A COMPARISON OF SIMILARITY MEASURES FOR CLUSTERING OF QRS COMPLEXES

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ABSTRACT

Similarity or distance measures play important role in the performance of algorithms for ECG clustering problems. This paper compares four similarity measures such as the city block (L_1 -norm), Euclidean (L_2 -norm), normalized correlation coefficient, and simplified grey relational grade for clustering of QRS complexes. Performances of the measures include classification accuracy, threshold value selection, noise robustness, execution time, and the capability of automated selection of templates. The clustering algorithm used is the so-called two-step unsupervised method. The best out of the 10 independent runs of the clustering algorithm with randomly selected initial template beat for each run is used to compare the performances of each similarity measure. To investigate the capability of automated selection of templates for ECG classification algorithms, we use the cluster centers generated by the clustering algorithm with various measures as templates. Four sets of templates are obtained, each set for a measure. And the four sets of templates are used in the k-nearest neighbor classification method to evaluate the performance of the templates. Tested with MIT/BIH arrhythmia data, we observe that the simplified grey relational grade outperforms the other measures in classification accuracy, threshold value selection, noise robustness, and the capability of automated selection of templates.

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1. INTRODUCTION

The electrocardiogram (ECG) is the record of variation of bioelectric potential with respect to time as the human heartbeats. Due to the ease of recording ECG in a noninvasive manner, ECG plays an important role in patient monitoring and diagnosis today. Visual analysis of long term ECG is tedious since a large

amount of data may be obtained in the case of monitoring ECG signals of a patient continuously during 24 hours. In this case, typically, there could be more than 100 thousands heartbeats generated a day for analysis. Computer-based methods for analysis and interpretation of ECGs have been developed in order to overcome this difficulty. However, classification or clustering of the ECG is a difficult problem even with the aid of a computer, since ECGs differ significantly even for the same type and for the same patient. Due to the importance of the problem, a lot of efforts and methodological studies have been reported on this subject.

Generally speaking, in classification algorithms

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for the ECG, a similarity measure is used to measure the distances between the query beat and the templates in the database, or adjustable weights in the artificial neural network used, for ranking. The smaller the distance is, the more similar the template or the adjustable weight is to the query. Then, a threshold value on the measurements is used for the help with the decision-making. It is known that the distance or similarity measure used in a clustering or classification algorithm will have large effect on the performance of the classification procedure. In [1], performance of several similarity measures in four types of clustering algorithms was investigated on the practical medical data set containing both numerical and categorical of attributes. In [2], nine image similarity measures were compared for texture image retrieval. In this paper, we compare similarity measures for clustering of the QRS complexes.

Distance measures widely used in the time domain ECG classification algorithms include the L_1 -norm (city block) [4], L_2 -norm (Euclidean distance) [3,5] normalized cross correlation [6], likelihood function [7], and Mahalanobis distance [8]. In Mahalanobis distance, the covariance matrices can be hard to determine accurately, and the memory and the time requirements grow quadratically rather than linearly with the number of features. These problems may be insignificant when only a few features of the ECG are needed, but they become quite serious when the number of features becomes large. A likelihood function is usually used in an algorithm such as a linear discriminant, where the likelihood function of the data is maximized with respect to the parameters of the model. The model is of suitable functional form with parameters to be adjusted so that it approximates the distribution of the data. The computational load of this approach is very high.

The grey relational grade [9] is also a distance measure whose value is within the interval (0, 1]. For a given reference sequence and a given set of comparative sequences, grey relational analysis [9] can be used to determine the grey relational grade between the reference and each comparative sequence in the given set. Then the best comparative sequence is the one having the largest grey relational grade. Recently, an unsupervised algorithm has been developed by using a modified grey relational grade as the distance measure for data clustering and showed that it could achieve a good performance [10]. The original grey relational grade is simplified for the reduction of computation, in this paper.

