Arrhythmia Detection from Heartbeat Using *k*-Nearest Neighbor Classifier

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***Abstract*—Automatic interpretation of electrocardiography provides a non-invasive and inexpensive technique to analyze the heart activity for different cardiac conditions. The emergence of smartphones and wireless networks has made it possible to perform continuous Holter monitoring on patients or potential patients. Recently, much attention has been paid to the development of the monitoring methodologies of heart activity, which include both the detection of heartbeats in electrocardiography and the classification of types of heartbeats. However, many studies have focused on classifying limited types of heartbeats. We propose a system for classification into 17 types of heartbeats. This system consists of two parts, the detection and classification of heartbeats. The system detects heartbeats through repetitive features and classifies them using a *k*-nearest neighbor algorithm. Features such as the QRS complex and P wave were accurately extracted using the Pan-Tompkins algorithm. For the classifier, the distance metric is an adaptation of locally weighted regression. The system was validated with the MIT-BIH Arrhythmia Database. The system achieved a sensitivity of 97.22 % and a specificity of 97.4 % for heartbeat detection. The system also achieved a sensitivity of 97.1 % and a specificity of 96.9 % for classification.**

Keywords—Arrhythmia detection, classifier, k-nearest neighbor, locally weighted regression, ECG, QRS complex, Pan-Tompkins algorithm

I. Introduction

The symptoms of arrhythmia are diverse, ranging from minor chest palpitations, chest pain, and fainting (syncope) to sudden heart attack, depending on the type and severity of heart disease [1]. Thus, it is important for patients showing symptoms of arrhythmia, even if these symptoms are mild, to be diagnosed as early as possible [2]. Many patients are unaware of their symptoms and wish to avoid the hassle of visiting a hospital. Moreover, even those who seek diagnosis may show normal cardiac behavior during their visit [2]. For these reasons, there have been growing demands for a remote electrocardiography (ECG) monitoring system that can function anywhere and anytime [3]. Fortunately, the recently developed Holter monitoring device can be integrated with modern smartphones to serve this function, allowing patients to continue their normal routines (see Fig. 1) [4]. The ECG signal is sent over a wireless network to a decision support system, which saves and interprets the signal. The ECG signal includes a heartbeat, which is characterized by five peaks and valleys, and features labeled as P, Q, R, S, and T, as depicted in Fig. 2. These features are used to analyze the heartbeat. The system can detect arrhythmia by classifying the heartbeats with these features. If the system identifies the heartbeats as signifying a dangerous condition, it alerts the monitoring center to make a diagnosis and help the patient to take immediate appropriate action.

