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DLCSS: A new similarity measure for time series data mining

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ABSTRACT

The Longest Common Subsequence (LCSS) is considered as a classic problem in computer science. In most studies related to time series data mining, LCSS had been mentioned as the best and the most usable similarity measurement method. The results of time series data mining under LCSS strongly depend on the similarity threshold, because the similarity measurement approach in LCSS is a zero–one approach. Since there is no knowledge about the data, and it is very difficult to determine the right amount of similarity threshold, using LCSS can actually lead to poor results. In this research, a new similarity measurement method named Developed Longest Common Subsequence (DLCSS) has been suggested for time series data mining based on LCSS. In DLCSS, by defining two similarity thresholds and determining their values, LCSS' shortcoming was eliminated. The performance of DLCSS was compared with performance of LCSS and Dynamic Time Warping (DTW) using 1-Nearest neighbor and k-medoids clustering techniques. This evaluation was carried out on 63 time series datasets of UCR collection. Using these results, it could be claimed that the 1-NN accuracy and clustering accuracy under DLCSS is better than that of under LCSS and DTW with at least 99.5% and 99% confidence, respectively. Also, DLCSS has better effect in correctly predicting the number of clusters compared to LCSS and DTW. In addition, the effect of DLCSS in determining the better cluster representatives is greater than that of under LCSS and DTW with at least 99.95% confidence.

1. Introduction

A time series is a sequence of numbers that represent the time characteristics of an event at any point in time (Morris and Trivedi, 2009). It exists in all areas, for example in medicine (the heart rate data, the intensity breathing data and the neurotoxicity of the brain for a period of time), in meteorology (the daily temperature and humidity of a location), in sales (daily, weekly, monthly or annual sales) and in other different areas. It has three important features. (i) High-dimension. A time series can include hundreds or more members which occupy high memory space and increase the data mining computation time. (ii) Data-dependency. The value of each member of a time series depends on the value of its former members, such that this feature plays a significant role in time series data mining. (iii) Continuous updating. Some time series are constantly updated in most real-time applications (Fu, 2011; Keogh and Kasetty, 2003; Sangeeta and Geeta, 2012; Lin et al., 2004).

On the other hand, data mining is a useful tool for discovering knowledge from a wealth of data. Various data mining techniques such as classification, clustering, discovering attractive and repetitive patterns and outlier (anomaly) detection have been widely used in different domains such as medicine, meteorology, sales and etc (Fu, 2011). These techniques are mainly designed for non-temporal data. Therefore, applying these techniques for time series data mining is a challenging task and requires some modifications in the corresponding algorithms (Liao, 2005). These changes include reducing the dimension and choosing an appropriate similarity measurement method. The purpose of reducing the time series dimension is reducing the calculation time and the required memory space. It should be conducted in such a way that the amount of lost knowledge due to the reduction of the time series does not prevent achieving the right result (Lin J. Keogh et al., 2003). A survey of various types of dimension reduction methods was carried out by Aghabozorgi et al. (2015). Choosing an appropriate similarity measurement method is another important and effective factor in the quality of results and it is one of the issues that have been considered in time series data mining research in recent years (Muller, 2007; Ding et al., 2008). Generally, time series data mining desperately needs an appropriate similarity measurement method (Salvador and Chan, 2007; Chen and Ng, 2004).

Many similarity measurement methods have been proposed to measure the similarity of time series, but the Longest Common Subsequence (LCSS) and Dynamic Time Warping (DTW) are the most widely used and the most effective ones in relation to time series data mining (Aghabozorgi et al., 2015; Wang et al., 2013). LCSS has been intrinsically designed to measure the similarity of two sequences of characters, which was later developed to measure the similarity of time

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series by defining and determining the similarity threshold (Aghabozorgi et al., 2014). In LCSS, the value of similarity threshold has a tremendous impact on the quality of time series data mining and this is a major drawback of this method.

