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Evolutionary Optimization of Atrial Fibrillation Diagnostic Algorithms

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EVOLUTIONARY OPTIMIZATION OF ATRIAL FIBRILLATION DIAGNOSTIC ALGORITHMS

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ABSTRACT

The goal of this research is to introduce an improved method for detecting atrial fibrillation (AF). The foundation of our algorithm is the irregularity of the RR intervals in the electrocardiogram (ECG) signal, and their correlation with AF. Three statistical techniques, including root mean squares of successive differences (RMSSD), turning points ratio (TPR), and Shannon entropy (SE), are used to detect RR interval irregularity. We use the Massachusetts Institution of Technology / Beth Israel Hospital (MIT-BIH) atrial fibrillation databases and their annotations to tune the parameters of the statistical methods by biogeography-based optimization (BBO), which is an evolutionary optimization algorithm. We trained each statistical method to diagnose AF on each database. Then each trained method was tested on the rest of the databases. We were able to obtain accuracy levels as high as 99% for the detection of AF in the trained databases. We obtained accuracy levels of up to 75% in the tested databases.

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NOMENCLATURE

Action Potential	AP
Acyclic Graph Support Vector Machine	AGSVM
Atrial Fibrillation	AF
Atrioventricular	AV
Biogeography-Based Optimization	BBO
Electrocardiogram	ECG
False Negative	FN
False Positive	FP
Habitat Suitability Index	HSI
Heart Rate Variability	HRV
Massachusetts Institution of Technology / Beth Israel Hospital	MIT-BIH
Normal Sinus Rhythm	NSR
Particle Swarm Optimization	PSO
Root Mean Squares of Successive Differences	RMSSD
Sample Entropy	SampE
Shannon Entropy	SE
Sinoatrial	SA
Suitability Index Variable	SIV
True Negative	TN
True Positive	TP
Turning Points Ratio	TPR

CHAPTER I

INTRODUCTION

Section 1.1 gives the problem overview. Section 1.2 gives a brief discussion of the motivation for AF detection. Section 1.3 provides a literature review related to the topics discussed in this thesis. Section 1.4 summarizes the contributions of this thesis.

1.1 Problem Overview

AF is known as the most common arrhythmia. More than seven million Americans are known to have this disease, and the number of people who have AF is going to increase, especially in among the older generation [1]. Since it increases the risk of heart failure, AF has a direct impact on the life span and quality of life [2], [3].

We implemented diagnostic algorithms and then implemented them via MATLAB® and C# software to detect portions of a patient's electrocardiogram (ECG) that have the characteristics of AF. This was done by detecting the RR intervals of the

ECG data. As the RR intervals are highly irregular in AF, we base our algorithm on RR interval irregularity.

Three statistical techniques, namely RMSSD, TPR, and SE, were used to detect RR interval irregularity in a given ECG. In order to optimize the tuning parameters of the three statistical methods mentioned above, we used the MIT-BIH AF database. MIT-BIH AF has 25 databases. Each database included data of approximately 10 h duration and was annotated by either N (normal) or AF (atrial fibrillation). Whenever there was heart rate variability (HRV), the database is annotated as AF, and otherwise it is annotated as N. We optimized the tuning parameters of the statistical methods with BBO, which is an evolutionary optimization algorithm. We thus found the best values of the tuning parameters for each statistical method trained in every database. This resulted in a total of 75 sets of tuning parameters (3 statistical methods, and 25 databases). Then, each trained method was tested on the remaining 24 databases. Then the statistical methods with the best sensitivity, specificity, and accuracy in determining AF for each database, and the average accuracy of the remaining databases, were evaluated.

1.2 Motivation for AF Detection

Sanoski [30] showed that around 40% of patients diagnosed with AF did not have any symptoms, and AF was detected only by the diagnosis of one of the complications or risk factors associated with AF. One of the most important problems is that short-term and treatable AF can lead to debilitating permanent AF and other more serious complications.

Chest pains, heart palpitations, fainting, and congestive heart failure could be symptoms of AF. As these symptoms are common in many cardiac diseases, AF is often

overlooked. If AF becomes a chronic condition, fatigue, palpitation, and fainting can last from minutes to years. AF is more common among older patients and usually becomes a chronic problem. AF is usually diagnosed first with an ECG.

Obesity, coronary artery disease, diabetes, heart failure, hypertension, hyperthyroidism, myocardial infarction, and alcoholism are known risk factors associated with AF [27], [38] . AF has a direct impact on morbidity and mortality [30] . By increasing the prevalence of risk factors, the complications of AF will be increased.

More than 7 million people in the United States suffer from AF, and this statistic is around 4.5 million people in Europe [27], [38] . It is estimated that this number will exponentially increase during the next 50 years if the current methods continue to be used for treatment. Keech *et al*. [28] investigated the increasing number of hospital inpatient episodes diagnosed by AF in addition to AF burden on hospital care compared to the total burden of cardiovascular (CV) conditions in Scotland from 2004 to 2008 (Table I). Although these data are limited to Scotland, we can presume that similar trends hold in the USA. During the study period, there were 20 AF patients per 1,000 individuals in 2004, increasing to 24.2 patients per 1,000 in 2008. That is a gradual increase from 28,613 patients in 2004 to 36,204 patients in 2008; i.e., a 26.5% increase over the five-year study period. The increase was 17.7% for CV conditions including AF.

Year	Hospital Inpatient Episodes		Hospital Treated Patients		Hospital Discharges•		Inpatient Bed Days	
	AF Patients	CV Patients	AF Patients	CV Patients	AF Patients	CV Patients	AF Patients	CV Patients
2004	28,613	147,566	21,907	102,552	41,085	208,602	344,164	1,458,203
2005	30,410	158,959	22,942	109,124	44,573	224,971	364,419	1,508,261
2006	32,551	167,995	24,262	114,540	47,250	235,637	390,256	1,561,310
2007	34,671	173,636	25472	117,431	51,631	246,630	402,229	1,549,716
2008	36,204	173,704	26,510	117,343	54,686	251,052	394,128	1,515,705
Five Year Increase	26.5%	17.7%	21%	14.4%	33.1%	20.3%	14.5%	3.9%
•includes inpatient and outpatient charges and deaths								

TABLE I: BURDEN OF ATRIAL FIBRILLATION (AF) IN COMPARISON WITH THE TOTAL BURDEN OF CARDIOVASCULAR (CV) CONDITIONS IN SCOTLAND. AT 25% OF THE TOTAL CARDIOVASCULAR BURDEN, AF COSTS ARE INCREASING RELATIVELY FASTER. BASED ON [28].

We can also see the same increasing trend for hospital treated patients with AF. Overall, AF presents a significant and increasing burden on hospital care. Developing a practical method to diagnose AF in its early stages could save lots of money and time in the treatment of AF over long periods of time.

Atrial fibrillation treatment depends on how often the patient has symptoms, how severe the symptoms are, and whether the patient has other heart diseases. Medicines, medical procedures, and lifestyle changes are considered general treatment options. Patients with AF may be at risk of stroke. The stagnant blood in the atria can lead to blood clot formation. Clot movement to the brain can lead to stroke. Therefore, the most crucial part of treating AF is the prevention of blood clots. Blood-thinning medicines, warfarin (Coumadin®), dabigatran, heparin, and aspirin, may be prescribed to prevent blood clots [39]. Some medicines may also be prescribed to slow down the rate of ventricle beating and bring the heart rate back to its normal level. Beta blockers like metoprolol and atenolol, calcium channel blockers like diltiazem and verapamil, and

digitalis like digoxin, are medicines that may be used to control heart rate. In order to keep a normal heart rhythm, rhythm control treatment can be used. This is recommended for patients who are not doing well with heart rate control treatment or for those who have recently been diagnosed with AF. Medicines or procedures may be prescribed to control the hearts rhythm. Amiodarone, sotalol, flecainide, propafenone, dofetilide, and ibutilide are medicines used to control heart rhythm. Several procedures to restore and maintain a normal heart rhythm may be used. Electrical cardioversion, for example, may be used as a treatment option for fast or irregular heartbeats. Low-energy shocks are given to the heart of the patient to trigger a normal rhythm.

Electrical cardioversion is not the same as the emergency heart shock procedure often seen on TV programs. Electrical cardioversion is planned in advance and done under carefully controlled conditions. Catheter ablation is another option if medicines or electrical cardioversion do not work. For this option, a vein is selected in the leg or arm and then a wire inserted through it and threaded to the heart. Radio wave energy is sent through the wire to destroy abnormal tissue that is disrupting the normal flow of electrical signals. It can be also used to destroy the AV node and can be followed by implanting a pacemaker to maintain normal heart rhythm.

Another procedure to restore normal heart rhythm is called maze surgery, which involves open-heart surgery. For this procedure, the surgeon makes small cuts or burns in the atria. These cuts or burns prevent the spread of disorganized electrical signals. This procedure is used when a patient needs heart surgery for other reasons like heart valve disease [39].

1.3 Literature Review

AF detection algorithms are based on either the absence of P wave [4]-[12] or the RR interval variability in the given ECG [13]-[23]. In the first category, the detection algorithms are based on the inconsistency in the contraction of atria, resulting in no distinguishable P wave in the ECG. However, the main problem with these algorithms is that the low amplitude of P-waves can be susceptible to noise [23]. The second group of algorithms does not involve morphological changes of the P-wave but rely on the RR intervals and their irregularities. As the QRS complex is the most obvious feature in the ECG and also has the least susceptibility to muscle noise, the second group of AF detection algorithms is more reliable.

Different methods for detecting AF have been developed by considering the RR intervals; some examples are the Lorenz distribution of a time series of RR intervals [18], neural networks [21], Markov models [22], wavelet transforms [13], [16], and the coefficient of variation and Kolmogorov–Smirnov test[20]. Another study used the variance histogram of RR intervals for detection of atrial fibrillation [19]. Although almost all of them claimed high accuracy in detecting AF, their algorithms are dependent on the robustness of the training data; this means that by changing the characteristics of AF compared to the training data, the detection accuracy is reduced [23].

Measuring the unpredictability and the complexity of heart rate by using statistical methods has increasingly been applied since it is non-invasive and can be detected from shorter ECG records. Dash *et al*. [23] used a combination of TPR with RMSSD and SE. They tuned the parameters of the statistical methods by considering the same database (MIT-BIH AF) and then tested their algorithm on the short term MIT-BIH

Arrhythmia Database. They achieved high accuracy (around 90%) for the MIT-BIH AF, and then acceptable accuracy (around 82%) for the MIT-BIH Arrhythmia Database.

Other research was done in classification of the ECG signals based on the distinguishable features of different heart arrhythmias [24]. They proposed a new method of classification based on the multiclass support vector machine (SVM); it was called directed acyclic graph support vector machine (DAGSVM). The method discriminated between four types of ECG beats, including normal beat, atrial fibrillation beat, ventricular tachyarrhythmia beat, and congestive heart failure beat, by using the MIT-BIH databases. Then classification accuracy was evaluated by automatically detecting the best discriminating features and by determining the best required model amongst three kernel functions: linear, polynomial, and radial basis function. Empirical mode decomposition and singular value decomposition were used to extract and select the features [24]. Then cross-validation and particle swarm optimization (PSO) were used to optimize performance in terms of classification accuracy by selecting the best model and by estimating the best parameters of the SVM classifier. It was concluded that the DAGSVM obtained average accuracy of 98.96% on classification of the four classes of ECG datasets [24].

