



AUTOMATIC DETECTION OF ATRIAL FIBRILLATION BASED ON RR INTERVAL

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Keywords

*Atrial fibrillation,
Discrete wavelet transform,
Support vector machine,
Normal sinus rhythm,
RR interval.*

Abstract

Heart diseases are rapidly increasing worldwide and in our country. This increase causes difficulties in the diagnosis processes of heart diseases. Considering these problems, the studies of engineering applications related to medical science give effective results in terms of solutions. By means of engineering devices and algorithms, positive contributions are made to medical applications. These contributions assist physicians especially in the diagnosis stages and speed up these processes. In this study, a new algorithm is developed so that Atrial Fibrillation (AF), which is the most common type of arrhythmia encountered, can be automatically detected at a high success rate. Electrocardiogram (ECG) data used in this study were obtained from physiobank ATM database. 31 samples of Atrial Fibrillation Rhythm (AFR) and 31 samples of Normal Sinus Rhythm (NSR) were obtained from this database. RR Interval (RRI) sequences being 12 hours long are used in the study. The change of the RRI sequences is an important parameter for AF. The RRI sequences are re-sampled using signal pre-processing techniques. The Discrete Wavelet Transform (DWT) was then applied to the resampled signals. In this way, feature extraction process is performed and the wavelet energies of these signals are visually examined with boxplot. The wavelet energies of the RRI sequences are classified by the Support Vector Machine (SVM). Finally, AFR and NSR are successfully separated as 99.60% achievement.

ATRİYAL FİBRİLASYONUN RR ARALIĞI İLE OTOMATİK TESPİTİ

Anahtar Kelimeler

*Atriyal fibrilasyon,
Ayrık dalgacık dönüşümü,
Destek vektör makinası,
Normal sinüs ritim,
RR aralığı.*

Öz

Kalp hastalıkları dünya genelinde ve ülkemizde hızlı bir biçimde artmaktadır. Bu artış kalp hastalıklarının tanı süreçlerinde zorlukların oluşmasına neden olmaktadır. Bu sorunlar düşünüldüğünde mühendislik uygulamalarının tıp bilimi ile ilgili olan çalışmaları çözümler açısından etkili sonuçlar vermektedir. Mühendislik sayesinde geliştirilen cihazlar ve algoritmalar sayesinde tıp uygulamalarına olumlu katkılar sağlanmaktadır. Bu uygulamalar özellikle hekimlere tanı aşamalarında yardımcı olmakta ve bu süreçleri hızlandırmaktadır. Bu çalışmada en sık rastlanan aritmi çeşidi olarak karşımıza çıkan Atriyal Fibrilasyon'un (AF) otomatik olarak tespitinin yüksek başarı oranında yapılması tasarlanmıştır. Bu çalışmada kullanılan Elektrokardiyogram (EKG) verileri, Phsiyobank ATM veritabanından elde edilmiştir. Bu veritabanından 31 adet Atriyal Fibrilasyon Ritmi (AFR) ve 31 adet Normal Sinüs Ritmi (NSR) olan sinyaller alınmıştır. Bu sinyaller 12'şer saatlik uzunlukta olup çalışmada RR Aralıkları dizileri kullanılmıştır. RRA dizilerinin değişimi AF için önemli bir parametre olarak karşımıza çıkmaktadır. Sinyal işleme teknikleri ile RR Aralıkları zaman ekseninde yeniden örneklenmiştir. Ardından yeniden örneklenmiş sinyallere Ayrık Dalgacık Dönüşümü (ADD) uygulanmıştır. Bu sayede özellik çıkarımı işlemi yapılmış ve bu sinyallerin dalgacık enerjileri boxplot ile görsel olarak incelenmiştir. RRA dizilerinin dalgacık enerjileri Destek Vektör Makinası (DVM) ile sınıflandırma işlemine tabi tutulmuş ve %99,60 oranında başarıyla AFR ve NSR birbirinden ayrılmıştır.

