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Paper:

Fuzzy Association Rule Mining Based Myocardial Ischemia Diagnosis on ECG Signal

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A fuzzy association rule mining based method is proposed for myocardial ischemia diagnosis on ECG signals. The proposal provides interpretable and understandable information to doctors as an assistant reference, while rule mining on fuzzy itemsets guarantees that the feature segmentation before rule extraction is feasible and effective. A set of fuzzy association rules is mined through experiments on data from the European ST-T Database, and classification results of myocardial ischemia and normal heartbeats on the test dataset using the extracted rules obtained values of 83.4%, 80.7%, and 81.4% for sensitivity, specificity, and accuracy, respectively. The proposed method aims to become a helpful tool to accelerate the diagnosis of myocardial ischemia on ECG signal, and to be expanded to other heart disease diagnosis areas such as hypertensive heart disease and arrhythmia.

Keywords: time series data, ECG, heart disease, myocardial ischemia diagnosis, fuzzy association rule mining

1. Introduction

How to provide an intelligent approach allowing doctors to diagnose ischemia more quickly and accurately is a key issue for related research work. Diverse algorithms and techniques have been applied to evaluate the ST segment, T wave changes, and to detect ischemia on ECG signals. The majority of the proposals aim at directly providing automatic detection results to the doctor. Support vector machine/regression is one of the most popular algorithms used in this area [1, 2]. Neural networks are popular algorithms owing to their powerful problem-solving ability [3, 4] and Hidden Markov Models are also widely and well applied for ECG analysis [5]. Wavelet theory has drawn significant attention and has been implemented [6]. To benefit from distinct models, hybrid methods are constantly used [7]. Although methodologies and algorithms addressing ischemia detection on ECG signals have been developed for some time, a diagnosis in reality cannot rely solely on these proposed methods owing to the extreme complexity of the ECG signals from different patients. The practical experience of the doctor is always necessary for a myocardial ischemia diagnosis.

A method based on fuzzy association rule mining is proposed for the diagnosis of myocardial ischemia on an ECG signal. Its implementation is composed of four steps: significant feature extraction from each heartbeat, fuzzy transformation of the above features, association rule mining on fuzzy itemsets, and automatic ischemia and normal heartbeat classification using the extracted rules. The goal of the proposed method is to provide doctors with a set of fuzzy association rules that reveal strong connections between significant heartbeat features and ischemia as an assistant tool to facilitate the diagnosis. Features to be extracted include ST segment deviation, ST segment duration, ST segment area, T wave peak, T wave area, and T wave direction. Segmentation of the above features is realized by fuzzy *c*-means clustering and the membership function parameters of each feature are determined based on the above fuzzy *c*-means clustering results. Then, association rules are mined on the fuzzy itemsets. A validation algorithm using these extracted rules is proposed for automatic heartbeat classification on an ECG signal.

The proposal inherits the merits of the association rule based method. The output of the proposed method is interpretable information allowing doctors to understand the underlying correlation before they make a diagnosis. This proposal aims at providing a useful, crucial medium for the myocardial ischemia diagnosis process. Furthermore, it reveals the strong relationships between different feature types increasing the possibility of achieving accurate results for ischemia detection. To obtain meaningful rules, extracted features must be segmented to different intervals before conducting the association rule mining. In the proposed method, fuzzy *c*-means clustering is applied to determine an approach to discretize the features. In this fashion, feature segmentation becomes more functional and effective.

Experiments are conducted on a PC with a dual-core processor (2.5 GHz) and 8 GB memory. The simulation software is from Matlab. The data used in the experiment are the ECG recordings from the European ST-T

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Database [8, 9]. This database, collected by PhysioNet, is intended for the evaluation of algorithms for ST segment and T wave changes, the most common pathological changes of myocardial ischemia. The experiment data are divided into training and test datasets. A set of significant features are first extracted from each individual heartbeat in the training dataset. Then, each extracted feature is segmented into several intervals using a fuzzy c-means clustering algorithm. The training data are used to train the fuzzy membership functions. In the next step, the experiment data are transformed to fuzzy values. Finally, an association rule mining algorithm is performed to extract the fuzzy association rules. In the validation process, these mined rules are applied to the test dataset to confirm the effectiveness of the automatic myocardial ischemia classification.