To detect arrhythmia, many methods using machine learning

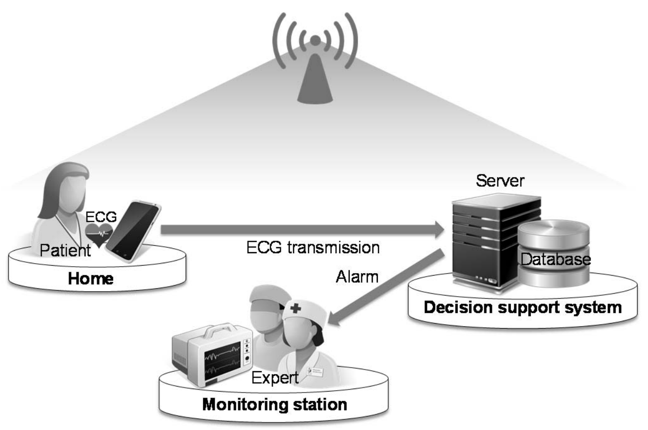

Figure 1. Overview of system architecture

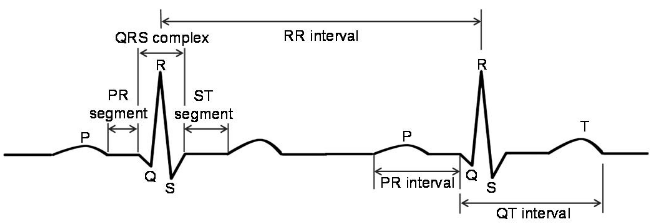

Figure 2. The structure of an ECG signal

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have been proposed [5-17]. Some of these studies used a k-nearest neighbor (k-NN) classifier [5, 6]. The k-NN classifier has the advantage of being simple and often functions very well as a lazy learning method when the target function is very complex [21, 22]. One study extracted features using a Hermitian basis function and classified heartbeats using a simple k-NN classifier [5]. Although the results of the study were worthy of attention, the study only considered a small set of heartbeats and classified just 7 types of heartbeats. Another study used features identified by wavelet transform and classified heartbeats using pruned fuzzy k-NN [6]. The study considered 6 types of heartbeats. Because these researches were only considered limited types of heartbeats, experts would require additional effort and time for diagnosis. This is the problem that we are going to address.

In this study, we propose a system that classifies heartbeats into 17 types for a reliable and automatic decision support system. The system consists of two parts: heartbeat detection and classification. We adapted the well-known Pan-Tompkins algorithm [23] to accurately detect heartbeats and extract features. We also adapted a k-NN algorithm using locally weighted regression (LWR) to classify heartbeats according to their extracted features. We demonstrated the effectiveness of this system by means of extensive experiments using the MIT-BIH Arrhythmia Database [24].

Our work makes the following two contributions. Firstly, we offer a guide to the systematic design of an automatic classification system for decision support in ECG monitoring. This can provide a low-cost solution to both patients and monitoring centers, because the patients do not have to visit the hospital and the experts at the monitoring station can monitor the ECGs of patients anywhere at any time. Secondly, our automatic algorithm for heartbeat detection and classification helps patients or medical personnel to make more accurate immediate diagnoses by reducing the number of false alarms and missing events.

The rest of this paper is organized as follows. In section II, we briefly review previous works on heartbeat detection and classification systems. In section III, we propose our ECG monitoring system to tackle the problems found in the previous works. In section IV, we profile the dataset that was used in the experiment. In section V, we evaluate the accuracy of our system in terms of sensitivity and specificity. Finally, we provide the concluding remarks and directions for future study in section VI.

II. Previous Work

A. Feature Extraction

Heartbeats reflect two main activities, ventricular and atrial [25]. Ventricular activity is characterized by the QRS complex and the T wave. The QRS complex has been used as the simplest noninvasive diagnostic method for a variety of heart diseases [7]. Pan and Tompkins developed a real-time algorithm for detecting the QRS complex in heartbeats [23]. Their algorithm has been the most widely used for the detection of both heartbeats and QRS complexes. A number of studies have proposed systems for the detection of heartbeats using the QRS complex [7-18]. Some studies explored the characterization of ECG using the wavelet feature for classification [6, 8, 9, 16, 19]. Other studies used waveform features [10-15, 19], whereas additional researchers used higher-order statistics and Hermite coefficients for feature extraction [5, 7, 20].

Atrial activity is characterized by the P wave. Heartbeat characterization methods based on P wave detection using a localized search area [25-27], or ventricular and atrial source separation [28, 29] have thus been presented.

B. Classification

Recently, a number of automatic classification methods for heartbeat classification have been proposed based on machine learning algorithms [5-19]. Some studies used the support vector machine, which is known to be an excellent and generalizable tool for classification [7-8]. Other studies used artificial neural networks [9, 15, 17, 18]. In addition, some studies used linear discriminates [10, 11, 13], while a few studies used decision trees [12, 16]. One study used conditional random fields as a classifier, based on sequential observations of heartbeats [19]. Another study used dynamic Bayesian networks to consider information from adjacent events [14]. Additionally, several studies used k-NN classification [5, 6]. These studies using k-NN presented powerful classification results.