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1. Introduction

Heart-borne diseases are important factors that cause situations like death, paralysis, etc. According to the World Health Organization (WHO), 15 million individuals are affected annually by heart disease. (Sejr et al. 2017). This situation makes the diagnosis and treatment stages of heart-related diseases important. Therefore, the engineering studies realized in medical sector affect significantly the development of the stages of diagnosis and treatment. The heart acts as a pump and produces electrical signals. By means of these signals, the various diagnostic procedures can be proposed for cardiological diseases. These signals recorded from ECG, Holter ECG, Patient Monitor etc. are made into interpretable expressions. These expressions obtained by means of the designed algorithms facilitate to the physicians for diagnostic steps. In the study, an algorithm is designed to detect automatically the AF. The overview of the study is shown in Figure 1. In the study, at first, the database obtained from PhysioBank is re-arranged for only AF and NSR comparison. This database contains RRI sequences being defined time variabilities between consecutive QRS complexes in ECG signals. During the preprocessing stage, these signals are interpolated and resampled. Afterward, by use of the DWT method, the discriminative features of these signals are determined and are applied to SVM. As a conclusion, the classification method is tested and validated. The detection of AF in the early stages is so significant in terms of minimizing the effects on the individual. (Güzeler, 2017).

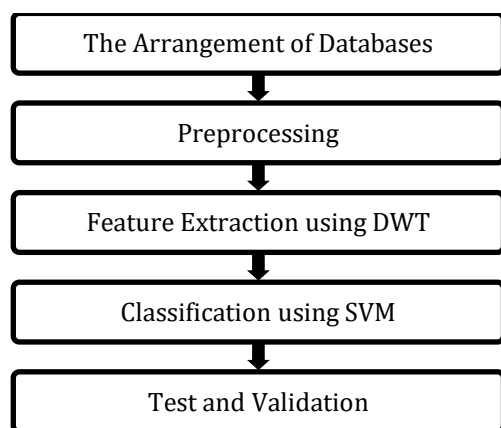


Figure 1. Process Steps of the Work

In this context, an original software is designed for the

classification of AFR and NSR in the study. This software is aimed at achieving higher accuracy levels of accuracy compared to software designed in other studies in the literature.

2. Scientific Literature Scanning

A lot of studies have been available with different techniques for the automatic detection of AF in literature. E. Ros et al. (2004) studied the paroxysmal type of AF. They have used the P wave and RRI parts of the signals as parameters and applied them into the classification algorithm. They achieved a classification success rate of 68% to 80%. K. Jiang et al. (2012) found AF automatically through the Holter ECG recordings in their study. They captured P and R waves and performed the feature extraction process for the classification algorithm. As a result, they obtained a sensitivity value of 96.3%. C. Gumbner et al. (2012) explained that AF primarily causes ischemic insult in their studies. They stated that AF can be noticed in the Holter ECG the end of their 9-month study at the University of Heidelberg. They distinguished AF at 99.33% and 99.42% accuracy rates using the Naive Bayes and Gaussian Mixture Model classification methods. A. Haerberlin et al. (2014) were registered with AF patients. They analyzed the RRI of the signals found in the recordings they received and achieved a success rate of between 98.5% and 80.21%. S. Asgari et al. (2015) used pre-processing, property extraction and AF classification as materials and methods. The preprocessing phase is composed of data partitioning, bandpass filtering, Stationary Wavelet Transform (SWT) method. They express the feature subtraction phase with the peak of the mean power ratio and the power spectral density and recording energy entropy. Using the power ratio peak feature, they derive the power spectra of approximations obtained at wavelet transform levels. They performed logarithmic entropy processing with the wavelet transform. In the classification phase, they used the Gaussian kernel function with SVM. MIT-BIH AF database was used as the database. As a result, they found AF with a 97% success rate. J. Felix et al. (2015) performed a separation process using the Continuous Wavelet Transform (CWT) for the signals obtained from atrial electrograms. Low and high-pass filters were applied to the system. As a result of these processes, they detected 99.18% of the sensitivities on average. K. H. Yoon et al. (2015) received RRI series from MIT-BIH AF, MIT-BIH NSR, BIDMC and CHF RRI databases. By normalized these series, have been analyzed RR