The proposed fuzzy association rule mining method is explained in detail in Section 2. Experiments and evaluations of the proposed method on the data from the European ST-T database are shown in Section 3. Section 4 presents the conclusions.

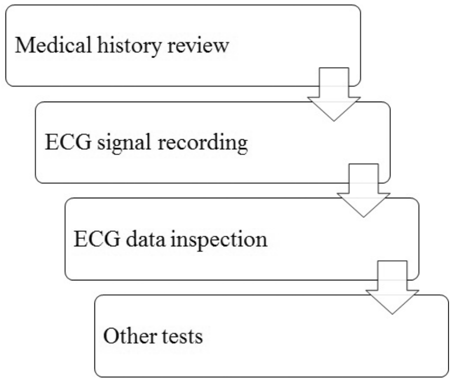

Fig. 1. Current myocardial ischemia diagnosis process.

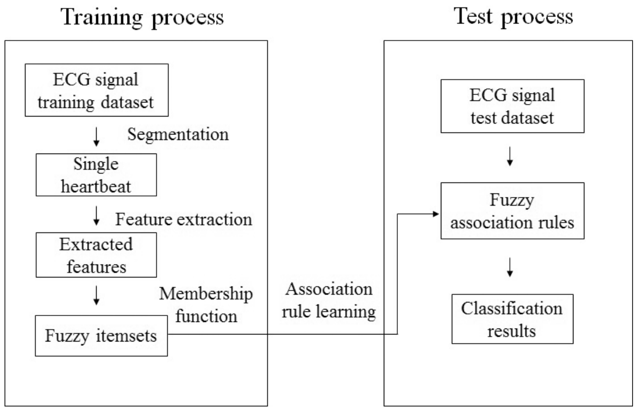

Fig. 2. Fuzzy association rule mining and classification on ECG signal.

2. Fuzzy Association Rule Mining on ECG Signal

2.1. Motivation of the Proposal

An ECG signal records a pattern reflecting the electrical activity of the heart and typically requires a trained clinician and doctor to interpret the context of the signs and symptoms presented by the patient. It can provide information regarding the rhythm of the heart. This includes whether the electrical impulse consistently arises from an area of the heart where expected and at the appropriate rate, whether the impulse is conducted normally throughout the heart, and whether any area of the heart is contributing more or less than expected to the electrical activity. Current advanced ECG recording equipment often includes analysis software that attempts to interpret the pattern. However, the generated diagnostic results may not always be sufficiently accurate to be used as the only evidence for a heart disease diagnosis.

According to summary information from the Mayo Clinic [10], which is considered as one of the best medical research institutions in the world, the current diagnosis of myocardial ischemia is described in the following and illustrated in **Fig. 1**. To begin, the medical history of a potential patient is reviewed by a clinician and possibly the nurse will conduct the ECG recording. Then, the clinician inspects the recorded ECG data carefully to form an opinion as to whether there is any abnormality on the ECG signal caused by myocardial ischemia. If the abnormalities on the ECG signals are not sufficiently prominent to support an accurate diagnosis by the doctor and clinician, further tests such as a CT scan or coronary angiography are performed to collect additional detailed information for diagnosis. The practical clinical experience accumulated by clinician is critical for the diagnosis. The proposal aims to provide interpretable rule mining results, reveal strong connections between different segmentations or intervals on a single heartbeat, and finally assist professional clinicians in the forming of their myocardial ischemia diagnosis.