In a recent study, an iPhone App was created by using the Objective-C programming language. For ECG signal acquisition, the iPhone 4S videos were recorded and the signal achieved by averaging 50 × 50 pixels of the green band for every frame [46], [47]. As the sampling rate for iPhone 4S is 30 frames/s or lower (based on the processing load), the pulsatile signal was down sampled to 30 Hz. The final result appears as either NORMAL or AF DETECTED. Such terms are related to the detection

of RR interval variability by the statistical algorithms used in the research. Root Mean Squares of Successive Differences, Shannon Entropy, and Sample Entropy were used to detect atrial fibrillation in the given ECG [25]. Then, by using 64-beat segments from the MIT-BIH databases, they achieved beat-to-beat accuracy values of 94%, 93%, and 96% for RMSSD, SE, and SampE, respectively. There are two main problems with their algorithm: first, down-sampling the signal may result in the loss of important features of the QRS section. Montavon [26] showed that the main features of the QRS section could be found between 5 and 90 Hz. Second, they changed the definition of the accuracy in their article. After correctly defining the terms specificity and sensitivity (see Section 3.2.5, Equations (5) and (6) in this thesis), they defined the accuracy as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where:

TP = True Positive (both the algorithm and database annotated as AF),

TN = True Negative (both the algorithm and database annotated as normal),

FP = False Positive (the algorithm denoted as AF, the database denoted as normal)

FN = False Negative (the algorithm denoted as normal, the database denoted as AF)

Although their definition seemed correct, according to the definition of accuracy used in this thesis (Equation 7), their accuracy decreased from 96% to less than 80%.

Many studies reported the characteristics of atrial fibrillation and whether its RR sequence is deterministic or randomly distributed [17], [45]. Our algorithm used the statistical methods to analyze RR interval variability and complexity. Finding the sensitivity, specificity, and the accuracy of 1, 0.99, and 0.99, respectively, in training the methods proves this hypothesis.

By using BBO, we were able to enhance the accuracy of the diagnosis algorithms in previous studies, and we also found out which statistical methods had the best accuracy to detect RR interval irregularity. However, there are some other heart arrhythmias which also have RR interval irregularity in the ECG, like atrial flutter (AFL). That is why AF is mostly overlooked as mentioned before. Classification of different types of heart arrhythmias which have the same feature of the RR interval irregularity in the ECG can help us diagnose the arrhythmia as AF or other.

1.4 Thesis Organization and Contribution

The foundation of our algorithm is the generally accepted hypothesis that RR intervals in an ECG diagnosed as AF are highly irregular [23]. Three statistical methods, including turning points ratio (TPR), Shannon entropy (SE), and root mean squares of successive differences (RMSSD), were used to evaluate the irregularity of RR intervals.

In our method, we trained our algorithm with each of 25 MIT-BIH AF databases to find the tuning parameters of the three statistical methods. We tuned the statistical methods with BBO for each database, one at a time, and tested our algorithm on the remaining 24 databases. This is the first time that BBO has been used to tune the variable parameters of statistical methods for AF detection. In addition, we evaluated the capability of each statistical method to detect AF in a given ECG. We were able to demonstrate their ability to detect AF. Accuracy was more than 99% for some databases. We also obtained the average accuracy for all 25 databases with the trained parameters. We could achieve average accuracy of 75% by using the trained parameters of RMSSD, 71% by using the trained parameters of SE, and 54% by using the trained parameters of TPR.

If AF can be easily detected with high certainty and early in its pathology, the risk of complications due to late detection can be drastically reduced in addition to saving on health care costs. Detecting AF with this method could save lives, improve the quality of life of millions of people at risk, and provide economic advantages.

Chapter 2 presents a summary of normal heart function and ECGs in Sections 2.1 and 2.2. Section 2.3 talks about the background of AF and its comparison with normal heart function.

Chapter 3 illustrates a brief review of our detection algorithm and our MATLAB® and C# software. This section includes a discussion of the MIT-BIH AF databases (Section 3.1), and a brief overview of the detection algorithm (Section 3.2). The latter section includes all the steps of the detection process, including RR interval estimation of the ECG data (Section 3.2.1), and the use of the three statistical methods, including RMSSD (Section 3.2.2), TPR (Section 3.2.3), and SE (Section 3.2.4), in order to detect the RR interval irregularity in a given ECG. Section 3.2.5 explains how we trained and tested our algorithm using the MIT-BIH AF database. Finally, Section 3.3 talks about BBO as an evolutionary algorithm to find the best algorithm tuning parameters.

Chapters 4 and 5 discuss our results, conclusions, and future work.

CHAPTER II

BACKGROUND

AF is known as the most common sustained cardiac rhythm disorder in clinical practice [27], [29]. It is characterized by improper function of the atria because of disrupted electrical pathways and structural changes in the heart [30]. It can be difficult to diagnose AF in many cases because it does not present specific symptoms. For a better understanding of AF, we first consider the normal function of the heart, and compare it with the functionality of the heart with AF.

2.1 Normal Heart Function

Contraction of cardiac muscle cells is due to the action potentials (APs) that lead to the pumping of the blood through the body. Some cardiac cells generate their own AP for rhythmic contraction (autorhythmic cardiac cells) [31] and work with contractile cardiac cells to pump the blood. The rate of generating AP is different among autorhythmic cells. Those with the fastest rate are in the sinoatrial (SA) node, which is

why the SA node is called the pacemaker and is the main source of the force for heart contractions [31]. After initiating APs in the SA node, the excitation travels through the reminder of the heart for a full contraction (Figure 1). APs initially propagate through the atria since the atria must contract before the ventricles to pump blood to the ventricles; and then, APs spread through the ventricles, which contract to pump blood to the lungs or the rest of the body.

The sinoatrial node is about 15 mm long and 5 mm wide and its cells are self-excitatory, pacemaker cells. The generation of APs is at the rate of around 70 per minute. Electrical signals propagate throughout the atria by activating other myocardial cells. However, this propagation is unable to pass the boundary between the atria and ventricles because of the non-conducting barrier of fibrous tissue. The spread of the impulses from the SA node throughout the atria is still a topic of controversy [32], [33]. But it is generally accepted that nodal cells' depolarization can travel directly to adjacent myocardial cells, and with the help of ordered myofibrils, this excitation can reach both the left atrium and the atrioventricular node.

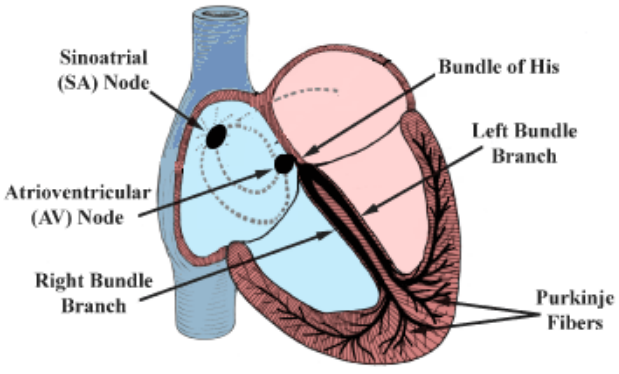

FIGURE 1: THE CONDUCTION SYSTEM OF THE HEART. NORMAL EXCITATION ORIGINATES IN THE SINOATRIAL (SA) NODE, THEN PROPAGATES THROUGH BOTH ATRIA. THE ATRIAL DEPOLARIZATION SPREADS TO THE ATRIOVENTRICULAR (AV) NODE, PASSES THROUGH THE BUNDLE OF HIS (NOT LABELED), AND THEN TO THE PURKINJE FIBERS WHICH MAKE UP THE LEFT AND RIGHT BUNDLE BRANCHES; SUBSEQUENTLY ALL VENTRICULAR MUSCLE BECOMES ACTIVATED. TAKEN FROM [34]. USED WITH PERMISSION.

The AV node has an intrinsic frequency of about 50 pulses per min, which can change depending on the pulse frequency with which it is triggered. The bundle of His (named after German physician Wilhelm His) is responsible to propagate electrical signals from the AV node to the ventricles. The normal wave of cardiac depolarization travels through the bundle of His and then spreads to the left and right bundle branches, resulting in depolarization of the upper regions of the left and right ventricles. Lastly, the signal travels to the Purkinje fibers (named after Jan Evangelista Purkinje) attached on the one side to the bundles and on the other side to the inner sides of the ventricular walls; and consequently ventricular myocardial depolarization spreads. The conducting system in ventricles has a higher speed than the velocity of the propagation of activation from the AV node in the atria (Figure 1).

2.2 Normal Electrocardiogram

Recording this electrical activity forms the ECG which is due to depolarization (contraction) and repolarization (relaxation) of cardiac muscle cells, which is followed by electrical current propagating through the chambers and tissues of the heart. When the electrical activity reaches the surface of the body, it can be measured by electrodes fixed on the skin, the output of which will be the voltage (vertical) and time (horizontal) signal. The morphological feature of the ECG shows the depolarization and repolarization of the atria and ventricles (Figure 2).

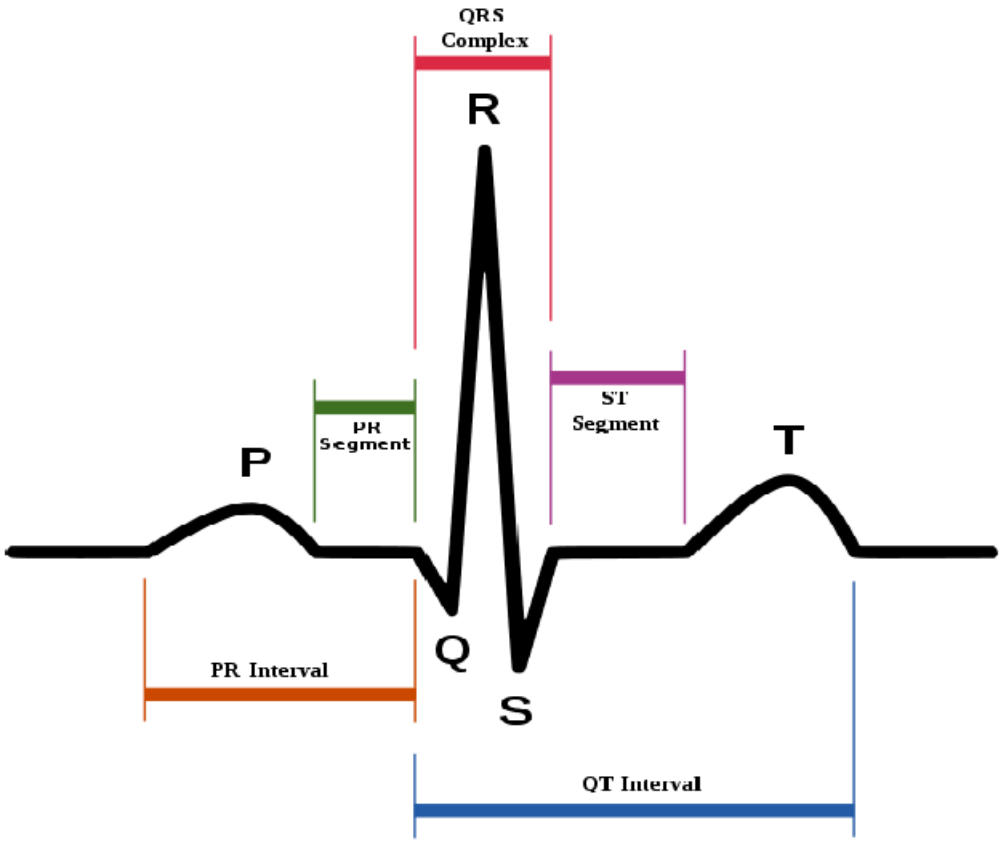

FIGURE 2: NORMAL ELECTROCARDIOGRAM (ECG) SIGNAL. TAKEN FROM [52]. THIS FIGURE IS IN THE PUBLIC DOMAIN.

From the above, we can see that the first structure to be depolarized during normal sinus rhythm is the right atrium, immediately followed by the left atrium. Therefore, the electrical signal known as the P wave on a normal ECG originates from the atria (plural of atrium). In fact, the P wave is the sum of the electrical signals, which are usually superimposed from the atria. That is why we usually have only one P wave in most leads of an ECG. The P wave is followed by a short physiological delay, which is known as the PR interval, the time required for the signal to reach the atrioventricular (AV) node before its spread through the ventricles. There is no electrical activity in the normal ECG during this time, and it appears as a straight horizontal or isoelectric line.