variations of consecutive with RMS value, simple entropy and Shannon entropy in the way three levels statistical system. They achieved an accuracy of approximately 96%. N. Nuryani et al. (2015) distinguished NSR from AFR by applying a direct SVM classification algorithm to RRI of ECG signals with 97.50% accuracy. M. Carrara et al. (2015) classified the NSR and AFR signals with the RRI series by the multivariate regression model and the k-NN method and found 98% accuracy. K. Padmavathi and K. S. Ramakrishna (2015) performed feature extraction using the Yule-Walker and Burg's methods in their work. They analyzed these results in k-NN and SVM classifiers and user data with a maximum length of 30 seconds. M. S. Kim et al. (2015) caught the R-points from AFR and NSR signals. They have removed the RRI period from here. They used DWT to extract features from the signals. From these properties, they obtained energy levels with HFD. These levels are separated by the Poincare Plot and have a sensitivity ratio of 99.94%. J. Oster and G. D. Clifford (2015) extracted RRI sequences from ECG records consisting of AFR and NSR. Classification algorithms have been applied to these properties and have achieved approximately 95% success rate. G. Dakos et al. (2015) performed an automatic AF detection study with the aim of investigating the effects of AF on hypertension. Patients received Hypertension patients. The P waves of AFRs have been investigated in terms of energy. The energy outputs of P waves are calculated by Wavelet Transform (WT). Based on these determinations, they formed day-risk graphs. S. Ladavich and B. Ghoraani (2015) have designed a discrimination algorithm based on the presence or absence of a P wave in the AFR and NSR signals. They used the Gaussian model here. They achieved a success rate of 98.05%. J. Ródenas et al. (2015) analyzed the QT intervals of AFR and NSR signals over ECG according to wavelet entropy. They have analyzed data have been classified. The AFR and NSR separation rates were found to be 96.40%. M. García et al. (2016) isolated AFR and NSR data using the QT intervals of the ECG signal. During these operations, they extracted energy from the WT. As a result, NSR and AFR datas have dissociated on 91.20% success rate. S. H. Lee et al. (2016) designed an algorithm for heart pumping. In this algorithm, amplitude values of heartbeats are captured and the AFR is decomposed according to the success rate of 96.64%. K. K. Patro et al. (2016) analyzed the P, QRS and T waves of ECG signals with various arrhythmias according to WT and achieved an average success rate of 98.70% with the capture of these points. Furthermore, P, QRS and T points of the AFR signals have been detected with a 100% success rate at this stage. R. Mabrouki et al. (2016) performed AF detection via RRI through nonlinear statistical analysis. Here, they obtained 97.91% success rate from the MIT-BIH AF Database and 99.65% from the MIT-BIH Arrhythmia Database. C. Yuan et al. (2016) obtained AF capture success rate of 96.56% with complex learning method using RRI. A. Kennedy et al.

(2016) created a new database and obtained ECG signals. They analyzed the RRI series obtained from these markers with CoSen, CV, RMSSD, and MAD methods. After that, they achieved success rates with 97.6% and 92.8% sensitivity. B. Ayers et al. (2016) classified RRI sequences by the RdR map method and achieved a success rate of 83%. A. Deshmukh et al. (2016) classified the RRI obtained from the Holter ECG Signals. As a result, they achieved a 95% success rate as 94.7% continuous detection as part detection. I. A. Marsili et al. (2016) have designed an algorithm that makes it possible to capture the AFR for the Holter device in their study. This algorithm is based on the capture of QRS complexes by ECG signals. R points were analyzed according to a certain threshold level. AFRs with 98% success rate were distinguished. S. Mittal et al. (2016) performed AF detection from ECG signals at various time intervals. As a result, they achieved success rates changing between 39% and 96%. It is stated that these rates vary according to the time intervals and the types of signals received. S.-M. Shan et al. (2016) used data from 468 patients for AF detection. Here, they analyzed the heart rate data using the Fotopletismogram method. Afterward mentioned datas were classified with SVM and have been provided 97.1% success rate. P. Kora and K. S. R. Krishna (2016) have applied CWT on NSR and AFR datas and made feature extraction. The extracted features have optimized by Bat algorithm. Finally, the resulting data were analyzed according to the designed artificial neural network. They achieved a 96.97% success rate. J. A. Annavarapu and P. Kora (2016) performed feature extraction from AFR and NSR by Conjugate Symmetric-Complex Hadamard transformation. These features have classified with the Lvenberg-Marquardt neural network. As a result, they achieved a success rate of 99.97%. S. Islam et al. (2016) performed AF detection according to Heart Rate Variability (HRV). Here they normalize the signal at various stages. As a result, they achieved a success rate of 96.39%. A. Gutiérrez-Gnecchi et al. (2017) pre-processed 17 ECG signals from PhysioNet with WT. Obtained of the P and T waves positionals datas have classified with the probabilistic network. As a result, they have caught various types of arrhythmias at various rates. Achieved 92.69% success rate for AFR. T. Hurnanen et al. (2017) performed an analysis of CHD change with seismocardiogram. AFR and NSR with Linear Least-Squares classification. S. Islam et al. (2017) performed multi-parameter feature extraction from RRI by means of the Heaviside function. They classified the features with SVM and achieved 99.17% results. This result is also compared with the previous study (Islam et al., 2016). F. T. Johura et al. (2017) studied the RRI of NSR and AFRs in their work. Here they caught the R-points and formed the RRI series. As a result, they obtained a sensitivity of 98% compared to the threshold level algorithm. P. Kora et al. (2017) have made feature extraction for R waves of AFR and NSR with Hadamard Transform. By using SVM and SVM like classifiers, have obtained accuracy rate. They

perceived sensitivity by 96.97% in their study. P. Sanders et al. (2016) classified the RRI and P waves of the NSR and AFR signals as taking every two minutes. They achieved a success rate of 99.4%. D. Riera et al. (2017) classified AFR and NSR data by photoplethysmography with SVM. They achieved success at various ratios.