2.2. Flowchart of Fuzzy Association Rule Mining Process

Each step of the proposed fuzzy association rule mining based method is elaborated in detail. The flowchart of the proposed method is presented in **Fig. 2**.

In the training process, each individual heartbeat is extracted from a long duration ECG signal according to the attribute documents provided by PhysioNet. Then, normal and ischemia heartbeats are separated based on their annotation files, where heartbeats are labeled individually via two cardiologists working independently. Following this, the J point detection is conducted and a set of features are extracted based on the J point from each heartbeat. Fuzzy c-means clustering is applied on every feature type, to determine the parameters for the feature's corresponding membership functions. After transforming features to fuzzy itemsets, the association rule mining is performed. A set of fuzzy association rules is obtained from the last mining process. These rules have their individ-

Table 1. Feature extraction from single heartbeat.

Features	Description
ST segment deviation	80 milliseconds if heart rate does not exceeds 120 bpm or 60 milliseconds otherwise after J point
ST segment duration	The time duration of ST segment deviation
ST segment deviation area	The sum of ST segment amplitude
T wave peak	The amplitude of T wave peak
T wave area	The sum of T wave amplitude
T wave direction	The abnormality of T wave sometimes includes reverse direction

ual realistic meaning and are intended to be helpful in the ischemia diagnosis process. Finally, in the test process, these extracted rules are applied to the ECG test dataset to confirm the effectiveness and accuracy for automatic classification of ischemia and normal heartbeats.

2.3. Feature Extraction from Single Heartbeat

To acquire features from each heartbeat, noise elimination is a necessary task. In this proposal, baseline wandering, which is primarily caused by respiration and electrode impedance change due to perspiration and increased body movement, is removed using Infinite Impulse Response (IIR) high pass zero phase filtering. This is proven to be an effective algorithm for baseline wandering removal [11].

Because myocardial ischemia always causes morbid change of the ST segment and T wave, several features of these two parts are extracted. After the J point detection algorithm is applied, the following features are collected based on this key point for each single heartbeat, as indicated in **Table 1**.

As illustrated in the following figures, feature extraction in the proposed method focuses primarily on the two most significant parts: ST segment and T wave. The deviation at a certain point and the area of these two parts are extremely critical for ischemia and normal heartbeat detection. Moreover, the direction of the T wave is also obtained: it is one of the most obvious changes in an ischemia heartbeat [12]. These features, of each heartbeat, are described in **Figs. 3** and **4**.

The above features are crucial elements employed to distinguish between ischemia and normal heartbeats. The association rules in the proposal are expected to reveal strong relationships between these features allowing them to be meaningful and worthwhile for myocardial ischemia diagnosis.

2.4. Fuzzy Transformation of Heartbeat Features

Before conducting the association rule mining task, the continuous-valued features that are obtained in the last step must be segmented into intervals. In previous research, distinct discretization methods such as equal depth binning algorithm and CT-Disc algorithm are applied [13]. Instead of crisp intervals, a fuzzy c-means clustering algorithm is performed to discretize these continuous-valued features to fuzzy itemsets in the proposal, as illustrated in **Fig. 5**.

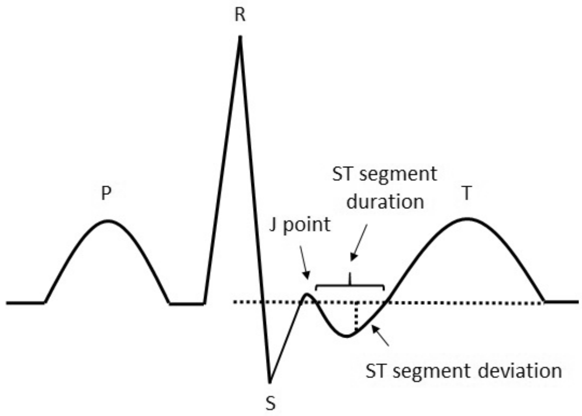

Fig. 3. Heartbeat features: ST segment part.