In this paper, we compare performances of four similarity measures, namely, the L_1 -norm, the L_2 -norm, the normalized cross correlation, and the simplified grey relational grade, that are relatively simple in computation. Performances of the measures include

classification accuracy, threshold value selection, noise robustness, execution time, and the capability of automated selection of templates. The four similarity measures are compared in a clustering algorithm for clustering the ECG. The clustering algorithm used in this paper is the so-called two-step unsupervised method [6], which was reported to have a better performance than the hierarchical cluster analysis approach. It is known that the initial template beat may affect the performance of clustering algorithms. To avoid this, the best out of the 10 independent runs of the clustering algorithm with randomly selected initial template beat for each run is used to compare the performances of each similarity measure. For each run, the threshold values used for the decision-making are selected to make the algorithm have the best result.

The resulting cluster centers of the clustering algorithm can be used as templates representing that cluster. In this viewpoint, the cluster centers may have the potential to be templates that can be used in algorithms for real time classification of the ECG. To investigate the capability of automated selection of templates of the measures for ECG classification algorithms, we use the cluster centers generated by the clustering algorithm with each of the four measures as templates. Four sets of templates are obtained, each set for a measure. And the four sets of templates are used in the k-nearest neighbor classification method to evaluate the performance of the templates.

The remainder of this paper is organized as follows. The simplified grey relational grade is developed in Section 2. Section 3 describes the ECG data and the methods used. Experimental results are shown in Section 4. Finally, some conclusions are given in Section 5.

2. SIMPLIFIED GREY RELATIONAL GRADE AND THE OTHER MEASURES

In this section, we introduce the grey relational grade developed in [9] and simplify it for our purpose. Denote $y = \langle y(1), y(2), \dots, y(n) \rangle$ as the reference sequence, and $x_i = \langle x_i(1), x_i(2), \dots, x_i(n) \rangle$, $i=1,2,\dots,m$, as the comparative sequences. Define the grey relational coefficient between y and x_i at the k -th datum as [9]

$$r(y(k), x_i(k)) = \frac{\Delta_{\min} + \xi \cdot \Delta_{\max}}{\Delta_i(k) + \xi \cdot \Delta_{\max}} \quad (1a)$$

where $\Delta_i(k) = |y(k) - x_i(k)|$, $\Delta_{\max} = \max_i \max_k \Delta_i(k)$, $\Delta_{\min} = \min_i \min_k \Delta_i(k)$, $k=1,2,\dots,n$, and $\xi \in (0,1]$ is the distinguishing coefficient controlling the resolution between $\Delta_{\max}$ and $\Delta_{\min}$. The weighted average of the

grey relational coefficients, termed by the grey relational grade, can be computed by

$$g(y, x_i) = \sum_{k=1}^n [w(k) \cdot r(y(k), x_i(k))] \quad (2)$$

where $w(k) \geq 0$ is the weighting function with $\sum_{k=1}^n w(k) = 1$. The weighting function can be seen as a window that can be used to emphasize a segment of ECG signal such as P wave. In this paper, we deal only with QRS complex classification problem, and we select the weighting function as $w(k) = 1/n$ for all k . From (1a) and (2), it can be seen that $0 < g(y, x_i) \leq 1$ and that the smaller the absolute value $\Delta_i(k)$, the larger the grey relational grade, and vice versa. The best comparative sequence is the one with the largest grey relational grade to the reference. Hence, the grey relational grade can be used as a distance measure.