III. Classification of Heartbeat Type

A. Heartbeat Detection

Our system considers both the QRS complex as ventricular activity and the P wave as atrial activity for features. In order to extract features, our system looks for heartbeats in ECG signal using the Pan-Tompkins algorithm. This algorithm consists of a band-pass filter, a differentiator, a squaring operator, and an integrator over a moving window. Figure 3 depicts the step-by-step output of the algorithm from 100 that is record-id in the MIT-BIH Arrhythmia Database. Figure 3(a) depicts the original ECG signal. The band-pass filter is created by combining a low-pass filter with a high-pass filter. This reduces noise such as muscle noise, 60 Hz interference, baseline wandering, and T wave interference in the ECG signal. The difference equation of the low-pass filter is

$$y(nT) = 2y(nT-T) - y(nT-2T) + x(nT) - x(nT-6T) + x(nT-12T), \quad (1)$$

and the difference equation of the high-pass filter is

$$y(nT) = 32x(nT-16T) - [y(nT-T) + x(nT) - x(nT-32T)]. \quad (2)$$

We set the low-pass filter with a cutoff frequency of 11 Hz and the high-pass filter with a cutoff frequency of 5 Hz, as shown in

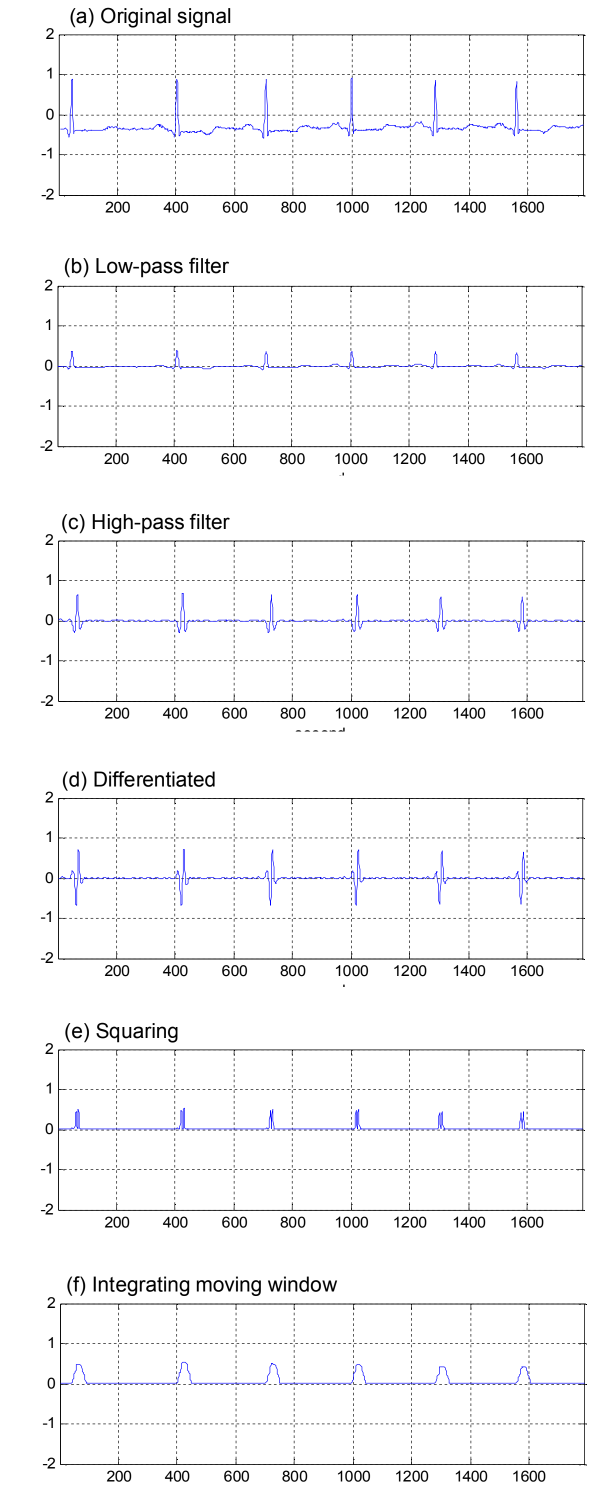

Figure 3. Step by step output of the Pan-Tompkins algorithm

Figs. 3(b) and 3(c). After being filtered, the ECG signal is

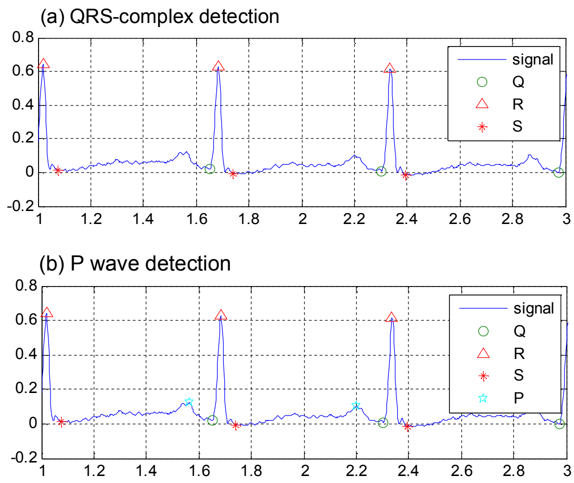

Figure 4. Results of feature extraction from record 100.dat

differentiated to provide slope information by following the difference equation

$$y(nT) = (1/8T)[-x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T)]. \quad (3)$$

This approximates the ideal derivative between dc and 30 Hz. Figure 3(d) shows the results of this derivative. Next, the signal is squared point by point. This makes all data points in the processed signal positive and emphasizes the higher frequencies, as shown in Fig. 3(e). The difference equation of squaring is

$$y(nT) = [x(nT)]^2. \quad (4)$$

The moving-window integration is performed to obtain waveform feature information that is then added to the slope of the R wave. It is achieved with the following different equation:

$$y(nT) = (1/N)[x(nT-(N-1)T) + x(nT-(N-2)T) + \cdots + x(nT)], \quad (5)$$