When all these studies were examined, different methods were used for the detection of AF. When these methods were examined, the detection of AFR arrhythmia have been done with situations of the disappearance of the P wave, the disordering of the RRI sequences and the changing of the basal line due to the effects of fibrillation waves. However, studies with P wave showed low success rates. On the other hand, high success rates were obtained from determinations of RRI sequence irregularities (Jiang et al., 2012). In another study, it was also stated that the use of RRI sequences is a more successful way to perform automatic AF detection (Mittal et al., 2016).

Looking at previous studies, ECG signals were not analyzed as raw. There are certain pre-processing and feature extraction operations. Studies in this context show that WT is a widely used method at various stages (Gutiérrez-Gnecchi et al 2017; García et al 2016; Kora and Krishna 2016, Felix et al 2015, Kim et al 2015, Dakos et al., 2015). The evaluation of the results obtained from the pre-processing and feature extraction stages is at least as important as these steps. However, there is a good classification method, which shows the efficiency of the proposed method. According to some studies, boxplot include statistical effective and important visual information for data classify (Ródenas vd. 2015; Ros vd. 2004). But, boxplot is not enough for classification with artificial intelligence and software. According to lots of studies, SVM which is a common classification method provides easy and fast comparison of for a large of data sets (Asgari vd. 2015; Nuryani vd. 2015; Padmavathi ve Ramakrishna 2015; Shan vd. 2016; Islam vd. 2017; Kora vd. 2017; Rivera vd. 2017).

3. Material and Method

3.1. Material

3.1.1. Electrocardiogram (ECG) Signal

The measurement system is generally expressed in the form of an ECG, which shows conditions such as heart rhythm and conduction disturbances, contraction, myocardial infarction, effects of certain medications, and electrolyte irregularity (Morris et al., 2003).

The ECG Mark consists of the P wave, QRS complex and T wave. The fact that the signals are above or below this line is expressed as a deflection. The heart mark and RRI have been expressed in Figure 2 as a whole.

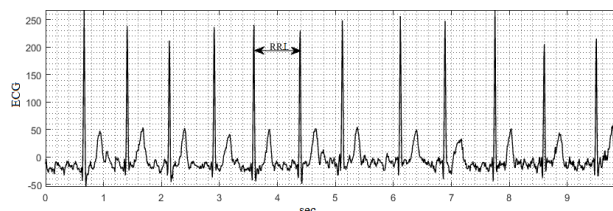


Figure 2. ECG Signal and RRI

3.1.2. Atrial Fibrillation (AF) Arrhythmia

AF is a common type of arrhythmia (Morris et al., 2003, Sejr et al. 2017). In AF, excitations in the atrial appendage of the heart are abnormally shaped and assume a complex structure when passing through the AV. During AF, heart rate increases excessively but is limited to around 150 beats/min (Clinic 2017).

The AF on the ECG seems to be in the form of the missing P wave and disordering QRS complex (Morris et al., 2003). As is seen at Figure 3, AF, disorder RRI sequences.

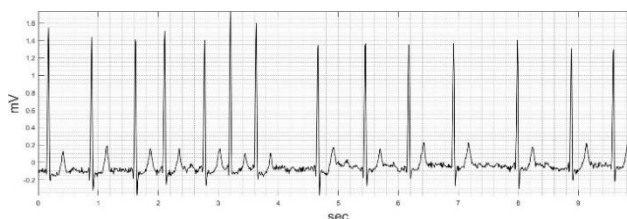


Figure 3. Effect of AF on ECG

3.1.3. Database

Open PhysioBank ATM database is used to access the work on the internet. This database for researchers includes cardiovascular and complex biological signals (Goldberger et al., 2000).