Due to the importance and the influence of similarity measurement method in the quality of time series data mining results and LCSS shortcoming, a new method of measuring similarity for univariate, discrete and finite time series based on LCSS method has been proposed. The new method has two similarity thresholds. Comparing the results under this method with the results under LCSS method on time series datasets represents that there is less sensitivity to similarity thresholds and better results would be achieved. In general, a comprehensive review of the performance of the proposed method with LCSS and DTW methods has been conducted on a number of time series datasets consisting of univariate, discrete and finite time series, all of which show the superiority of the proposed method over these methods.

The rest of this paper is organized as follows. First, LCSS method, famous and common similarity measurement methods, and LCSS based methods would be discussed. Then, the proposed method and its specifications will be described. Finally, the 1-Nearest neighbor and K-medoids clustering techniques are conducted under DTW, LCSS and proposed methods for the time series datasets and the results would be analyzed.

2. Background

LCSS is a classic problem in computer science. This method uses point to point similarity definition and edit-based distance measuring approach (Aghabozorgi et al., 2014; Esling and Agon, 2012). The purpose of LCSS is finding the longest common subsequence of the two sequences of characters. The most important feature of LCSS is that it can ignore noise and distortion values. This method was actually created to compare two sequences of characters. The similarity in LCSS is defined as the equality of the two characters.

Suppose that $S_X = (x_1, x_2, \ldots, x_n)$ and $S_Y = (y_1, y_2, \ldots, y_m)$ are two sequences of character with n and m lengths, respectively. Their LCSS is indicated with $LCSS(S_x, S_y)$ equals to M(n,m), such that M(n,m) is calculated using Eq. (1) and $0 \le M(n,m) \le \min(n, m)$ is always present.

$$M(i,j) = \begin{cases} 0 & ; i = 0 \text{ .or. } j = 0 \\ 1 + M(i-1, j-1) & ; x_i = y_j,\ i \ge 1 \text{ .or. } j \ge 1 \\ \text{Max} \begin{cases} M(i-1,j) \\ M(i,j-1) \end{cases} & ; x_i \ne y_j,\ i \ge 1 \text{ .or. } j \ge 1 \end{cases} \tag{1}$$

The equation of $Sim(S_x, S_y) = \frac{2*LCSS(S_x,S_y)}{m+n}$ is used to compare the LCSS of two sequences with the LCSS of two other sequences, which is within the range of 0 to 1. The higher the value of this equation, the greater the similarity of the two sequences, and the smaller the value of this equation, the more different the two sequences are.

In order to use LCSS method to measure time series similarity, some changes have to be made in similarity definition. So, the definition of similarity would be modified. When the absolute value of the two data's difference of two time series is less than or equal to the similarity threshold ($\in$), then the two data are considered to be similar, otherwise they are different (Vlachos et al., 2002; Chen et al., 2005). Based on this description, the Eq. (1) is rewritten as Eq. (2). The logic used in this equation could be displayed in Fig. 1.

$$M(i,j) = \begin{cases} 0 & ; i = 0 \text{ .or. } j = 0 \\ 1 + M(i-1, j-1) & ; \left|x_i - y_j\right| \le \in,\ i \ge 1 \text{ .or. } j \ge 1 \\ \text{Max} \begin{cases} M(i-1,j) \\ M(i,j-1) \end{cases} & ; \in < \left|x_i - y_j\right|,\ i \ge 1 \text{ .or. } j \ge 1 \end{cases} \tag{2}$$

In analyzing the role of similarity threshold in this method, it can be briefly stated that the result of LCSS method is strongly influenced

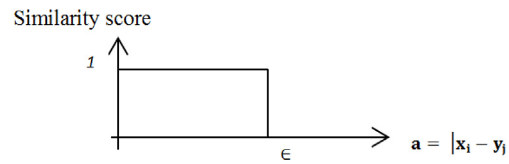

Fig. 1. Conceptual description of similarity threshold in LCSS.