The main difficulty of using (1a) is it needs to determine two control factors, $\Delta_{\max}$ and $\Delta_{\min}$. These two control factors may vary as a new reference sequence is presented to a fixed set of comparative sequences. In this case, the analytical process must be done all over again in order to calculate $\Delta_{\max}$ and $\Delta_{\min}$ and to obtain the newly best comparative one. It seems inefficient for a real-time ECG analysis. Therefore, we propose an approach in the following for simplifying the computation. From the definition of $\Delta_{\min}$, we observe that if we define a temporary set by adding the reference into original set of comparative sequences then $\Delta_{\min} = 0$ for the temporary set of comparative sequences to the reference. By doing this, the best comparative sequence in the temporary set to the reference is always the reference itself. However, it was pointed out that adding a new comparative sequence might change the values of the grey relational grade of original comparative sequences, but it did not change their relative rank [9]. Therefore, for any reference sequence, we can always let $\Delta_{\min} = 0$ then the best comparative sequence in the original set is the one having the largest grey relational grade except the reference itself in the temporary set, and it is the same one having the largest grey relational grade in the original set.

Now, the problem of finding the best comparative sequence by using (1a) and (2) is reformulated as finding the best comparative sequence by using (1b) in the below and (2).

$$r(y(k), x_i(k)) = \frac{\xi \cdot \Delta_{\max}}{\Delta_i(k) + \xi \cdot \Delta_{\max}} \quad (1b)$$

Inspiring of the dependence of the value of $\Delta_{\max}$ to the reference sequence, we replace (1b) with the one in the following.

$$r(y(k), x_i(k)) = \frac{d_{\max}}{\Delta_i(k) + d_{\max}} \quad (1c)$$

where $d_{\max}$ is a positive real constant. If we use (1c) and (2) as the similarity measure for ranking the comparative sequences, the result will be the same as that obtained by using (1b) and (2). By this way, the best comparative sequence can be found by using (1c) and (2). The grade obtained by (1c) and (2) is called the simplified grey relational grade, denoted by d_{sg} , in this paper. The range of the simplified grey relational grade is still in the interval (0, 1). Note that, for a specific sequence in the comparative set, its simplified grey relational grade value and its grey relational grade value obtained by (1a) and (2) may be different, but the rank of the sequence in that set is always the same by using either of the three measures.

The other measures used in this paper are summarized in the following. Denote the city block or L_1 distance of two sequences x and y by

$$d_{L1}(y, x) = \sum_{k=1}^n |y(k) - x(k)| \quad (3)$$

The Euclidean distance or L_2 distance is defined by

$$d_{L2}(y, x) = \sqrt{\sum_{k=1}^n (y(k) - x(k))^2} \quad (4)$$

The Euclidean distance is not always the best measure. The fact that the distances in each element of the sequences are squared before summation places great emphasis on those elements for which the dissimilarity is large. Finally, the normalized cross correlation is defined by

$$d_{cc}(y, x) = \frac{\sum_{k=1}^n (y(k) - \bar{y})(x(k) - \bar{x})}{\sqrt{\sum_{k=1}^n (y(k) - \bar{y})^2 \sum_{k=1}^n (x(k) - \bar{x})^2}} \quad (5)$$

where

$$\bar{y} = \frac{1}{n} \sum_{k=1}^n y(k) \quad \bar{x} = \frac{1}{n} \sum_{k=1}^n x(k)$$

A distance function with a wide range may cause a problem in the selection of the threshold value for decision-making when it is used in a clustering algorithm. From the definition of each distance function, we see that $d_{L1} \in [0, \infty)$, $d_{L2} \in [0, \infty)$, $d_{cc} \in [-1, 1]$,

and $d_{sg} \in (0, 1]$. For the easy selection of the threshold value, d_{L1} and d_{L2} are usually normalized, and the absolute value of d_{cc} is used in clustering algorithms. Let the normalized d_{L1} and d_{L2} be denoted by $\hat{d}_{L1}$ and $\hat{d}_{L2}$, respectively. Finally, define the similarity measure for each distance function as

$$s_{L1} = 1 - \hat{d}_{L1} \quad (6)$$

$$s_{L2} = 1 - \hat{d}_{L2} \quad (7)$$

$$s_{cc} = |d_{cc}| \quad (8)$$

$$s_{sg} = d_{sg} \quad (9)$$

From these definitions, we see that all similarity measures lay within the range $[0, 1]$ except $s_{sg} \in (0, 1]$ and that, for all similarity measures, the larger the measurement of two sequences, the more similar of the two sequences.