The database named Long Term AF Database (LTafDB) is used for AF. This database contains long-term signals for AF. The data bank contains 24-hour Holter ECG signals from 84 pieces' individuals who have persistent or paroxysmal AF arrhythmias. ECG signals have been recorded with 128 Hz sampling frequency and 12-bit resolution (Anonymous 1). The database is including various rhythms like NSR, SVTA, VT, AFR, VB, T (Ventricular Trigeminy), IVR (Idioventricular Rhythm), AB (Atrial Bigeminy), SBR (Sinus Bradycardia). This study specifically included the separation of Permanent AFR from NSR, so no NSR data were included. Therefore, 31 Permanent AFR data in the database were used for analysis.

Two different databases, MIT-BIH Normal Sinus Rhythm Database (NSrDb) and Normal Sinus Rhythm RRI Database, were used for NSR. The MIT-BIH

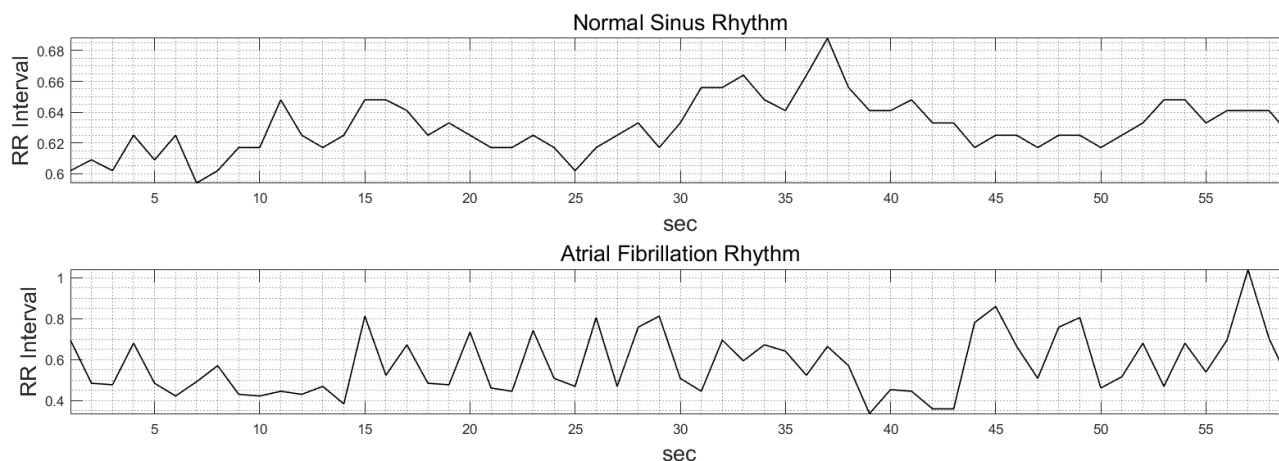


Figure 4. RR Interval based on time

Normal Sinus Rhythm Database (NSRdb) consists of 18 long-term ECG signals which are form of NSR

The database consists of 5 males ranging in age from 26 to 45 years and 13 female females ranging in age from 20 to 50 (Anonymous 2). All the signals obtained from this database are used in the algorithm developed in this study. 12-hour RRI sequences were taken from the relevant database. The Normal Sinus Rhythm RRI Database (NSRDB) contains 54 long-term NSR ECG records. These records were taken from 30 males aged between 28.5 and 76 years and 24 females between 58 and 73 years of age (Anonymous3). The first 13 records from this database and 12-hour RRI sequences were taken from these datas too.

3.2. Method

3.2.1. Pre-Processing Steps

The highest amplitude signal of the QRS complex at ECG is R waves. It is expressed as the RRI between two consecutive R waves. The change in RRI is also referred to as Heart Rate Variability (HRV).

An irregular change of RRI is the most effective way to detect AF (Islam et al., 2017). Considering this situation, the most effective method for separating AFR from NSR is HRV. The RRI records of the signals from the stated databases have been downloaded and made available for loading into the compiler environment. All RRI data were loaded into the compiler environment in individual sequences. Outputs are graphically checked.

When the RRI series are examined, ectopic and/or artifacts may be encountered. Artifacts and ectopics are occurred from, record devices, changes due to the movement of the patient, external effects, etc. (Camm et al., 1996). These artefacts and ectopics have been seem to affect the results negatively in experimental studies. Elliptical and artefacts have cleared from RRI data by the designed threshold algorithm. At this

stage, the threshold value has been specified 2 seconds and the RRI data of more than 2 seconds was removed.