The largest part of the normal ECG signal is made by depolarization of the ventricles and is known as the QRS complex. This is because of the greater muscle mass in the ventricles compared to the atria. In the QRS complex, the Q wave is the first initial downward or negative deflection, and is followed by the R wave, the next upward deflection. Finally, the S wave is the next deflection downwards, provided that it crosses the isoelectric line to become briefly negative before returning to the isoelectric baseline. Repolarization of the myocardium is also shown as an electrical signal known as the ST segment (isoelectric segment) and the T wave (an upright deflection of variable amplitude and duration). Another important feature of the normal ECG is the distance between R peaks, which is known as the RR interval. Heart rate variability (HRV) is the change of beat-to-beat intervals, also known as RR intervals. HRV relates to the fluctuations of the heart rate around an average heart rate (number of RR intervals per minutes) (Figure 3). During running, for example, HRV decreases as heart rate increases. HRV could be an indicator for many types of heart arrhythmia like AF [50].

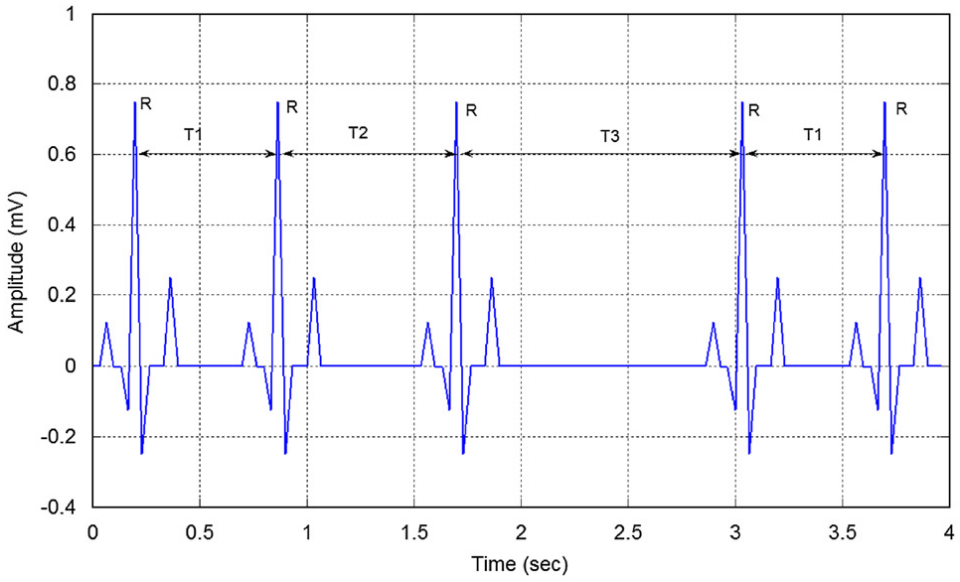

FIGURE 3 : RR INTERVALS, VARIATION OF BEAT TO BEAT INTERVALS. TAKEN FROM [1]. USED WITH PERMISSION.

The RR interval is a measurement of the distance between two consecutive heart beats. As the R wave is the tallest and the most conspicuous wave in the ECG, it is usually chosen to measure heart rate. It is the same as the distance of P-to-P or any two analogous points on consecutive beats in most rhythms. Consistency in the RR intervals indicates that the rhythm is regular. This means that the beats are evenly spaced. The term *irregular* refers to heart beats that are not evenly spaced. Heart rate also refers to the number of beats per minute. The most distinguishable feature of atrial fibrillation is heart rate variability (HRV) or irregularity in RR intervals, as shown in Figure 3.

An ECG test is used to check heart problems when a patient has abnormal symptoms such as dizziness, chest pain, or an abnormal heart rate. It can show various heart problems, like a previous heart attack, an enlarged heart working under strain, and irregular heartbeats known as arrhythmias. For evaluating the ECG, the physician may record the test in different conditions, depending on the symptoms of the patient and type of arrhythmia. The standard ECG is taken while the patient is resting. An exercise ECG (also known as stress test or treadmill test) is taken while the patient is exercising. This shows the functionality of the heart under stress. The recorded ECG can be used for diagnosing coronary heart disease, which is equal to pathologic narrowing of the arteries of the heart. It is also a useful test for patients with heart surgery or heart attack to evaluate the amount of safe activity the patient can have. Holter monitor or ambulatory ECG is another ECG test for recording the electrical activities of the heart for a period of 24 hours or longer by using an electronic recorder carried with a patient. It can show occasional irregular heartbeats that may not appear in short duration ECG recording.

Currently, Holter monitoring is the most common method for diagnosing AF. It is attached to the patient with 3 or 5 leads and records the electrical activities of the heart over a period of 24 hours or more. Then, the recording can be evaluated to diagnose AF or other heart arrhythmias. However, as it can be affected by noise, paroxysmal AF, which appears for very brief segments, may not be detectable; Figure 4 shows a sample of a Holter monitoring for around 20 seconds. Holter monitoring is time-consuming and irregularities can be easily overlooked [35].

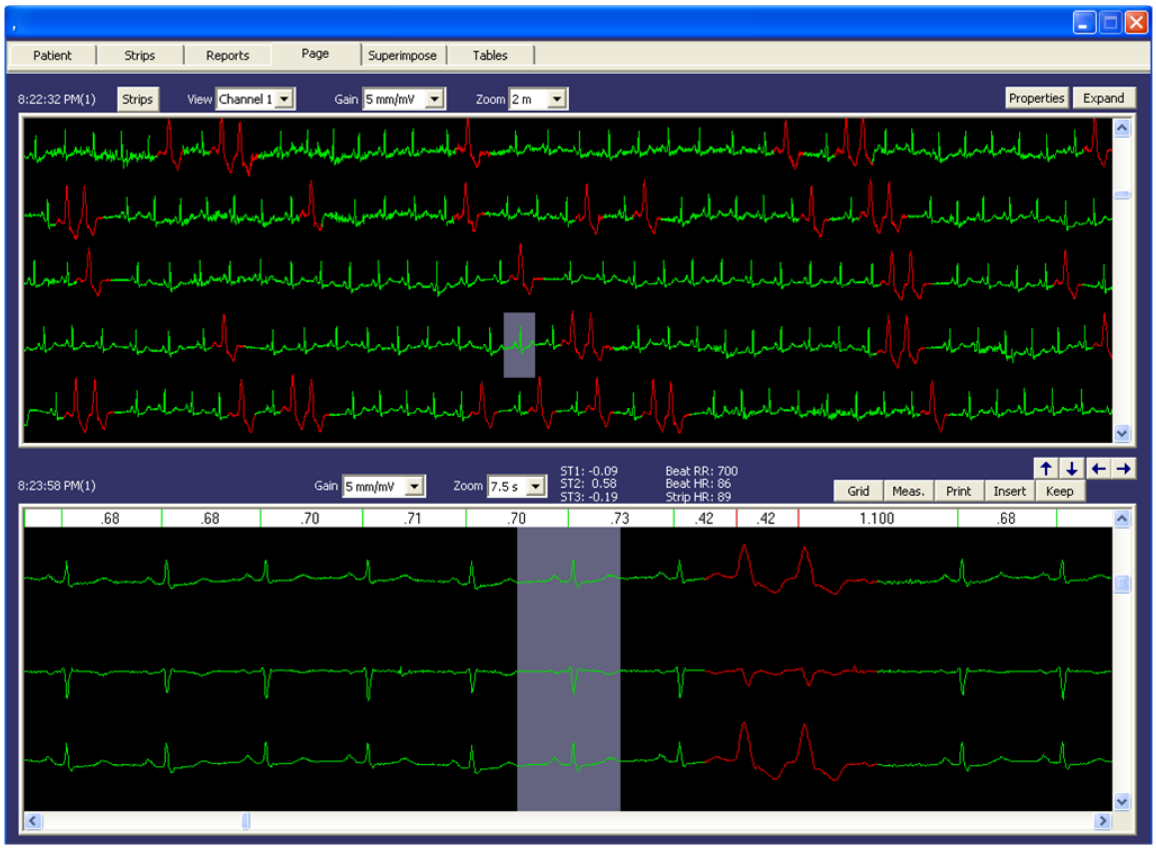

FIGURE 4: HOLTER MONITOR. DATA OBTAINED FROM A HOLTER MONITOR CAN BE AFFECTED WITH NOISE AND REQUIRES THOROUGH ANALYSIS FOR DIAGNOSING AF. TAKEN FROM [35]. USED WITH PERMISSION.

2.3 Other Heart Arrhythmias

There are four main types of arrhythmias, including premature (extra) beats, supraventricular arrhythmias, ventricular arrhythmias, and bradyarrhythmias. Premature beats are harmless most of the time and do not cause any symptoms. Fluttering in the chest or a feeling of a skipped heartbeat are common symptoms of premature beats. Most of the time, they do not require any treatment, especially in otherwise healthy people. When they occur in the atria, they are called premature atrial contractions (PACs). Premature ventricular contractions (PVCs) refer to the premature beats that occur in the ventricles. Most of the time they are naturally generated; but they can result from heart disease too. Stress, too much exercise, or too much caffeine or nicotine could be other factors causing premature beats [55].

Supraventricular arrhythmias are fast heart rates (tachycardias) that begin in the atria or AV node. Atrial fibrillation (AF), atrial flutter, paroxysmal supraventricular tachycardia (PSVT), and Wolff-Parkinson-White (WPW) syndrome are four types of supraventricular arrhythmias. Atrial flutter is similar to AF, but in atrial flutter, unlike AF, the electrical signals of the heart spread through the atria in a fast and regular rhythm instead of the irregular rhythm in AF. Atrial flutter is much less common but has symptoms and complications similar to those of AF [55].

Fast heart rate that begins and ends suddenly is known as PSVT. PSVTis related to the electrical connection between the atria and the ventricles. Electrical signals can reenter the atria instead of traveling to the ventricles, causing extra heartbeats. It is not usually dangerous and is more common in young people. It may happen during vigorous physical activity.

WPW syndrome is a type of PSVT and refers to a condition in which the electrical signals of the heart travel a longer pathway from the atria to the ventricles, resulting in disruption in the timing of the electrical signals, and can lead to much faster contraction of the ventricles. It can be life threatening [55].

Ventricular arrhythmias start in the ventricles, and include ventricular tachycardia and ventricular fibrillation. They often need medical care immediately. Ventricular arrhythmias can be caused by coronary heart disease, heart attack, a weakened heart muscle, and other problems.

Ventricular tachycardia refers to the fast and regular beating of the ventricles. It may last for only a few seconds or for much longer. Only those fast beats which last more than few seconds are dangerous. Ventricular tachycardia can lead to more serious arrhythmias, like ventricular fibrillation [55].

When disorganized electrical signals cause the ventricles to quiver instead of pump normally, ventricular fibrillation occurs. If ventricles do not pump the blood to the body, death can occur within a few minutes. In order to prevent death, an electric shock should be given to the heart (defibrillation). Ventricular fibrillation may occur during or after a heart attack or in a weak heart.

The situation in which the heart rate is slower than normal is known as bradyarrhythmias. Not enough blood reaches the brain because of the slow heart rate. This can cause you loss of consciousness. Bradyarrhythmias can be caused by different factors, including heart attacks, changing the normal pattern of the heart's electrical activity (like aging), an imbalance of the blood’s substances (like potassium), medicines

such as beta blockers, calcium channel blockers, some antiarrhythmia medicines, and digoxin [55].

2.4 Abnormal Heart Function in Atrial Fibrillation

As mentioned before, electrical signals in a normal heart contraction are coordinated and result in a steady contraction and recovery period. In AF, uncoordinated electrical impulses disrupt the steady activation of the atria. An absence of P-waves and an irregularity among RR intervals in the ECG are the main morphological changes compared to a normal ECG (Figure 5).

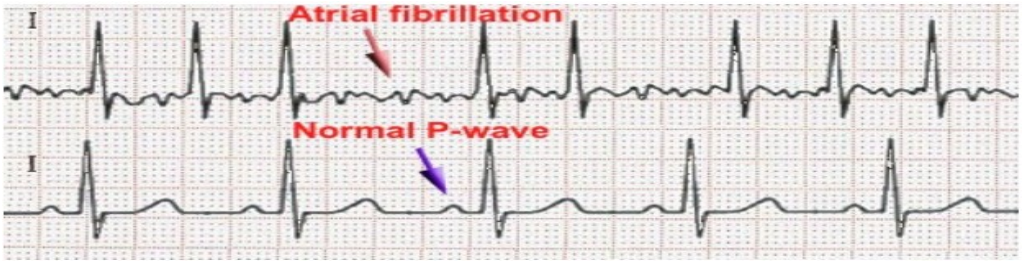

FIGURE 5: COMPARISON OF THE ECG OF THE NORMAL HEART AND AF. TAKEN FROM [35]. USED WITH PERMISSION.