by the similarity threshold, such that the less the similarity value, the lower the LCSS value, and the greater the similarity value the higher the LCSS value would be. In other words, it uses a zero–one approach to identify similarities. That is, two data from two time series may be either similar or different. For example, if the absolute value of difference of the two data of the two time series equals 0.249 and the similarity threshold value is 0.25, then these data are be similar to each other. But if the absolute value of difference of these data equals 0.251, they are not to be similar to each other. The appropriate value of similarity threshold depends on the nature of the time series dataset, but since there is no knowledge about the nature of the dataset and its features, applying this method can lead to poor results.

Following are some of the well-known and commonly used methods for measuring the similarity of time series and LCSS-based developed methods.

2.1. Well-known and common methods

The first well-known groups of similarity measurement methods are edit-based distance measurement methods that by defining the similarity threshold, they can also be used to measure the similarity of time series (Esling and Agon, 2012). These methods are based on counting the minimum number of necessary editing operations (including removal, placement, and insertion) to convert a sequence to another one. Levenshtine distance measurement method (Levenshtein, 1965), edit distance for real sequence method (EDR) (Chen et al., 2005) and edit distance with real penalty method (ERP) (Vlachos et al., 2002) are some of these methods. Although these methods are useful for measuring similarity, they are rarely used in time series data mining.

The second well-known groups of time series similarity measurement methods are shape-based distance measurement methods (Esling and Agon, 2012). This group of criteria is based on direct application of the raw values of the time series. LP-NORMS (Yi and Faloutsos, 2000), Short Time Series method (STS) (Moller-Levet et al., 2003) and Dynamic Time Warping method (Muller, 2007; Berndt and Clifford, 1994) are the most commonly used methods of this group. Lp-norms methods cannot identify the similarity of two time series that are similar in shape but this similarity occurs with a time delay. The weakness of STS method is similar to that of Lp-norms method. But, DTW has tackled this problem and has a better performance, a wider application and better results than that of time series measurement methods (Aghabozorgi et al., 2015).

The third famous group is feature-based measurement group (Esling and Agon, 2012). This group focuses on extracting a set of features from time series and calculating the similarities based on these features, therefore, they do not directly use raw time series data to calculate the similarity of the two time series. Pearson correlation coefficient is one of these methods. Another method, called cosine angle, uses Pearson's correlation coefficient root. The shortcomings of these methods are similar to Lp-norms method.

Interestingly, the performance of all the above methods is such that it cannot be specifically state that a particular method is appropriate for any time series database. In other words, based on the research carried out, it can be concluded that each of these methods are suitable for a group of time series data sets and are not good for the other ones. Also, it has been represented that DTW and LCSS methods had been widely used and they have better performance than the other methods (Aghabozorgi et al., 2014; Vlachos and Gunopulos, 2004; Vasimalla, 2014; Gorbenko and Popov, 2012; Zhang et al., 2006; Grabusts and Borisov, 2009; Ozkan and Turksen, 2015; Gorecki, 2014; Aghabozorgi and Wah, 2014; Lines and Bagnall, 2015). As far as our objective is to provide a new method for LCSS troubleshooting, we will investigate in the following whether there has been any action to tackle this problem or not.

2.2. LCSS-based methods

Numerous studies have been carried out about developing LCSS method. One of them is Constrained Longest Common Subsequence (C-LCSS) method that calculates the LCSS of the two sequences in relation to a third sequence (Tsai, 2003). The application of this method is limited to biological sequences, so it is could not be used in time series data mining. Another one is Multiple Longest Common Subsequence (MLCSS) method that calculates the LCSS of more than two sequences (Sankoff, 1972; Smith and Waterman, 1981). This method is considered as an Np-Hard problem for more than three sequences, and it is necessary to use heuristic methods to solve it. Generally and because of its nature, this method is could not be used in time series data mining. The third one is called Weighted Longest Common Subsequence (WLCSS) or Heaviest Common Subsequence (HCSS) and it is a method that calculates the LCSS of two sequences with the highest weights (Amihood et al., 2010). Due to the nature of this method, it could not be used in time series data mining. Another one is Flexible Longest Common Subsequence (FLCSS) that is a new type of LCSS that seeks to find a common subsequence of the two sequences with the most consecutive points (Guo et al., 2013). This method is not also practically used in time series data mining.

