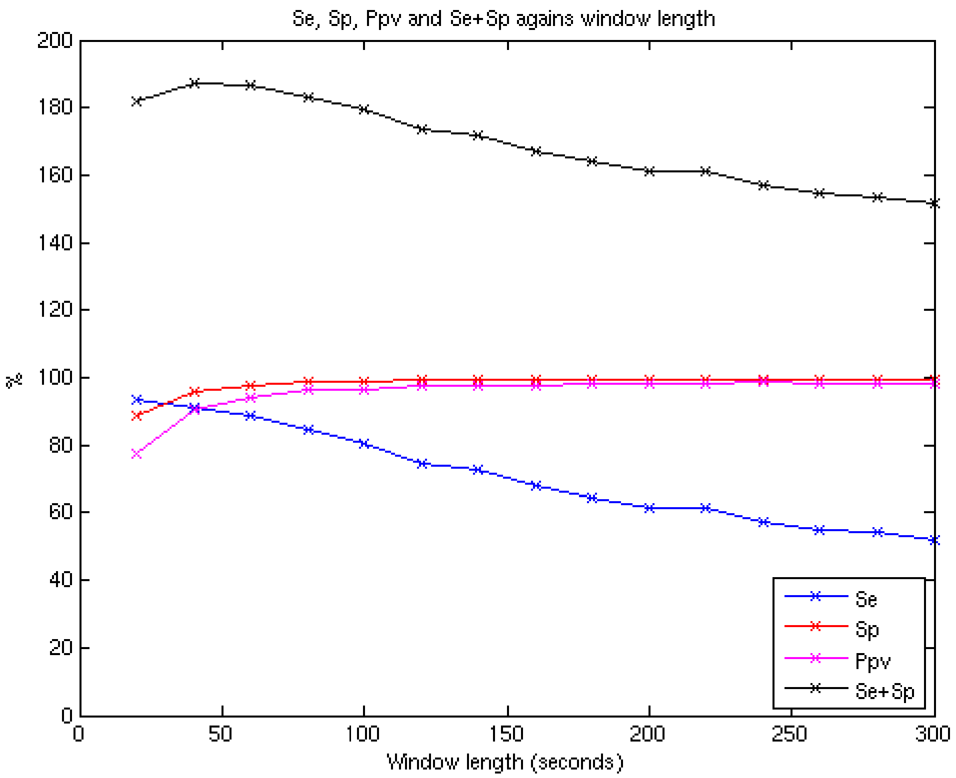
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 40 seconds,
giving Se=91.1968%, Sp=96.0761% and Ppv=90.3239%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 40, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

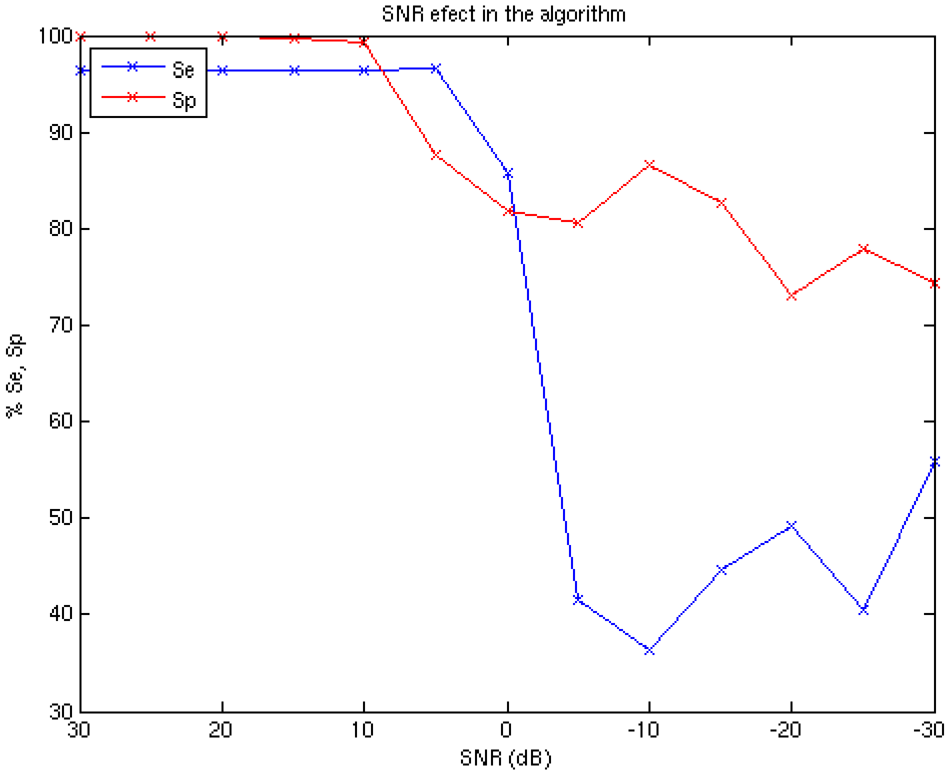
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	94.6619	94.1985	9.56805	5.79853	1.79793
MIT_BIH_AF_04043m	73.5078	97.8181	90.2293	7.41198	3.82101
MIT_BIH_AF_04048m	45.9731	99.5952	52.9127	0.930168	1.80191
MIT_BIH_AF_04126m	81.345	88.4566	21.5045	11.8095	1.84264
MIT_BIH_AF_04746m	96.7808	99.7701	99.7906	1.81721	2.1975
MIT_BIH_AF_04908m	89.1658	98.8327	87.6686	1.99041	4.08332
MIT_BIH_AF_04936m	83.8289	96.6114	98.5203	12.7084	2.32975
MIT_BIH_AF_05091m	52.789	99.1685	13.0399	0.94077	1.4901
MIT_BIH_AF_05121m	91.9776	92.5183	95.4945	7.82393	2.12915
MIT_BIH_AF_05261m	76.9389	97.2492	26.9545	3.01529	1.81334
MIT_BIH_AF_06426m	97.2765	62.8234	98.1902	4.3086	2.72523
MIT_BIH_AF_06453m	66.2519	99.449	57.5489	0.921165	1.38594
MIT_BIH_AF_06995m	94.1843	87.6114	87.1452	9.29029	2.58073
DATABASE_TOTAL	91.1968	96.0761	90.3239	5.3221	2.30758

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 50, has this robustness against the noise
SNR       Se          Sp          PPV
 30       96.4046      99.838     98.9798
 25       96.4046      99.838     98.9798
 20       96.4046      99.838     98.9798
 15       96.4046     99.6825     98.0195
 10       96.3999     99.3625     96.1016
  5       96.5583     87.6432     56.0226
  0       85.7988     81.9046     43.5974
 -5       41.6049     80.5589     25.8643
-10       36.3557     86.6455     30.7387
-15       44.6325     82.7588     29.6775
-20       49.2276     73.0233      22.928
-25        40.418     77.9243     22.9866
-30       55.8878     74.4471     26.2838
```



Published with MATLAB® 7.8

A.1.4.4 Kolmogorov Smirnov Test (DRR intervals) for all signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

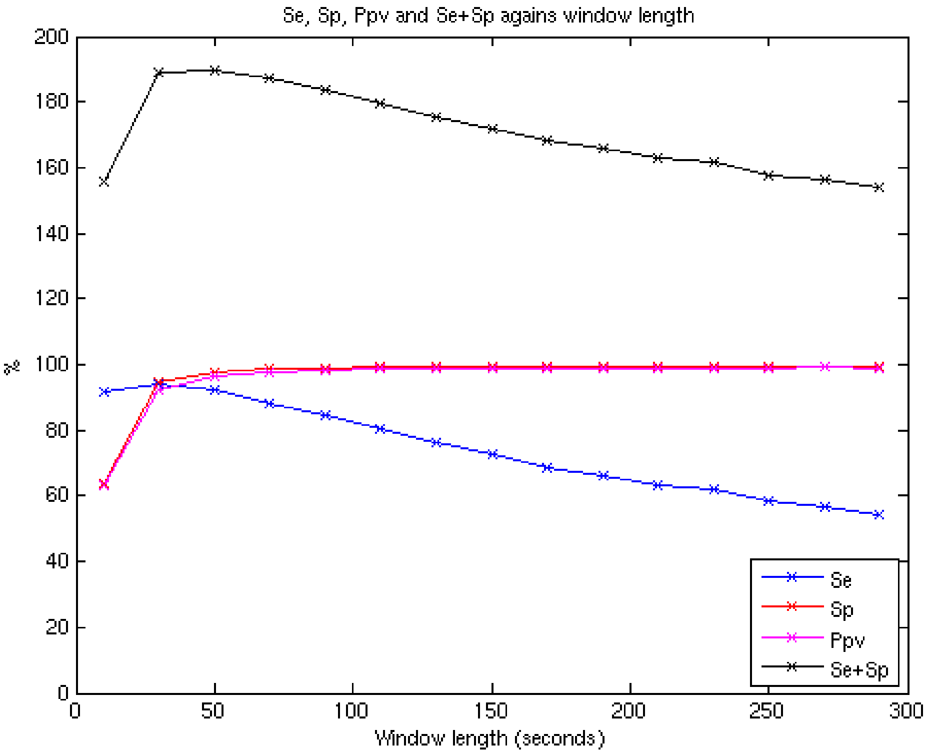
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 50 seconds,
giving Se=92.0001%, Sp=97.8075% and Ppv=96.5367%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 50, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	95.49647	94.83443	10.70451	5.161301	1.517139
MIT_BIH_AF_04043m	66.85735	98.17084	90.92162	8.563899	3.650943
MIT_BIH_AF_04048m	30.69273	99.63075	45.12895	1.044672	1.633946
MIT_BIH_AF_04126m	77.39315	93.16565	30.56715	7.42458	1.667593
MIT_BIH_AF_04746m	96.60167	99.84192	99.85568	1.87865	1.947418
MIT_BIH_AF_04908m	85.121	99.31774	91.96775	1.875619	3.687791
MIT_BIH_AF_04936m	82.09703	96.83841	98.57216	13.87372	1.967619
MIT_BIH_AF_05091m	51.86705	99.59061	23.03173	0.5218472	1.318045
MIT_BIH_AF_05121m	90.9586	93.90463	96.26723	7.96157	1.862609
MIT_BIH_AF_05261m	44.98678	98.2891	25.75593	2.404973	1.635391
MIT_BIH_AF_06426m	96.89207	65.32443	98.32832	4.539538	2.438968
MIT_BIH_AF_06453m	58.30424	99.61235	62.90596	0.8482162	1.243917
MIT_BIH_AF_06995m	93.65206	91.13793	90.41824	7.676096	2.341626
MIT_BIH_AF_07162m	92.28018	69.36416	99.99938	7.720253	1.476471
MIT_BIH_AF_07859m	92.73333	100	100	7.266635	3.589856
MIT_BIH_AF_07879m	97.07256	99.64036	99.75682	1.908392	2.363045
MIT_BIH_AF_07910m	96.44866	99.86672	99.27647	0.6780863	1.242486
MIT_BIH_AF_08215m	97.63125	100	100	1.909772	1.514924
MIT_BIH_AF_08219m	91.8897	96.0686	86.54918	4.833485	3.001389
MIT_BIH_AF_08378m	84.86653	99.7787	99.02313	3.33891	1.607236
MIT_BIH_AF_08405m	90.17795	99.57969	99.82094	7.209204	2.779014
MIT_BIH_AF_08434m	94.60939	99.49078	88.19707	0.6979543	1.446564
MIT_BIH_AF_08455m	94.20956	99.84919	99.92871	4.051822	2.534725
DATABASE_TOTAL	92.00008	97.80755	96.53668	4.510416	2.107335

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A.1.4.5 Coefficient of Variation Test (RR intervals) for the first 13 independent signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

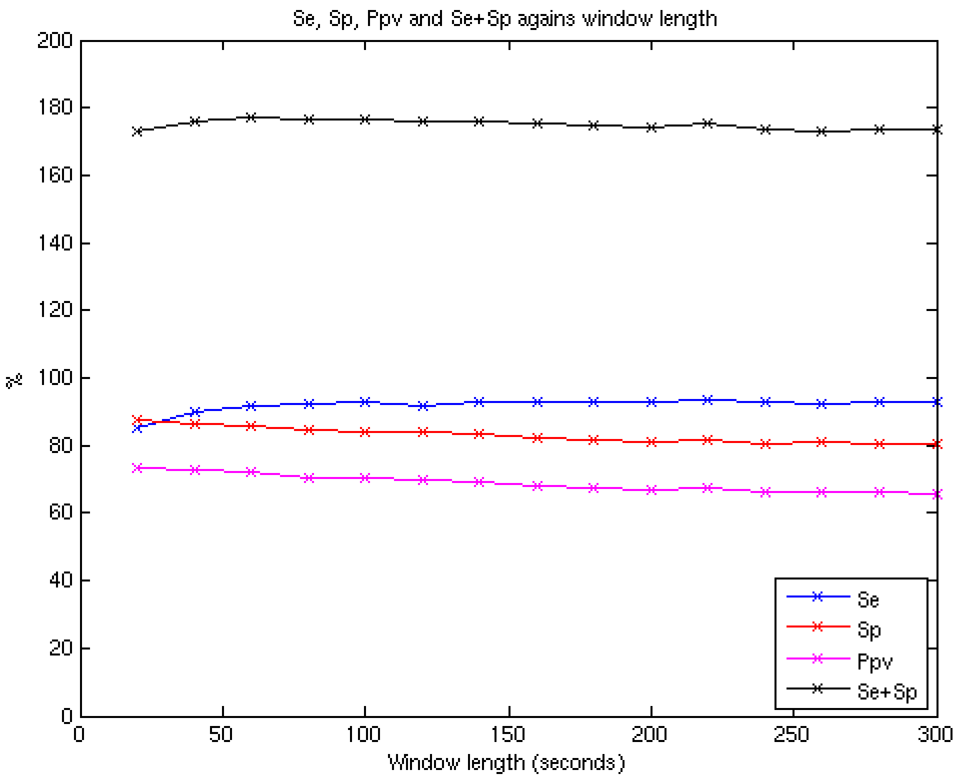
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 60 seconds,
giving Se=91.6415%, Sp=85.5759% and Ppv=71.9595%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 60, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

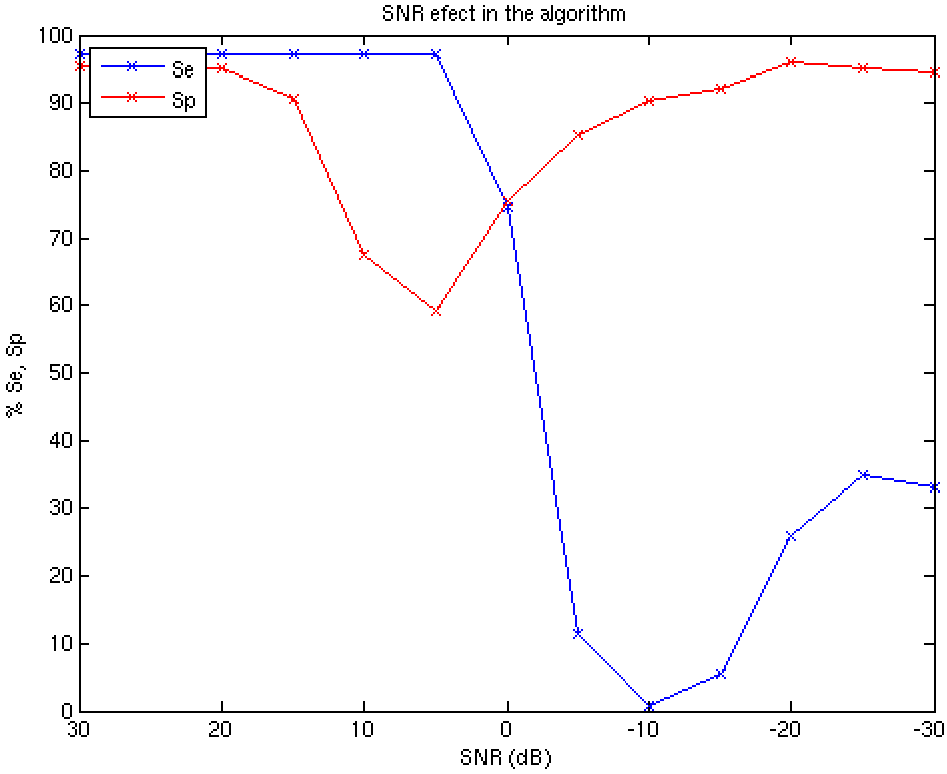
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	88.9831	88.5991	4.81722	11.3984	0.958312
MIT_BIH_AF_04043m	81.7824	88.7464	66.6156	12.7538	1.26227
MIT_BIH_AF_04048m	42.2201	91.3142	4.58885	9.16678	0.953578
MIT_BIH_AF_04126m	69.593	68.6897	7.95369	31.2765	0.910275
MIT_BIH_AF_04746m	97.0531	94.2824	95.054	4.24634	1.01113
MIT_BIH_AF_04908m	94.6757	89.9867	47.5051	9.60368	1.26442
MIT_BIH_AF_04936m	93.335	86.4856	95.1039	8.46151	1.13542
MIT_BIH_AF_05091m	33.2842	87.8925	0.645114	12.2362	0.912492
MIT_BIH_AF_05121m	88.9607	75.1688	86.0922	16.0953	1.06827
MIT_BIH_AF_05261m	53.1496	74.6411	2.69078	25.6388	1.02699
MIT_BIH_AF_06426m	96.6693	36.4262	97.1283	5.9226	1.16864
MIT_BIH_AF_06453m	65.6615	96.073	15.8622	4.26611	0.80318
MIT_BIH_AF_06995m	84.9631	88.902	87.2387	12.9561	1.1653
DATABASE_TOTAL	91.6415	85.5759	71.9595	12.679	1.04925

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 90, has this robustness against the noise
SNR       Se          Sp            PPV
 30       97.0583      95.3882      77.4314
 25       97.0583      95.3882      77.4314
 20       97.0583      95.0995      76.3527
 15       97.0582      90.7873      63.2013
 10       97.0785      67.4925      32.7434
  5       97.0619       59.164      27.9271
  0       74.7141      75.3903      33.1073
 -5       11.2981       85.168      11.0464
-10      0.643417      90.3353      1.07366
-15       5.50412      92.2742      10.4058
-20       25.9456      95.8706      50.5999
-25       34.7891      95.0004      53.1478
-30       33.0207      94.4249      49.1239
```