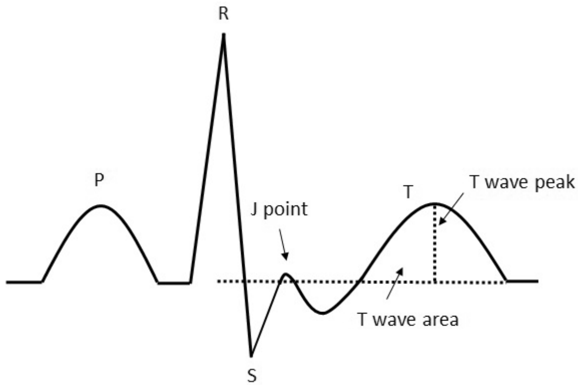

Fig. 4. Heartbeat features: T wave part.

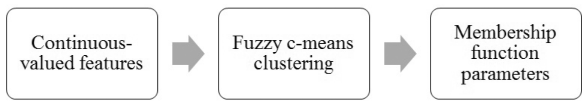

Fig. 5. Membership function construction process.

The advantage of conducting association rule mining on fuzzy itemsets instead of crisp sets is comprehensively discussed and proven in [14]. It is possible to overlook important values because of excluding values near the sharp boundary. The effect of the sharp boundary problem is that, for association rule mining, the values within an interval may not satisfy the support threshold. However, if the values near both boundaries are considered, the partition of a certain discrete interval may become meaningful. In fuzzy set theory, an element can belong to a set with membership value in $[0,1]$. For attribute x and its domain D_x, the mapping of the membership function is $f_x(x) : D_x \to [0,1]$ [14]. Fuzzy itemsets provide a smooth

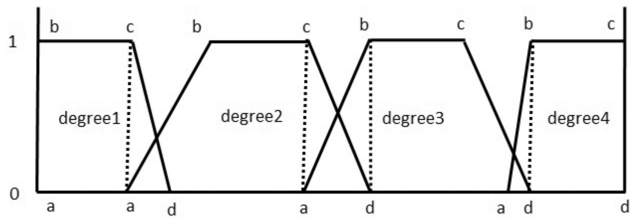

Fig. 6. Parameter setting of membership functions.

change between intervals to resolve the above problem.

In the proposal, fuzzy c-means clustering is applied to determine the membership function parameters for each extracted heartbeat feature. Fuzzy c-means clustering is widely applied in many application areas [15].

The example in **Fig. 6** is used to explain how the parameters of the membership functions are determined using fuzzy c-means clustering algorithm. In this example, each extracted feature from Section 2.3 is clustered to four categories called degree1, degree2, degree3, and degree4. Every membership function has four parameters, a, b, c, and d. The setting of these parameters for the first, the last, and the otherwise membership functions are explained individually in the following discussion. The c and d of membership function degree1 are the minimum and maximum of cluster degree1 from the results of the fuzzy c-means clustering. For the last membership function, degree4 in the above example, a and b of membership function degree4 are the minimum and maximum of cluster degree4, respectively. The degree of membership function 0 and 1 are assigned to a and b of the first membership function, d and c of the last membership function, respectively. For any other membership functions, b and c are the minimum and maximum of its corresponding cluster, whereas a is the maximum of the previous cluster and d is the minimum of the following cluster. This explanation describes the determination of the membership function parameters.