3. MATERIAL AND METHOD

The MIT/BIH Arrhythmia Database [11], sampled at 360 Hz with 11-bit resolution, was used in this study. Excluding records containing paced beats (102, 104, 107, and 217), we used the other 44 records of the MIT/BIH Database. Raw data from single channel (channel 1) were used (with some beats missing). The size of each QRS complex was 73 samples (about 200 ms) with the R wave at the center. This study did not investigate the problem of QRS detection from the ECG, instead the position of annotation labels provided with the MIT/BIH Database was used to identify the R wave. The AAMI recommended practice [12] was used to combine the MIT/BIH beat types into four classes. Class N contains normal, bundle branch block, and supraventricular ectopic beats, class V contains ventricular ectopic beats, class F contains fusion of ventricular and normal beats, and class Q contains unclassifiable beats. The detail is listed in Table I.

Without feature extraction, the QRS morphology with 73 samples was used in this study. To test the robustness of the similarity measures to high frequency noise and power line interference, we did not use any data-preprocessing step such as filtering in this study. However, the mean value was subtracted from each beat to remove the baseline wander [3].

The so-called two-step clustering algorithm used in this study was suggested in [6]. The algorithm takes the first beat of the ECG as the template and compares it to all successive beats by one of the similarity measures (6)-(9). The beats showing certain degree of

similarity are put together to form a cluster. By this we mean that if the measurement exceeds a threshold value, the compared beat belongs to the same cluster as the template. If no measurement exceeds the threshold value, the template itself forms a cluster. When all successive beats have been compared, the first beat of the residual QRS complexes is taken as a new template, and it is used to iterate the whole procedure until no QRS complex is left unclassified. In the second step of the algorithm, the clusters are merged by the same way used in the first step. However, in this step, we use the cluster center to represent the cluster and select a slightly lower threshold value than that used in step one. Finally, all beats in one-element clusters are collected in a signal cluster, and they are assigned as unclassifiable beats (class Q).

The two-step clustering algorithm described in the above was used to evaluate performances of the four similarity measures (6)-(9). For a fair comparison, we used the best result of each measure for comparing the performances of each measure. As mentioned before, the performances include the accuracy, the execution time, the variation of threshold for the best result for each record, and the noise robustness. In addition, we evaluated the capability of the measures for the automated selection of templates from an existing ECG recording of a specific patient for designing a customized ECG classifier for that patient [3]. The two-step clustering algorithm is designed for analyzing existing long term ECG recordings that may be obtained by a Holter type monitor, and it is not for real time analysis. When real time analysis is needed, we may use the clustering algorithm to analyze the previous recorded ECG of the patient, select templates from each resulting cluster automatically, recognize the templates by an expert, and use the templates in some classification algorithms for real time analysis such as the k -nearest neighbors method described in the below. This approach could be used to design a customized real time ECG classifier. By this way, only a few

Table I . Mapping the MIT/BIH database beat types to the AAMI beat classes

Description	MIT label	Test label
Normal beat	1	N
Left bundle branch block beat	2	N
Right bundle branch block beat	3	N
Bundle branch block beat (unspecified)	25	N
Nodal (junctional) premature beat	7	N
Atrial premature beat	8	N
Supraventricular premature beat	9	N
Aberrated atrial premature beat	4	N
Nodal (junctional) escape beat	11	N
Atrial escape beat	34	N
Ventricular premature beat	5	V
R-on-T ventricular premature beat	41	V
Ventricular escape beat	10	V
Fusion of ventricular and normal beat	6	F
Unclassifiable beat	13	Q
Others	Other	Q

templates need to be recognized manually. Instead of the resulting cluster center, the ECG beat nearest to the cluster center was selected as the template. For simplicity, only the measure with the best performance in the two-step algorithm was used in the classification algorithm.