Improper bioelectrical and mechanical functioning of the atria result from AF. Disordered electrical impulses also cause improper functioning of the ventricles. The SA node generates normal impulses, but such impulses are overwhelmed by disordered impulses of the atria and pulmonary veins, resulting in uncoordinated contraction (Figure 6).

Studies show that AF causes structural remodeling of atria which may require surgical intervention [36], [51]. The disrupted electrical pathways cause the atria to quiver at irregular intervals at more rapid heart rates. As a result, the ventricles do not fill effectively and thus, the heart does not have adequate blood output to the lungs and the rest of body. Not having enough blood output means that insufficient oxygen and

nutrients to vital organs and tissues are provided. Such a condition is much more important during activities with more stress on the body like exercise, when the ventricles should increase blood supply to the rest of the body. So during strenuous activities, as the heart of a person suffering from AF does not provide an adequate increase of blood supply, vital organs may not receive the nutrients and oxygen needed for efficient function.

Three kinds of AF have been diagnosed: (1) Paroxysmal AF, which is defined when the arrhythmia is self-terminating and typically lasts for less than seven days. (2) Persistent AF, which is defined when the arrhythmia is not self-terminating and lasts for more than a week. Because of not being self-terminating, some drugs may be prescribed to actively terminate AF. (3) Permanent AF, which is defined as constant arrhythmia and lasts for more than a year [31]. The first two types of AF may not have any symptoms and may result in more dangerous permanent AF [37].

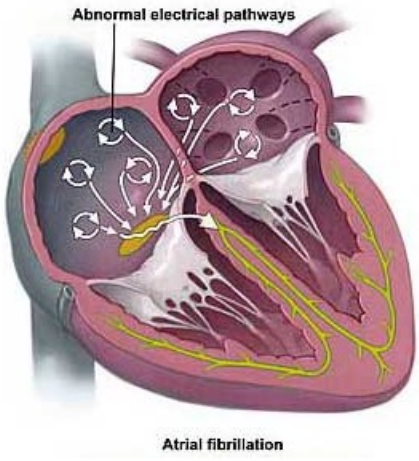

FIGURE 6: AF DUE TO UN-COORDINATED PROPAGATION OF ELECTRICAL SIGNALS FROM THE SA NODE. TAKEN FROM: HTTP://WWW.SAINTVINCENTHEALTH.COM/SERVICES/HEART/HEART-RESOURCE-LIBRARY/ATRIAL-FIBRILLATION/DEFAULT.ASPX. USED WITH PERMISSION.

Patients with paroxysmal or persistent AF may not have any symptoms, and only those with permanent atrial fibrillation may have noticeable symptoms.

CHAPTER III

METHODS

This chapter begins by introducing the MIT-BIH AF database in Section 3.1, which is used for training the algorithm developed for AF diagnosis. This is followed by Section 3.2, which gives a broad view of our detection algorithm. Five steps, including RR interval estimation, RMSSD and its usage in detecting AF, TPR and its usage in detecting AF, SE and its usage in detecting AF, and finally, the methods for training and testing our algorithms are explained in Section 3.2. Finally, Section 3.3 includes a brief overview of BBO as an evolutionary algorithm and its role in optimizing the tuning parameters in our detection algorithms.

Current methods of detecting AF focus on statistical analysis which leads to the detection of anomalous heart signals in real-time. In our research, we show the improvements of the results of AF diagnosis by statistical analysis, and we discuss our method's restrictions and limitations. As mentioned before, the main symptom of AF in

the heart signal is the variability and complexity in the duration of RR intervals, and this is the feature that is exploited by our AF detection algorithms.

3.1 AF Databases

Several databases of standard ECGs are available. The American Heart Association (AHA) Databases are for evaluation of ventricular arrhythmias. They contain 155 recordings of ambulatory ECGs. The signals were sampled at 250 Hz and with a resolution of 12 bits over 20 mV. Each record has 2.5 hours of unannotated signals in addition to 30 minutes of annotated signals. Recordings belong to eight groups based on different levels of ectopic excitation. In the first group, Records 1001 to 1020 show no extra systoles, but records 8001 to 8010 have ECGs with ventricular fibrillation and show the highest level of ventricular ectopy [67].

The Ann Arbor Electrogram Libraries consist of more than 800 intracardiac electrograms and surface ECGs. This is a valuable database for the evaluation of algorithms for implantable cardiac devices [67]. The Common Standards for Electrocardiography (CSE) database has been mostly used as a reference for the evaluation of diagnostic ECG analyzers. Around 1000 recordings, measured with 12 or 15 leads, are available in this database [67].

PhysioNet (http://physionet.org/) is a research resource with the goal of stimulation of current research and new investigations in the study of complex biomedical and physiologic signals. It includes three major components: PhysioBank, PhysioToolkit, and PhysioNetWorks [56].

PhysioBank is the name of an archive which includes well-characterized digital recordings of physiologic signals, time series, and related data for the biomedical research community usage. This archive currently has more than 50 collections of cardiopulmonary, neural, and other biomedical signals from both healthy subjects and patients with a variety of conditions with major public health implications, like sudden cardiac death, epilepsy, congestive heart failure, sleep apnea, gait disorders, and aging. The data was gathered from a wide range of studies and saved as a collection by members of the research community [56].

The library of software known as PhysioToolkit is intended for physiologic signal processing and analysis, detection of physiologically significant events using both classical techniques and novel methods based on statistical physics and nonlinear dynamics, creation of new databases, interactive display and characterization of signals, simulation of physiologic and other signals, quantitative evaluation and comparison of analysis methods, and analysis of non-equilibrium and non-stationary processes. All PhysioToolkit software is available in source form under the GNU General Public License (GPL).

The development of data and software resources, which will eventually become components of PhysioBank and PhysioToolkit, has been conducted in a virtual laboratory known as PhysioNetWorks. PhysioNetWorksprovides secure workspaces for active researchers to create well-organized and documented data and software repositories during the conduct of their research. With the completion of research and publications, the repository can be shared with a group of colleagues or the research community at large.

A wide variety and large quantity of well-characterized data and related open-source software was collected and created for biomedical research by PhysioNet during its first 12 years. They were often created at great expense, and are available for re-use and further study without any cost by a worldwide community of more than 40,000 researchers, clinicians, educators and students, and medical instrument and software developers. As of June 2011, a search in Google Scholar finds over 5000 publications and citations for PhysioNet and related terms [56].

Since 1975, the laboratories of PhysioNet at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center) and at MIT have supported research into arrhythmia analysis and related subjects. The MIT-BIH AF database includes 25 long-term ECG recordings of human subjects with atrial fibrillation (mostly paroxysmal). Each recording is 10 hours in duration and contains two ECG signals, each sampled at 250 samples per second with 12-bit resolution over a range of ±10 millivolts. The original analog recordings were collected by using ambulatory ECG recorders with a typical recording bandwidth of approximately 0.1 Hz to 40 Hz [57].

For finding threshold values of statistical AF detection methods, including SE, RMSSD, and TPR, we used the MIT-BIH atrial fibrillation databases and their annotations. These databases include RR time series from 250 Hz ECG recordings. The MIT-BIH atrial fibrillation database is an ideal database as it has 25 ECG recordings with a total of 299 AF episodes. Each record is approximately 10 h in duration.

These databases are available at http://physionet.org/cgi-bin/atm/ATM. There are different options to select the signal format based on user need. These options are as follows: the type of database (includes ECG signals extracted from patients with different

heart diseases), record number, annotations (what type of annotations to download), length (duration of signal), time format, and data format. In the Toolbox section of the web page, we can select the format of the databases. For example, by selecting the option "Show RR intervals as a text," we can download a text file of RR intervals along with its time of recording; or by selecting "Export signals as .mat," we can download the selected data in the form of a file that is readable by MATLAB.

By considering the annotations and RR intervals of each database (selected from "Toolbox" section), we defined separate matrices with annotation of 0 and 1 for each database in C# and MATLAB. These matrices were used to obtain a mathematical cost function for tuning the parameters of the statistical AF detection methods. For this purpose, we defined an algorithm based on the start time of the RR intervals and the annotation time of the selected database. The annotation file tells you at what time the selected signal has the characteristics of AF (atrial fibrillation) or N (normal). We considered other heart arrhythmia annotations as N. Therefore, in our algorithm, based on the start time of the AF or N annotation, we annotated RR intervals as 1 for AF, and 0 for N. In other words, whenever the RR beat was annotated as normal (shown as N in the annotated database), we would record 0 for the RR beat, and if the RR beat was annotated as atrial fibrillation (shown as AF in the annotated database), we would record 1 for the RR beat. This resulted in a matrix of 1's and 0's with the same length as the RR interval database. Another thing which should be taken into consideration was that we did not include other heart arrhythmias in our algorithm. So if there was an annotation for other heart arrhythmias which was neither atrial fibrillation nor normal, we would consider it as normal and annotate it with 0.

Although the databases included the annotations of RR intervals (0 or 1) for each beat based on heart rate variability, and such annotations were highly correlated with the annotations AF and N, we found that lots of RR intervals were missing in the databases and this could have a large impact on the final results of the AF detection. We therefore developed an algorithm to correct this shortcoming. The procedure is explained in Appendix A, and that is why we decided to detect AF based on the database annotations and not on the heart rate variability.

There are two ways to download the required data from the Physionet. The easiest way is to go to the http://physionet.org/cgi-bin/atm/ATM and select "MIT-BIH Atrial Fibrillation Database (afdb)" in the Database window. Then you have 25 records which could be selected in the record window. For having access to the RR intervals, you should select "Show RR intervals as text" in the Toolbox window and also select "unaudited beat annotations (qrs)" in the annotations window. In order to have access to the N and AF annotations, you should select "Show annotations as text" in Toolbox window and also select "reference rhythm annotations (atr)" for the Annotations window. If you click on the ".txt" file in the window titled by "The output below was prepared using this command:", you will have the desired database. In order to evaluate the signal more accurately with clear annotations and differences between the RR intervals, please see http://www.physionet.org/lightwave/.

Another way that we used for collecting the required databases was to download the PhysioToolkit. It is helpful software for viewing, analyzing, and simulating the required data. For more information and exploring how to work with it please see http://www.physionet.org/physiotools/getting-started.shtml.

3.2 AF Detection Algorithms

We developed our algorithm based on the generally accepted hypotheses that AF results in a significant increase in both the variability and complexity of the RR interval series [23]. For our AF detection algorithms, each series of RR intervals in each database was first divided into overlapping N beat segments. N as well as other parameters was optimized by biogeography-based optimization (BBO), as discussed in Section 3.3. These variables were tuned separately for each statistical method (RMSSD, SE, and TPR). The statistical methods analyze the heart rate variability (HRV) to determine whether or not each N beat segment has the characteristics of AF.

These statistical methods are as follow: TPR, which is a nonparametric test that measures the randomness of the RR interval fluctuations; RMSSD, which is a parametric test that measures the variability of the RR intervals; and SE, which is a parametric test that measures the complexity of the RR intervals. As RMSSD and SE are parametric tests, they were affected by distribution assumptions. Therefore, we removed the shortest M (another parameter that was tuned by BBO) and longest M beats of each N beat segment prior to implementing RMSSD and SE. In the final analysis, each N beat segment of RR intervals annotated as AF if the corresponding statistical method classified it as AF.

3.2.1 RR Interval Estimation

The first step of our algorithm was to determine the RR intervals. For that purpose, we used a variation of the heart beat detection algorithm introduced by Pan and Tompkins [40]. We extracted the QRS sequences of the heart beats in the ECG. We used

a band pass filter with a pass band frequency range of 5 to 90 Hz [26]. In order to isolate the QRS sequence, we performed a three-step process (Figure 7).