Published with MATLAB® 7.8

A.1.4.6 Coefficient of Variation Test (RR intervals) for all signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

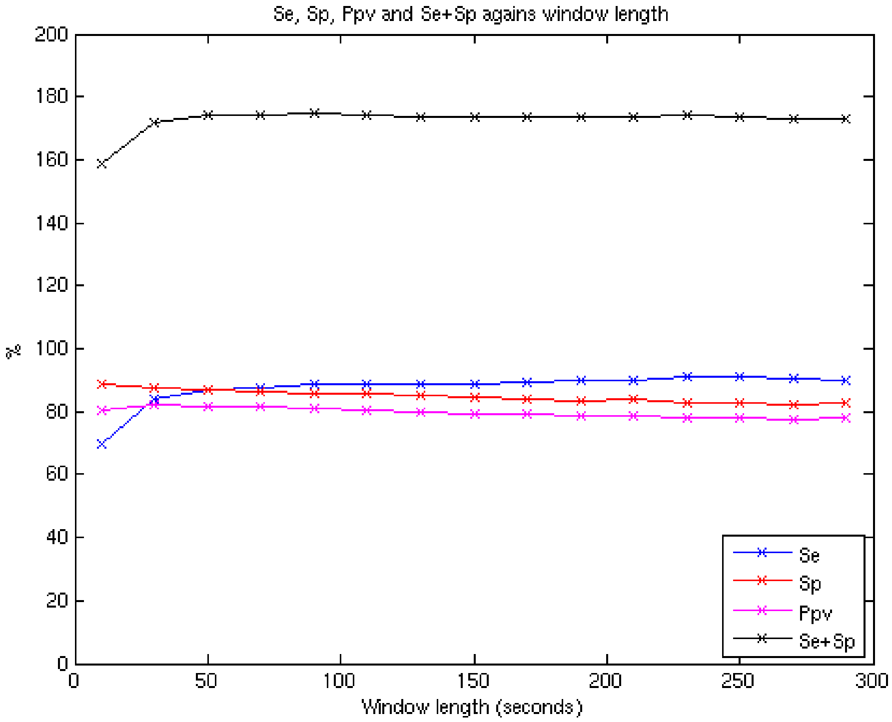
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 90 seconds,
giving Se=88.6053%, Sp=85.8832% and Ppv=80.726%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 90, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	48.66715	88.86522	2.756037	11.39376	0.8034703
MIT_BIH_AF_04043m	80.62978	85.90402	61.04907	15.23033	1.04936
MIT_BIH_AF_04048m	61.97086	90.09783	5.831202	10.17775	0.8003133
MIT_BIH_AF_04126m	48.62102	67.21028	5.450426	33.48536	0.8004206
MIT_BIH_AF_04746m	98.88506	94.66092	95.44821	3.096062	0.8429737
MIT_BIH_AF_04908m	93.51576	89.60563	46.50976	10.04977	1.050241
MIT_BIH_AF_04936m	93.76349	79.34477	92.62904	10.06279	0.8521118
MIT_BIH_AF_05091m	23.88899	87.93834	0.4656165	12.21258	0.6899257
MIT_BIH_AF_05121m	91.74387	72.98506	85.52778	15.10191	0.9040978
MIT_BIH_AF_05261m	51.16331	71.50299	2.313908	28.76186	0.8738963
MIT_BIH_AF_06426m	97.53295	17.59059	96.53326	5.726306	0.9327931
MIT_BIH_AF_06453m	81.75824	96.8597	22.69358	3.308673	0.6121905
MIT_BIH_AF_06995m	87.81411	90.67516	89.37204	10.67447	1.033976
MIT_BIH_AF_07162m	94.16522	69.36416	99.99939	5.835249	0.7438538
MIT_BIH_AF_07859m	53.14685	100	100	46.85294	1.053718
MIT_BIH_AF_07879m	97.70401	96.18898	97.49581	2.897523	0.991338
MIT_BIH_AF_07910m	98.87775	95.22113	80.3743	4.174691	0.6997006
MIT_BIH_AF_08215m	98.45435	96.4467	99.13799	1.93543	0.7345884
MIT_BIH_AF_08219m	99.12511	62.33432	42.01184	29.72379	0.952347
MIT_BIH_AF_08378m	59.37521	93.42144	70.65437	13.74818	0.8079969
MIT_BIH_AF_08405m	89.3717	94.76535	97.79545	9.129349	0.9979637
MIT_BIH_AF_08434m	93.00685	91.40984	30.33593	8.52841	0.6959972
MIT_BIH_AF_08455m	92.24003	96.03013	98.11795	6.591536	1.004672
DATABASE_TOTAL	88.60535	85.88319	80.72599	13.02733	0.8664324

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A.1.4.7 Coefficient of Variation Test (DRR intervals) for the first 13 independent signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

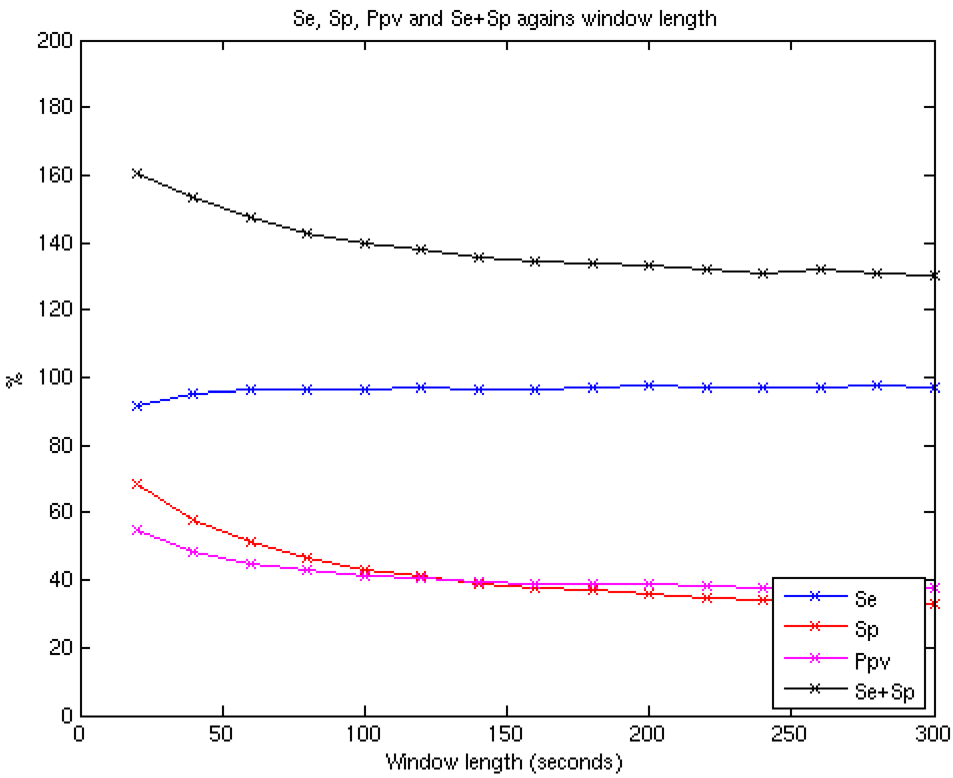
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 20 seconds,
giving Se=91.8056%, Sp=68.7615% and Ppv=54.8056%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 20, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

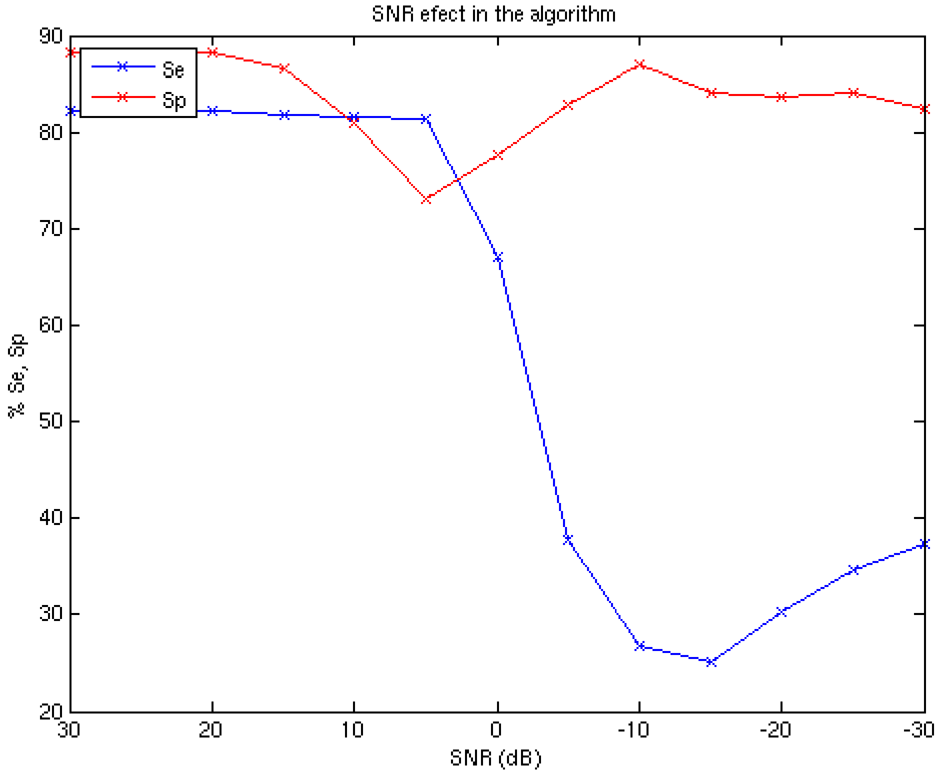
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	89.3018	79.3371	2.72605	20.5987	2.39386
MIT_BIH_AF_04043m	90.1954	87.6878	66.7628	11.7726	3.25573
MIT_BIH_AF_04048m	62.1738	79.3642	2.89482	20.8042	2.36516
MIT_BIH_AF_04126m	70.2873	31.8662	3.85587	66.696	2.29119
MIT_BIH_AF_04746m	92.2718	86.2962	88.4036	10.5308	2.60322
MIT_BIH_AF_04908m	92.9423	81.9791	33.4716	17.0465	3.27514
MIT_BIH_AF_04936m	90.1538	87.1309	96.3652	10.478	2.93323
MIT_BIH_AF_05091m	66.8449	85.5927	1.08397	14.4515	2.04635
MIT_BIH_AF_05121m	92.7887	47.0247	75.307	23.9064	2.71582
MIT_BIH_AF_05261m	67.1811	60.1591	2.17629	39.7495	2.46325
MIT_BIH_AF_06426m	92.1102	51.3394	97.6959	9.63223	2.93644
MIT_BIH_AF_06453m	95.4902	76.2255	4.3325	23.5597	1.90028
MIT_BIH_AF_06995m	95.7113	10.5481	48.8606	49.2783	3.04786
DATABASE_TOTAL	91.8056	68.7615	54.8056	24.5073	2.63289