The membership function value for each extracted feature is calculated using

$$\mu(x,a,b,c,d) = \begin{cases} 0, & x \leq a, x > d \\ \dfrac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x \leq c \\ \dfrac{d-x}{d-c}, & c < x \leq d \end{cases} \quad . \quad . \quad . \quad (1)$$

2.5. Association Rule Mining on Fuzzy Itemsets

Association rule mining is a striking method for discovering interesting relations between variables in a large database. It is first proposed by R. Agrawal in [16] and is applied to supermarket sales data for determining strong relationships between different merchandises in large-scale transaction data in the retail industry [17]. The goal is to discover whether the customer who buys certain goods is likely to also buy other specific goods. This market retail analysis through association rule mining is the foundation for further business decisions, such as merchandise placement and pricing adjustments. From the business analysis area, association rule mining has expanded to numerous other application areas, including the medical and the financial fields. Let $I = \{i_1, i_2, \ldots i_m\}$ be a set of m attributes called items. Let $T = \{t_1, t_2, \ldots t_n\}$ be a set of transactions called a database. Each transaction in T contains a subset of items in I. A rule is defined in the form of $A \Rightarrow B$, where $A, B \subseteq I$ and $A \cap B = \varphi$.

Table 2. Fuzzy association rule mining steps.

Step	Actions
(1)	Transform continuous-valued data to fuzzy items via membership functions.
(2)	Calculate scalar cardinality of each fuzzy itemset, prune those support-unsatisfied candidate 1-itemsets to form large 1-itemsets. Set $r = 1$.
(3)	Generate candidate $(r+1)$-itemsets from large r-itemsets, calculate fuzzy value for every itemsets pair by using the minimum operator, calculate mean of above fuzzy value in all tuples. Put them in large $(r+1)$-itemsets if their supports are larger than the predefined minimum support.
(4)	Go to next step, if large $(r+1)$-itemsets is null; otherwise, set $r = r+1$, repeat above (3).
(5)	Calculate confidence value for every possible association rules, compare it to predefined minimum confidence value, then prune those unsatisfied ones.

Several algorithms can implement the rule mining process. In summary, there are two steps for the search of association rules: finding frequent itemsets in a database using a minimum support threshold; and calculating the confidence value for each possible rule that is formed from the acquired frequent itemsets, saving those that satisfy the confidence threshold value. Apriori algorithm, the most common mining algorithm, uses breadth-first search and a hash tree structure to count candidate itemsets efficiently, generates candidate itemsets of length k from itemsets of length $k-1$, and prunes the candidates that have an infrequent sub-pattern.

However, because of fuzzy itemsets used in the proposal, these traditional rule mining algorithms are not directly suitable. The proposed association rule mining is performed by combining the implementation of Apriori algorithm and the method proposed in [18], which processes continuous-valued data to discover association rules between fuzzy itemsets. The applied algorithm in the proposal is comprehensively discussed as follows in detail in **Table 2**.

Input: a set of continuous-valued data $T = \{t_1, t_2, \ldots t_n\}$, a set of membership functions f, a minimum support threshold value α, and a minimum confidence threshold value β.

Output: a set of fuzzy association rules with confidence values.

The results of the above algorithm are a set of fuzzy

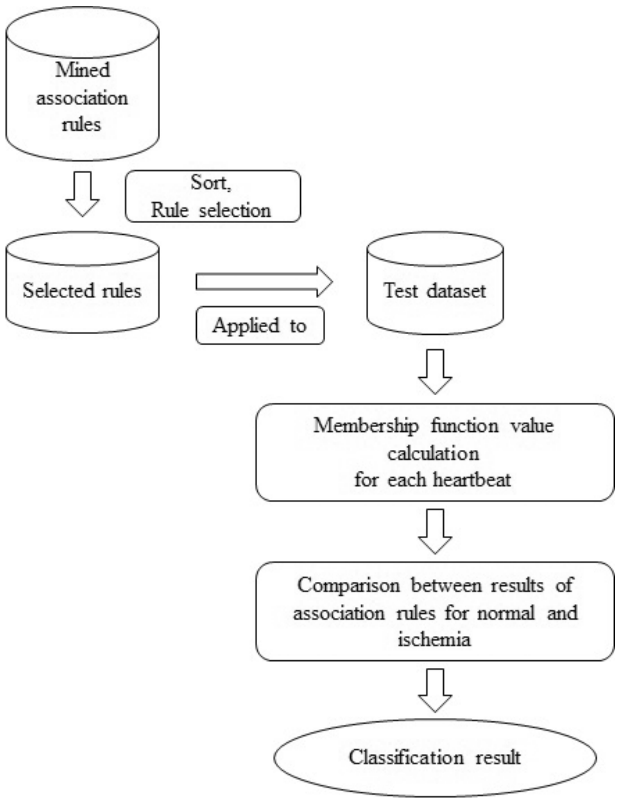

Fig. 7. Classification via fuzzy association rules process.