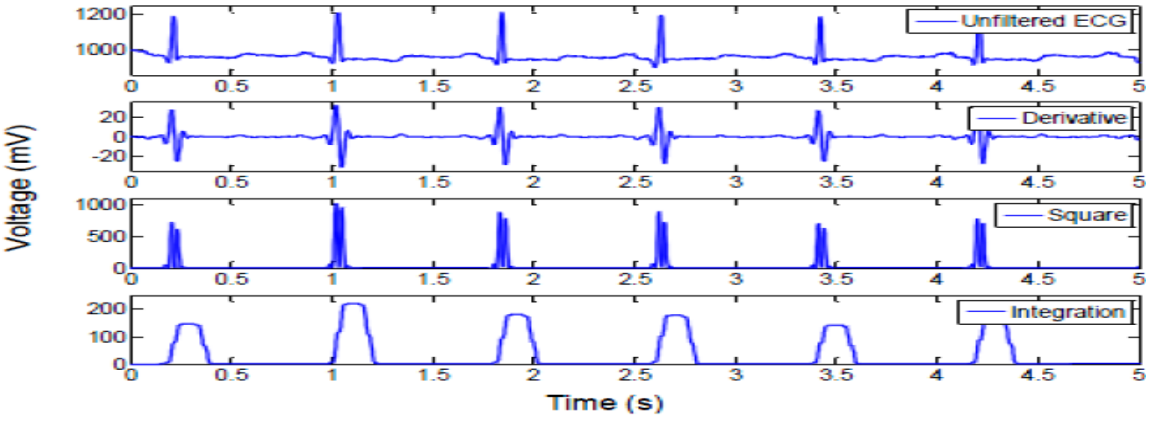

FIGURE 7: THE QRS ISOLATION PROCESS. TAKEN FROM [26]. USED WITH PERMISSION.

First, we differentiated the ECG waveform to increase the magnitude of the QRS sequence. Second, for eliminating negative portions of the waveform, and to further increase the magnitude of the differentiated QRS sequence, we squared the results of the previous step. Lastly, we integrated the signal to better detect the local maximum values of the QRS sequence. Moving-window integration with a window size of 150 milliseconds was used [41].

Once the QRS waveforms were isolated, we detected the peaks of the beats. Peak values were considered as the points at which the QRS segments changed slope. After peak detection, we specified the time between QRS segments which was equal to the time of the RR interval of each beat. After determining the RR intervals for each signal, we designed an algorithm to classify a heart rhythm into two major categories: normal sinus rhythm, or AF. Three statistical methods were used for detection of the irregularity

of the RR intervals, which defined heart rate variability (HRV): RMSSD, TPR and SE [25].

3.2.2 Root Mean Squares of Successive Differences

RMSSD is a parametric test and measures the variability within a data set. The mathematical definition of the RMSSD is the square root of the average of the squares of each of the differences between the RR intervals. Firstly, we divided each series of RR intervals into overlapping N beat segments. As RMSSD was affected by the distribution assumption, we removed the M largest and the M smallest RR intervals. Therefore, the $N - 2M$remaining RR intervals were evaluated as follows:

$$\text{RMSSD}=\sqrt{\frac{1}{N-2M-1}\sum_{1}^{N-2M-1}(a_{j+1}-a_j)^2} \qquad (2)$$

In this equation N is the number of RR intervals which determines our moving window, M is the number of outliers of largest and smallest RR intervals, and a_j is the j-th RR interval. We divided the RMSSD by the mean RR value for each segment to compensate for any changes in the heart rate over time and for premature ventricular contractions. In our algorithm, the beats classified as AF or N based on the term RMSSD / (mean RR); if the result was bigger than the threshold, the evaluated beat was annotated as AF.

We had three tuning parameters for RMSSD which need to be determined by our optimization algorithm. Table II shows the ranges which were considered for tuning parameters according to previous studies.

Moving Window (N)	[50 – 160]
Number of Outliers (M)	[0 – 20]
Threshold Value	(0,1)

TABLE II: TUNING PARAMETERS FOR RMSSD. THIS TABLE SHOWS THE PARAMETERS OF RMSSD AND THE ALLOWABLE RANGE OF EACH OF THEM. PARENTHESES "()" SHOW THAT THE PARAMETER IS A REAL NUMBER IN THE GIVEN RANGE. SQUARE BRACKETS "[]"SHOW THAT THE PARAMETER IS AN INTEGER IN THE GIVEN RANGE.

3.2.3 Turning Points Ratio

Turning Points Ratio (TPR) is a non-parametric statistical method which measures the randomness of RR intervals. As it is a nonparametric test, it is not affected by the distribution of the data set, unlike SE and RMSSD. The points which are either greater or less than both the following and previous points will be considered as turning points. TPR evaluates the number of turning points in the RR interval sequence relative to the maximum possible number of turning points. White noise is expected to have a turning point about every 1.5 data points. The expected number of turning points is $\frac{2l-4}{3}$ with a standard deviation of $\sqrt{\frac{16l-29}{90}}$ for a set of random data points of arbitrary length l [53].

In our algorithm, if the TPR of the selected sequence of RR intervals was greater or less than threshold values, the related beats would be considered as AF. Therefore, for the TPR, we had three parameters which needed to be tuned (Table III).

Moving Window (N)	[50 – 160]
Upper Threshold	(0.5,1)
Lower Threshold	(0,0.7)

TABLE III: TUNING PARAMETERS FOR TPR. THIS TABLE SHOWS THE TUNING PARAMETERS OF TPR AND THE SELECTED RANGE OF EACH OF THEM. PARENTHESES "()" SHOW THAT THE PARAMETER IS A REAL NUMBER IN THE GIVEN RANGE. SQUARE BRACKETS "[]"SHOW THAT THE PARAMETER IS AN INTEGER IN THE GIVEN RANGE.

3.2.4 Shannon Entropy

Another parametric statistical method which measures the uncertainty of a random variable is Shannon Entropy (SE). The complexity of a data set and the predictability of the following data points are related to SE. As SE is also a parametric method, like RMSSD, it is sensitive to outliers. Therefore, the M smallest and M largest RR intervals were determined to be outliers in our moving window of length N.

SE is 0 for a completely predictable constant single value; and its value for completely random data, like white noise, would be 1. As atrial fibrillation is associated with higher uncertainty, it would have a higher SE value than a normal sinus rhythm.

After removing outliers, the remaining data points in each N beat segment were used to construct a histogram with n equally spaced bins. Therefore, n was another parameter tuned by BBO. We need to use enough bins to provide sufficient resolution. As the number of bins approached infinity, the value of SE became zero. Finally, the number of RR intervals in each bin was counted.

The probability for each bin is defined as follows:

$$P(i) = \frac{N_i}{l - N_{outliers}} \tag{3}$$

N_i is the number of beats in that particular bin, l is the segment length, and $N_{outliers}$ is the number of outliers. Shannon Entropy is then calculated by equation (4):

$$SE = \sum_{i=1}^{n} P(i) \frac{\log(P(i))}{\log(\frac{1}{n})} \quad (4)$$

If the moving window had SE > threshold value the representative beat would be annotated as AF. Therefore, we had four tuning parameters for SE, as shown in Table IV.

Moving Window (l)	[50 – 160]
Number of Outliers (M)	[0 – 20]
Number of Bins (n)	[14 – 38]
Threshold value	(0,1)

TABLE IV: TUNING PARAMETERS FOR SE. THIS TABLE SHOWS THE TUNING PARAMETERS OF SE AND THE GIVEN RANGE OF EACH OF THEM. PARENTHESES "()" SHOW THAT THE PARAMETER IS A REAL NUMBER IN THE GIVEN RANGE. SQUARE BRACKETS "[]"SHOW THAT THE PARAMETER IS AN INTEGER IN THE GIVEN RANGE.

In the previous studies [23], [53], the optimum beat numbers of the moving window, the number of outliers, the lower thresholds, and the upper thresholds for the statistical techniques were evaluated. The ranges which we used in Table II, Table III, and Table IV are based on previous results, and are also based on the initial results of our program. If our program output the minimum or maximum value as the optimum parameter, we would expand the range of the tuning parameter in a second evaluation. This trend continued until no minimum or maximum number in the selected range was output as the best solution.

3.2.5 Training and Testing the Algorithm

We trained our algorithm with MIT-BIH AF databases and their annotated RR intervals to find the optimal values for the parameters of each statistical method. By using

BBO [42], we found out which tuning parameters and threshold values provided the best sensitivity, specificity, and finally the best accuracy for each of the patient data sets. The annotations of the MIT-BIH AF were used as the reference for tuning the parameters. Therefore, the cost function of our algorithm was defined by the beat to beat differences between the reference annotations and the annotations of our algorithm.

Then we divided the AF diagnosis of each beat into four categories: True Positive (both the algorithm and database annotated as AF), True Negative (both the algorithm and database annotated as normal), False Positive (those that the algorithm denoted as AF, but the database denoted as normal), and False Negative (those that the algorithm denoted as normal, but the database denoted as AF). After determining these values, the performance of our algorithm was calculated by measuring the sensitivity and the specificity. Sensitivity measures the ability of the algorithm to detect AF and specificity measures the ability of the algorithm to detect normal beats [25]. Lastly, the accuracy of the algorithm is defined as the product of sensitivity and specificity as follows.

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (5)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (6)$$

$$Accuracy = Sensitivity \times Specificity \quad (7)$$

In the training process, we were able to obtain an accuracy of more than 99% for both Root Mean Square of Successive Differences and Shannon Entropy. Accuracy was more than 98% for Turning Point Ratio. The highest average accuracy in the testing process of the algorithm was 75% achieved by using the trained parameters of the RMSSD method. Details will be discussed in Chapter 4.

3.3 Biogeography-Based Optimization

BBO is relatively new evolutionary algorithm and has shown good performance on unconstrained and constrained benchmark functions [58]-[61] and on real-world optimization problems such as sensor selection [42], economic load dispatch[62], robot controller tuning [63], satellite image classification [64], and power system optimization [65]. Differences between BBO and GAs were discussed in [54]. Markov model comparisons and benchmark simulation results were evaluated to show that the BBO is a competitive evolutionary algorithm (EA) [66]. It was also proven that BBO with mutation converges to the global optimum of any binary or discrete optimization problem [66].

Before talking about BBO, we will first provide a quick review of other EAs. Tabu search (TS) is an EA which was introduced in 1986 [68]. Tabu, or taboo, means forbidden or banned and refers to forbidden speech or items which can be based on religion, morality, or culture. As it is based on the natural world, it can be used to create an EA. The main idea of the TS is that if a certain region of a search space has already been visited during the search process, then it is forbidden (taboo) to be evaluated again [44]. The same idea could be applied to the search strategy. This means that if a certain strategy has already been used during the search process, that strategy should be disregarded from using it again.

The artificial fish swarm algorithm (AFSA) [69] is based on the swarming behavior of fish. Different behaviors of fish were evaluated to create an algorithm that can find the solution to an optimzation problem. For example, when the fish is alone or when the optimization process has stagnated (failure of the best individual in the

population to significantly improve in new generations), random behavior occurs [69]. Another example is the chasing behavior of fish. This happens when another fish, which is chased, is at the location of highest food concentration. Such behaviors in AFSA are nicely discussed in [44]. Overall, in AFSA, the fish changes its position only if the new position is better than the old one. This behavior is similar to particle swarm optimization (PSO).

In PSO, groups of individuals work together to improve both collective performance and individual performance on some task. Such behaviors can be seen not only among animals but also among humans. By improving our performance at some task, we adjust our approach based on some basic ideas, including inertia, influence of society, and influence of neighbors [44], [70].

Another EA which is based on the food forging behavior of animals is group search optimization (GSO).The algorithm is very similar to AFSA and bacterial forging optimization. However, GSO is based on the behavior of land-based animals [71]. Some animals try to find food by searching (producers), and some others (joiners) try to follow other animals and exploit their food-finding success. The last group of animals (rangers) randomly walks to search for resources. The migration in BBO (which will be discussed in this chapter) is conceptually similar to a combination of two ideas from the GA literature: global recombination and uniform crossover [54]. In global recombination, which originated with evolutionary strategies (ES), many parents can contribute features to a single offspring. “Global recombination strays from the biological foundation of GAs because individuals in nature cannot have more than two parents” [54].