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 10, has this robustness against the noise
SNR       Se           Sp            PPV
 30       82.2051       88.1735       53.1213
 25       82.2051       88.1698       53.1135
 20       82.2106       88.1346       53.0411
 15       81.8404       86.6446       49.9747
 10       81.6375       80.8671       41.0238
  5       81.4783       73.0001        32.974
  0       67.1066       77.7129       32.9247
 -5       37.8302       82.7384       26.3231
-10       26.8482       87.0711       25.2914
-15        25.073       84.1544       20.5059
-20       30.3604       83.6824       23.2729
-25       34.6363       84.1552       26.2735
-30       37.3428       82.3967       25.6964
```



Published with MATLAB® 7.8

A.1.4.8 Coefficient of Variation Test (DRR intervals) for all signals (MIT AF database)

ATRIAL FIBRILLATION DETECTION

Contents

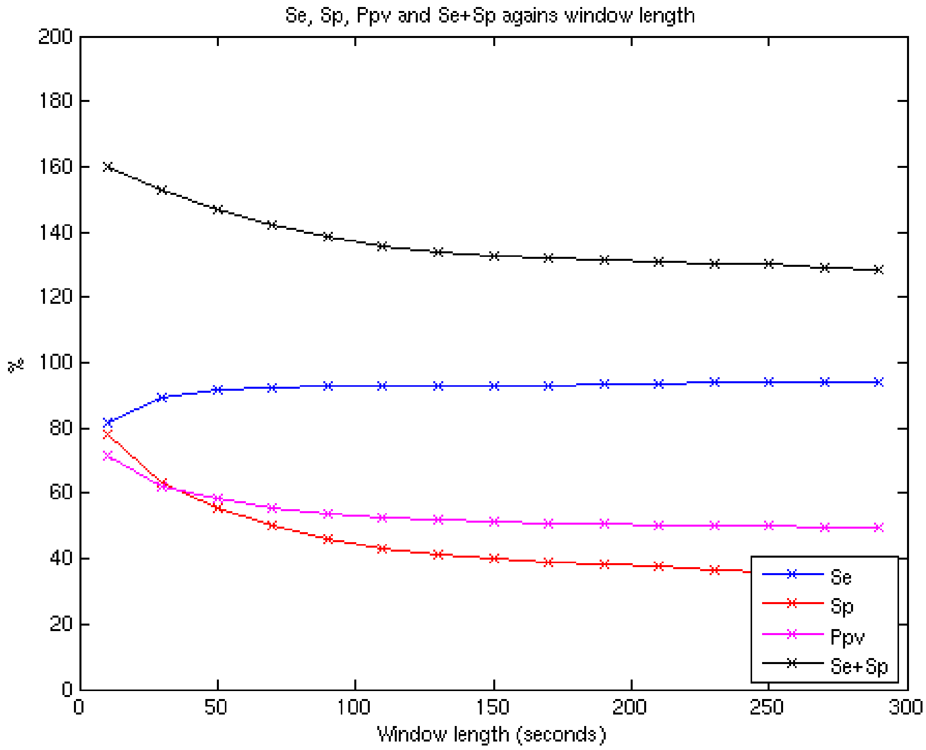
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 10 seconds,
giving Se=81.6963%, Sp=78.1918% and Ppv=71.6238%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 10, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	82.01116	85.98301	3.655227	14.04258	5.821978
MIT_BIH_AF_04043m	83.77821	92.76076	76.05847	9.173941	7.980174
MIT_BIH_AF_04048m	53.77076	88.33317	4.361347	12.00546	6.101436
MIT_BIH_AF_04126m	70.5248	49.9556	5.194055	49.27467	5.673228
MIT_BIH_AF_04746m	85.84375	93.49662	93.72836	10.56705	5.645305
MIT_BIH_AF_04908m	86.24212	87.59632	40.17403	12.52295	7.278099
MIT_BIH_AF_04936m	82.30001	94.77069	98.24716	14.96604	7.12883
MIT_BIH_AF_05091m	60.8842	92.43709	1.865949	7.637262	4.474418
MIT_BIH_AF_05121m	85.16164	62.51225	79.71188	23.13629	5.751428
MIT_BIH_AF_05261m	60.40726	71.38581	2.709761	28.75715	5.202197
MIT_BIH_AF_06426m	84.50443	70.95063	98.46135	16.08492	6.842436
MIT_BIH_AF_06453m	86.36824	87.09954	7.018919	12.90861	5.3314
MIT_BIH_AF_06995m	89.7846	28.0736	52.70248	42.82108	7.839164
MIT_BIH_AF_07162m	64.19752	100	100	35.8018	4.53566
MIT_BIH_AF_07859m	88.42681	4.761905	99.99951	11.57357	6.967166
MIT_BIH_AF_07879m	86.89915	83.07183	88.63642	14.61994	6.976366
MIT_BIH_AF_07910m	83.54896	88.70803	59.70984	12.15288	4.585805
MIT_BIH_AF_08215m	85.79587	82.76719	95.39947	14.7905	5.114214
MIT_BIH_AF_08219m	87.01161	27.45239	24.82212	59.69078	6.767275
MIT_BIH_AF_08378m	88.05347	80.97703	56.53703	17.47057	4.975842
MIT_BIH_AF_08405m	71.73245	92.62814	96.19523	22.46042	7.751226
MIT_BIH_AF_08434m	91.86366	93.60001	36.60039	6.467125	5.242034
MIT_BIH_AF_08455m	77.39433	87.46795	93.26904	19.50012	6.895578
DATABASE_TOTAL	81.69626	78.19177	71.62384	20.39749	6.125272

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A.1.5 Cerutti et al

A.1.5.1 Autoregressive (AR) model: P (percentage of power)

ATRIAL FIBRILLATION DETECTION

Contents

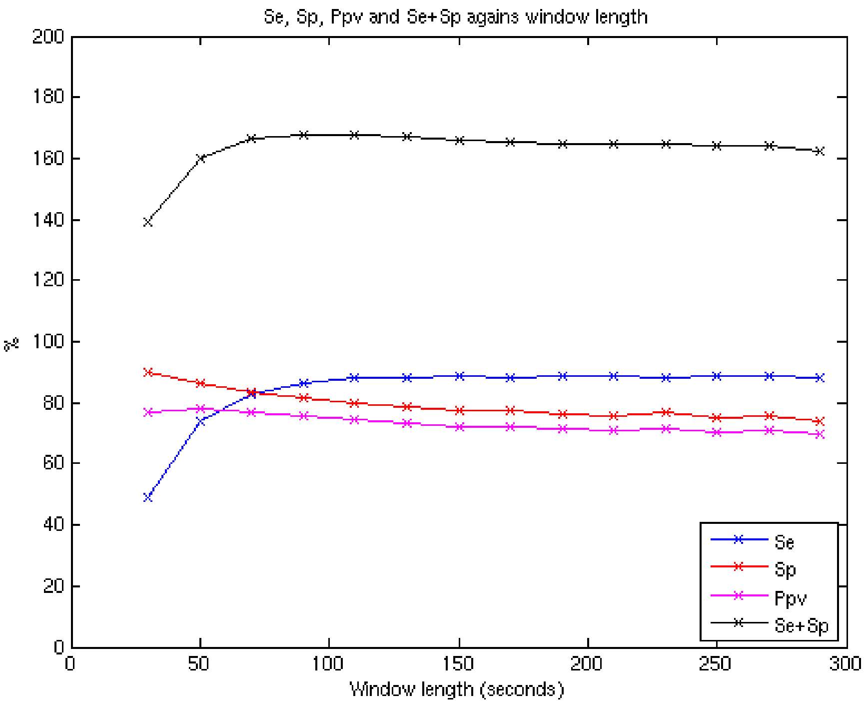
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 110 seconds,
giving Se=88.0623%, Sp=79.8279% and Ppv=74.5291%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 110, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

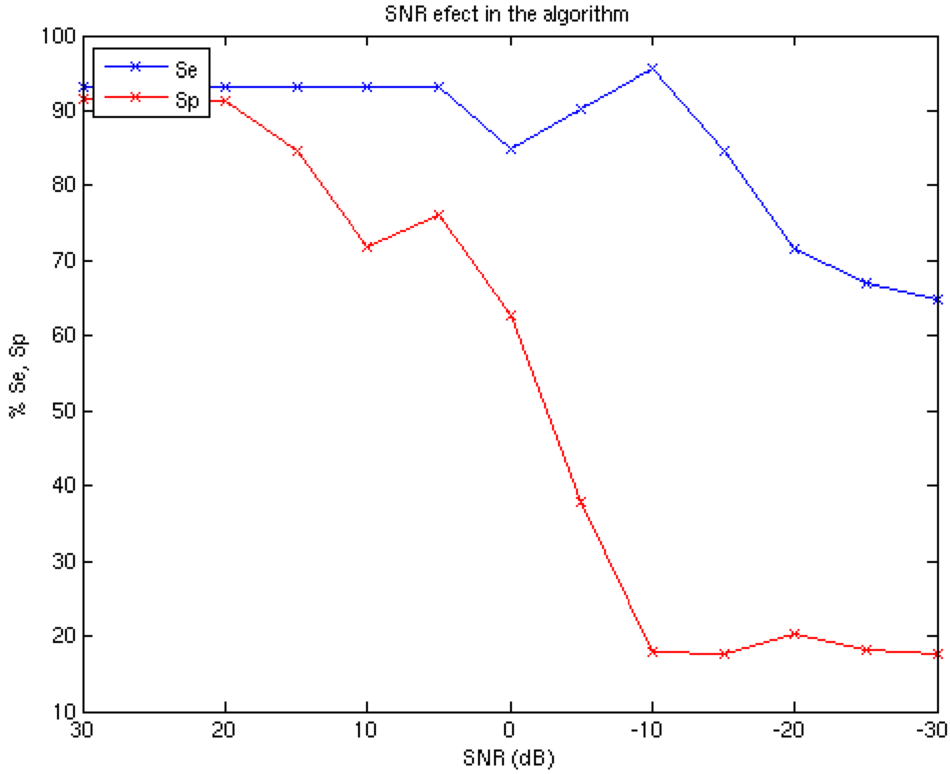
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	18.68182	81.17868	0.639515	19.22396	0.5412029
MIT_BIH_AF_04043m	65.38558	84.04332	52.8923	19.96949	0.65914
MIT_BIH_AF_04048m	0	77.45066	0	23.30817	0.5426378
MIT_BIH_AF_04126m	55.88125	51.27495	4.268293	48.55268	0.5312806
MIT_BIH_AF_04746m	91.70278	94.90428	95.32164	6.795713	0.5944049
MIT_BIH_AF_04908m	89.41654	88.06374	42.21324	11.81606	0.6785865
MIT_BIH_AF_04936m	52.79943	90.6884	95.13141	38.67854	0.6091482
MIT_BIH_AF_05091m	0	91.61561	0	8.600268	0.5713349
MIT_BIH_AF_05121m	87.24268	52.38121	75.74773	25.64619	0.6419958
MIT_BIH_AF_05261m	46.05708	85.17106	3.936399	15.33827	0.644575
MIT_BIH_AF_06426m	94.93015	88.90997	99.43446	5.349336	0.6305342
MIT_BIH_AF_06453m	26.50506	82.35402	1.665391	18.26867	0.5535636
MIT_BIH_AF_06995m	82.22486	61.57156	65.61177	28.69296	0.6424606
MIT_BIH_AF_07162m	83.2723	100	100	16.72739	0.5344169
MIT_BIH_AF_07859m	94.02569	100	100	5.974281	0.6582045
MIT_BIH_AF_07879m	98.59525	81.94232	89.23767	8.016687	0.6434505
MIT_BIH_AF_07910m	95.19984	91.84429	68.87937	7.62087	0.5259504
MIT_BIH_AF_08215m	98.71672	75.20627	94.34115	5.815674	0.5322014
MIT_BIH_AF_08219m	78.77017	68.72905	40.94896	29.10341	0.6202836
MIT_BIH_AF_08378m	95.11509	80.19502	55.93645	16.68572	0.5786215
MIT_BIH_AF_08405m	98.35695	87.10073	95.19506	4.771274	0.6841581
MIT_BIH_AF_08434m	74.56551	80.00334	13.04149	20.20691	0.5529403
MIT_BIH_AF_08455m	98.35729	94.18584	97.43308	2.92871	0.6781932
DATABASE_TOTAL	88.06234	79.82788	74.52914	16.8677	0.6021428

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 110, has this robustness against the noise
SNR       Se          Sp            PPV
 30       93.1105      91.5633      64.2753
 25       93.1105      91.5633      64.2753
 20       93.1105      91.2079      63.3224
 15       93.1105       84.553      49.5628
 10       93.1105      71.8567      35.0376
  5       93.1105      76.0239      38.7666
  0       84.8319       62.752      27.0756
 -5       90.3004       37.832      19.1458
-10       95.6401      17.8324      15.9489
-15       84.7404      17.5744      14.3543
-20        71.463      20.3852      12.7652
-25       67.1031      18.2529      11.8025
-30       64.9232      17.5421      11.3755
```



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A.1.5.2 Autoregressive (AR) model: M (maximum modulus)

ATRIAL FIBRILLATION DETECTION

Contents

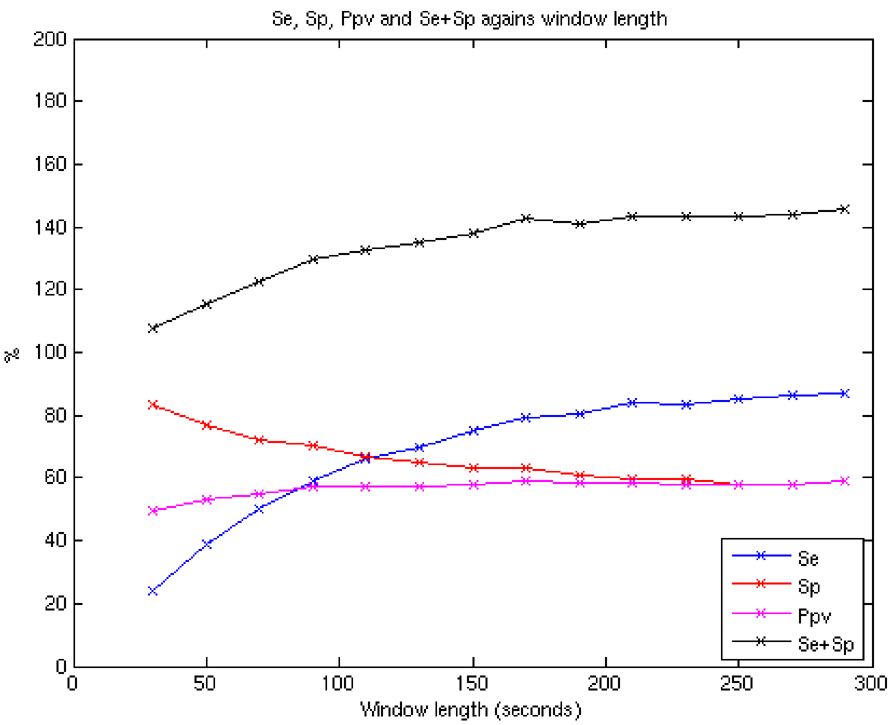
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 290 seconds,
giving Se=87.194%, Sp=58.7563% and Ppv=58.8724%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 290, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

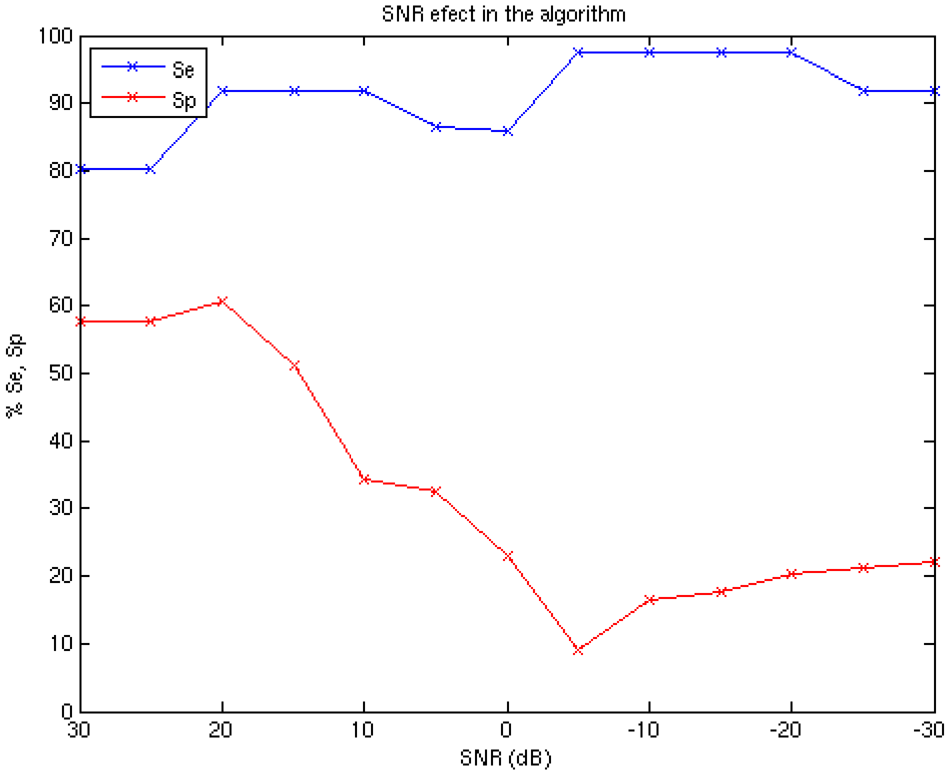
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	63.1523	59.19076	0.9934876	40.78372	0.3405096
MIT_BIH_AF_04043m	62.71252	65.02139	32.98851	35.476	0.3792515
MIT_BIH_AF_04048m	16.47116	52.44175	0.3415125	47.91068	0.3385912
MIT_BIH_AF_04126m	21.38592	55.0134	1.814581	46.24499	0.3350489
MIT_BIH_AF_04746m	91.00499	63.6589	73.92591	21.82035	0.3428026
MIT_BIH_AF_04908m	80.18673	83.73986	32.94393	16.58204	0.380188
MIT_BIH_AF_04936m	90.08337	67.59775	91.27152	14.6393	0.3609777
MIT_BIH_AF_05091m	41.56371	72.46842	0.3553054	27.6044	0.3218528
MIT_BIH_AF_05121m	86.1108	36.29011	70.29939	31.99792	0.3565739
MIT_BIH_AF_05261m	87.48843	50.08535	2.260206	49.42761	0.3443413
MIT_BIH_AF_06426m	87.7667	40.10612	97.18482	14.17401	0.3645193
MIT_BIH_AF_06453m	71.70761	55.012	1.765466	44.80185	0.3196224
MIT_BIH_AF_06995m	89.84	62.44841	68.11569	24.6303	0.389381
MIT_BIH_AF_07162m	87.41906	100	99.99785	12.58258	0.3603308
MIT_BIH_AF_07859m	88.20681	100	99.99948	11.79359	0.4174497
MIT_BIH_AF_07879m	95.55238	26.92584	66.52496	31.68256	0.3972011
MIT_BIH_AF_07910m	82.61229	62.02529	31.21324	34.42168	0.3621894
MIT_BIH_AF_08215m	80.51214	32.6819	83.35517	28.70868	0.337905
MIT_BIH_AF_08219m	79.02751	69.5284	41.65579	28.42106	0.4142611
MIT_BIH_AF_08378m	78.12373	60.55628	36.14557	35.53896	0.3798006
MIT_BIH_AF_08405m	95.66541	45.34187	81.97433	18.32003	0.4106367
MIT_BIH_AF_08434m	59.79395	58.98534	5.538687	40.9834	0.3828071
MIT_BIH_AF_08455m	91.08513	31.02449	74.76636	27.4307	0.3879772
DATABASE_TOTAL	87.19402	58.75635	58.8724	29.7625	0.3662704