The last one is called the Longest Common Subsequence with Gapped Constraint (LCSSGC) method and it is a modified form of LCSS (Cheng et al., 2013). Due to the nature of this method, it could not be used in time series data mining.

In summary, all the LCSS-developed methods cannot be used in time series data mining. Therefore, the LCSS method still remains vulnerable to the sensitivity of this method to the similarity threshold value, and no method has been provided so far.

3. Proposed method

In this research, we provided a new method based on the LCSS, so that it will eliminate the zero–one approach present in LCSS. The new method has two similarity thresholds. The first and second similarity thresholds are called $\in_1$ and $\in_2$, respectively. The proposed method is named "Developed Longest common Subsequence" or "DLCSS" and Eq. (3) shows how to calculate DLCSS of two time series. In DLCSS, it is possible that the similarity of the two data in two time series be a value between zero and one.

$$M(i,j) = \begin{cases} 0 & ; i = 0 \text{ .or. } j = 0 \\ 1 + M(i-1, j-1) & ; \left|x_i - y_j\right| \leq \in_1,\ i,j \geq 1 \\ \text{Max}\begin{cases} \dfrac{\in_2 - a}{\in_2 - \in_1} + M(i-1,j-1) \\ M(i-1,j) \\ M(i,j-1) \end{cases} & ; \in_1 < \left|x_i - y_j\right| \leq \in_2,\ i,j \geq 1 \\ \text{Max}\begin{cases} M(i-1,j) \\ M(i,j-1) \end{cases} & ; \in_2 < \left|x_i - y_j\right|,\ i,j \geq 1 \end{cases} \tag{3}$$

$$a = \left|x_i - y_j\right|$$
$$i = 1,2,\ldots,n, \quad j = 1,2,\ldots,m$$
$$0 \ll DLCSS\left(TS_x, TS_y\right) = M(n,m) \leq min(n,m)$$

Fig. 2 represents the conceptual description of DLCSS similarity thresholds. In this figure, the similarity decision area has been divided into two sections. The first part contains values less than or equals $\in_1$ that expresses the definite similarity of the two data from two time series. The second part contains values greater than $\in_1$ and less than or equals $\in_2$ that expresses the conditional similarity of the two data. Unlike LCSS that represents the length of the longest common subsequence and is a natural number between zero and min(m,n), DLCSS represents the similarity score between two time series and is a real number between zero and min(m,n).

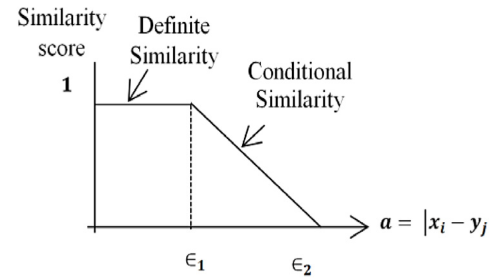

Fig. 2. Conceptual description of similarity threshold in DLCSS.

The logic used in DLCSS is described in the following:

- The two data of two time series will be certainly similar if the absolute of difference value between these data is smaller than or equal to $\in_1$. In this case, one unit will be added to the total similarity score before these two data.
- The two data from two time series may be similar if the absolute of difference value between these data is greater than $\in_1$ and smaller than or equal to $\in_2$. This condition may be correct with respect to the status before these data. So, if this condition is correct, then the value added to the total similarity score of the two time series equals to
  $\dfrac{\in_2 - a}{\in_2 - \in_1}$.
- The two data of the two time series are not definitely similar if the absolute of difference value between them is greater than $\in_2$. So the total similarity score is equal to the maximum similarity score before them.