The customized ECG classifier was implemented based on the k -nearest neighbors method. In the k -nearest neighbors algorithm, by the measure used, the query is compared to templates representing classes or types of the QRS (the class Q had no templates for it). Then, the similarity measurements are ranked, and the largest measurement exceeding a pre-defined threshold value indicates to which class the query belongs. When no measurement exceeds the threshold value, class Q is assigned to the query.

4. EXPERIMENTAL RESULT

All programs coded by Matlab® version R12 were executed by a personal computer with Intel® Pentium® 4 1.6 GHz processor and 512 MB RAM. In the two-step clustering algorithm, different initial templates may result in different performances. To have a fair comparison, we randomly selected 10 ECG beats from each test record as the initial templates for that record. Then, for each record, we used 10 runs, one initial template for a run, to evaluate the performances of each of the 4 similarity measures. By this way, each similarity measure was evaluated 10 times independently under the same clustering method with the same initial template for every test record. Then, for each measure, the best result of the 10 runs was selected for the comparison. In each run, the threshold value used in the first step of the algorithm was selected to make the algorithm have the best performance in accuracy, and in the second step it was selected to minimize the resulting number of clusters while keeping the accuracy obtained by the first step.

In respect to the performance in accuracy, the best clustering result of such a 10 runs for each measure for each of the selected MIT/BIH ECG record is listed in Table II. Table II shows that, over total 101,374 test ECG beats, S_{L1} , S_{L2} , S_{cc} , and S_{sg} achieve 99.46%, 99.38%, 99.66%, and 99.68% in accuracy, respectively. The simplified grey relational grade outperforms the other similarity measure functions in classification accuracy. Table III contains the details of the best result obtained by using S_{sg} for each record.

Table II also shows that the performance in accuracy of each measure on noisy records. Over 62,710 beats in 27 noisy records, S_{L1} , S_{L2} , S_{cc} , and S_{sg} achieve 99.50%, 99.46%, 99.82%, and 99.83% in accuracy, respectively. The simplified grey relational grade has the best performance in accuracy on noisy

records. It seems that all measures perform better on noisy records than clean records. This is because all of the worst cases of the measures appear on record 213 that is labeled clean. Excluding record 213, all measures perform better on clean records as shown in Table II.

Fig. 1 shows the variation of the threshold value used in the first step of the algorithm. Note that the threshold value reported is the minimum value for achieving the best performance in accuracy. For values larger than the minimum value, the accuracy can also be achieved but with a larger number of resulting clusters in this step. Though the resulting clusters in the first step will be merged in the second step of the algorithm, a larger number of clusters cause a more computational load in the second step. This figure depicts that, for different records, the minimal threshold value required for the simplified grey relational grade achieving the best result is relatively stable, comparing with the other measures. This is a particularly useful feature since we need not spend much time to decide the threshold, in practice, for analyzing various ECG recordings. The threshold in the second step of the algorithm is used to minimize the number of clusters by merging them. No significant difference in the number of final resulting clusters was observed for different measures. Once, the threshold values for the first and the second steps were decided for every record, we ran the program again with the fixed threshold values to examine the execution time for each measure. The result is also listed in Table II. From Table II, it is seen that, over 101,374 test beats, the clustering algorithm with the L_1 function takes the least time (35.73 sec.). The computational load caused by the additional procedure for normalizing the L_1 or the L_2 function seems that it can be negligible.

In a final cluster obtained by the clustering algorithm, the ECG beat being nearest to the cluster center was selected as the template for the k -nearest neighbors classification method to investigate the

Fig 1. The variation of the thresholds used in the first step of the clustering algorithm.