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 290, has this robustness against the noise
SNR       Se          Sp            PPV
 30        80.331      57.8191       23.6914
 25        80.331      57.8191       23.6914
 20        91.825      60.6298       27.5481
 15        91.825      51.2609       23.4969
 10        91.825      34.3968        18.579
  5       86.6243      32.6121       17.3252
  0       85.9025      23.1255       15.4097
 -5       97.6229      9.10903       14.9007
-10       97.6229      16.6042       16.0253
-15       97.6229      17.5411       16.1779
-20       97.6229      20.3517       16.6537
-25       91.8759      21.2886       15.9868
-30       91.8759      22.2255       16.1483
```



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A.1.6 Slocum et al

A.1.6.1 P wave and AA Spectrum Analysis after QRS complex removal (original)

ATRIAL FIBRILLATION DETECTION

Contents

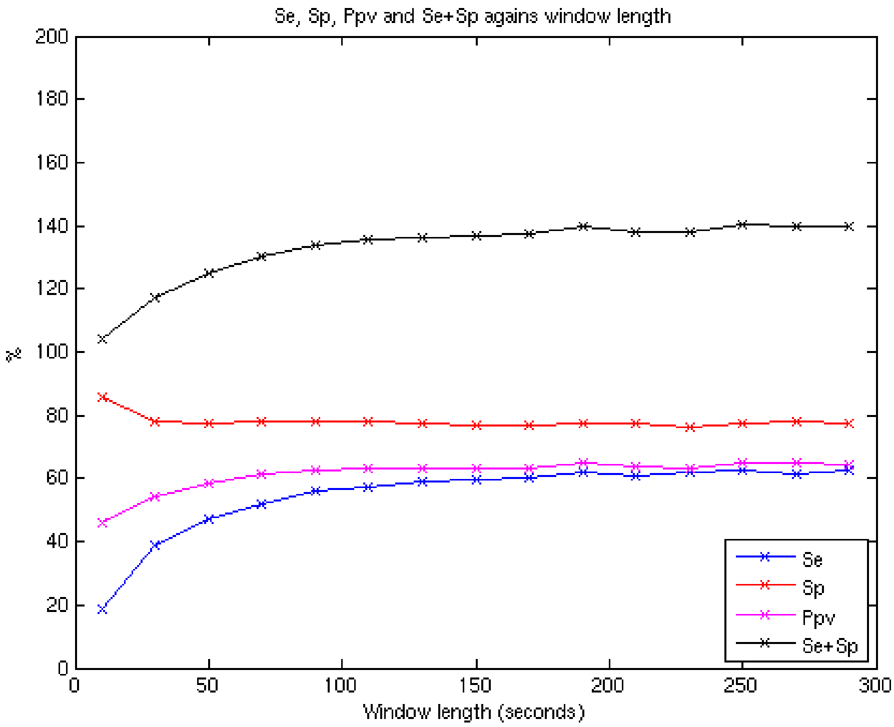
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 250 seconds,
giving Se=62.7997%, Sp=77.4575% and Ppv=64.9049%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 250, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

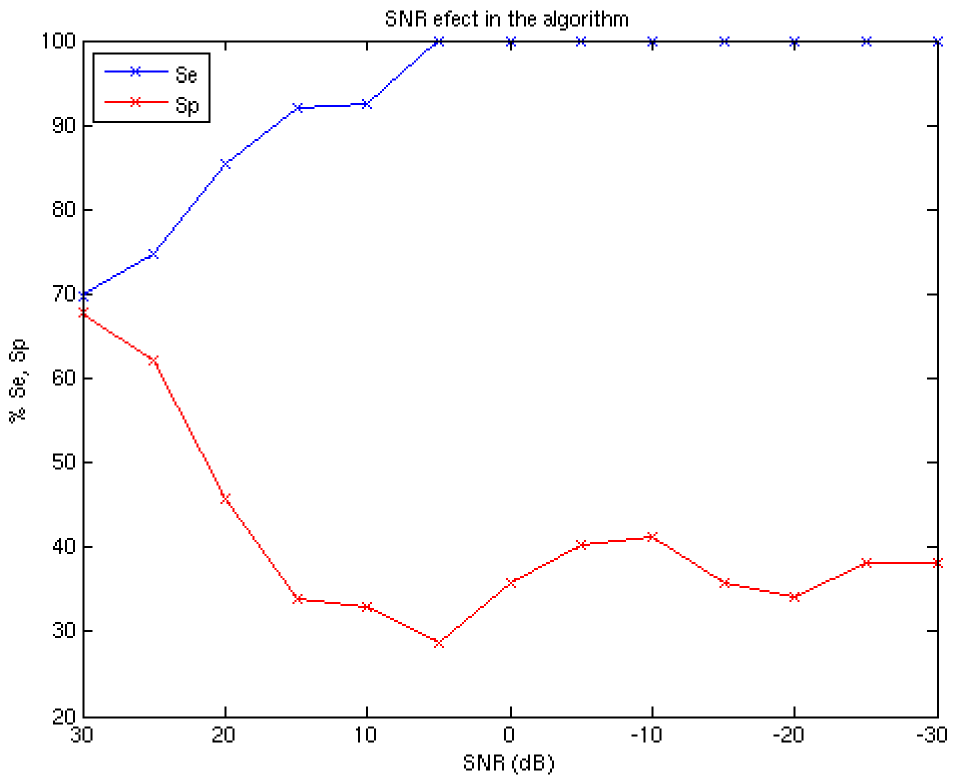
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	90.83107	91.02233	6.156622	8.9789	1.794704
MIT_BIH_AF_04043m	9.61445	93.11981	27.68818	24.84008	1.642265
MIT_BIH_AF_04048m	20.47808	97.46002	7.387882	3.29422	1.497696
MIT_BIH_AF_04126m	73.87175	49.97279	5.428938	49.13288	1.505103
MIT_BIH_AF_04746m	30.62219	98.4801	95.80022	37.5524	1.462256
MIT_BIH_AF_04908m	43.50913	82.48716	18.49838	20.77569	1.509211
MIT_BIH_AF_04936m	6.524001	82.77972	49.5088	72.22402	1.44471
MIT_BIH_AF_05091m	22.43223	61.94322	0.1390275	38.14989	1.316351
MIT_BIH_AF_05121m	67.8921	80.40474	85.74523	27.53478	1.648485
MIT_BIH_AF_05261m	67.45139	43.10768	1.540106	56.57533	1.545954
MIT_BIH_AF_06426m	88.15482	65.59164	98.19905	12.85778	1.606611
MIT_BIH_AF_06453m	40.71429	99.54799	50.38733	1.107976	1.354526
MIT_BIH_AF_06995m	71.08074	58.08743	60.22885	35.7833	2.111834
MIT_BIH_AF_07162m	10.18414	100	100	89.81417	1.371473
MIT_BIH_AF_07859m	97.28434	100	99.99953	2.716104	1.578592
MIT_BIH_AF_07879m	83.85347	75.15551	83.67488	19.6	1.539525
MIT_BIH_AF_07910m	50.84236	72.48801	25.94813	30.96209	1.410584
MIT_BIH_AF_08215m	82.33775	73.95559	92.97633	19.27818	1.538758
MIT_BIH_AF_08219m	34.05372	73.87568	26.40842	34.72053	1.552454
MIT_BIH_AF_08378m	60.21785	99.60785	97.59555	8.627218	1.627491
MIT_BIH_AF_08405m	82.0698	87.77408	94.5775	16.34492	1.540532
MIT_BIH_AF_08434m	82.44085	65.17916	8.694321	34.15343	1.345395
MIT_BIH_AF_08455m	96.18773	91.19092	96.0784	5.352714	3.529485
DATABASE_TOTAL	62.79971	77.45755	64.90488	28.39073	1.629304

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 250, has this robustness against the noise
SNR       Se          Sp            PPV
 30       69.84454     67.77263      26.10713
 25        74.7987     62.11902      24.35135
 20       85.40727     45.75697      20.42554
 15       92.11642     33.92837      18.51934
 10       92.42628      32.8482       18.3261
  5            100     28.75242      18.62059
  0            100     35.69822      20.22515
 -5            100     40.22115      21.42751
-10            100     41.35184      21.75077
-15            100     35.69831      20.22518
-20            100       34.083      19.82783
-25            100     38.12126      20.85199
-30            100     38.12126      20.85199
```



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A.1.6.2 P wave analysis considering the entire signal and AA Spectrum Analysis after QRS complex removal (proposed)

ATRIAL FIBRILLATION DETECTION

Contents

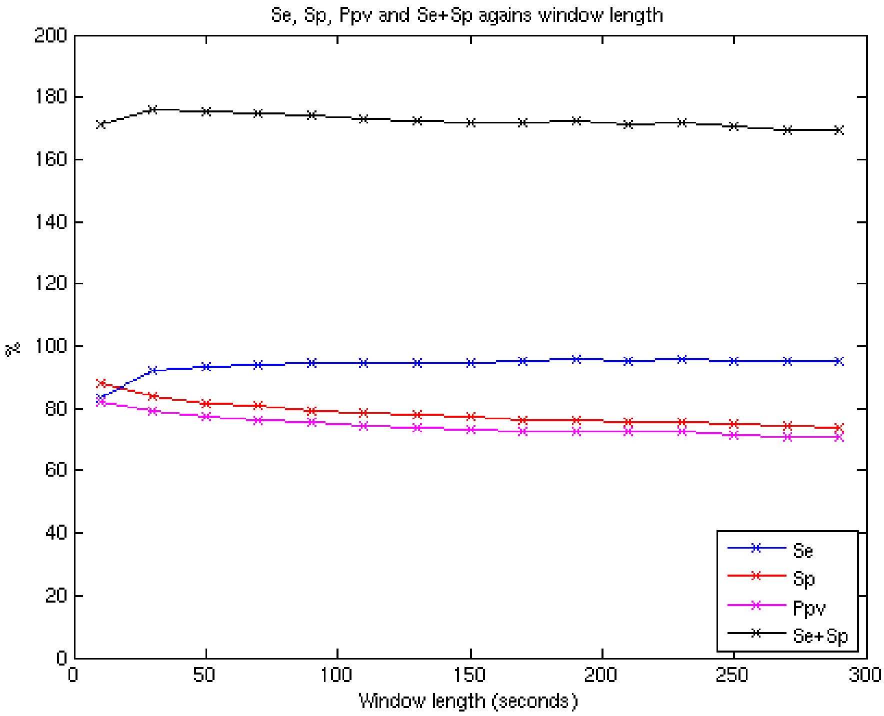
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 30 seconds,
giving Se=92.4326%, Sp=83.7592% and Ppv=79.0636%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 30, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

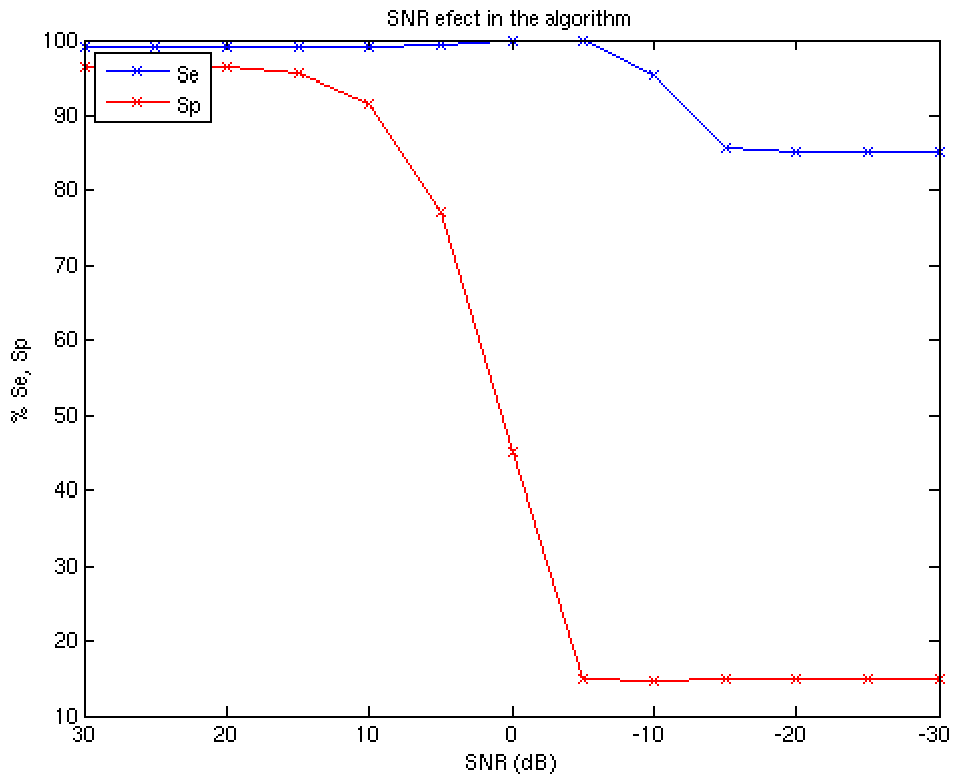
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	93.07694	94.5354	9.946128	5.473997	2.175369
MIT_BIH_AF_04043m	82.37025	94.54415	80.53277	8.074151	2.64648
MIT_BIH_AF_04048m	87.9737	96.8385	21.58891	3.248358	2.08067
MIT_BIH_AF_04126m	100	36.73065	5.788865	60.90172	2.237403
MIT_BIH_AF_04746m	99.567	93.90982	94.87442	3.08622	2.526772
MIT_BIH_AF_04908m	88.38145	99.18623	90.84818	1.718631	2.663917
MIT_BIH_AF_04936m	63.31714	91.10032	94.84898	28.93987	2.591793
MIT_BIH_AF_05091m	98.00387	76.0576	0.9575501	23.89068	2.249243
MIT_BIH_AF_05121m	77.40748	95.27954	96.59027	16.03995	2.486562
MIT_BIH_AF_05261m	97.20704	85.10237	7.926294	14.74001	2.190907
MIT_BIH_AF_06426m	94.5728	66.56955	98.30971	6.726082	2.683128
MIT_BIH_AF_06453m	45.00754	99.68746	61.88579	0.9221982	1.93937
MIT_BIH_AF_06995m	97.40201	4.465027	47.65506	51.69428	2.747305
MIT_BIH_AF_07162m	99.55729	100	99.99811	0.4445803	2.217742
MIT_BIH_AF_07859m	99.26686	100	99.99954	0.7335951	2.722509
MIT_BIH_AF_07879m	97.9741	78.50829	87.38695	9.751047	2.517547
MIT_BIH_AF_07910m	99.20776	97.56709	88.62655	2.169685	1.8956
MIT_BIH_AF_08215m	99.86604	99.31695	99.83549	0.2405668	2.344741
MIT_BIH_AF_08219m	98.014	70.93419	48.14154	23.22019	2.586936
MIT_BIH_AF_08378m	45.32069	99.92735	99.39717	11.48899	2.469407
MIT_BIH_AF_08405m	100	99.08614	99.64952	0.2539714	3.181088
MIT_BIH_AF_08434m	100	82.57985	18.75719	16.74661	2.178639
MIT_BIH_AF_08455m	97.51504	98.01797	99.10227	2.329911	2.762349
DATABASE_TOTAL	92.43255	83.75919	79.06355	12.7813	2.438934