The reasons for defining two similarity thresholds in the proposed method are as follows:

1- The second similarity threshold allows more data to become involved in the similarity of two time series.
2- The second similarity threshold gives a value between zero and one equals to the similarities of the two data. In summary, it assumes that the similarity is fuzzy.
3- The second similarity threshold is used to prevent outlier and noisy data to enter the similarity of the two time series.
4- The first similarity threshold is used to detect the definitive similarity of two data. This threshold helps to prevent data with low similarity entering the similarity of the two time series.

Range of similarity thresholds:

1- As mentioned earlier, the mission of $\in_1$ is to identify the definitive similarity of the two data. Definite similarity also means that the distance between two data is small enough. As a rule, the higher the value of $\in_1$, the greater the chances of the two data be placed in the definite similarity region, even if the two data are more distant. Since we want to identify those data that are truly similar, we should consider the value of this variable as small as possible. Therefore, this study will study the maximum value of $\in_1$ to 0.1.

Table 1
Name and specification of time series data sets that used in this research.

Row	Database name	K	L	N1	N2	Row	Database name	K	L	N1	N2
1	Statistical control	6	60	300	300	33	SonyII	2	65	27	953
2	Gun-point	2	150	50	150	34	sonySurface	2	70	20	601
3	CBF	3	128	30	900	35	StarLightCurve	3	1024	1000	8236
4	ECG	2	96	100	100	36	Two lead ECG	2	82	23	1139
5	Face4	4	350	24	88	37	Criket X	12	300	390	390
6	Medical	10	99	381	760	38	Criket Y	12	300	390	390
7	Sweedian	15	128	500	625	39	U wave X	8	315	896	3582
8	OSU	6	427	200	242	40	U wave Y	8	315	896	3582
9	Adiac	37	176	390	391	41	Insect wing	11	256	220	1980
10	Beef	5	470	30	30	42	Arrow head	3	251	36	175
11	Lighting	7	319	70	73	43	Beetle fly	2	512	20	20
12	Fish	7	463	175	175	44	Bird chicken	2	512	20	20
13	50words	50	270	450	455	45	Ham	2	431	109	105
14	Trace	4	275	100	100	46	Phalanges O-C	2	80	1800	858
15	Lighting7	7	319	70	73	47	Proximal POA	3	80	400	205
16	Distal	7	80	139	400	48	Proximal POC	2	80	600	291
17	Italy power demand	2	24	67	1029	49	Proximal PT	6	80	205	400
18	Middle-P-T	7	80	154	399	50	Toe segmentation1	2	277	40	228
19	Plane	7	144	105	105	51	Toe segmentation2	2	343	36	180
20	Car	4	577	60	60	52	Distal POA	3	80	139	400
21	Olive oil	4	570	30	30	53	Distal POC	2	80	276	600
22	Diatom size reduction	4	345	16	306	54	Distal PT	6	80	139	400
23	Symbol	6	398	25	995	55	Earth quakes	2	512	139	322
24	Worms	5	900	77	181	56	Middle POA	3	80	154	400
25	Two pattern	4	128	1000	4000	57	Middle POC	2	80	291	600
26	Wafer	2	152	1000	6164	58	Shapelet sim	2	500	20	180
27	Faceall	14	131	530	1690	59	Wine	2	234	57	54
28	Lighting2	2	637	60	61	60	Computers	2	720	250	250
29	ECGFiveday	2	136	23	861	61	Meat	3	448	60	60
30	Haptics	5	1092	155	308	62	Refrigeration	3	720	375	375
31	InLineSkate	7	1882	100	550	63	Worm two class	2	900	77	181
32	Motestrain	2	84	20	1252						

K: Number of cluster. L: length of time series.
N1: Number of time series in training database. N2: Number of time series in experimental database.