where N is the number of samples. This produces re-echo mountaintops, as shown in Fig. 3(f). A heartbeat is found over one mountaintop. Within the heartbeat, the system identified the QRS complex. Q is the starting point, S is the ending point, and R is the peak of the mountaintop. Then, the system finds the P wave using the QRS complex. The P wave is located between the S point of the current heartbeat and the Q point of the next heartbeat. The system divides this area into two and uses a peak in the second sub-range as the P point. Figure 4 depicts the sample results of QRS complex and P wave detection from 100 that is record-id in the MIT-BIH Arrhythmia Database.

B. Feature Extraction

Our system is primarily concerned with the QRS complex and P wave as features. The system uses ventricular features relating to the QRS complex and atrial features relating to the P wave. Features associated with fiducial points are calculated for each beat, such as the positions and amplitudes of points Q, R, S, and P. Features associated with heartbeat intervals are also calculated. One feature, the PR interval, is extracted from the beginning of the P wave and the beginning of the QRS complex. Four features are extracted from the consecutive R waves as the Pre-RR, Post-RR, Average-RR, Local-RR, and Variable-RR intervals, where the RR interval features can be calculated for the time elapsing between two consecutive R waves (see Fig. 2).

The Pre-RR interval is calculated between a previous R wave and a given R wave, and the Post-RR interval is calculated between a given R wave and the following R wave. The Average-RR interval is the mean of the RR intervals during 60 cycles, and the Local-RR interval is the mean of the RR intervals during 10 cycles. The Variable-RR is the mean of the RR intervals between Pre-RR and Post-RR intervals. The Average-RR and Local-RR intervals have been used differently in a few studies [8, 11]. The Local-RR interval was calculated as the mean of RR intervals in 10 heartbeats centered at the given beat, and the Average-RR interval was calculated as the mean of all RR intervals in the same ECG recording. Such an approach is not sufficient in real-time applications. Thus, one study adapted the definitions of the mean RR intervals to be within the corresponding past cycles of heartbeats [8]. In our system, the Local-RR and Average-RR intervals are calculated from the past 10 and past 60 cycles of heartbeats, respectively. Our system is thus realistic and ensures real-time feature extraction.