In uniform crossover, each solution feature in an offspring is generated independently from every other solution feature. By combining global recombination and uniform crossover, global uniform recombination is obtained. By considering the entire population as potential contributors to the next generation, and also using fitness-based selection for each solution feature in each offspring, we conclude that the GA algorithm is very similar to BBO; in other words, BBO is a generalization of a specific type of GA [54].

In order to improve the AF detection results, we found out which of the three statistical methods had the most accuracy for evaluating the ECG signals, and improved our results via BBO [42], [43]. This is the first time that an evolutionary algorithm was used to optimize the parameters of statistical methods for atrial fibrillation diagnosis. BBO was selected in this research because it was previously demonstrated to be an effective evolutionary algorithm for many real world optimization problems, like hydraulic prosthetic knee control optimization [42].

BBO is based on the concept of biogeography and species migration between islands (which are also known as habitats). Habitats are classified based on their habitability; geographical areas well-suited for species have a high habitat suitability index (HSI) [42]. The factors that characterize a habitat's HSI are known as suitability index variables (SIVs). Rainfall, diversity of vegetation, diversity of topographic features, land area, and temperature are some of the features that impact HSI In our research, the SIVs were the parameters used to determine the threshold values of the three statistical methods and other parameters defined in previous sections; therefore, we had 10 parameters total (Table V). The HSI was the cost of the detection algorithm, which was the error between

the annotated AF values and the actual annotated values determined by the detection algorithm. Good performance of a candidate solution was characterized by a low cost [44].

Moving Window (# of RR interval segment) for TPR	[50 – 160]
Moving Window (# of RR interval segment) for RMSSD	[50 – 160]
Moving Window (# of RR interval segment) for SE	[50 – 160]
Upper Threshold Value for TPR	(0.5,1)
Lower Threshold Value for TPR	(0,0.7)
Threshold Value for SE	(0,1)
Threshold Value for RMSSD	(0,1)
# of Bins for SE	[14 – 38]
# of Outliers for SE	[0 – 20]
# of Outliers for RMSSD	[0 – 20]

TABLE V: ALL AF DIAGNOSIS PARAMETERS TUNED BY BBO. PARENTHESES "()" SHOW THAT THE PARAMETER IS A REAL NUMBER IN THE RANGE SHOWN IN PARENTHESES. SQUARE BRACKETS "[]"SHOW THAT THE PARAMETER IS AN INTEGER IN THE GIVEN RANGE.

Habitats with high HSI have high emigration rates, and low immigration rates. This indicates that those habitats are likely to share their SIVs with other habitats. "This is because these habitats have a diverse set of populations with constant breeding, which leaves little room for immigration, and a lot of room for emigration" [41]. The opposite is true for habitats with low HSI. As the suitability of a habitat is related to its diversity, the HSI of low HSI habitats may increase by the immigration of species [42], which is why high HSI habitats resist changes compared to their low HSI counterparts.

In Figure 8, the immigration (λ) and emigration rates (μ) of a single habitat are shown. S1 and S2 are two candidate solutions with different measures of fitness. S1, which has low fitness (high cost), will have a large number of immigrations, and a small number of emigrations. S2, which has high fitness (low cost), will have a small number of immigrations, and a large number of emigrations. That is, good candidate solutions resist receiving features from other candidate solutions and vice versa [41], [44].

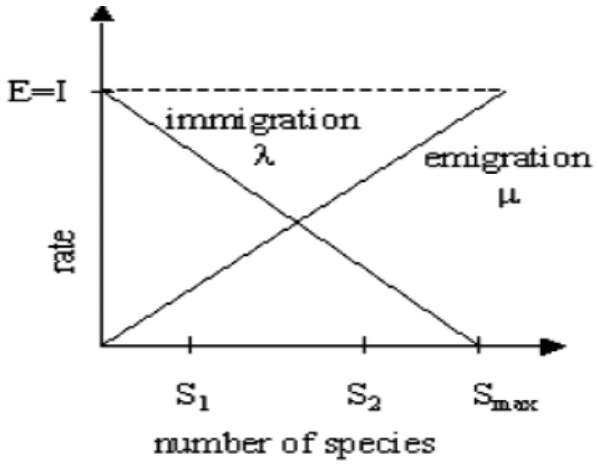

FIGURE 8: MIGRATION CURVES AND TWO CANDIDATE SOLUTIONS S1 AND S2, WHERE E AND I ARE THE MAXIMUM EMIGRATION AND IMMIGRATION RATES RESPECTIVELY. BASED ON [42]. COPYRIGHT © 2008, IEEE. USED WITH PERMISSION.

BBO also uses mutation and elitism to achieve optimal results for a given problem. In mutation, we replace each of the SIVs in the candidate solutions with a certain probability in each generation. If the SIV was selected to mutate, it is replaced randomly with another SIV selected from its given range. Mutation could lead to a better or worse new candidate solution, but in BBO, only the best solutions have a good chance to survive. Mutation was applied to each SIV after each cycle of migration.

One generation of BBO is completed when all the candidate solutions complete their cycles of migration and mutation. After completing a generation, features of the best

candidate solutions have been shared with other candidate solutions, have mutated, and most probably have resulted in better solutions.

Finally, elitism occurs when the best candidate solutions from the previous generation are added to the population. By using elitism, BBO guarantees that the best individuals never get worse from one generation to the next. The BBO algorithm is explained in detail as follows (although, for simplicity of notation, elitism is not included in the following description).

For each candidate solution $y_k, k \in \{1, \dots, N\}$, define emigration probability $\mu_{k\propto}$ fitness of $y_k, \mu_k \in [0,1]$
For each candidate solution μ_k define immigration probability $\lambda_k = 1 - \mu_k$
$z \longleftarrow y$
For each candidate solution z_k
    For each feature s
        Use λ_k to probabilistically decide whether to immigrate to z_k
        If immigrating then
            Use $\{\mu_k\}$ to probabilistically select the parent solution y_j
            $z_k(s) \longleftarrow y_j(s)$
        End if
    Next solution feature
    Probabilistically mutate z_k
Next candidate solution
$y \longleftarrow z$

FIGURE 9: A DESCRIPTION OF ONE GENERATION OF BBO. N IS THE NUMBER OF CANDIDATE SOLUTIONS, AND Z IS A TEMPORARY SET OF SOLUTIONS SO THAT NO SOLUTIONS ARE REPLACED IN A GIVEN GENERATION UNTIL AFTER THE COMPLETION OF THE MIGRATION AND MUTATION PROCESS. BASED ON [54].

The best BBO parameters for optimizing the tuning parameters of the AF detection methods are shown in Table VI.

Mutation Rate	0.1
Keep Rate	0.2
Population Size (Number of Candidate Solutions)	50
Number of Generations	100

TABLE VI: PARAMETER VALUES USED IN BBO.

Number of generations determines the number of repetitions of the main loop of the BBO algorithm. This number should be chosen based on the optimal output of the cost function. We chose 100 because increasing the number did not have any impact on the final optimum cost function. In other words, based on our experiments, after 100 generations we did not have any improvements of the cost function.

For population size (or number of habitats) we chose 50. By increasing the population size, we would have more candidate solutions to evaluate, resulting in more optimal solutions; however, more time would be required to process the solutions. Keep Rate determines the portion of the new population which was chosen from the best results of the old population. We kept 20% of the old population in each generation. As we have 50 individuals in the population, the number of kept solutions would be 10, and therefore 40 candidate solutions were chosen from the new population. This parameter defines the elitism option. Finally, Mutation Rate is the probability of mutating the candidate solutions. In our algorithm, the mutation rate is 10%.

These values were achieved by trials considering the maximum accuracy of the final results and the time required to run the program. Before choosing these parameters, the best results were achieved by 60 generations, a population size of 30, 5% keep rate, and 2% mutation rate. By increasing the number of generations, population size, keep

rate, and mutation rate, we were able to be more certain about the maximum accuracy achieved by the program.

CHAPTER IV

RESULTS

We used the RR intervals of 25 patients diagnosed with atrial fibrillation. These data can be found in the MIT-BIH AF. Based on the annotations which were available for each database, we defined a vector for each database with the same length as the number of RR intervals and annotated each RR interval with 1 or 0, where 1 indicates that the RR interval was diagnosed as AF, and 0 corresponds to normal. We also generated three vectors which were the results of the evaluation of RR interval variability determined by root mean squares of successive differences, Shannon entropy, and turning points ratio. In these three vectors 1 represents AF and 0 shows normal RR intervals.

Therefore, four vectors with annotations of 0 or 1 for each heart beat in each database were defined based on the RR intervals, including the one vector defined on the basis of the annotations in the MIT-BIH AF database, and three vectors based on the RR interval variability evaluation of the three statistical methods. The beat to beat differences between the MIT-BIH AF annotations, and the statistical method annotations, defined the

cost functions for each AF detection method. These cost functions were used by biogeography-based optimization (BBO) to optimize the AF detection algorithm tuning parameters. We defined the specificity, sensitivity, and accuracy of each detection method. Based on the vectors defined above, each beat was categorized into one of four groups.

If the beat was correctly flagged as AF, then it was considered a true positive (TP). If the best was correctly flagged as normal, then it was considered a true negative. If the beat was incorrectly flagged as normal, then it was considered a false negative (FN). Finally, if the beat was incorrectly flagged as AF, then it was considered a false positive (FP). The performance of each AF detection algorithm was calculated by calculating the sensitivity (Equation 5) and the specificity (Equation 6). Sensitivity measures the ability of the algorithm to detect AF, and the specificity measures the ability of the algorithm to detect normal beats [25]. The accuracy of the algorithm is the ultimate measure of performance and is defined as the product of sensitivity and specificity (Equation 7). The cost function of the BBO is defined based on accuracy and is used to optimize the tuning parameters of the statistical methods:

$$Cost\ function = 1 - accuracy \tag{8}$$

Each generation, BBO tries to reduce the cost function, or maximize the accuracy. We had 10 tuning parameters (Table V) for the statistical methods which are tuned by using the BBO. Figures 10 and 11 show how BBO optimized the detection accuracy by tuning the parameters of the RMSSD as the statistical AF detection method. RMSSD showed the highest average accuracy (more than 99%) for records 00735, 04746, 08215, and 08455. Record 04746 was selected for Figures 10 and 11 to show how BBO finds the

minimum cost in each generation and finally solves for tuning parameters that give the highest accuracy.

Initial Generation Cost= 0.0111396937358171 n_beats= 111 M_outliers= 11 Threshold= 0.106779255208922

Generation 1 Cost= 0.0108763130167041 N_beats= 111 M_outliers= 11 Threshold= 0.105402126527964

Generation 2 Cost= 0.0108763130167041 N_beats= 111 M_outliers= 11 Threshold= 0.105402126527964

Generation 3 Cost= 0.0103622011237688 N_beats= 125 M_outliers= 11 Threshold= 0.10297194658917

Generation 4 Cost= 0.0100726734382413 N_beats= 121 M_outliers= 11 Threshold= 0.0969434562795183

Generation 5 Cost= 0.0100083339525685 N_beats= 125 M_outliers= 11 Threshold= 0.100028091834807

Generation 6 Cost= 0.0100083339525685 N_beats= 125 M_outliers= 11 Threshold= 0.100028091834807

Generation 7 Cost= 0.0099855765841464 N_beats= 125 M_outliers= 11 Threshold= 0.0969434562795183

Generation 8 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 9 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 10 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 11 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 12 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 13 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

Generation 14 Cost= 0.0098096261534445 N_beats= 123 M_outliers= 10 Threshold= 0.100028091834807

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Generation 98 Cost= 0.00972262456629724 N_beats= 123 M_outliers= 11 Threshold= 0.0931333345727444

Generation 99 Cost= 0.00972262456629724 N_beats= 123 M_outliers= 11 Threshold= 0.0931333345727444

Generation 100 Cost= 0.00972262456629724 N_beats= 123 M_outliers= 11 Threshold= 0.0931333345727444

Accuracy = 1− Cost= 0.990277375433703

FIGURE 10: OPTIMIZING RMSSD PARAMETERS BY USING BBO. COST HERE DEFINED AS 1-ACCURACY; N_BEATS IS OUR MOVING WINDOW FOR SELECTING RR INTERVALS IN RMSSD ALGORITHM; M_OUTLIERS IS NUMBER OF MINIMUMS AND MAXIMUMS WHICH ARE DISREGARDED FROM THE MOVING WINDOW; AND FINALLY THRESHOLD IS THE THRESHOLD VALUE FOR RMSSD.