2- The mission of $\in_2$ is to identify the conditional similarity of the two data. As previously defined, conditional similarity is detected compared to adjacent data. As a rule, the value of $\in_2$ can be greater than of $\in_1$ and the maximum possible value for it can also be one. But in practice, the value of $\in_2$ cannot be greater than 0.6. Because, the similarity of the two data with a distance greater than 0.6 is completely meaningless. So we consider the maximum possible value for $\in_2$ to 0.6.

4. Experimental results and discussion

In this study, 63 data sets from UCR collection (https://www.cs.ucr.edu/eamonn/time_series_data_2018/) were used. Their names and specifications have been presented in Table 1. Each time series data set has two distinct subsets, which includes the training and the experimental data sets. In each subset, the class of each time series has been specified.

For example the "statistical control" data set has 6 clusters (class), the length of each time series is 60 and the number of time series in the training and experimental data sets are 300 and 300, respectively. The training data set is used to discover patterns that exist in data set, and the experimental data set is used to determine the quality of identified patterns. The application of these data sets would be explained in more detail below.

In this research, the 1-Nearest neighbor (1-NN) and k-medoids clustering techniques have been used. The 1-NN technique is one of the techniques available in classification and the k-medoids clustering technique is one of the partitioning clustering techniques. In addition, validity indicator is the accuracy index. So, the performance of the proposed method would be compared with the performance of LCSS and DTW methods in the 1-NN and k-medoids clustering techniques.

All the required programs in this research have been written by MATLAB software.

4.1. The nearest neighbor (1-NN) results

In this section, the results of implementation the 1-NN technique under DTW, LCSS and DLCSS methods have been presented and analyzed. DLCSS method has been considered in two different modes, the first mode is $\in_1 = 0.05$ and $\in_2$ with different values and second mode is $\in_1 = 0.1$ and $\in_2$ with different values.

The 1-NN method has been used to recognize the class of time series of the experimental data set compared to the time series class of the training data set. The evaluation process has been illustrated in Fig. 3. This process has two steps.

First step: The similarity of any time series of the experimental data set is measured with any time series of the training data set using similarity measurement method (DLCSS, DTW and LCSS).

Second step: The time series class of the experimental data set is equivalent to the most similar time series of training data set to that time series.

After implementing these steps, the accuracy index of this technique would be calculated. The **accuracy index** is the ratio of the number of time series of experimental data set that their class has been correctly determined to the total number of time series of the experimental data set.

In Table 2, the results of 1-NN technique under DTW have been presented. For example, for "statistical control" data set, the class of 97.33% of time series of the experimental data set has been correctly recognized. As it can be seen, the accuracy of some data sets is very low, such as OSU and Middle-P-T data sets with 46.28% and 58.4% accuracies, respectively. In general, mean accuracy of 1-NN under DTW method for all the data sets is equal to **72.38%**.

In Table 3, the results of the 1-NN technique under LCSS have been presented. For example, for "statistical control" data set when $\in = 0.05$, the class of 69.67% of time series of experimental data set had been correctly identified. In most cases, the accuracy is changed by changing the similarity threshold. In "statistical control" data set, by increasing

Table 2
Accuracy and mean accuracy of the 1-NN technique under DTW.