Table II . Results of ECG beats clustering using various measures on 44 MIT/BIH ECG data files

Record	No. of beats	Accuracy (%)				Noisy
		s_{L1}	s_{L2}	s_{cc}	s_{sg}	
100	2271	100	100	100	100	
101	1864	100	100	100	100	Y
103	2084	100	100	100	100	Y
105	2572	98.60	99.61	99.96	99.73	Y
106	2027	98.67	96.35	100	99.95	
108	1773	99.38	99.89	99.94	99.89	Y
109	2531	100	99.96	100	100	
111	2124	100	100	100	100	Y
112	2539	100	100	100	100	Y
113	1794	100	100	100	100	
114	1879	100	99.89	99.89	99.84	Y
115	1952	100	100	100	100	Y
116	2411	99.96	99.96	100	99.96	
117	1534	100	100	100	100	Y
118	2287	99.78	99.96	99.96	99.96	Y
119	1987	100	100	100	100	
121	1863	100	100	100	100	Y
122	2476	100	100	100	100	
123	1517	100	100	100	100	
124	1619	99.94	99.82	100	100	
200	2600	99.69	99.35	99.92	99.92	Y
201	2000	99.55	99.50	100	100	Y
202	2136	100	100	100	100	
203	2980	97.68	98.05	99.66	99.66	Y
205	2656	99.74	99.81	99.70	99.74	
207	2331	97.43	94.21	99.96	99.96	Y
208	2953	97.97	97.56	97.53	98.04	Y
209	3004	100	100	100	100	
210	2650	99.58	99.77	99.93	99.55	Y
212	2747	100	100	100	100	Y
213	3250	95.94	95.54	95.02	95.54	
214	2260	98.85	99.87	99.74	99.87	Y
215	3363	100	100	100	100	Y
219	2287	97.60	97.60	97.51	97.55	
220	2047	100	100	100	100	
221	2427	99.67	99.51	100	100	Y
222	2482	100	100	100	100	Y
223	2605	99.54	99.62	99.54	99.62	Y
228	2053	99.95	99.95	100	100	Y
230	2255	100	100	100	100	Y
231	1573	99.94	99.94	100	100	
232	1780	100	100	100	100	Y
233	3078	99.77	99.81	99.84	99.84	
234	2753	100	100	100	100	Y
Total	101374	99.46	99.38	99.66	99.68	
Beats in noisy records	62710	99.50	99.46	99.82	99.83	
Beats in clean records	38664	99.40	99.25	99.40	99.44	
Beats in clean records excluding 213	35415	99.72	99.59	99.80	99.80	
Execution time (sec)		35.73	38.06	50.05	41.50	

capability of the measures for the automated selection of templates. For each record, there were four sets of templates, each for a measure. For simplicity, only the set of templates generated by using the simplified grey relational grade is reported in Table IV. Note that there are no templates for class Q in Table IV.

The measurement of the L_1 or the L_2 distance function needs to be normalized over all measurements before comparing with the threshold for assigning the query to class Q. Therefore, the two distance functions are inadequately to be measures in real time classification algorithms. On the other hand, the normalized correlation coefficient function performed

Table III . Details of the clustering result using the simplified gray relation grade