C. k-Nearest Neighbor and Locally Weighted Regression Classifiers

The *k*-NN method is the most basic instance-based learning algorithm. Given query instance x_q, the algorithm first locates the nearest training example x_n and takes votes among its *k*-NNs. The system represents instances that are composed of the extracted features in vector space as:

$$< a_1(x_i),\ a_2(x_i), \cdots\ a_{14}(x_i) >, \qquad (6)$$

where $a_r(1 \le r \le 14)$ are the extracted features, and x_i is an instance from the training set. For a given instance, the system extracts 14 features from a heartbeat. The nearest neighbors of an instance can be calculated using various distance measures. Our system uses Euclidean distance as a distance measure. The Euclidean distance is ordinarily used to calculate a distance between two vectors as follows:

$$d(x_i,\ x_j) \equiv \sqrt{\textstyle\sum_{r=1}^{n}(a_r(x_i) - a_r(x_j))^2}. \qquad (7)$$

An arbitrary instance x_i is described by the feature vector (6) such that $a_r(x_i)$ denotes the value of the *r*th feature of instance x_i.

TABLE I. NUMBER OF HEARTBEATS FOR EACH TYPE

Heartbeat Type	Annotation	# of heartbeats
Normal beat (NOR)	N	74976
Left bundle branch block beat (LBBB)	L	8068
Right bundle branch block beat (RBBB)	R	7250
Atrial premature beat (APC)	A	2544
Aberrated atrial premature beat (AP)	a	138
Nodal (junctional) premature beat (NP)	J	84
Supraventricular premature beat (SP)	S	2
Premature ventricular contraction (PVC)	V	7120
Fusion of ventricular and normal beats (VFN)	F	802
Atrial escape beat (AE)	e	16
Nodal (junctional) escape beat (NE)	j	230
Ventricular escape beat (VE)	E	106
Paced beat (PACE)	/	7024
Fusion of paced and normal beat (FPN)	f	982
Unclassifiable beat (UN)	Q	32
Ventricular flutter wave (VF)	!	324
Non-conducted P wave (NCP)	x	4

Then, the distance between two instances x_i and x_j is defined to be $d(x_i,\ x_j)$, as defined in (7). The algorithm calculates the mean values of the k nearest training instances rather than calculating their most common value.

The *k*-NN algorithm can be considered as an approximation of $f(x)$ that is calculated from the Euclidean distance at the single query point $x = x_q$. It is fair to consider whether the *k* neighbors could generate an error in the case when an outlier is contained within the *k* neighbors. Thus, our system uses locally weighted regression (LWR) as a generalization of *k*-NN. The application of LWR constructs an approximating $f(x)$ over a local region surrounding the query point x_q. Local means that the function is approximated based only on data near the query point. The target function of LWR is approximated near x_q using a linear function of the form

$$\hat{f}(x_i) = w_0 + w_1 a_1(x_i) + \cdots + w_{14} a_{14}(x_i). \qquad (8)$$

The distance between x_i and x_q is used as a weighted value, where $w_i \equiv 1/d(x_q - x_i)^2$.

Study [21] derived a method for choosing weights that minimized the squared error summed over the data set of training instances:

$$\mathrm{E} \equiv (1/2)\textstyle\sum_{x_i \in Data}(f(x_i) - \hat{f}(x_i))^2. \qquad (9)$$

The gradient descent training rule is

$$\Delta \mathrm{w_{ji}} = \eta \sum_{x_i \in Data} (f(x_i) - \hat{f}(x_i))\, a_j(x_i), \qquad (10)$$

where η is a constant learning rate.

This study also derived a local approximation rather than a global one. The local approximation is to redefine the error criterion, E, by fitting the local training instances. It is combined by minimizing the squared error over the k nearest neighbors and minimizing the squared error over all neighbors of the training instances.

$$E'(x_q) \equiv (1/2) \sum_{x \in knn\ of\ x_q} \left(f(x) - \hat{f}(x)\right)^2 K(d(x_q, x)), \qquad (11)$$

where K is a decreasing function that weighs the error of each training instance and the query point x_q. The gradient descent training rule of equation (12) is

$$\Delta \mathrm{w}_{\eta} = \eta \sum_{x \in knn\ of\ x_q} K\left(d(x_q, x)\right) \left(f(x_i) - \hat{f}(x_i)\right) a_j(x_i), \qquad (12)$$

where the value of j is 1 to 14.