Row	Database name	Accuracy %	Row	Database name	Accuracy %	Row	Database name	Accuracy %
1	Statistical control	97.33	22	Diatom size reduction	96.41	43	Beetle fly	70
2	Gun point	90.67	23	Symbol	94.27	44	Bird chicken	75
3	CBF	99	24	Worms	45.33	45	Ham	42.86
4	ECG	79	25	Two pattern	100	46	Phalanges O-C	69.23
5	Face4	81.82	26	Wafer	98.04	47	Proximal POA	74.64
6	Medical	65.39	27	Faceall	84.74	48	Proximal POC	87.63
7	Sweedian	72.16	28	Lighting2	86.9	49	Proximal PT	74
8	OSU	46.28	29	ECGFiveday	75.84	50	Toe segmentation1	76.31
9	Adiac	74.03	30	Haptics	41.23	51	Toe segmentation2	86.11
10	Beef	63.33	31	InLineSkate	38.9	52	Distal POA	83
11	Lighting	68.49	32	Motestrain	81.16	53	Distal POC	71.83
12	Fish	75.43	33	SonyII	84.58	54	Distal PT	72.75
13	50words	66.39	34	sonySurface	65.23	55	Earth quakes	62.42
14	Trace	100	35	StarLightCurve	66.1	56	Middle POA	64.50
15	Lighting7	68.49	36	Two lead ECG	89.47	57	Middle POC	79
16	Distal	70.5	37	Criket X	69.99	58	Shapelet sim	56.11
17	Italy power demand	93.97	38	Criket Y	56.4	59	Wine	57.4
18	Middle-P-T	58.4	39	U wave X	65.61	60	Computers	54.80
19	Plane	100	40	U wave Y	40.93	61	Meat	93.33
20	Car	71.67	41	Insect wing	27.27	62	Refrigeration	33.33
21	Olive oil	83.33	42	Arrow head	70.31	63	Worm two class	71.27
Mean accuracy %							**72.38**	

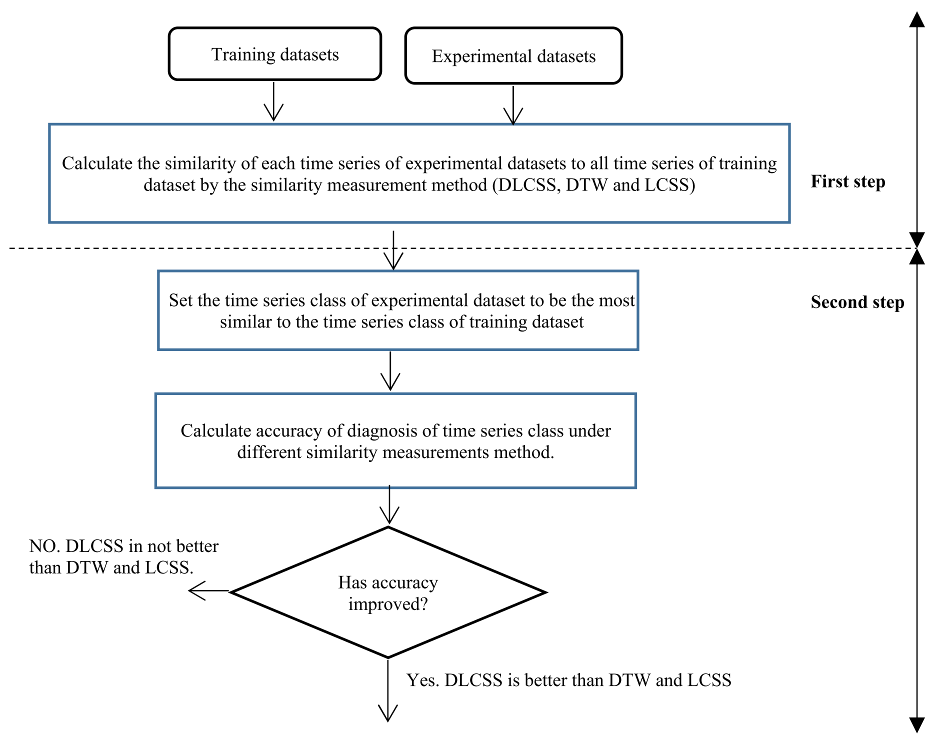

Fig. 3. Evaluation process by 1-nearest neighbor method.

the similarity threshold from 0.05 to 0.35, the accuracy increases from 69.67% to 94.67%. The mean and standard deviation of these values are 87.95% and 8.63%, respectively. As another example, this trend for "Gun-Point" data set is initially ascending and then descending, so that its maximum occurs at $\in = 0.15$ and the mean and standard deviation of these values are 93.33% and 5.05%, respectively. In general, the mean of these standard deviations for all datasets is **4.80%**, and it indicates the high impact of similarity threshold on the accuracy.