Record	Number of beats					Clustering results (true positive)				
	N	V	F	Q	Sum	N	V	F	Q	Acc (%)
100	2270	1			2271	2270	1			100
101	1862			2	1864	1862			2	100
103	2084				2084	2084				100
105	2526	41		5	2572	2523	40		2	99.73
106	1507	520			2027	1507	519			99.95
108	1744	16	2	11	1773	1744	16	1	10	99.49
109	2491	38	2		2531	2491	38	2		100
111	2123	1			2124	2123	1			100
112	2539				2539	2539				100
113	1794				1794	1794				100
114	1832	43	4		1879	1832	43	1		99.84
115	1952				1952	1952				100
116	2302	109			2411	2302	108			99.96
117	1534				1534	1534				100
118	2261	16		10	2287	2261	16		9	99.96
119	1543	444			1987	1543	444			100
121	1862	1			1863	1862	1			100
122	2476				2476	2476				100
123	1514	3			1517	1514	3			100
124	1567	47	5		1619	1567	47	5		99.81
200	1772	826	2		2600	1772	825	1		99.19
201	1763	198	2	37	2000	1763	198	2	37	99.7
202	2116	19	1		2136	2116	19	1		99.95
203	2531	444	1	4	2980	2531	435	1	3	98.59
205	2574	71	11		2656	2574	71	4		99.74
207	1649	682			2331	1649	681			99.28
208	1587	992	372	2	2953	1577	970	347	1	98.04
209	3003	1			3004	3004	1			100
210	2445	195	10		2650	2443	193	2		99.55
212	2747				2747	2747				100
213	2668	220	362		3250	2665	198	242		95.54
214	2001	256	1	2	2260	2001	253			99.73
215	3198	164	1		3363	3196	164	1		99.85
219	2089	64	1	133	2287	2089	62	1	79	97.55
220	2047				2047	2047				100
221	2031	396			2427	2031	396			100
222	2482				2482	2482				100
223	2118	473	14		2605	2115	453	1		98.62
228	1691	362			2053	1691	360			99.90
230	2254	1			2255	2254	1			100
231	1569	2		2	1573	1569	2		2	100
232	1780				1780	1780				100
233	2236	831	11		3078	2236	831	6		99.68
234	2750	3			2753	2750	3			100

Table IV . Templates for ECG beats classification

Record	No. of templates	Record	No. of templates	Record	No. of templates
100	1N1V	119	1N2V	213	4N6V5F
101	1N	121	2N1V	214	3N9V
103	2N	122	4N	215	4N5V
105	18N4V	123	1N1V	219	7N5V
106	2N9V	124	2N6V2F	220	2N
108	17N10V1F	200	4N18V1F	221	2N5V
109	6N4V1F	201	6N4V2F	222	2N
111	1N1V	202	10N3V1F	223	6N17V1F
112	3N	203	19N20V1F	228	5N6V
113	2N	205	2N4V2F	230	1N1V
114	3N3V1F	207	8N24V	231	1N2V
115	1N	208	11N13V8F	232	3N
116	4N2V	209	2N1V	233	4N13V3F
117	3N	210	7N14V3F	234	3N1V
118	6N4V	212	3N		

worse than the simplified grey relational grade in accuracy, the selection of thresholds, noise robustness, and the execution time. As a consequence, the only similarity measure used in the k -nearest neighbors classification algorithm was the simplified grey relational grade. The threshold value used for the

classification was 0.85 for all test records.

Table V contains the classification results of the k -nearest neighbors method with the four sets of templates. Over total 101,374 test ECG beats, the sets of templates generated by using S_{L1} , S_{L2} , S_{CC} , and S_{SG} in the clustering algorithm achieve 99.53%, 99.53%, 99.40%, and 99.61% in classification accuracy, respectively. The set of templates generated by using the simplified grey relational grade achieves the best classification accuracy.

5. CONCLUSION

In this paper, the performances of four similarity measures used in the so-called two-step clustering algorithm for ECG complexes have been investigated. The performances included the classification accuracy, the selection of thresholds, the execution time, noise

robustness, and the capability of the automated selection of templates. It is found that the simplified grey relational grade outperforms the other measures in classification accuracy, noise robustness, the selection of thresholds, and the capability of the automated selection of templates. And the best measure in the execution time is the L_1 distance function.