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 30, has this robustness against the noise
SNR       Se          Sp            PPV
 30       99.07249     96.47627       82.09017
 25       99.07249     96.37934       81.68772
 20       99.07249     96.37934       81.68772
 15       99.07249     95.60393       78.60497
 10       99.17807      91.5502       65.67648
  5       99.31917     77.13119       41.45228
  0        99.9136     45.05004       22.86445
 -5            100     14.82729       16.06533
-10       95.24457     14.63353       15.38955
-15        85.7337     15.02117        14.1241
-20       85.13927     15.02117       14.03993
-25       85.13927     15.02117       14.03993
-30       85.13927     15.02117       14.03993
```



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A.1.7 Schmidt et al

A.1.7.1 RRI & PWA

ATRIAL FIBRILLATION DETECTION

Contents

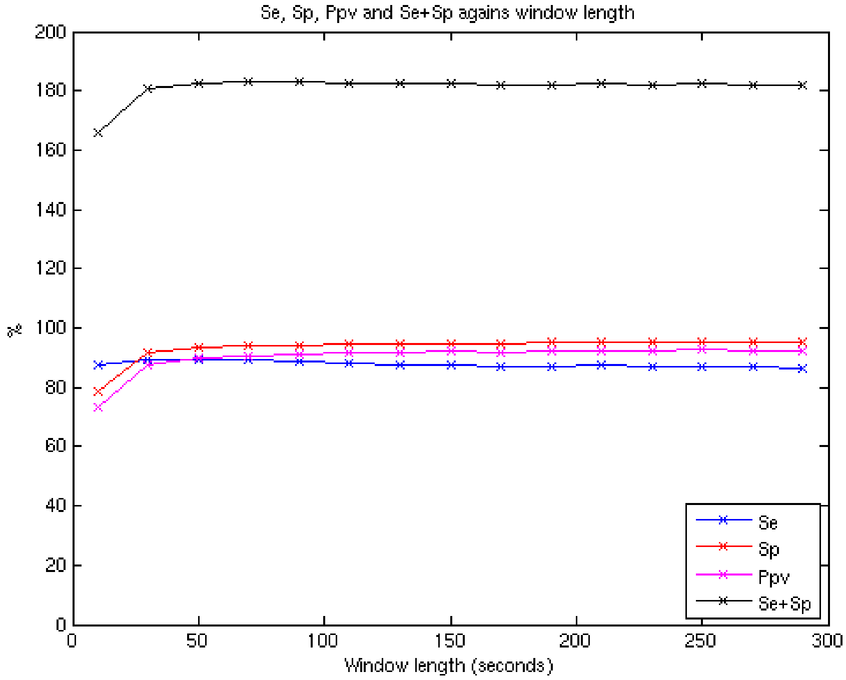
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 70 seconds,
giving Se=89.1423%, Sp=93.9885% and Ppv=90.7797%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 70, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

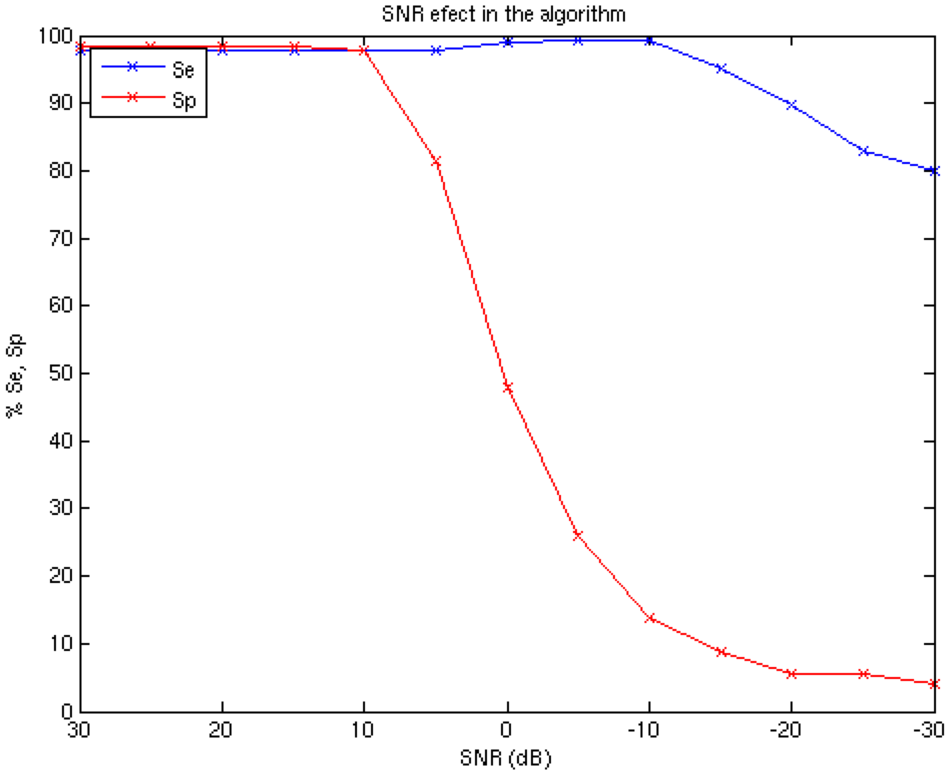
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	91.08189	6.778171	8.860659	2.506767
MIT_BIH_AF_04043m	64.03689	96.71848	84.24472	10.3105	3.22919
MIT_BIH_AF_04048m	65.4977	94.88868	11.25236	5.399283	2.661315
MIT_BIH_AF_04126m	98.55527	92.57461	34.03669	7.201589	2.622021
MIT_BIH_AF_04746m	99.80637	99.50867	99.56708	0.3332479	3.475625
MIT_BIH_AF_04908m	92.92316	94.28748	60.14634	5.828351	3.795042
MIT_BIH_AF_04936m	87.02779	94.00905	97.40914	11.02657	3.144955
MIT_BIH_AF_05091m	0	99.80945	0	0.4257335	2.291697
MIT_BIH_AF_05121m	95.15402	93.34082	96.11094	5.510278	2.313216
MIT_BIH_AF_05261m	82.63078	93.57852	14.51311	6.564032	2.330795
MIT_BIH_AF_06426m	99.37791	47.18998	97.61432	2.916728	2.451167
MIT_BIH_AF_06453m	49.88796	99.28701	44.10053	1.263772	2.081963
MIT_BIH_AF_06995m	97.59408	73.79503	76.88176	14.97836	2.332363
MIT_BIH_AF_07162m	99.23135	100	99.99811	0.7705176	2.498003
MIT_BIH_AF_07859m	37.06891	100	99.99877	62.93126	2.579586
MIT_BIH_AF_07879m	93.00676	100	100	4.216621	2.452219
MIT_BIH_AF_07910m	98.40856	99.10274	95.44499	1.008608	2.30022
MIT_BIH_AF_08215m	99.92318	99.59676	99.90287	0.1401948	2.675167
MIT_BIH_AF_08219m	96.23191	77.52085	54.0971	18.44006	2.661679
MIT_BIH_AF_08378m	73.78845	98.1134	91.18035	6.972091	2.450541
MIT_BIH_AF_08405m	99.5791	99.48807	99.80253	0.4461989	2.685423
MIT_BIH_AF_08434m	100	93.73924	39.11363	6.018688	2.543587
MIT_BIH_AF_08455m	99.35376	99.70419	99.86748	0.5382065	2.757717
DATABASE_TOTAL	89.14235	93.98847	90.77966	7.945253	2.645229

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 70, has this robustness against the noise
SNR        Se           Sp            PPV
 30        97.7085       98.2895       90.3031
 25        97.7085       98.2895       90.3031
 20        97.7085       98.2895       90.3031
 15        97.7085       98.2895       90.3031
 10        97.7085       97.8373       88.0455
  5        97.7085       81.3288       46.0369
  0        99.0957       47.8595       23.6544
 -5        99.4056       25.9741       17.9598
-10        99.4056       13.7623       15.8189
-15         95.244       8.78717       14.5466
-20        89.7464        5.6295       13.4225
-25        82.8105       5.62951        12.515
-30        80.0361       4.04651       11.9703
```



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A.1.7.2 RRI & FA

ATRIAL FIBRILLATION DETECTION

Contents

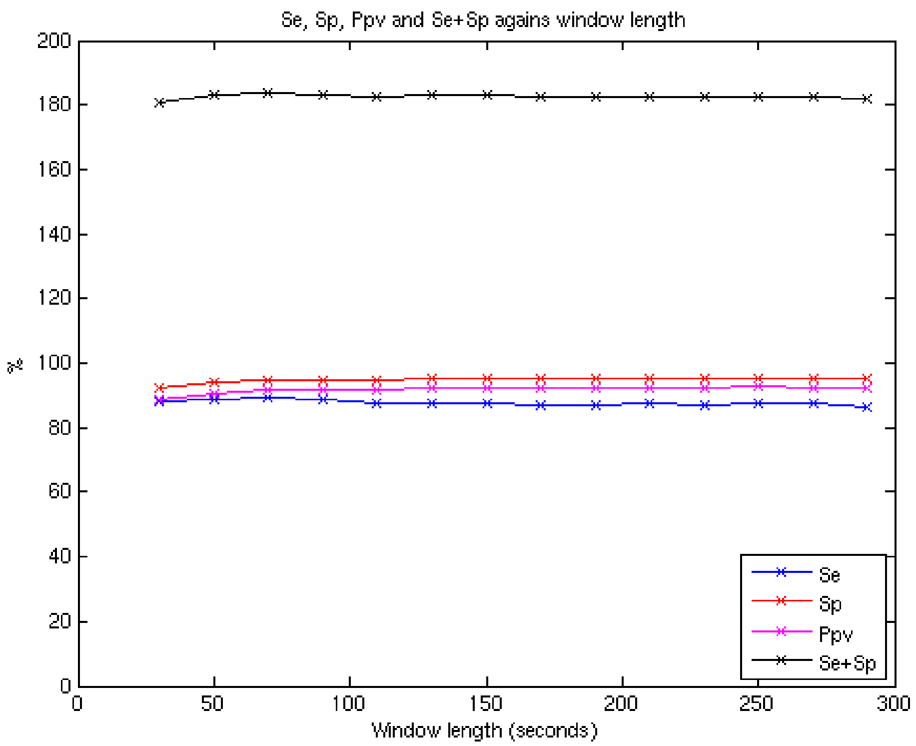
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 70 seconds,
giving Se=89.2016%, Sp=94.578% and Ppv=91.6157%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 70, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

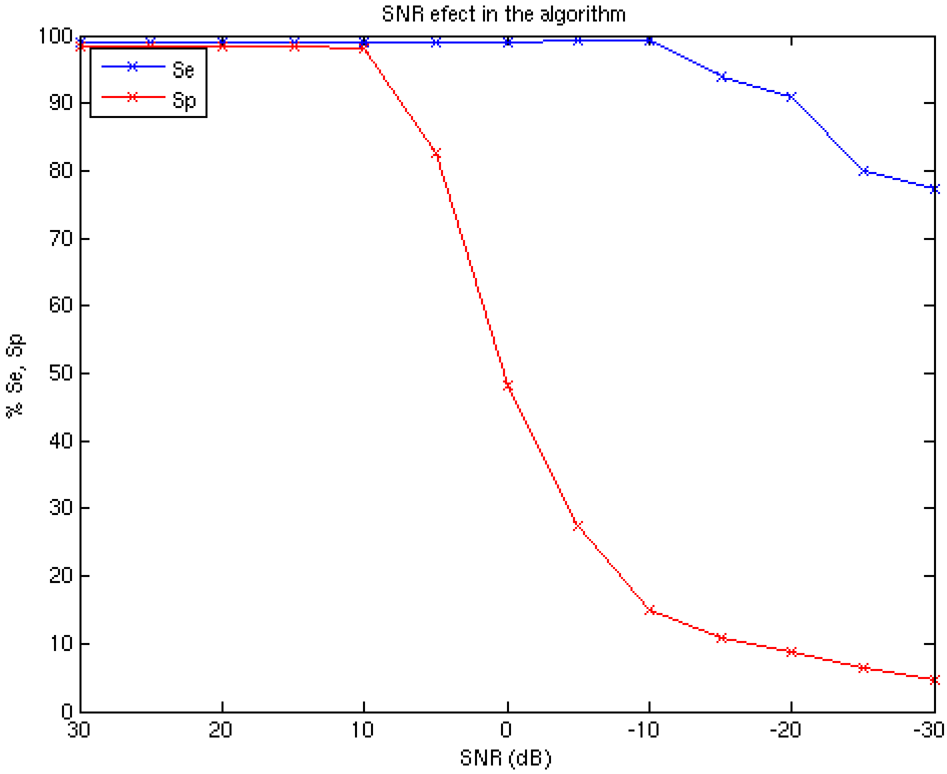
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	90.69922	6.517473	9.240856	1.669005
MIT_BIH_AF_04043m	61.83246	96.59883	83.28143	10.87854	1.619977
MIT_BIH_AF_04048m	65.4977	94.88868	11.25236	5.399283	1.557
MIT_BIH_AF_04126m	96.26001	94.85524	42.10908	5.092192	1.559489
MIT_BIH_AF_04746m	99.80637	99.50867	99.56708	0.3332479	1.376969
MIT_BIH_AF_04908m	92.92316	94.49522	61.03084	5.638253	1.897123
MIT_BIH_AF_04936m	87.22222	94.38681	97.59615	10.79468	1.683098
MIT_BIH_AF_05091m	0	99.61891	0	0.6158318	1.299923
MIT_BIH_AF_05121m	94.55399	92.82195	95.79517	6.080573	1.368362
MIT_BIH_AF_05261m	82.63078	93.57852	14.51311	6.564032	1.645783
MIT_BIH_AF_06426m	99.32184	50.29424	97.75016	2.833845	1.478164
MIT_BIH_AF_06453m	49.88796	99.28701	44.10053	1.263772	1.303293
MIT_BIH_AF_06995m	97.10184	82.71151	83.3758	10.50021	1.790471
MIT_BIH_AF_07162m	99.80165	100	99.99812	0.2002225	2.743397
MIT_BIH_AF_07859m	38.2095	100	99.99881	61.79067	1.726836
MIT_BIH_AF_07879m	93.63731	100	100	3.836424	1.573597
MIT_BIH_AF_07910m	99.59368	99.10274	95.49676	0.8185093	1.529367
MIT_BIH_AF_08215m	99.21549	99.59676	99.90218	0.71049	2.059836
MIT_BIH_AF_08219m	94.56777	78.03245	54.23557	18.39813	1.876677
MIT_BIH_AF_08378m	73.30492	98.22594	91.61221	6.984171	1.355821
MIT_BIH_AF_08405m	99.84236	99.48807	99.80305	0.2561005	1.830839
MIT_BIH_AF_08434m	100	94.92571	44.2154	4.878098	3.665933
MIT_BIH_AF_08455m	99.62858	99.70419	99.86785	0.3481081	2.789011
DATABASE_TOTAL	89.20156	94.57796	91.61569	7.567799	1.799999