association rules with corresponding confidence value. The degrees that appear in the fuzzy association rules are called dominant feature degrees in the proposal. The rules for ischemia and normal heartbeat detection expect different dominant feature degrees, which means the proposed method can distinguish the significant discriminations between ischemia and normal heartbeats.

2.6. Classification of Ischemia and Normal Heartbeats

Upon completion of the fuzzy association rule mining, a validation method is proposed for the automatic classification of ischemia and normal heartbeats on the test dataset. The scheme of the validation process is presented in **Fig. 7**.

The validation process of the fuzzy association rules is different from the process for rules on crisp sets or discrete segments. For example, the methods CPAR [19] and CBA-CB [20] cannot be directly applied to the experiment. Therefore, a validation method is proposed based on these traditional algorithms. An explanation of the proposed method follows **Fig. 7**.

The fuzzy association rules obtained from Section 2.5 are sorted by their confidence values. Then, k rules with descending confidence are selected by the condition that the sum of their support is not less than 100%. These selected rules are applied to each test heartbeat data, which are previously transformed to fuzzy values via membership functions. Each test heartbeat data is calculated twice, by the set of rules for ischemia and the set of rules for normal, separately. The calculation is performed by iterating every rule and summing their fuzzy values. Subsequently, the calculation results are compared between ischemia and normal. The test heartbeat is classified to the class that "wins" the above comparison. Through the above process, each single test data is classified as either myocardial ischemia or normal.

3. Experiments on European ST-T Database

3.1. European ST-T Database

This open data source is collected for the evaluation of ischemia detection algorithms. Each record in this database is two hours in duration and contains two signals, both sampled at 250 Hz with 12-bit resolution over a nominal 20 mV input range. As an open data source, it has made a great contribution to the heart disease diagnosis research community. For each recording, there are two important data files. The "Signals" file contains the recorded physiologic signals; the "Annotations" file describes the annotation information, such as ischemic, normal, or artefact, for every individual heartbeat. The experiment data in the proposal is from the Modified Lead II (MLII) of recordings e0103, e0104, e0147, e0159, e0162, and e0206. The experiment dataset contains 39,705 beats after artefacts and other irrelevant abnormal heartbeats are eliminated according to their corresponding "Annotations" data files. 16,318 beats are used as the training dataset. Of these, 8,567 are ischemic heartbeats, while the remainder are normal heartbeats. On the other hand, there are 23,387 heartbeats in the test dataset, 6312 are ischemic heartbeats and 17,075 are normal heartbeats.

Extracted features are determined based on the explanations of the ST segment and T wave episodes from the PhysioNet website. Because ST segment deviation is the most common standard change due to myocardial ischemia, it should be the first necessary feature. This feature is measured by capturing the value 80 milliseconds after the J point if heartbeat is not larger than 120 bpm, otherwise the value 60 milliseconds after the J point is selected. The ST segment duration and ST segment area are also selected because they contains additional detailed information regarding the ST segment. For the T wave, the amplitude peak, area, and direction are measured for further evaluation because they can provide concrete information regarding the T wave change.

3.2. Fuzzy Association Rule Extraction Experiment

Before executing the rule mining, the fuzzy c-means clustering algorithm is performed on the extracted features. Each feature is clustered to eight categories in the experiment. Therefore, there are eight membership functions for every feature. In the proposal, they are named degree1 to degree8. According to the description in Section 2.4, four parameters are determined for the eight membership functions. The parameters of the ST segment deviation membership functions are presented in **Tables 3** and

Table 3. Parameters of ST segment deviation membership functions (1).