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REFERENCE

1. Hirano S, Sun X, and Tsumoto S: On similarity measures for cluster analysis in clinical laboratory examination database, in Proc. 2002 IEEE 26th Ann. Int. Computer Software and Applications Conf. 2002; 1170-1175.
2. Kokare M, Chatterji BN, and Biswas PK: Comparison of similarity metrics for texture image retrieval, in Proc. 2003 IEEE Conf. on Convergent Technologies for Asia-Pacific Region 2002; 2: 15-17.
3. Hu YH, Palreddy S, and Tompkins WJ: A patient-adaptable ECG beat classifier using a mixture of experts approach, IEEE Trans. Biomed. Eng. 1997; 44: 891-900.
4. Rappaport SH, Gillick L, Moody G.B, and Mark RG: QRS morphology classification: Quantitative evaluation of different strategies, Computers in Cardiology 1982; 33-36.
5. Lagerholm M., Peterson C, Braccini G, Edenbrandt L, and Sornmo L: Clustering ECG complexes using Hermite functions and self-organizing maps, IEEE Trans. Biomed. Eng. 2000; 47: 838-848.
6. Maier C, Dickhaus H, and Gittinger J: Unsupervised morphological classification of QRS complexes, Computers in Cardiology 1999; 683-686.
7. De Chazzal P, O'dwyer M, and Reilly RB: Automatic classification of heartbeats using ECG morphology and heartbeat interval features, IEEE Trans. Biomed. Eng. 2004; 51: 1196-1206.
8. Moraes JCTB, Seixas MO, Vilani FN, and Costa EV: A real time QRS complex classification method using Mahalanobis distance, Computers in Cardiology; 2002: 201-204.
9. Deng JL: Introduction to grey system theory, J. Grey Syst. 1989; 1: 1-24.
10. Chank KC. and Yeh MF: Grey relational analysis

Table V . Results of ECG beats classification using various sets of templates

Record	No. of beats	Accuracy (%)			
		T_{L1}	T_{L2}	T_{CC}	T_{SG}
100	2271	100	100	100	100
101	1864	99.95	99.95	99.95	99.95
103	2084	100	100	99.95	100
105	2572	99.73	99.77	99.69	99.77
106	2027	100	100	100	100
108	1773	99.15	99.38	98.87	99.32
109	2531	100	100	100	100
111	2124	100	100	100	100
112	2539	100	100	100	100
113	1794	100	100	100	100
114	1879	100	100	99.89	99.89
115	1952	100	100	100	100
116	2411	99.96	99.96	99.96	99.96
117	1534	100	100	100	100
118	2287	99.56	99.61	99.56	99.96
119	1987	100	100	100	100
121	1863	100	100	100	100
122	2476	100	100	100	100
123	1517	100	100	100	100
124	1619	99.94	99.94	99.88	99.81
200	2600	99.77	99.73	99.73	99.65
201	2000	98.15	98.15	98.15	99.95
202	2136	100	100	100	100
203	2980	98.49	98.49	98.42	98.69
205	2656	99.77	99.81	99.74	99.74
207	2331	99.40	99.40	98.07	99.36
208	2953	98.34	98.07	97.93	98.17
209	3004	100	100	100	100
210	2650	99.62	99.77	99.81	99.55
212	2747	100	100	100	100
213	3250	96.43	96.40	96.31	96.15
214	2260	99.78	99.87	99.69	99.65
215	3363	100	100	99.97	99.94
219	2287	94.18	94.18	94.62	97.55
220	2047	100	100	100	100
221	2427	100	100	100	100
222	2482	100	100	100	100
223	2605	99.54	99.54	96.93	99.04
228	2053	99.95	99.95	99.81	99.90
230	2255	100	100	100	100
231	1573	99.87	99.87	100	100
232	1780	100	100	100	100
233	3078	99.81	99.84	99.64	99.68
234	2753	100	100	100	100
Total	101374	99.53	99.53	99.40	99.61

- based approach for data clustering, IEE Proc. Vis. Image Signal Process. 2005; 152: 165-172.
11. MIT/BIH database distributor, Beth Israel Hospital, Biomedical Engineering, Division available in the address: <http://ecg.mit.edu/>, USA, 1979.
 12. Recommended Practice for Testing and Reporting Performance Results of Ventricular Arrhythmia Detection Algorithms, Association for the Advancement of Medical Instrumentation, 1987.