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 70, has this robustness against the noise
SNR       Se           Sp            PPV
 30       99.0957       98.5157      91.5851
 25       99.0957       98.5157      91.5851
 20       99.0957       98.5157      91.5851
 15       99.0957       98.5157      91.5851
 10       99.0957       98.0634      89.2955
  5       99.0957       82.6857      48.2679
  0       99.0957       48.3118      23.8121
 -5       99.4056        27.331       18.234
-10       99.4056       15.1192      16.0313
-15       93.8568       10.8225       14.645
-20        90.907       8.75856       13.973
-25       80.0361       6.30794      12.2239
-30       77.2617       4.49879       11.652
```



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A.1.7.3 PWA & FA

ATRIAL FIBRILLATION DETECTION

Contents

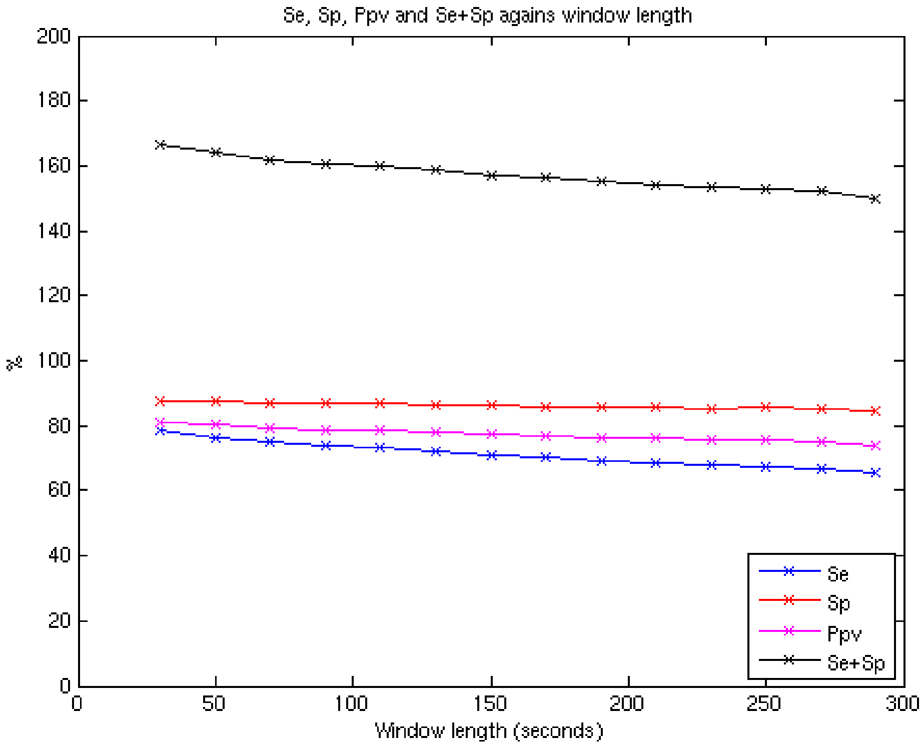
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 30 seconds,
giving Se=78.7366%, Sp=87.6948% and Ppv=80.9512%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 30, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

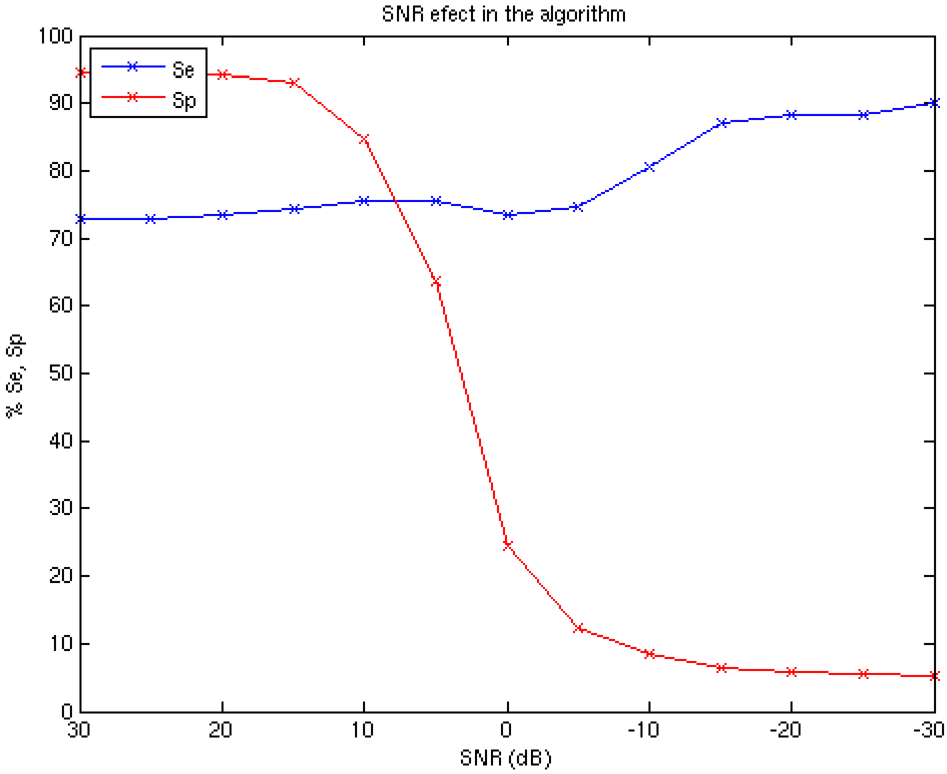
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	56.78228	94.38227	6.15105	5.859972	2.818976
MIT_BIH_AF_04043m	86.79158	92.43559	75.86791	8.778298	3.100484
MIT_BIH_AF_04048m	41.89192	99.18035	33.58578	1.38094	2.806139
MIT_BIH_AF_04126m	97.82289	49.29611	6.977081	48.88795	2.676376
MIT_BIH_AF_04746m	99.07943	53.57859	70.73022	22.2605	2.678835
MIT_BIH_AF_04908m	92.15763	90.31413	46.6217	9.53087	2.981307
MIT_BIH_AF_04936m	80.20826	84.23235	93.02028	18.68009	2.899002
MIT_BIH_AF_05091m	42.48571	91.85237	1.216634	8.263956	2.626177
MIT_BIH_AF_05121m	84.97184	90.76379	94.10229	12.90994	2.838006
MIT_BIH_AF_05261m	74.56308	90.99572	9.849146	9.218261	2.818921
MIT_BIH_AF_06426m	97.74015	60.85262	98.12808	3.936861	2.825926
MIT_BIH_AF_06453m	73.33226	99.00472	45.378	1.281514	2.485862
MIT_BIH_AF_06995m	97.37846	49.37098	63.18128	27.99295	2.981916
MIT_BIH_AF_07162m	71.94002	100	100	28.05945	2.595803
MIT_BIH_AF_07859m	68.19132	100	100	31.80853	3.093093
MIT_BIH_AF_07879m	64.57522	97.13873	97.16713	22.50172	3.053249
MIT_BIH_AF_07910m	68.17253	94.65095	71.01635	9.618739	2.588962
MIT_BIH_AF_08215m	77.54272	100	100	18.09728	2.682627
MIT_BIH_AF_08219m	77.70023	92.29857	73.5271	10.85272	3.056199
MIT_BIH_AF_08378m	80.39127	98.79431	94.6307	5.053119	2.876461
MIT_BIH_AF_08405m	56.4	96.74102	97.82448	32.38881	3.098779
MIT_BIH_AF_08434m	67.79487	89.9298	21.30728	10.92603	2.655333
MIT_BIH_AF_08455m	77.79435	99.3395	99.62303	15.56359	3.066282
DATABASE_TOTAL	78.73656	87.69479	80.95122	15.88038	2.839335

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 30, has this robustness against the noise
SNR        Se           Sp            PPV
 30        72.9141       94.5382       68.5173
 25        72.9141       94.5382       68.5173
 20        73.5086       94.3444       67.9373
 15        74.2087       93.0048       63.3622
 10        75.5387       84.5958       44.4268
  5        75.5387       63.7583       25.3614
  0        73.2982       24.3348       13.6385
 -5        74.5737        12.331       12.1784
-10        80.5187       8.45422       12.5405
-15        87.0584       6.51585       13.1807
-20        88.2474        5.7405       13.2415
-25        88.2474       5.54666       13.2179
-30         90.031       5.25591       13.4134
```



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A.1.8 Babaezaideh et al

A.1.8.1 RRI

ATRIAL FIBRILLATION DETECTION

Contents

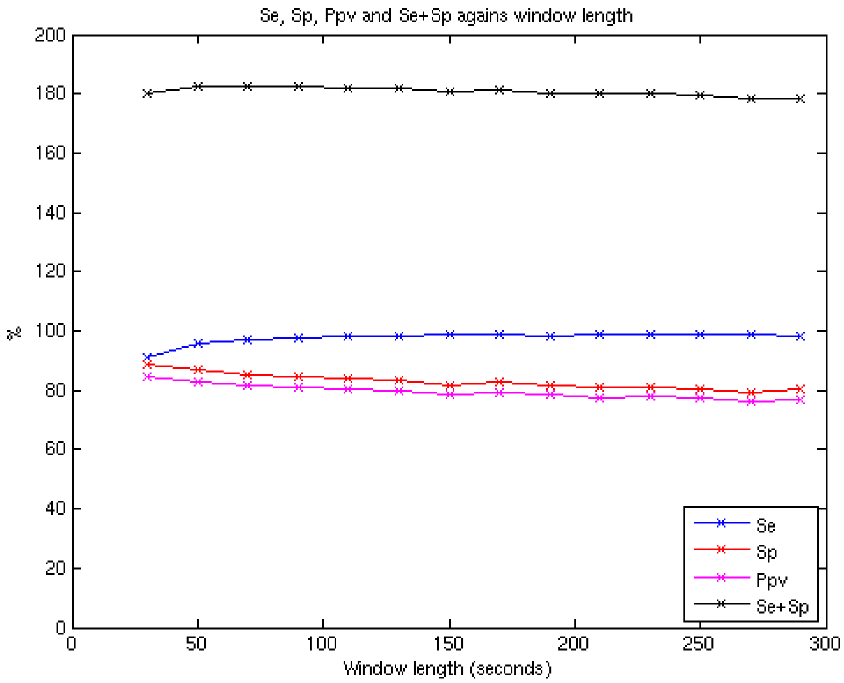
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 70 seconds,
giving Se=97.1823%, Sp=85.4404% and Ppv=81.6935%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 70, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

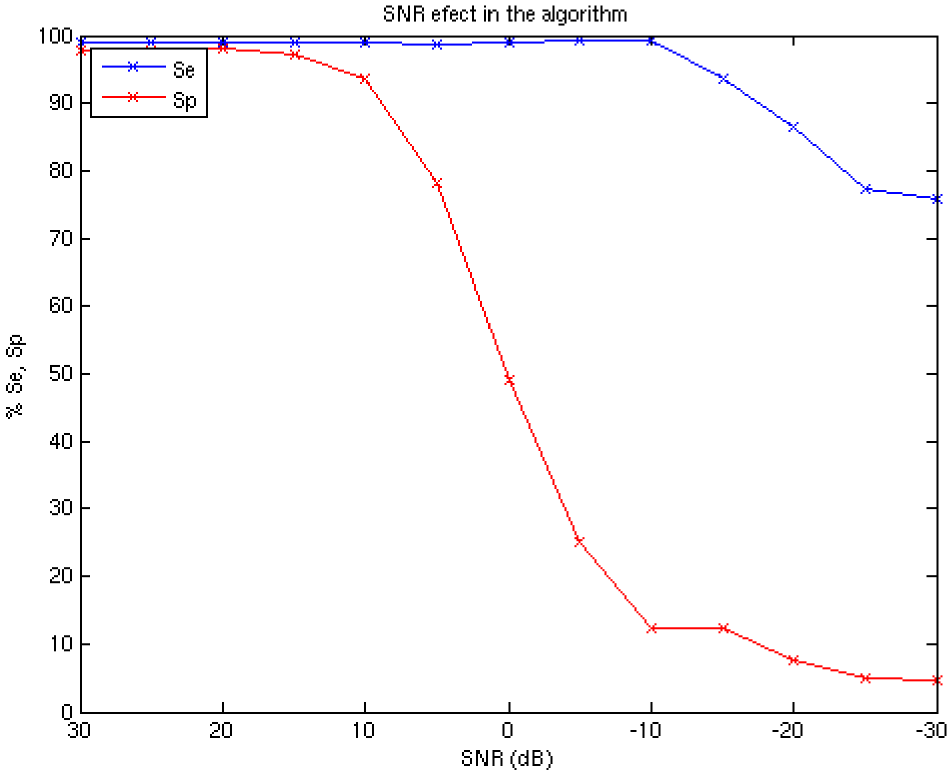
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	84.95929	4.133031	14.94381	1.251209
MIT_BIH_AF_04043m	86.12995	85.6089	62.16877	14.27885	1.304344
MIT_BIH_AF_04048m	69.34497	88.39945	5.58437	11.78724	1.010004
MIT_BIH_AF_04126m	98.7695	68.68679	10.92308	30.18747	1.260663
MIT_BIH_AF_04746m	99.94712	98.85737	99.00034	0.563973	1.905179
MIT_BIH_AF_04908m	99.9922	90.78862	50.17766	8.429983	1.332407
MIT_BIH_AF_04936m	90.51596	89.4748	96.31599	9.741749	1.281993
MIT_BIH_AF_05091m	17.41195	92.41923	0.5395714	7.757513	1.078522
MIT_BIH_AF_05121m	98.95025	86.64644	92.79039	5.5453	1.306318
MIT_BIH_AF_05261m	85.035	94.38067	16.64229	5.741025	1.183804
MIT_BIH_AF_06426m	99.63263	40.02333	97.32437	2.970781	1.40755
MIT_BIH_AF_06453m	53.99267	95.29426	11.45506	5.166234	0.9469559
MIT_BIH_AF_06995m	99.57954	4.678016	48.26258	50.55457	1.172367
MIT_BIH_AF_07162m	99.42145	100	99.99811	0.5804192	1.110705
MIT_BIH_AF_07859m	88.7759	100	99.99949	11.22451	1.178024
MIT_BIH_AF_07879m	99.94285	88.03038	92.69006	4.786916	1.282713
MIT_BIH_AF_07910m	99.10371	99.00485	95.07275	0.9791044	1.000086
MIT_BIH_AF_08215m	99.75429	97.62175	99.43384	0.6568279	1.050292
MIT_BIH_AF_08219m	97.6543	72.09408	49.06697	22.38833	1.172218
MIT_BIH_AF_08378m	99.12559	84.82335	63.58778	12.15937	1.059183
MIT_BIH_AF_08405m	99.77612	97.26389	98.95561	0.9220531	1.222629
MIT_BIH_AF_08434m	100	95.71668	48.42639	4.117705	0.9718889
MIT_BIH_AF_08455m	99.62858	98.47093	99.32063	0.7283049	1.178466
DATABASE_TOTAL	97.18229	85.44044	81.69349	9.854809	1.202936