The RRI series obtained from the database are based on the number of heartbeats. However, in order to perform a time-frequency analysis of the RRI series, the heart rate should be translated to the time axis. In this way, a special algorithm in the literature has been used for a translation process (Saalasti 2003).

$$t(y) = RR(y) + t(y - 1) \quad y \in Z^+ \quad \& \quad t(0) = 0 \quad (1)$$

As expressed in Formula 1, the t array has formed new axis for RRI series. The RR series state the distance of the RRI's in the heart beat based on y variable. Here, by means of the algorithm have been generated the time axis by summing the times of RRI (Figure 4).

The necessity of resampling the RRI sequences in consideration of the information provided has emerged. When the previous studies were examined, it was seen that the most efficient sampling frequency in the HRV analysis was 4 Hz (Saalasti 2003; Malik 1996). At this stage, re-sampling was performed to make the data irregularly organized. This process was performed by Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation technique. Studies on interpolation show that the cubic interpolation type produces more efficient results than other interpolation types (Chen 2002).

3.2.2. Feature Extraction

The feature extraction process has been performed in order to be able to perform the separation and fixation process for the pre-processing RRI sequences. When the studies in the literature have been examined, WT is an effective method have been occurred as (Asgari et al., 2015, Felix et al., 2015, Kim et al., 2015, García et al. Gutierrez-Gnecchi et al., 2016). WT is an effective method for analyzing low and high-frequency information. Monitoring of minimal changes for HRV

has been possible with WT (Bilgin 2008). For all these reasons, WT has been used in this study.

The WT have been used for feature extraction. However, WT has two different types of commonly used variation. The first one is the DWT and the other is the CWT. The disadvantage of CWT analysis is that the number of parameters is more than needed (Bilgin 2008). Therefore, the DWT is preferred in the study.

$$\mathcal{W}_{x,y}(n) = |x|^{-\frac{1}{2}} \mathcal{W}\left(\frac{n-y}{x}\right) \quad x, y \in \mathbb{R}, x \neq 0 \quad (2)$$

The General Wavelet Equation is expressed in Formula 2 where x and y are scale and transformation parameters. The time expression has been shown with n parameter.

$$\varphi_{i,k}(n) = 2^{-\frac{i}{2}} \varphi(2^{-i}n - k) \quad (3)$$

In Formula 3, DWT is expressed in terms of two scales and positions. Parameter of n indicate the discrete time. While i denotes the amount of new scale, k is the amount of horizontal axial displacement. Parameter of φ is scale function. DWT divide data into two separate frequency bands as approach and details. When the scaling function and the input mark come together, the formulas of approach, and detail coefficients arise (Bilgin 2008).

$$C(i, k) = \sum_{n=1}^M s(n) \varphi_{i,k}(n) \quad (4)$$

In Formula 4, C is expressed as the coefficients of the approach and detail components obtained by DWT. Where s is the signal that is being decomposed (Radenas et al. 2015). Parameter of φ is scale function.

Ratios of wavelet energy have been created for RRI sequences which is applied DWT.

$$De_i = \frac{\sum_{k=1}^{d_i} C(i, k)^2}{\sum_{i=1}^n \sum_{k=1}^{d_i} C(i, k)^2} \quad (5)$$

In Formula 5, the De is the ratio of the wavelet energy. Decomposition levels have been shown as parameter n and d . Coefficients of approximation and detail have been shown on parameter of C . (Ródenas et al., 2015).

3.2.3. Classification

In this study, RRI sequences which have been completed the stages of preprocessing and feature extraction have been compared with boxplot as NSR and AFR. The data visually interpreted by boxplot are classified by SVM.

$$\mathcal{L}(a) = \sum_{i=1}^k a_i - \frac{1}{2} \sum_{i=1}^k \sum_{l=1}^k a_i a_l y_i y_l x_i x_l \quad (6)$$

The Langrage factors expressed in Formula 6 form the basis of SVM. Here, symbols of x and y are the vectors of the training data. Symbol of a is the Langrage multipliers and as if k is the amount of data.

In this paper, Kernel function use to compute the elements of the Gram matrix for SVM structure. In this context Radial Basis Function (RBF) which is a kind of Kernel Function have been used in SVM structure.

4. Research Findings

4.1. Experimental Results

The energy values obtained for analyzes of db1, db2, db3, db4, db5, and db6 Daubechies wavelets at 4 levels for 62 NSR and AFR RRI sequences as a result of DWT analysis were converted to graphs according to boxplot.

As shown in Figure 5, all levels of decomposition in the db1 wavelength are expressed graphically. Here, the AFR and NSR RRI sequences were found to be ethical in the separation of the wavelet energies. Removal of the offset value from the RRI series at this stage has also removed the possibility of AFR interference with other arrhythmias.