To classify types of heartbeats, the system commonly utilizes LWR considering 29 nearest neighbors.

IV. DATA

We used the well-known MIT-BIH Arrhythmia Database to train and test the classifier. The database contains 48 half-hour recordings each containing two ECG lead signals (denoted as lead A and lead B). In 45 recordings, lead A is a modified limb lead II (MLII), and lead B is commonly a modified lead V1. In the other recordings, lead A is V5 and lead B is V2 or MLII. The lead signals were band-pass filtered at 0.1-100 Hz and digitized at 360 Hz. The database has been used extensively in validating algorithms for arrhythmia classifiers [5-20]. Thus, the database can also provide a basis for comparison with other methods.

The database contains approximately 109,000 heartbeats. All recordings have an annotation associated with each heartbeat. The annotation provides the location of the QRS complex and the types of the heartbeats. The annotation types can be used to determine the truth of classification. Our system considers 17 annotation types. Table I shows the heartbeat types considered in the system and the number of each type of heartbeat. The 17 types include normal (NOR), left bundle branch blocks (LBBB), right bundle branch block (RBBB), atrial premature (APC), aberrated atrial premature (AP), nodal premature (NP), supraventricular premature (SP), premature ventricular contraction (PVC), fusion of ventricular and normal (VFN), atrial escape (AE), ventricular escape (NE), ventricular escape beat (VE), paced (PACE), fusion of paced and normal (FPN), ventricular flutter wave (VF), non-conducted P wave (NCP) and

TABLE II. RESULTS OF HEARTBEAT DETECTION

Rec.	Se.	Sp.	Rec.	Se.	Sp.
100	99.96	100.00	201	95.14	99.38
101	99.84	99.82	202	99.30	99.72
102	99.82	98.91	203	95.53	95.37
103	99.67	100.00	205	99.37	99.25
104	96.58	75.30	207	86.83	99.90
105	96.17	92.82	208	94.11	96.23
106	93.99	99.80	209	98.59	99.90
107	99.86	50.05	210	97.58	98.42
108	96.38	84.03	212	99.53	99.85
109	99.64	99.84	213	98.48	94.52
111	99.58	99.62	214	98.22	99.30
112	99.60	99.53	215	98.88	99.88
113	99.94	100.00	217	96.75	96.08
114	99.52	99.16	219	93.12	100.00
115	99.59	100.00	220	99.03	100.00
116	98.80	99.67	221	98.21	99.67
117	99.80	99.74	222	94.31	98.26
118	99.09	97.19	223	98.34	100.00
119	94.94	99.50	228	96.26	87.15
121	99.31	99.15	230	91.57	100.00
122	99.96	100.00	231	78.17	100.00
123	100.00	100.00	232	98.13	99.22
124	99.14	99.63	233	97.30	99.22
200	93.19	95.80	234	99.46	100.00

Rec., record; Se., sensitivity; Sp., specificity

TABLE III. TEN-FOLD CROSS VALIDATION RESULTS OF A *K*-NN CLASSIFIER FOLLOWING THE SIGNAL

Lead	Se.	Sp.	Accuracy
A	96.50	96.20	96.35
B	88.30	88.90	88.60
A+B	97.10	96.90	97.00

Se., sensitivity; Sp., specificity

TABLE IV. SENSITIVITY AND SPECIFICITY RESULTS OF *K*-NN AND LWR FOR TEN-FOLD CROSS VALIDATION AND 5:5 TESTING

Classifier	Training Ratio	Se.	Sp.	Accuracy
k-NN	50%	96.90	96.30	96.60
	90%[a]	97.10	96.90	97.00
LWR	50%	96.90	96.30	96.60
	90%[a]	97.10	96.90	97.00
	50%[b]	96.60	95.80	96.20

a: 10-fold cross validation; b: $k = 29$ (others $k = 1$). Se., sensitivity; Sp., specificity