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 70, has this robustness against the noise
SNR       Se           Sp            PPV
 30       98.8196       97.7922       87.9474
 25       98.8196       97.7922       87.9474
 20       98.8196       98.0184       89.0467
 15       98.8196       97.1138       84.8064
 10       98.8196       93.7217        71.957
  5       98.6853       78.0959       42.3456
  0       99.0957       48.9902       24.0527
 -5       99.4056       25.0695       17.7816
-10       99.4056       12.1793       15.5782
-15       93.6813       12.3769       14.8425
-20       86.5238       7.59171       13.2428
-25       77.2617       4.95108        11.701
-30       75.8745       4.72494       11.4909
```



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A.1.8.2 RRI & PWA(location & morphology)

ATRIAL FIBRILLATION DETECTION

Contents

PARAMETERS:

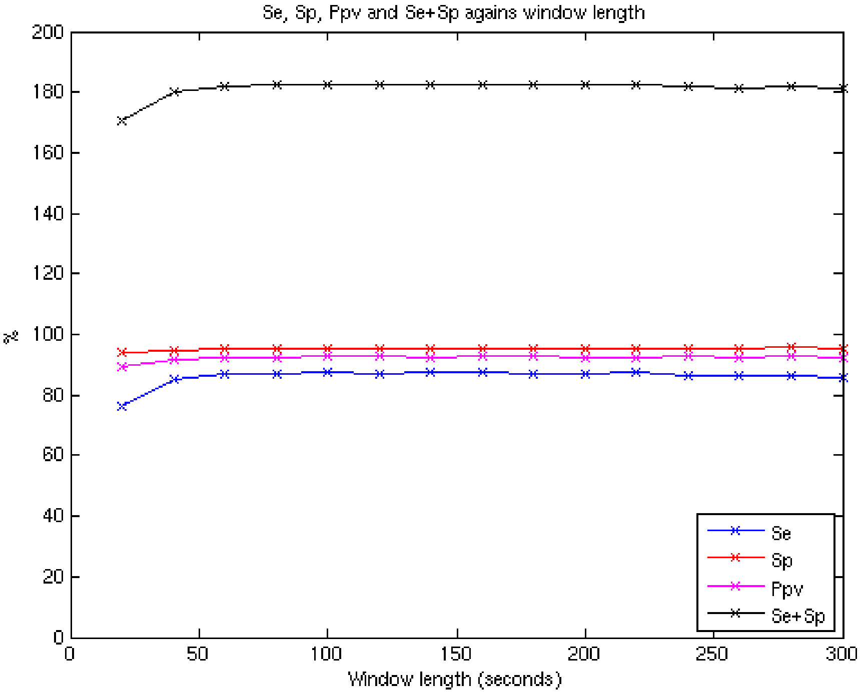
The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
This test evaluates the performance of the algorithm under study for
different window length and determines which window length obtains the
best performance.
```

```
The optimal window length is: 160 seconds,
giving Se=87.2713%, Sp=95.4706% and Ppv=92.7556%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 160, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

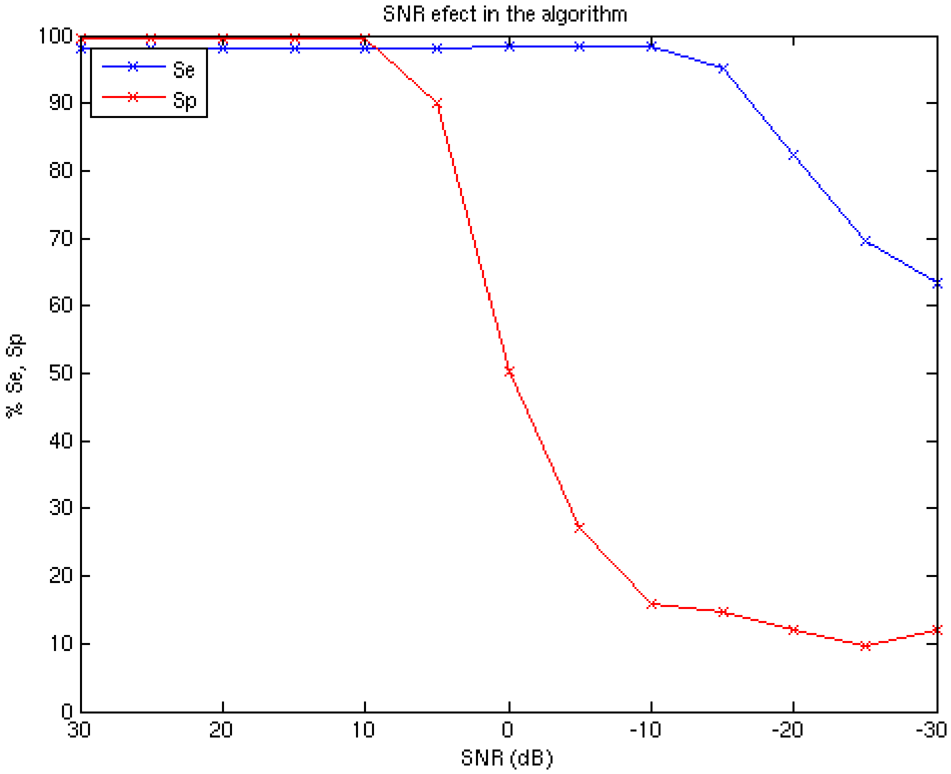
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	88.4402	92.70157	7.285139	7.325881	1.007782
MIT_BIH_AF_04043m	30.47377	98.93933	88.72912	15.78588	1.263087
MIT_BIH_AF_04048m	64.75708	94.9362	11.23209	5.359481	0.9919738
MIT_BIH_AF_04126m	90.32143	97.64312	59.83673	2.630864	1.046463
MIT_BIH_AF_04746m	99.81276	99.05267	99.16868	0.5437248	1.079503
MIT_BIH_AF_04908m	83.1647	94.85908	59.8812	6.128772	1.278445
MIT_BIH_AF_04936m	86.8788	92.61258	96.8224	11.52446	1.193208
MIT_BIH_AF_05091m	0	100	100	0.2356351	1.045215
MIT_BIH_AF_05121m	98.63474	92.21985	95.68988	3.696935	1.123932
MIT_BIH_AF_05261m	73.31676	96.56486	21.97175	3.737866	1.066587
MIT_BIH_AF_06426m	99.20009	24.2765	96.7131	3.993532	1.132975
MIT_BIH_AF_06453m	36.36393	99.4382	42.19072	1.265045	0.8905748
MIT_BIH_AF_06995m	96.69886	81.88901	82.66203	11.12482	1.187922
MIT_BIH_AF_07162m	99.50292	100	99.99811	0.4989485	0.9182565
MIT_BIH_AF_07859m	24.33226	100	99.99813	75.66785	1.285924
MIT_BIH_AF_07879m	96.56488	100	100	2.071225	1.179943
MIT_BIH_AF_07910m	99.1962	99.70712	98.46899	0.3744178	0.9031865
MIT_BIH_AF_08215m	99.9225	99.1713	99.80233	0.2223173	0.9648165
MIT_BIH_AF_08219m	95.21692	82.43638	59.87856	14.80473	1.202081
MIT_BIH_AF_08378m	74.27265	98.20706	91.6316	6.796788	1.014398
MIT_BIH_AF_08405m	99.84713	99.89134	99.95813	0.1405859	1.193377
MIT_BIH_AF_08434m	97.29472	95.32539	45.56645	4.598469	0.9442492
MIT_BIH_AF_08455m	99.71566	99.63531	99.83726	0.3091108	1.25236
DATABASE_TOTAL	87.27134	95.47061	92.75557	7.802732	1.094185

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 160, has this robustness against the noise
SNR       Se          Sp            PPV
 30       97.9352      99.4249       96.5231
 25       97.9352      99.4249       96.5231
 20       97.9352      99.4249       96.5231
 15       97.9352      99.4249       96.5231
 10       97.9352      99.4249       96.5231
  5       97.9352      90.1207       61.7748
  0       98.4147      50.3976       24.4399
 -5       98.4147      27.1371       18.0457
-10       98.4147      15.7653       15.9993
-15        95.244      14.7315       15.4044
-20       82.2159      12.0907       13.2295
-25       69.5331      9.50625       11.1319
-30       63.3379      12.1146       10.5136
```



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A.1.9 Couceiro et al

A.1.9.1 Neural Network Classifier (RRI & PWA & FA)

ATRIAL FIBRILLATION DETECTION

Contents

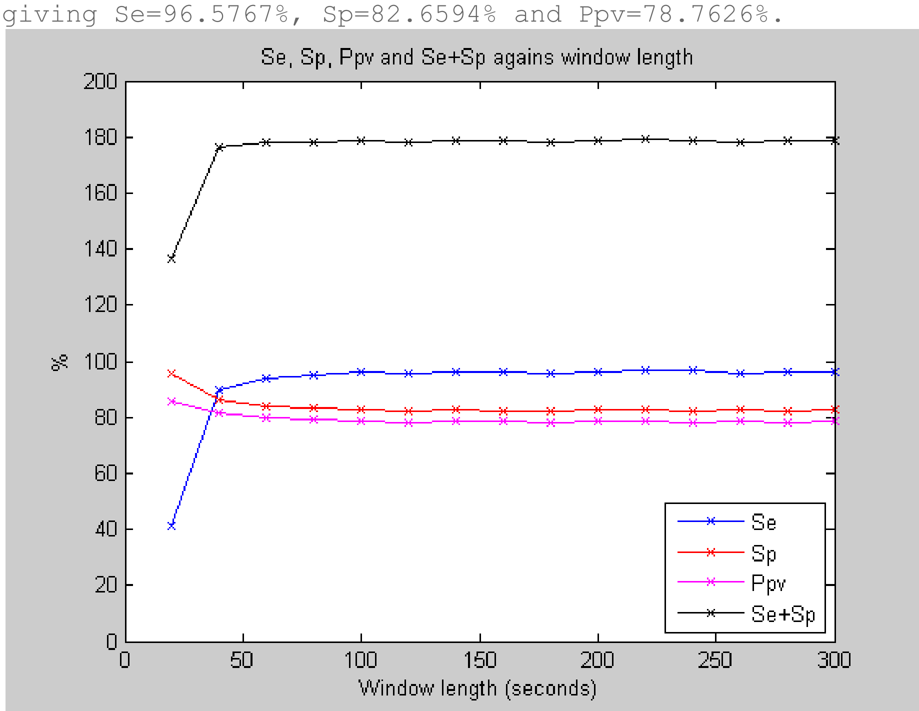
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 220 seconds,
giving Se=96.5767%, Sp=82.6594% and Ppv=78.7626%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 220, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

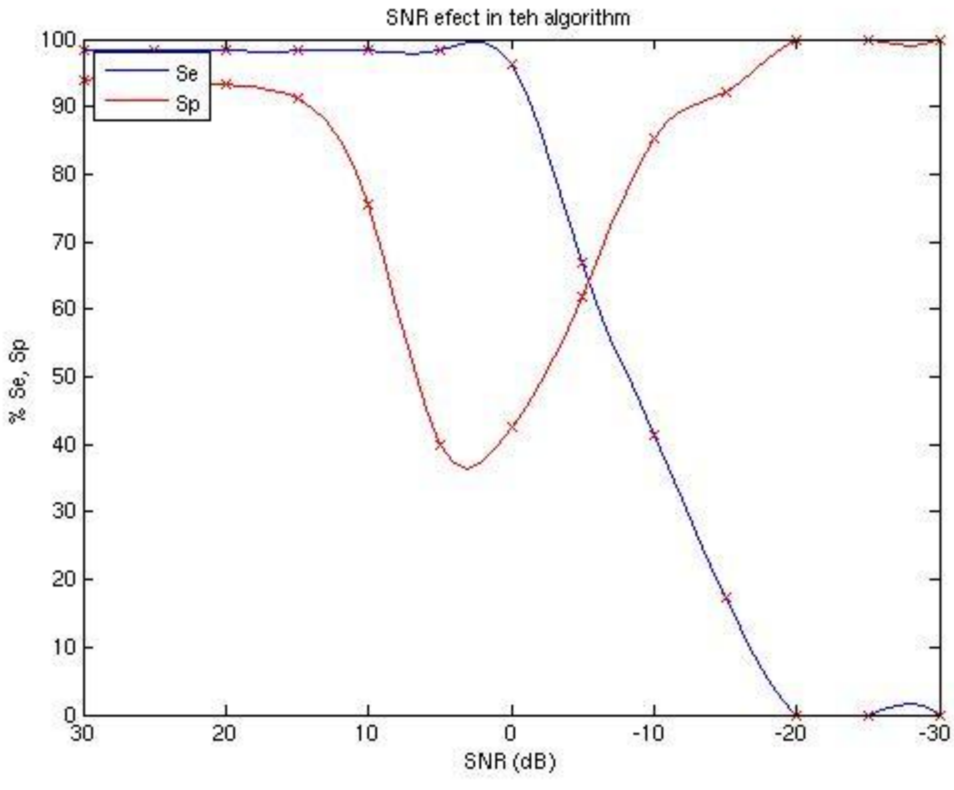
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	100	81.40587	3.369807	18.47434	2.53164
MIT_BIH_AF_04043m	80.31583	82.42654	55.60074	18.02742	3.428331
MIT_BIH_AF_04048m	89.57359	90.62903	8.640577	9.381311	2.487678
MIT_BIH_AF_04126m	100	61.68122	9.210989	36.88483	2.534187
MIT_BIH_AF_04746m	99.94712	97.23602	97.61569	1.324388	2.707976
MIT_BIH_AF_04908m	96.24448	88.76558	44.54197	10.59336	3.327199
MIT_BIH_AF_04936m	95.11623	73.97242	90.44744	10.77189	2.979742
MIT_BIH_AF_05091m	55.51816	93.54354	1.990549	6.546065	2.222098
MIT_BIH_AF_05121m	99.20939	81.42122	90.33935	7.256218	2.81059
MIT_BIH_AF_05261m	98.17807	62.55363	3.343415	36.98249	2.605967
MIT_BIH_AF_06426m	99.76494	0	95.92451	4.291802	3.01878
MIT_BIH_AF_06453m	40.71429	98.45471	22.90336	2.189069	2.249341
MIT_BIH_AF_06995m	98.16621	53.07461	65.13281	25.65456	3.028182
MIT_BIH_AF_07162m	99.7745	100	99.99812	0.2273794	2.286377
MIT_BIH_AF_07859m	94.39748	100	99.99952	5.602949	3.254193
MIT_BIH_AF_07879m	100	98.42302	98.97303	0.6258364	3.09323
MIT_BIH_AF_07910m	98.47903	94.601	78.48371	4.75272	2.204023
MIT_BIH_AF_08215m	99.72065	99.1713	99.80193	0.3852588	2.48436
MIT_BIH_AF_08219m	100	39.14558	31.14745	47.718	3.209924
MIT_BIH_AF_08378m	92.82218	95.94542	85.89287	4.710725	2.591549
MIT_BIH_AF_08405m	83.96744	98.89082	99.49417	11.8852	3.199416
MIT_BIH_AF_08434m	100	95.94263	49.7807	3.900493	2.337253
MIT_BIH_AF_08455m	97.94656	98.8371	99.47364	1.778897	3.231301
DATABASE_TOTAL	96.5767	82.65942	78.76262	11.7775	2.774928

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 220, has this robustness against the noise
SNR       Se           Sp             PPV
 30       98.23922       93.98234       72.68785
 25       98.23922       93.98234       72.68785
 20       98.23922       93.27159       70.41633
 15       98.23922       91.13939        64.3807
 10       98.23922       75.50307       39.53194
  5       98.41472       39.99494       21.09677
  0       96.26339         42.487       21.43693
 -5       66.80882       61.85025       22.20865
-10       41.46975        85.4382       31.70632
-15       17.43916       92.18177       26.66661
-20              0            100            100
-25              0            100            100
-30              0            100            100
```



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A.1.9.2 Linear Classifier (RRI & PWA & FA)

ATRIAL FIBRILLATION DETECTION

Contents

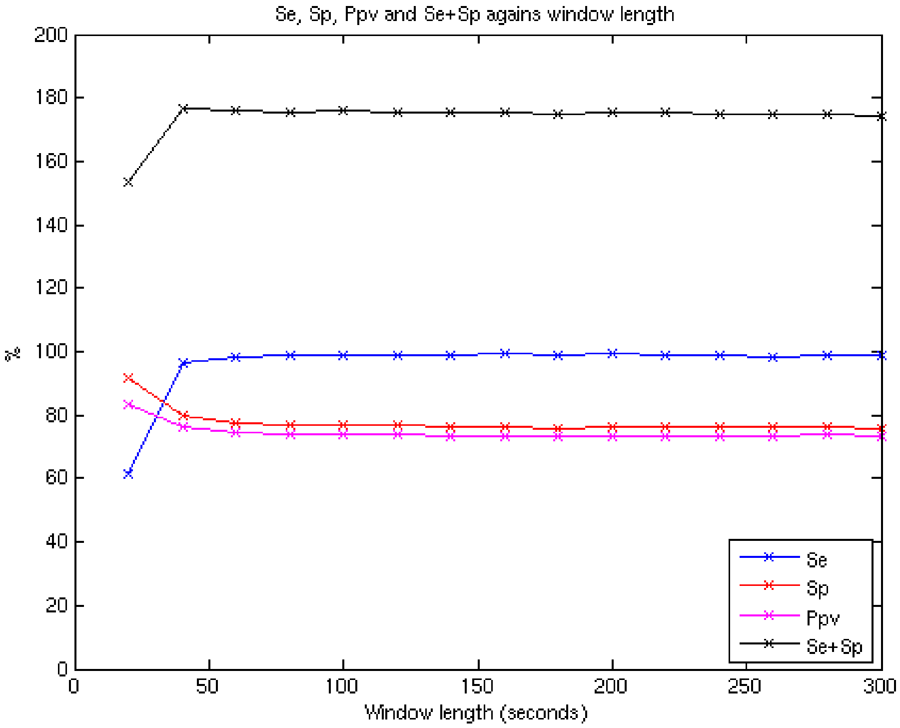
PARAMETERS:

The performance is measured by: Sensitivity (Se) [%] Specificity (S) [%] Positive Predictive Accuracy or Value (PPV) [%] Error Rate (Err) [%] Computation tiem (TComp) [seconds/hour of signal]

WINDOW LENGTH TEST

Description:

```
 This test evaluates the performance of the algorithm under study for
 different window length and determines which window length obtains the
 best performance.
The optimal window length is: 40 seconds,
giving Se=96.6504%, Sp=79.704% and Ppv=76.0404%.
```



DATABASE EVALUATION

Description:

This test evaluates the performance of the algorithm under study on the database from "data" folder.

The method for a window length of 40, SE, SP, PPV, Err and the algorithm duration per hour of the signal, and per each signal of database is

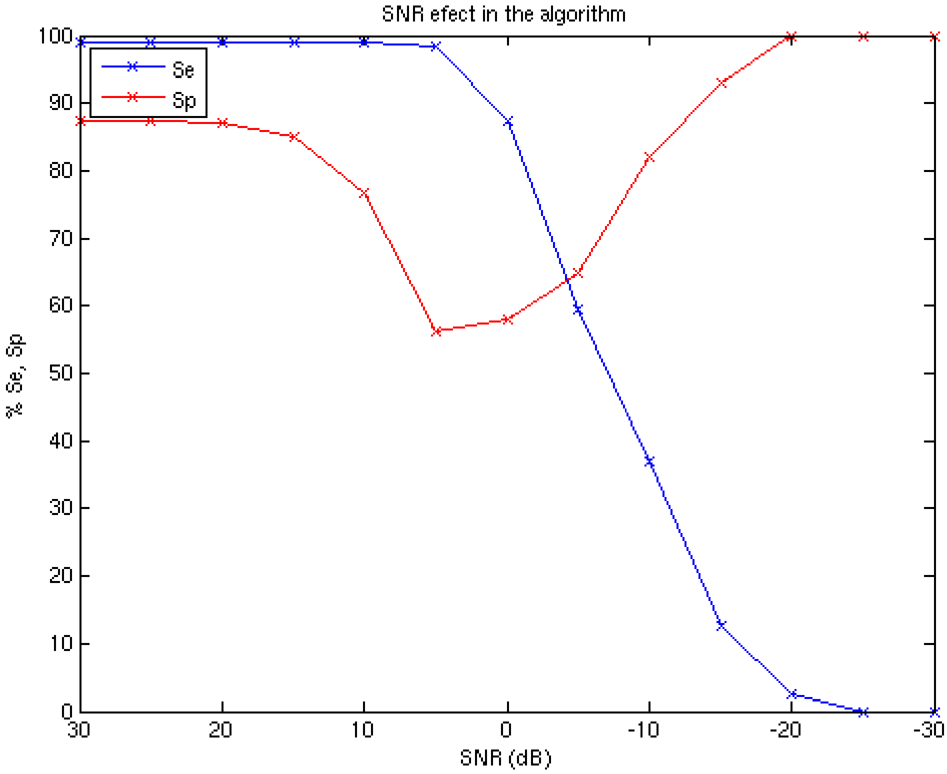
File	Se	Sp	Ppv	Err	TComp
MIT_BIH_AF_04015m	97.36971	84.66891	3.955411	15.24927	10.80157
MIT_BIH_AF_04043m	92.77488	88.47918	68.82462	10.59655	11.73038
MIT_BIH_AF_04048m	98.92454	85.73016	6.418988	14.14057	10.9421
MIT_BIH_AF_04126m	98.61797	60.61209	8.870287	37.96568	11.04712
MIT_BIH_AF_04746m	99.93789	93.63559	94.67473	3.017893	11.52867
MIT_BIH_AF_04908m	98.06682	89.48598	46.30406	9.787828	12.04562
MIT_BIH_AF_04936m	93.32927	87.84353	95.48071	8.132843	11.59571
MIT_BIH_AF_05091m	77.9504	91.36449	2.087531	8.667117	10.99474
MIT_BIH_AF_05121m	97.10146	72.17769	85.68556	12.07808	11.76051
MIT_BIH_AF_05261m	87.45673	65.71427	3.255807	34.00261	11.53739
MIT_BIH_AF_06426m	95.2778	48.14547	97.62494	6.738922	11.60536
MIT_BIH_AF_06453m	85.9513	91.25115	9.972488	8.80794	10.67424
MIT_BIH_AF_06995m	99.08548	24.59392	53.98836	40.26655	11.50853
MIT_BIH_AF_07162m	95.48362	100	99.99803	4.518171	10.73913
MIT_BIH_AF_07859m	95.1578	100	99.99952	4.842631	11.81677
MIT_BIH_AF_07879m	98.91938	93.22237	95.6862	3.341517	11.82938
MIT_BIH_AF_07910m	99.48661	88.01206	62.48524	10.06991	10.67852
MIT_BIH_AF_08215m	98.98051	95.22699	98.86147	1.743104	10.91286
MIT_BIH_AF_08219m	98.99357	27.78619	27.39851	56.84254	12.01769
MIT_BIH_AF_08378m	91.16167	95.09805	83.18722	5.729163	10.97851
MIT_BIH_AF_08405m	96.15249	97.7182	99.09493	3.412385	11.83029
MIT_BIH_AF_08434m	100	90.80133	30.42171	8.843007	10.84955
MIT_BIH_AF_08455m	98.48454	97.93006	99.07196	1.686401	11.75495
DATABASE_TOTAL	96.65035	79.70399	76.04035	13.51876	11.35563

ROBUSTNESS TO NOISE TEST

Description:

This test evaluates how robust the algorithm is against noise. Signal to Noise Ratio (SNR) is going to be varied to see how the performance changes.

```
The method for a window length of 40, has this robustness against the noise
SNR       Se           Sp            PPV
 30       99.03769      87.32826       56.0271
 25       99.03769      87.32826       56.0271
 20       99.03769      87.06981      55.52908
 15       99.03769      85.13144      52.05852
 10       99.03769      76.73183      40.96409
  5       98.41472      56.08349      26.75744
  0       87.44097      58.04205      25.35878
 -5       59.53378      64.73511      21.58176
-10       36.92541      82.11309      25.18004
-15       12.68285      93.02186      22.85714
-20       2.378035           100           100
-25              0           100           100
-30              0           100           100
```



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A.2 Published results

Several papers from the literature have been considered to study different AF detection methods. Some of them published the results, the database used, and some other characteristics that are summarized in *Table 18.*

Table 18: The published results of the papers

Method	Sub Method	Year	Database	Process	Details	RESULTS Se	Sp	PPV	Err	NPV-	FPR
Moody et al [9]	**RRI**	1983	MIT/BIH Arrythmia DB	Markov		90.03		80.14			
				Markov + 1st order filter		36.15		82.34			
				Markov + interpolation		88.22		81.31			
				Markov + 1st filter + inter		96.09		86.79			
				R-R predictor array		95.44		80.52			
			MIT/ BIH "AF" DB	Markov	Threshold + hyteresis	**99.59**		**65.97**			**21.32**
				Markov + 1st filter + inter		**93.58**		**85.92**			**6.37**
				Mar + 1st filt + inter + PVC		**90.65**		**82.38**			
				RR predictor array		**75.79**		**91.93**			**3.76**
Scolum et al [38]	**FA&PWA**	1992	WI DB	PWA– correlation FA- Power Spectrum Analysis	Training Set	69.7	90	85.2		78.3	
					Test Set	68.3	87.8	84.8		73.5	
					Combined Set	68.9	88.9	85		75.8	
					Combined Set (original system)	98.6	84	84.9		98.6	
Artis [24]	**RRI**	1992	MIT/BIH ecg DB	ANN(Artificial Neural Networks)		84.87		75.38			
			MIT/ BIH AF DB			**92.69**		**92.34**			**3.04**
			AHA DB								2.83
Cerutti et al [31]	**RRI**	1997	MIT/ BIH AF DB + IISS	Autoregressive model (AR)	P(% power)	93.3		94.4			
					M(max modules poles)	93.3		78.9			
				Entropy	MCCE	93.3		73.3			
Young et al [8]	**RRI**	1999	MIT/BIH Arrythmia DB	HMM		97.7	88.73	86.77	7		
				AE		94.24	90.26	86.95	9.36		
				LPC		94.23	78.54	72.95	14.42		
				RRvar		99.57	56.54	61.27	25.88		
				RR100		34.72	93.89	79.7	30.28		
			MIT/BIH AF DB	HMM		**94.75**	**93.51**	**91.38**	**5.97**		
				AE		**94.06**	**92.56**	**90.41**	**6.54**		
				LPC		**91.68**	**83.14**	**79.06**	**13.16**		
				RRvar		**60.31**	**92.47**	**85.46**	**21.14**		
				RR100		**97.48**	**55.96**	**61.89**	**26.47**		

Tatento et al [13]	**RRI**	2000	MIT/BIH AF DB	KS , Pc=0.01	RR	53.9	98.9				
					DR	93.2	96.7	95.2		95.2	
			MIT/BIH Arrythmia DB		RR	25.9	93.2				
					DR	88.8	64.1				
Tatento et al [14]	**RRI**	2001	MIT/BIH AF DB	CV test (CV=0.156-0.324; Rcv=35%)	RR	**86.6**	**84.3**	**79.8**		**89.8**	
				CV test (CV=0.221-0.459; Rcv=35%)	DR	**83.9**	**83.7**	**78.7**		**87.9**	
				KS test (Pc=0.000011; Neq=100)	RR	**93.5**	**93.6**				
				KS test (Pc=0.01; Neq=100)	RR	**66.3**	**99**	**98**		**80.4**	
				KS test (Pc=0.003944; Neq=100)	DR	**96.5**	**96.5**				
				KS test (Pc=0.01; Neq=100)	DR	**94.4**	**97.2**	**96.1**		**96**	
			MIT/BIH Arrhythmia DB	KS test (Pc=0.01; Neq=100)	DRR (200 series)	88.2	87.6	62.4			
				KS test (Pc=0.01; Neq=100)	DRR (total data)	94.4	97.2				
				CV test	DRR (total data)	84	84				
Christov et al [36]	**PWA**	2001				79.1	97.9				
Christov et al [35]	**PWA&FA**	2001		ECG Database		95.7	98.3				
Duverney et al [32]	**RRI**	2002	SR group	WT (wavelet transf) + fractal analysis	Derivation Set		99.9				
			CAF group			99.7					
			SR group		Validation Set		99.9				
			CAF group			92.2					
			PAF group			96.1	92.6				
Ying et al [15]	**RRI &PWA & FA**	2005	Belt DB(Philips)	RR1,PtemMat,QTCan	LCD	99.32	95.71	88.71	2.65		
					QDC	99.46	100	100	2.67		
					3-KNN	99.35	94.64	92.86	0.71		
					10-ANN	99.11	96.43	92.86	0.69		
				RR5, PtemMat	LCD	98.13	96.79	78.57	4.5		
					QDC	98.27	98.1	85.71	3.68		
					3-KNN	98.17	95.12	85.71	3.43		
					10-ANN	99.85	96.31	85.71	2.24		
				RR1,RR6	LCD	97.9	93.33	85.71	4.63		
					QDC	95.24	94.64	92.86	3.65		
					3-KNN	92.25	91.79	85.71	7.52		
					10-ANN	95.1	94.64	92.86	2.96		
			MIT/BIH AF DB	RR		**89.85**	**89.14**	**76.5**			
				QTCan9	10-NN	**81.06**	**75.29**	**56.91**			
				RR1,PtemMat,QTCan	LCD	**90**	**84.68**		**4.32**		

					QDC	93.83	90.12	79.15	3.61		
					3-KNN	NA	NA		NA		
					10-ANN	91.45	92.01		2.12		
				RR5, PtemMat	LCD	89.23	86.12		4.5		
					QDC	91.15	87.96		3.68		
					3-KNN	NA	NA		NA		
					10-ANN	91.65	87.47		2.24		
Petrucci et al [29]	**RRI**	2005	MIT/BIH AF DB	DRR based on MDW	(Gross)	**92**		**78**			
				DRR based on MDW	(Aver)	**93**		**70**			
				RR prematurity based on MDW	(Gross)	**91**		**92**			
				RR based prematurity on MDW	(Aver)	**92**		**92**			
Bock [26]	**RRI & PWA**	2005	MIT/BIH Arrhythmia DB			XX					
Logan et al [18]	**RRI**	2005	MIT/BIH AF DB	QRS detector *wqrs* to compute R-R		**96**	**89**				
Linker [28]	**RRI**	2006	examples		19RR	98	98.7				
					7RR	98	97.2				
Wild [33]	**PWA**	2006	MIT/BIH AF DB	P wave template matching		**81.28**	**71.89**				
				P wave template matching+ sliding w	w= 11 P waves long	**92.47**	**83.68**				
				P wave template matching+ sliding w	w= 31 P waves long	**88.98**	**87.99**				
Dotsinsky et al [34]	**PWA**	2007	Schiller DB			XX					
Weng et al	**AA**	2008	MIT/BIH AF DB	Stationary Wavelet Tranform (SWT)		**90**	**85**				
				STFT		**84**	**78**				
Chou [40]	**RRI & FA**	200x	MIT/BIH Arrhythmia DB	combined features		92.31	90		9.17		
				frequency features	power				12.84		
				temporal features	WT,RR	**XX**			18.37		
Ghodrati [11]	**RRI**	2008	MIT/BIH Arrhythmia DB	NADev with interval constraint		91		58			
				NADiff with interval constraint		92		73			
			MIT/BIH AF DB	NADev with interval constraint		**86**		**90**			
				NADiff with interval constraint		**89**		**87**			
			Draeger AF DB	NADev with interval constraint		85		96			
				NADiff with interval constraint		87		94			
Ghodrati [11]	**RRI**	2008	MIT/BIH Arrhythmia DB	L1 (Gaussian) with interval constraint		90		70			
				L2 (Laplace) with interval constraint		92		73			
			MIT/BIH AF DB	L1 (Gaussian) with interval constraint		**88**		**84**			
				L2 (Laplace) with interval constraint		**89**		**87**			
			Drager AF DB	L1 (Gaussian) with interval constraint		86		90			
				L2 (Laplace) with interval constraint		87		94			

Schmidt et al [21]	**RRI & PWA & FA**	2008	ECG DB	Markov, template matching ...		XX					
Couceiro et al [25]	**RRI & PWA & FA**	2008	MIT/BIH AF DB	Markov, KL divergence		93.8	96.09				
Kim et al [47]	**RRI**	2008	MIT-BIH AF DB	different time periods	XX						
Babaeizadeh et al [22]	**RRI**	2009	MIT/BIH AF DB	Markov	Gross	94	98	97			
					Average	91	96	86			
	RRI & PWA			RRI+ PWA (location + morphology	Gross	94	99	98			
					Average	89	96	88			
	RRI & PWA			[RRI+ PWA (location + morphology] + corrector + hysteresis	Gross	93	98	98			
					Average	91	96	89			
Dash et al	**PWA**	2009	MIT/BIH AF DB	3 statistical meth: RMSSD, TPR, SE		**94.4**	**95.1**				
			MIT/BIH Arrhythmia DB		with ectopy		96.2				
					without ectopy		69.4				
			MIT/BIH Arrhythmia DB		with ectopy	96.5	91.2				
					without ectopy	90.2					
Suzana et al [17]	**PWA**	2010	ECG DB	Phase 1		65	85	75			
				Phase 2		90	55.6	73.7			
				Phase 3		95		95			
				Overall		83.3	71.1	78.6			
Kurzweil et al [23]	**RRI & PWA**	2010		QRST detection + Atrial Process ...							
Pei-Chann		2010	Taoyuan Hospital			68.49	96				