Boxplot results have indicated that SNRs and AFRs seperated effective for this method. In this context, by artificial intelligence have been used, created classification structure.

Leave One Out Cross Validation (LOOCV) method was used for the validation of the study. LOOCV have been provided a kind of dynamic scaling for classification systems. Thus the following parameters have been calculated.

$$specificity = \frac{TN}{TN + FP} \times 100 \quad (7)$$

$$sensitivity = \frac{TP}{TP + FN} \times 100 \quad (8)$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (9)$$

In Formulas 7, 8 and 9, TN means True Negative, TP means True Positive, FP means Faslse Positive and FN is False Negative. Depending on these parameters, the specificity, sensitivity and accuracy rates are calculated in percentage.

DWT have been applied on RRI sequences. These obtained datas have been classified with SVM and results have been recorded. By these results have been

specified the most successful frequency band because the decomposing levels of DWT which are D1, D2, D3, D4 ve A4 have been calculated mean sensivity, mean specivity and mean accuracy values. Approximation parameter of DWT have been shortly stated **A**, and as for Detail parameter of DWT have been shortly stated as **D**.

When Table 1 is taken into consideration, it is seen that the best level of decomposition is **db1** level 1 according to the classification results.

Here, the mean specificity rate is 100% at all levels. The average accuracy rate was 99.22% and the overall average success rate was 99.60%.

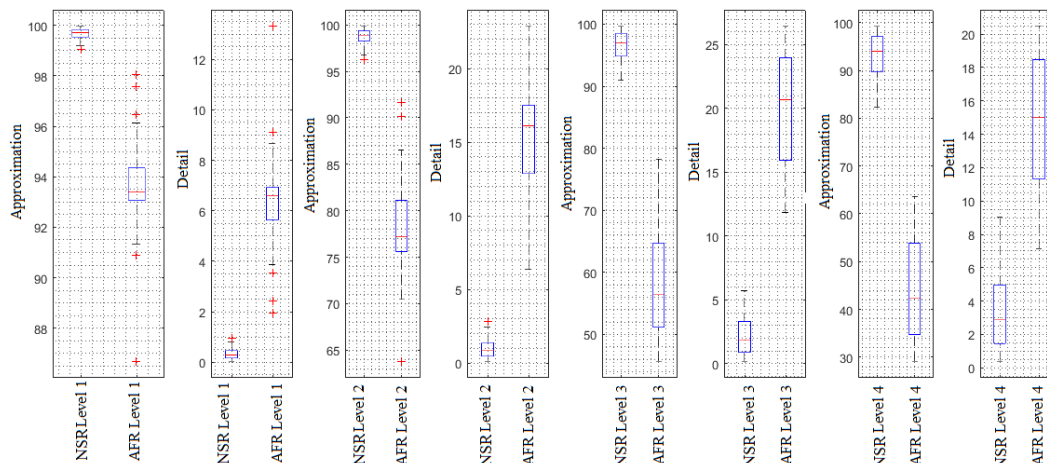


Figure 5. Discrimination of NSR and AFR Energy Levels According to boxplot at db1 Wavelet

All experimental studies have shown that Daubechies (db) ripple gives better results than other wavelets. For this reason, db1, db2, db3, db4, db5, and db6 wavelets were analyzed in the study.

5. Conclusion and Discussion

In this study, a specific algorithm has been designed for automatic AF detection based on separation of NSR and AFR signals from 12-hour Holter ECG recordings.

This algorithm is codified in the compiler environment. RRI sequences from 12-hour ECG signals were pre-processed by ectopic and artifact clearing, resampling and interpolation procedures. The preprocessing stage has made the data ready for feature extraction.

The feature extraction of RRI sequences has been done with DWT, which is widely used in signal processing applications.

Table 1. Mean Values of Decomposition Levels According to Wavelet Types

	%Specificity (mean)				%Sensitivity (mean)				%Accuracy (mean)			
	Detail 1	Detail 2	Detail 3	Detail 4	Detail 1	Detail 2	Detail 3	Detail 4	Detail 1	Detail 2	Detail 3	Detail 4
db1	100	100	100	100	99.22	97.01	96.36	92.73	99.60	98.39	97.98	95.97
db2	100	100	100	100	97.70	97.01	96.36	89.95	98.79	98.39	97.98	94.35
db3	100	100	100	100	97.70	97.01	94.29	89.95	98.79	98.39	96.77	94.35
db4	100	100	100	100	96.19	96.28	93.50	89.37	97.98	97.98	96.37	93.95
db5	100	100	100	100	96.92	96.28	93.50	89.95	98.38	97.98	96.37	94.35
db6	100	100	100	100	96.19	96.28	93.50	90.56	97.98	97.98	96.37	94.75