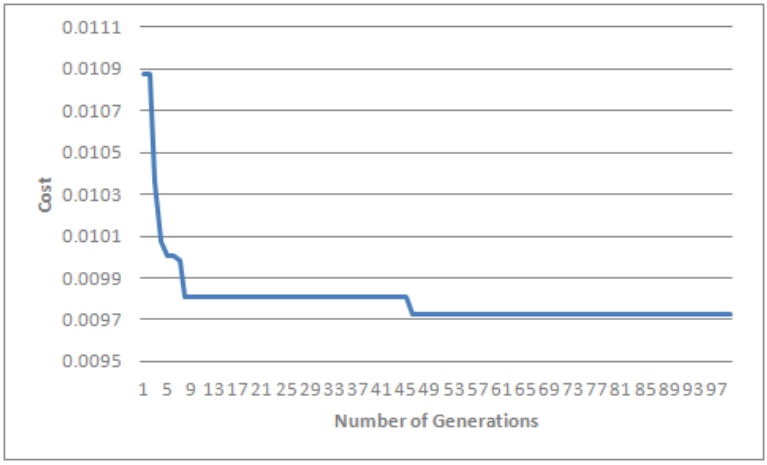

FIGURE 11: COST VS. 100 GENERATIONS FOR RMSSD BY USING BBO.

As can be seen in Figures 10 and 11, in each generation, BBO kept the best solution from one generation to the next. Each generation (100 in our algorithm), the cost of each individual (50 in our algorithm) was calculated and then sorted from minimum to maximum, and the best one was preserved for the next generation. Sometimes the best solution appeared in an early generation (in this case, in generation 47) and remained the best in the following generations. This was because we selected an acceptable population size for our algorithm. In fact, there was a trade-off between the size of the population and the generation limit. For example, if we selected a smaller population, the best solution might appear in later generations. But if the population size was too small, the best solution might never appear in the population. Therefore, by choosing an acceptable population size and generation limit, we made sure that BBO performed as well as possible.

The data presented in Figures 12 and 13 show the capability of BBO in tuning the parameters of the SE. As can be seen, the best cost was found after the 12th generation. These figures show that by optimizing the SE parameters, the statistical method is able to

detect AF with an accuracy of 99%. Records 08215 and 08455 in the training databases showed the best performance in terms of accuracy. Record 08215 was selected for the following figures to show the capability of BBO to tune the parameters of SE for the highest accuracy.

Initial Generation Cost= 0.009296279239 $N_$beats= 66 $M_$outliers= 13 Threshold= 0.7611819099451 $n_$bins= 32

Generation 1 Cost= 0.009296279239553 $N_$beats= 66 $M_$outliers= 13 Threshold= 0.7611819099451 $n_$bins= 32

Generation 2 Cost= 0.009296279239553 $N_$beats= 66 $M_$outliers= 13 Threshold= 0.7611819099451 $n_$bins= 32

Generation 3 Cost= 0.008500282147575 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7615733097779 $n_$bins= 32

Generation 4 Cost= 0.008500282147575 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7615733097779 $n_$bins= 32

Generation 5 Cost= 0.008500282147575 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7615733097779 $n_$bins= 32

Generation 6 Cost= 0.008463476889218 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7615733097779 $n_$bins= 34

Generation 7 Cost= 0.008366047732972 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7632903469860 $n_$bins= 34

Generation 8 Cost= 0.008366047732972 $N_$beats= 70 $M_$outliers= 13 Threshold= 0.7632903469860 $n_$bins= 34

Generation 9 Cost= 0.007720494717098 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 34

Generation 10 Cost= 0.00772049471709 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 34

Generation 11 Cost= 0.00772049471709 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 34

Generation 12 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 33

Generation 13 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 33

Generation 14 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.7632903469860 $n_$bins= 33

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Generation 98 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.763290346986 $n_$bins= 33

Generation 99 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.763290346986 $n_$bins= 33

Generation 100 Cost= 0.00756292275816 $N_$beats= 66 $M_$outliers= 11 Threshold= 0.763290346986 $n_$bins= 33

Accuracy = 1− Cost= 0.992437077241838

FIGURE 12: OPTIMIZING SE PARAMETERS BY USING BBO. COST HERE DEFINED AS 1-ACCURACY; N_BEATS IS OUR MOVING WINDOW FOR SELECTING RR INTERVALS IN SH ALGORITHM; M_OUTLIERS IS THE NUMBER OF MINIMUMS AND MAXIMUMS WHICH ARE DISREGARDED FROM THE MOVING WINDOW; THRESHOLD IS THE THRESHOLD VALUE FOR SE; AND FINALLY N_BINS IS THE NUMBER OF THE SELECTED BINS.

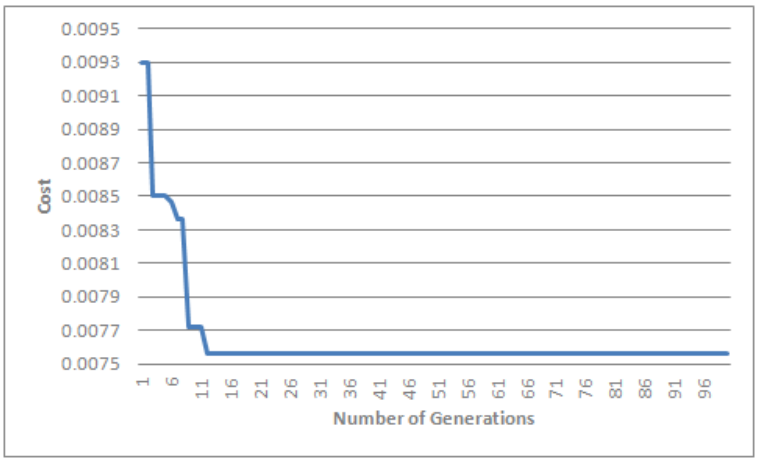

FIGURE 13: COST VS. 100 GENERATIONS FOR SE BY USING BBO.

Figures 14 and 15 show 98% accuracy for the ability of TPR to detect AF. Record 08215 showed the highest accuracy in detecting AF by the use of TPR method. This record was chosen in Figures 14 and 15 to show the ability of BBO to tune the parameters of TPR.

Initial Generation Cost= 0.020944013083 N_beats= 137 Threshold1= 0.53423807776 Threshold2= 0.85609632414

Generation 0 Cost= 0.020944013083 N_beats= 137 Threshold1= 0.53423807776 Threshold2= 0.85609632414

Generation 1 Cost= 0.020590635379 N_beats= 117 Threshold1= 0.50369140280 Threshold2= 0.91304857007

Generation 2 Cost= 0.019919421985 N_beats= 119 Threshold1= 0.51314058269 Threshold2= 0.88774937461

Generation 3 Cost= 0.019919421985 N_beats= 119 Threshold1= 0.51314058269 Threshold2= 0.88774937461

Generation 4 Cost= 0.019784626784 N_beats= 117 Threshold1= 0.51509741036 Threshold2= 0.85668510978

Generation 5 Cost= 0.018899323076 N_beats= 113 Threshold1= 0.51305878700 Threshold2= 0.89631980066

Generation 6 Cost= 0.018899323076 N_beats= 113 Threshold1= 0.51305878700 Threshold2= 0.89631980066

Generation 7 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 8 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 9 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 10 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 11 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 12 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 13 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 14 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

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Generation 47 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 48 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Generation 49 Cost= 0.018389371021 N_beats= 110 Threshold1= 0.51305878700 Threshold2= 0.88774937461

Accuracy= 1− Cost= 0.98161062897846

FIGURE 14: OPTIMIZING TPR PARAMETERS BY USING BBO. COST HERE DEFINED AS 1-ACCURACY; N_BEATS IS OUR MOVING WINDOW FOR SELECTING RR INTERVALS IN TPR ALGORITHM; THRESHOLD1 IS THE LOWER THRESHOLD VALUE FOR TPR; AND THRESHOLD2 IS THE UPPER THRESHOLD VALUE FOR TPR.

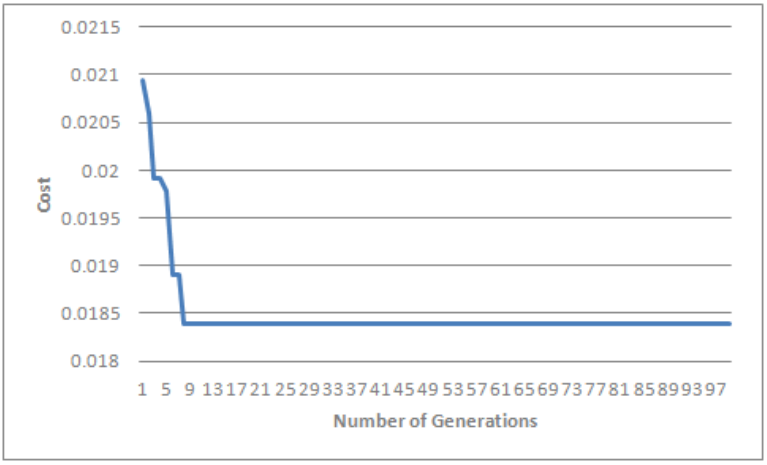

FIGURE 15: COST VS. 100 GENERATIONS FOR TPR BY USING BBO.

Figures 10–15 show the training of the statistical methods. These figures show the databases with the highest accuracy in the training process. For RMSSD, for example, we can see the increase in the accuracy from around 98% in generation 1 to more than 99% in the last generation. The same trend of increasing the accuracy by 1% is shown for TPR and SE. However, this does not mean that these databases give the best test results. This will be discussed more later.

The next three tables show the training sensitivity, specificity, and accuracy of the statistical methods applied to the MIT-BIH AF databases. RMSSD showed its capability to detect AF by achieving the accuracy of 99% for some of the databases (Table VII). This fact is apparent in the databases with high accuracy which is the result of the AF detection with high specificity and high sensitivity. Such a trend is also obvious in the accuracy results achieved by SE (Table VIII) and TPR (Table IX).

Database	Sensitivity	Specificity	Accuracy
00735	1	0.99	0.99
03665	0.93	0.80	0.75
04015	1	0.91	0.91
04043	0.95	0.76	0.71
04048	0.97	0.96	0.93
04126	0.95	0.93	0.89
04746	1	0.99	0.99
04908	0.96	0.92	0.88
04936	0.86	0.88	0.76
05091	0.92	0.92	0.84
05121	0.97	0.88	0.86
05261	0.86	0.79	0.67
06426	0.89	0.47	0.42
06453	0.88	0.94	0.83
06995	0.93	0.91	0.85
07162	1	0	0
07859	0.87	1	0.87
07879	1	0.89	0.89
07910	0.99	0.98	0.97
08215	1	0.99	0.99
08219	0.90	0.74	0.67
08378	0.99	0.97	0.96
08405	1	0.97	0.97
08434	0.99	0.93	0.92
08455	1	0.99	0.99

TABLE VII: TRAINING ACCURACY OF RMSSD FOR DETECTING AF. THIS TABLE SHOWS THE SENSITIVITY, SPECIFICITY, AND ACCURACY OF RMSSD FOR EACH MIT-BIH AF DATABASE. BBO WAS USED FOR TUNING THE RMSSD PARAMETERS.