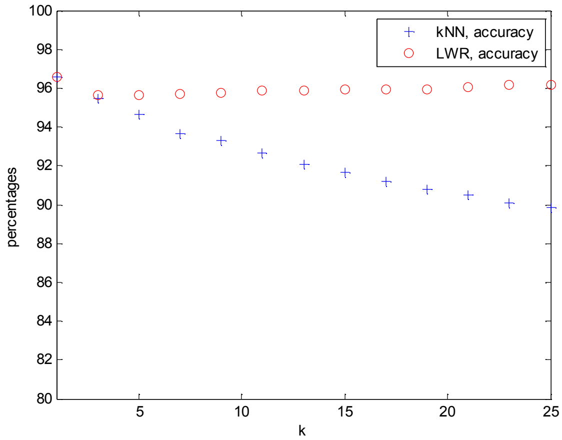

Figure 5. Comparison of classification accuracy for *k*-NN and LWR classifiers (*k* ranges from 1 to 25)

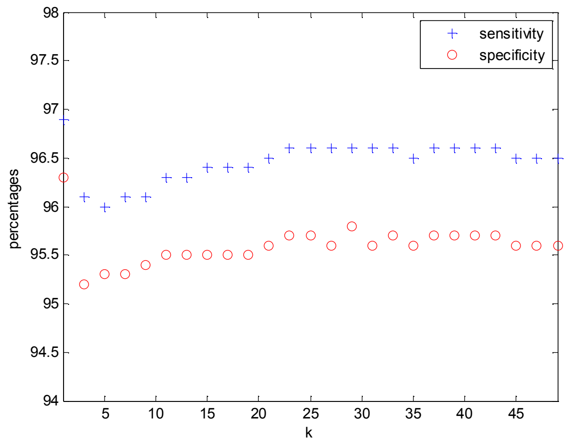

Figure 6. Sensitivity and specificity of a LWR classifier when *k* is varied from 1 to 45

unclassified (UN) heartbeats from the MIT-BIH Arrhythmia Database.

V. Results and Discussion

In this section, we present and discuss the results of our detection and classification of heartbeats. For performance evaluation, we used three standard metrics: sensitivity (*Se.*), specificity (*Sp.*), and accuracy (*Acc.*). These metrics are used to quantify the performance of the system. The sensitivity refers to the ability of the test to correctly identify a classified type with a true positive:

$$Se. = TP/(TP + FN), \tag{13}$$

where TP represents the true positive and FN represents the false negative. The specificity refers to the ability of the test to correctly identify a classified type without the positives:

Table V. Performance Summary for Each Type

Anno-tation	# classified	# for training	Se.	Sp.	Accuracy
N	37194	37488	99.20	94.70	96.95
L	3936	4034	97.60	99.70	98.65
R	3557	3625	98.10	99.80	98.95
A	983	1272	77.30	99.80	88.55
a	47	69	68.10	100	84.05
J	38	42	90.50	100	95.25
S	0	1	0	100	50
V	3108	3560	87.30	99.90	93.6
F	302	401	75.30	99.90	87.6
e	0	8	0	100	50
J	50	115	45.30	100	72.65
E	51	53	96.20	100	98.1
/	3389	3512	96.50	99.90	98.2
f	360	491	73.30	99.90	86.6
Q	3	16	18.80	100	59.4
!	133	162	82.10	100	91.05
X	0	2	96.90	100	98.45