Then the ratio of wavelet energy has been calculated. It has been observed that the resulting the wavelet energy datas are the appropriate data that can be used for automated detection. By all these processing steps SVM and automatic detection of AFR have been provided with a 99.60% success rate in detail component at level 1 in db1 wavelet. In this study has been shown that AFR in long-term recordings can be distinguished from NSR with high success rate DWT and SVM. This study, as shown in Table 2, achieved a high accuracy rate according to many the studies of AF detection. Classification of wavelet energy ratio has been seen a different method to other studies. For this

reason, the accuracy rate is quite high. This goal has been achieved and the work has been given a novel qualification. S. Asgari et al. (2015) have found P and R points on the ECG mark according to the fixed WT. While they are doing this, have examined the AFR sequences in separate parts. In this examination, feature extraction was done via the morphology of the ECG signal. This situation caused the success rate to remain at a certain level. J. A. Gutiérrez-Gnecchi et al. (2017) identified QRS points with WT on ECG markings in their study. These points were classified by probabilistic neural network and success rates were obtained for various arrhythmias including AFR.

Table 2. Comparison of This Work with Some Studies

Algorithm	%Specificity	%Sensitivity	%Accuracy	Type	Method	Number of Data
Asgari et. al. 2015	97.1	97	97.1	P and R Wave	WT and SVM	23 ECG with 10 Hours
Gutierrez-Gnecchi et al., 2017	-	-	92.69	RRI	WT and Probable Neural Network	17 ECG with 30 Minutes
García et al. 2016	94.53	91.21	93.32	QT Interval	WT and Combined Complex Classifier	23 ECG with 10 Hours
Nuryani et al. 2015	98.44	95.81	97.50	RRI	SVM	23 Patients ECG
Oster and Clifford 2015	-	-	95	RRI	SVM, CoSen, Poincare	25 ECG with 10 Hours Long
Kim et al. 2015	99.88	99.94	-	RRI	WT and SPSS	58 ECG with 24 Hours
Ródenas et al. 2015	94.14	96.47	95.28	QT Interval	Wavelet Entropy and Threshold Level Comparison	23 ECG with 10 Hours
This Work	100	99.22	99.60	RRI	WT and SVM	62 ECG with 12 Hours

M. García et al. (2016) examined AFR data independently from HRV. They analyzed the QT intervals on the ECG mark by WT. They used wavelet energy for this analysis. N. Nuryani et al. (2015) classified the RRI exchange data directly with SVM. At this stage, they carried out the test operations with Radial Based Function which is a method of SVM. Oster and Clifford (2015) analyzed AFR data with RRI. They used QRS. Long-Term AF database. CoSen, Poincare and SVM. M. S. Kim et al. (2015) studied 29 NSR and 29 AFR data. In this study, they have captured R points with DWT. They processed this data as HRV analysis. In this way, they achieved high sensitivity and clarity ratios. Ródenas et al. (2015) examined the QT interval of the signals they obtained from the database called MIT-BIH AF Database. In particular, they were able to distinguish wavelet entropy and AFR data by performing WT analysis. They compared the threshold value in this differentiation process. They made the analysis in the form of pulses. In the studies performed for the detection of AFR, ECG signals were mostly divided and processed. In this study, all data were analyzed. In this way, more data are tested compared to other studies. According to the results of the P-wave presence-absence test according to the morphological feature of the ECG signal with the AFR marker, the superiority of HRV analysis due to RRI

analysis was evident in this study. In addition, the success of classification with boxplot and SVM was increased compared to other studies. The advantages of classification are LOOCV. In this case, it has become one of the most important advantages of the study. This work constitutes the basic step of ancillary practice, which facilitates the diagnosis of AF, a type of arrhythmia that is particularly common in progressive heart diseases. Auto-detection of AF is an important application that provides serious convenience in terms of avoiding the drawbacks caused by AF. However, automatic detection increases reliability at high success rates. This study also contributes to this situation with the high success rate achieved. This information has been developed in the light of work whether it is instant detection, long-term detection, or applications to be added to mobile devices. Without this work, there was a basis for working towards reducing the effects and risks of AF, which was a serious discomfort. Development studies will guide the AF's advance detection efforts.

Conflict of Interest

No conflict of interest was declared by the authors.

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