Database	Sensitivity	Specificity	Accuracy
00735	0.83	0.82	0.68
03665	0.99	0.95	0.94
04015	0.98	0.92	0.90
04043	0.91	0.88	0.81
04048	0.80	0.94	0.75
04126	0.88	0.86	0.76
04746	0.93	0.91	0.84
04908	0.97	0.98	0.95
04936	0.83	0.85	0.71
05091	0.67	0.87	0.58
05121	0.95	0.86	0.82
05261	0.71	0.97	0.69
06426	0.79	0.74	0.59
06453	0.91	0.95	0.87
06995	0.92	0.88	0.81
07162	0.98	1	0.98
07859	0.95	1	0.95
07879	0.98	0.96	0.95
07910	0.98	0.99	0.97
08215	1	0.99	0.99
08219	0.91	0.93	0.85
08378	0.96	0.93	0.90
08405	0.99	0.99	0.98
08434	0.97	0.94	0.91
08455	0.99	1	0.99

TABLE VIII: TRAINING ACCURACY OF SE FOR DETECTING AF. THIS TABLE SHOWS THE SENSITIVITY, SPECIFICITY, AND ACCURACY OF SE FOR EACH MIT-BIH AF DATABASE. BBO WAS USED FOR TUNING THE SE PARAMETERS.

Database	Sensitivity	Specificity	Accuracy
00735	0.84	0.92	0.77
03665	0.86	0.68	0.59
04015	0.95	0.77	0.73
04043	0.77	0.79	0.62
04048	0.83	0.83	0.69
04126	0.85	0.70	0.60
04746	0.92	0.82	0.76
04908	0.92	0.97	0.90
04936	0.72	0.82	0.59
05091	0.84	0.76	0.64
05121	0.96	0.86	0.82
05261	0.79	0.77	0.60
06426	0.62	0.62	0.38
06453	0.81	0.87	0.70
06995	0.81	0.74	0.60
07162	0.72	1	0.72
07859	0.68	1	0.68
07879	0.96	0.86	0.83
07910	0.67	0.65	0.44
08215	1	0.98	0.98
08219	0.87	0.67	0.58
08378	0.96	0.97	0.93
08405	0.98	0.85	0.83
08434	0.85	0.61	0.51
08455	0.98	0.98	0.96

TABLE IX: TRAINING ACCURACY OF TPR FOR DETECTING AF. THIS TABLE SHOWS THE SENSITIVITY, SPECIFICITY, AND ACCURACY OF TPR FOR EACH MIT-BIH AF DATABASE. BBO WAS USED FOR TUNING THE TPR PARAMETERS.

After training the parameters of the statistical methods by BBO on 25 MIT-BIH AF databases (Tables VII, VIII and IX), we tested the results of each statistical method on the remaining 24 databases of the MIT-BIH AF together to see which statistical method has the best accuracy. We had 25 databases, and for each of them we obtained 3 sets of tuned variables, one each for RMSSD, SE, and TPR, resulting in 75 sets of optimized parameters. Then, we tested each optimized AF detection algorithm on all of the databases to find the average accuracy. The results are presented in Table X.

Database Used for Tuning Parameters	Average Accuracy			
	RMSSD	SE	TPR	Best Method
00735	0.66	0.63	0.53	RMSSD
03665	0.47	0.67	0.46	SE
04015	0.64	0.64	0.50	SE and RMSSD
04043	0.56	0.54	0.50	RMSSD
04048	0.59	0.69	0.46	SE
04126	0.64	0.68	0.54	SE
04746	0.68	0.67	0.50	RMSSD
04908	0.70	0.60	0.48	RMSSD
04936	0.68	0.71	0.48	SE
05091	0.58	0.62	0.43	SE
05121	0.70	0.68	0.52	RMSSD
05261	0.66	0.68	0.51	SE
06426	0.41	0.55	0.40	SE
06453	0.63	0.62	0.52	RMSSD
06995	0.65	0.69	0.54	SE
07162	0.66	0.65	0.48	RMSSD
07859	0.70	0.65	0.47	RMSSD
07879	0.73	0.65	0.48	RMSSD
07910	0.75	0.68	0.42	RMSSD
08215	0.73	0.67	0.48	RMSSD
08219	0.70	0.65	0.47	RMSSD
08378	0.71	0.66	0.47	RMSSD
08405	0.73	0.66	0.51	RMSSD
08434	0.74	0.68	0.50	RMSSD
08455	0.71	0.65	0.51	RMSSD

TABLE X: TEST RESULTS OF THE TUNED AF DETECTION ALGORITHMS ON ALL 25 DATABASES. THE HIGHLIGHTED CELLS IN EACH COLUMN SHOW WHICH DATABASE PROVIDED THE BEST TRAINING DATA FOR EACH AF DETECTION ALGORITHM.

Table X shows that the SE and RMSSD achieved the best accuracy among the three statistical methods. The highest average accuracy was 75% which was the result of detecting AF by using RMSSD. Although TPR performed worse than SE and RMSSD, using all three statistical methods may result in better AF diagnosis, as will be discussed in the next chapter. The tuning parameters achieved by BBO for the best average test accuracies of the statistical methods can be found in Table XI.

Best RMSSD Parameters		
Number of Selected Beats = 80	Number of Outliers= 15	RMSSD Threshold= 0.058
Best SE Parameters		
Number of Selected Beats = 61	Number of Outliers= 19	Number of Selected Bins= 34	SE Threshold = 0.644
Best TPR Parameters		
Number of Selected Beats = 158	Lower Threshold = 0.572	Upper Threshold = 0.829

TABLE XI: TUNING PARAMETERS ACHIEVED BY BBO FOR THE HIGHEST AVERAGE TEST ACCURACY OF THE STATISTICAL METHODS.

The accuracy values measured by our algorithm for the MIT-BIH AF databases are shown in Table X. Previous studies [23], [25], [35], [53] showed that the best value for the moving window length was 128; in our algorithm, the best moving window length was 80 for RMSSD, 61 for SE, and 158 for TPR. Previous studies showed that the best number of outliers was 16; in our algorithm, the best value for the number of outliers was 15 for RMSSD, and 19 for SE. Previous studies showed that the best values for the thresholds were 0.1 for RMSSD, 0.7 for SE, and 0.54 and 0.77 for TPR (lower and upper thresholds); in our algorithm, the best values for the thresholds were 0.058 for RMSSD, 0.64 for SE, and 0.57 and 0.83 for TPR.

When we user previously published values for AF detection algorithm tuning parameters, we obtain average detection accuracies of 71% for RMSSD, 51% for TPR, and 21% for SE. Therefore, by using BBO , we enhance the average accuracy of RMSSD by almost 4%, TPR by 3%, and SE by 50%. Table XI shows the values found by

BBO for AF detection with higher accuracy (compared to previous studies) by using statistical techniques.

CHAPTER V

CONCLUSION AND FUTURE WORK

Our results showed the capability of three statistical methods, including root mean squares of successive differences (RMSSD), Shannon entropy (SE), and turning points ratio (TPR), to detect atrial fibrillation from a given electrocardiogram. These statistical methods are based on the fact that in AF, RR intervals are irregular without any specific trend and behave like random numbers as shown in previous studies [23], [45]. We were able to obtain an AF detection training accuracy of 99% with RMSSD and SE. TPR also showed the capability of detecting AF with a training accuracy of 98%.

The key role of biogeography-based optimization as an evolutionary algorithm for tuning the parameters of the statistical methods should be taken into account. In order to show the reliability of our diagnosis algorithm, we trained and tested our algorithm on the MIT-BIH atrial fibrillation databases. We could achieve average test accuracy of 75% for RMSSD, 71% for SE, and 54% for TPR.

Such a diagnosis method may help physicians quickly detect AF during its early stages, before the patients' condition deteriorates and results in a higher risk of stroke and heart attack. Given the fact that the algorithms in this paper are capable of detecting AF in its initial stages, it could reduce the required money and time for detecting and treating AF.

As mentioned before, a new study showed the feasibility of detecting AF using an iPhone 4S [25]. The same method of diagnosis (AF detection based on the irregularity of RR intervals by using the statistical methods) was evaluated for detecting AF from a given ECG. By better improving the iPhone detection results, as we did in our research, such an application could be reliably used by patients. Therefore, smartphones using this application in the near future could help individuals discover if they have paroxysmal or persistent AF. This could even be in the case for those who may not show any symptom of the disease. Consequently, it might prevent more dangerous situations, like permanent AF.

Another important point that should be considered is that we used the three statistical methods separately for detecting AF in the given databases. The combination of the statistical methods to detect AF may be another way to detect AF with more accuracy. In our algorithm, RMSSD and SE showed a better ability to detect AF compared to TPR. But, we should assess whether this trend can be generalized for evaluating the irregularities of RR intervals with the combination of all the statistical methods or not. For this, we can tune the parameters to annotate a beat with AF if all the statistical methods annotate the beat as AF (RMSSD and SE and TPR), otherwise it

would be annotated as N. In addition, we can calculate the results with the term *"or"* instead of "and " to see the final accuracy.

Another option is to consider the combination of all three statistical methods by defining weighting parameters. In this way, we can define three weighting variables, and then we can tune the weighting variables to find the optimum values. The AF detection would then be given as follows:

$$Cost\ Function = \alpha \times RMSSD + \beta \times SE + \gamma \times TPR - MRF\ ,$$
$$\alpha, \beta, \gamma\ \epsilon [0,1] \tag{9}$$
$$\alpha + \beta + \gamma = 1$$

In Equation 9, RMSSD, SE, and TPR are outputs of the three AF detection algorithms. MRF is the same matrix which was annotated by 0 or 1 based on the annotation databases available for MIT-BIH AF databases. It was used as the main reference of beat to beat annotation of RR intervals. α, β, and γ are tuning parameters; in other words, they would determine how much contribution each method makes to the AF detection output.

Another way of evaluating the results of our algorithm is to consider the threshold values of the previous studies as they are very close to our final results; and then only tune the moving window (N), number of outliers(M), and number of the bins (n).

We can also extend this research to other evolutionary algorithms, including particle swarm optimization (PSO), differential evolution (DE), ant colony (ACO), genetic algorithm (GA), etc., to compare the results with the current work and find the best evolutionary algorithm for this application.

As mentioned, there is a work discussed the detection of atrial fibrillation from pulsatile signals in the human fingertip by using smart phone cameras. Previous studies also have discriminated between atrial fibrillation and other rhythms by considering the distribution of RR intervals, successive RR differences, or ratios of successive RR intervals [17], [51]. By using our research results to eliminate the shortcomings of these recent studies in order to increase their reliability and accuracy, it may be possible to develop an application for smartphones to detect not only atrial fibrillation, also other common heart arrhythmias.

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APPENDIX

APPENDIX A

MIT-BIH AF databases annotate each RR interval with 0 or 1 based on heart rate variability, and such annotations are very similar to the annotations for AF (atrial fibrillation) and N (normal). However, we found that lots of RR intervals were missing in the databases, and this can have a large impact on the results of AFdetection. We developed an algorithm to repair this shortcoming. In the databases, RR intervals were annotated with 0 or 1. Based on the value of the RR intervals, if there is heart rate variability (HRV), the RR interval was annotated with 1; otherwise it was annotated with 0. But as mentioned before, lots of RR intervals were missing in the databases, and therefore portions of the databases with missing RR intervals could impact the accuracy of the detection algorithm. We compared the databases that were annotated based on HRV, with the databases of RR intervals, and found where the RR intervals were missing. After fixing this problem, we took the newly added RR intervals, which were missing in the databases annotated with 0 or 1, and annotated them with 2. As a result, we created 25 matrices (one for each database), each of which had each record annotated with 0 or 1 or 2 (Table XII).

RR interval	HRV
0.496	1
0.932	0
0.928	0
0.930	0
0.896	1
0.944	0
0.952	0
0.940	0
2.862	0

XIIA

RR interval	HRV
0.496	1
0.932	0
0.928	0
0.930	0
0.896	1
0.944	0
0.952	0
0.940	0
0.944	2
0.944	2
0.974	2

XIIB

TABLE XII: RR INTERVALS ANNOTATED BY 0 OR 1 BASED ON HRV. THE LAST RR INTERVAL WITH THE VALUE OF 2.862 (SEC) IN TABLE A IS THE SUM OF THREE LOST RR INTERVALS SHOWN IN TABLE B

Another problem was that we did not know exactly how to replace 2s in the new databases; that is why we decided to detect AF based on the databases annotated by the diagnosis of AF, and not the heart rate variability.