	Degree1	Degree2	Degree3	Degree4
a	−0.3151	−0.3102	0.1076	0.2231
b	−0.3151	0.0323	0.1077	0.2236
c	−0.3102	0.1076	0.2231	0.3505
d	0.0322	0.1077	0.2236	0.3507

Table 4. Parameters of ST segment deviation membership functions (2).

	Degree5	Degree6	Degree7	Degree8
a	0.3505	0.4884	0.6471	0.8010
b	0.3507	0.4892	0.6474	0.8014
c	0.4884	0.6471	0.8010	1.2667
d	0.4892	0.6474	0.8014	1.6649

4 as examples. The range of the ST segment deviation is from −0.3151 to 1.6649. The parameter settings for the other features follow the same principle.

After transforming all the experiment data using the membership functions, there are additional parameters that must be determined for the rule mining process. The settings of the predefined support and confidence value are 5% and 0.7, respectively. The parameter settings of the association rule mining experiment are presented in **Table 5**. At this point, the rule mining is performed using the algorithm elaborated in Section 2.5.

The association rule mining process produced 43 rules. Of these, 19 rules are for normal heartbeat; 24 rules are for myocardial ischemia heartbeat. Some of the extracted rules are listed in the following **Tables 6** and **7**.

As highlighted previously, these obtained fuzzy association rules based on membership functions of each feature are meaningful and understandable to a human. Moreover, they reveal a strong relationship between different significant heartbeat features. These association rules can be used as an assistant reference to accelerate the diagnosis of myocardial ischemia.

The association rule results in **Tables 6** and **7** illustrate that dominant degrees of each feature as emphasized in Section 2.5, are actually distinct from each other, meaning that the significant discriminations between normal and ischemia heartbeats are captured by the proposed fuzzy association rule mining process.

3.3. Classification Evaluation of Extracted Rules

Although association rules are applied as reference information to help the diagnosis process with speed and accuracy, a validation method to detect ischemia on test dataset using these extracted rules is necessary. In this part of experiment, the validation is conducted using the method discussed in Section 2.6. In the rule selection step, the first 14 association rules with best confidence values are selected for normal heartbeat classification, while the first 12 rules are used for myocardial ischemia heartbeat detection. The classification result is displayed in **Table 8**.

Table 5. Parameter settings of the fuzzy association rule mining experiment.

Threshold settings	
Minimum support	5%
Minimum confidence	70%
Fuzzy itemset number	8

Table 6. Association rules for normal heartbeats.

Rule	**Confidence**
ST segment deviation area is degree2 and T wave area is degree7 and T wave peak is degree6	92.97%
ST segment deviation area is degree2 and T wave peak is degree6	91.33%
ST segment duration is degree7 and ST segment deviation area is degree2	87.91%
T wave area is degree7 and ST segment duration is degree7 and ST segment deviation area is degree2	86.92%

Table 7. Association rules for ischemia heartbeats.

Rule	**Confidence**
ST segment deviation area is degree6 and ST segment deviation is degree7	96.61%
ST segment deviation area is degree6 and T wave peak is degree7	95.40%
ST segment deviation is degree7 and ST segment duration is degree3 and T wave peak is degree7	95.22%
ST segment deviation is degree7 and T wave area is degree4 and T wave peak is degree7	94.82%
ST segment duration is degree3 and T wave area is degree4 and T wave peak is degree7	92.51%

Table 8. Classification results using fuzzy association rules.