Se., sensitivity; Sp., specificity

Table VI. Comparison of Previous Works and Our System

Method	# of beat types	# of features	Data size	Accuracy
[5]	7	20	11,549	99.42
[6]	6	11	104,700	97.32
our system	17	28	109,702	97.00

$$Sp. = TN/(TN + FP), \tag{14}$$

where TN represents the true negative and FP represents the false positive. The accuracy refers to the ability of the test to correctly identify a classified type with and without positives. It reflects both sensitivity and specificity:

$$Acc. = (TP + TN)/(TP + FP + FN + TN). \tag{15}$$

We evaluated the performance of the system in two parts. The first part was heartbeat detection, which further affects classification performance. Table II summarizes the results for the heartbeat detection algorithm applied to the database. The system achieved a sensitivity of 97.22 % and a specificity of 96.3 % for classification. Note that recording 107 had many abnormal beats with unusually large, atypically peaked P waves, resulting in an especially low rate of specificity of 50.05%. This performance can be improved through deeper analysis of the P wave, but this is beyond the scope of this study.

The second part of the evaluation was the classification performance for heartbeat types. To test the classifier, we produced two types of testing methods: 10-fold cross validation [23] and a simple testing method. In 10-fold cross validation, all heartbeats in the database are divided into 10 subsets of approximately equal size. The classifier is then trained 10 times, leaving out one of the subsets each time but using the omitted subset to compute the prediction error. The other procedure was a simple testing method. In this, training data is selected randomly from all heartbeats. The remaining data is utilized as testing data. The ratio of training data is set to 50% for all heartbeats.

Each heartbeat has two signals derived from lead A and lead B. The system validated the difference following two signals. Table III summarizes the results of differences following two signals. The system employed a k-NN classifier with 10-fold cross validation. In lead A, the results showed an accuracy of 96.35% and in lead B, the results showed an accuracy of 88.6%. The system illustrated distinctions between the two signals due to reasons such as sensor locations. In both lead A and lead B, the best accuracy was observed as 97%. Thus, the system utilizes both signals for classification.

Our system used both k-NN and LWR to classify types of heartbeat. The performance of classifiers is generally affected by the k value. We verified the variations in the performance of the two classifiers, with changing k values ($1 \leq k \leq 25$). Figure 5 provides a comparison of classification accuracy between the two classifiers. The performance of the k-NN classifier was decreased while the performance of LWR remained similar. The k-NN classifier showed poorer results with larger values of k because of fairly considering. The 1NN classifier showed the best results, with a sensitivity of 97.1% and a specificity of 96.9%. However, if the training data happens to include noise, the classifier can recognize a false event. Consequently, the 1NN classifier has potential risks.

Therefore, we investigated the optimal k value for the LWR classifier. Figure 6 provides results of sensitivity and specificity of the LWR classifier when k was varied from 1 to 49. In the case of LWR, the system had a sensitivity of 97.1% and a specificity of 96.9% when k was one. This result also has potential risks. Thus, we searched for an optimal k value excluding $k = 1$. When k was increased from 1 to 25, the performance of the classifier increased gradually; when k was increased from 27 to 45, the performance of the classifier remained similar. When the value of k was 29, the classifier showed the best results, with a sensitivity of 96.6% and a specificity of 95.8%.

Table V provides performance summaries for each type of heartbeat. For the types of beats with small numbers of samples, the performance results were very poor. These results indicate that the size of the training data set for a few types was too small. If data were to be collected for a long term to include many heartbeats for types that are rarer, the classifier may work well.

Table VI provides a summary of comparisons between previous works and our system. The methods in studies [5] and [6] used the k-NN algorithm as a classifier. The method in [5] showed a higher accuracy of 99.42%. However, the method only considered 7 types and a small data pool of 11,549 beats. Thus, these results cannot be generalized. The method in [6] showed a fine accuracy of 97.32 %, but only considered six types of heartbeat. In contrast, we verified that our classifier can identify 17 types of heartbeats and had similar performance in comparison with these other studies.

VI. Conclusion and Future Work

We proposed and evaluated a system for cardiac activity monitoring using a k-NN classifier. Our system detects heartbeats and categorizes them into 17 classes. Evaluation using the MIT-BIH Arrhythmia Database verified its accuracy in terms of high sensitivity and high specificity. In the future, we are going to apply a live mode to our system for practical use. We also plan to further improve the classification accuracy by considering many other features such as the T wave.

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