	Classified as normal	Classified as ischemia	Total
Normal	13,777	3,298	17,075
Ischemia	1,046	5,266	6,312

There are 23,387 heartbeats in the test dataset, in which there are 6,312 ischemia heartbeats and 17,075 normal heartbeats. In the classification experiment, 13,777 normal heartbeats are correctly detected as normal. On the other hand, 5,266 heartbeats are accurately classified as myocardial ischemia heartbeats. The sensitivity and specificity of the ischemia and normal classification are 83.4% and 80.7%, respectively.

3.4. Discussions Regarding Interpretability of the Mined Fuzzy Association Rules

The rule mining experiment confirms that the fuzzy association rules from the experiment are sufficiently clear and meaningful to assist doctors with ischemia diagnosis. It should also be mentioned that, according to the extracted rules, it is helpful for doctors to be informed of the background knowledge regarding the feature segmentation in the proposal.

From the association rule extraction results, it can be observed that the dominant feature degrees in the rules for ischemia and normal are considerably different. This confirms that the extracted rules are able to classify ischemia based on these distinct, meaningful rule elements and convincingly validates the classification process with the extracted rules. As expected, the validation results demonstrate the competitiveness and efficiency of the proposed method.

In addition to myocardial ischemia, there are other severe, threatening heart diseases. The diagnosis of these continues to rely upon doctors' practical experience, similar to the existing situation with ischemia. Because interpretable and understandable results can facilitate the diagnosis process, an objective of the proposal is to expand to other heart disease diagnosis areas.

4. Conclusion

In the fuzzy association rule mining experiment, a fuzzy c-means clustering algorithm is first performed on the extracted heartbeat features such as ST segment deviation and T wave peak, individually. Each of these features is clustered to eight categories named degree1 to degree8. Membership function parameters are determined based on these fuzzy c-means clustering results. Then, the experiment data are transformed to fuzzy values via these membership functions. Afterwards, a rule mining algorithm is executed to obtain fuzzy association rules. This rule mining algorithm is based on the implementation of Apriori algorithm and the proposal in [18]. In the rule mining experiment, the minimum confidence threshold is set at 0.7. The mining process successfully extracted 43 rules. Of these rules, 19 rules are for the normal heartbeats; 24 rules are for ischemia heartbeats. These association rules are first sorted by confidence value in the validation process. Then, several rules with descending confidence value are selected based on the condition that the sum of their support value is not less than 1. Afterwards, for each test heartbeat, the sums of the membership function values of both the sets, ischemia and normal rules, are calculated. Based on the comparison between ischemia and normal, the test heartbeat is classified to one of these two classes. 6,312 ischemia heartbeats and 17,075 normal heartbeats are used to validate the effectiveness of the automatic ischemia classification using association rules. The sensitivity and specificity of the ischemia and normal classification are 83.4% and 80.7%, respectively.

In the proposal, the focus is on mining association rules on fuzzy itemsets. The characteristics of the association rule mining based method ensures that the results of the proposal are meaningful and useful. The high interpretability of these mined rules is actually beneficial to the acceleration of an ischemia diagnosis. Compared to other discretization methods, the proposed method of using fuzzy c-means clustering before the rule mining task can produce more practical and feasible segmentation results. The classification results of the automatic ischemia detection using association rules confirms the effectiveness of the proposed method.

Although numerous algorithms and methods for heart disease detection on ECG signals have been proposed, the actual diagnosis of heart diseases such as myocardial ischemia cannot rely solely on these methods. The practical experience of a doctor is necessary for a final heart disease diagnosis. The proposed fuzzy association rule mining based method provides helpful information and can be adopted as a reliable medium to assist a heart disease diagnosis. The advantages and practicality demonstrate the competitiveness of the proposal and will lead to its implementation in other cardiovascular disease diagnosis fields. The proposed method aims to be a useful tool to accelerate the diagnosis of myocardial ischemia on ECG signals, and also to be applied to other heart disease diagnosis areas.

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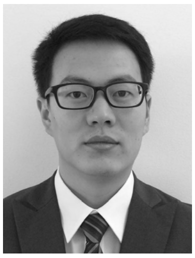

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