According to this results, the highest mean accuracy of 1-NN for all data sets has occurred in $\in = 0.25$ and equals **75.05%.** The interesting point of it (i.e., $\in = 0.25$) is the low accuracy for "Adiac" and "Olive Oil" data sets which is equal to 42.7% and 45%, respectively.

In Table 4, the results of the 1-NN technique under DLCSS method with $\in_1 = 0.05$ and different values for $\in_2$ (first mode) has been presented. For example, for "statistical control" data set, the mean and standard deviation of these accuracies are 90.61% and 2.43%, respectively. This standard deviation is less than the LCSS' standard deviation, so this method's accuracy is more stable than that of LCSS. In general, the mean standard deviation for all data sets is equal to **2.04%**. It shows the lower standard deviation than the LCSS method (**4.80%**). In a conclusion, DLCSS has more stable result than LCSS method. On the other hand, the accuracy obtained for "Adiac" and "Olive Oil" data sets are more than 80% and 70%, respectively. Also, the best situation for all datasets is equal to **77.88%,** where $\in_2 = 0.6$.

Again, the 1-NN technique under DLCSS was implemented for $\in_1 = 0.10$ and $\in_2$ with different values (second mode). The results had been represented in Table 5. For example, for "statistical control" data set, the mean and standard deviation of these accuracies are 90.83% and

Table 3
Accuracy and mean accuracy of the 1-NN technique under LCSS for different values of ∈.

Row	Database name	Accuracy %									
		∈							Mean	Std	Max
		0.05	0.10	0.15	0.20	0.25	0.30	0.35			
1	Statistical control	69.67	86.67	87	91.67	93	93	94.67	87.95	8.63	94.67
2	Gun-point	92.67	98	98.67	97.33	92.67	88.67	85.33	93.33	5.05	98.67
3	CBF	96.89	98.11	99.56	99.44	99.67	99.78	99.89	99.05	1.12	99.89
4	ECG	77	85	86	87	90	91	91	86.71	4.92	91.00
5	Face4	81.82	89.77	92.05	93.18	94.5	92.05	94.32	91.10	4.40	94.50
6	Medical	53.92	57.76	60.13	61.84	62.33	63.16	61.71	60.12	3.26	63.16
7	Sweedian	43.2	75.2	82.4	83.5	84.62	84.96	82.72	76.66	15.11	84.96
8	OSU	62.4	67.36	68.6	69.42	69.83	68.18	68.18	67.71	2.48	69.83
9	Adiac	77.92	66.88	55.19	48.86	42.7	33.38	26.23	50.17	18.20	77.92
10	Beef	56.67	70	70	76.67	73	63.33	56.67	66.62	7.89	76.67
11	Lighting	60.27	56.16	69.86	71.33	75.34	75.34	68.49	68.11	7.33	75.34
12	Fish	84	88	89.14	84.57	81.69	77.14	73.14	82.53	5.74	89.14
13	50words	60.5	68.35	73.11	73.51	73.95	75.35	77.03	71.69	5.61	77.03
14	Trace	92	97	100	99	98	96	94	96.57	2.82	100.00
15	Lighting7	60.27	56.16	69.86	71.23	75.34	75.34	68.49	68.10	7.32	75.34
16	Distal	69.5	73.5	74	75.25	75.5	76	76.25	74.29	2.34	76.25
17	Italy power demand	78.52	82	87.56	90.18	91.74	92.42	93.72	88.02	5.73	93.72
18	Middle-P-T	58.4	61.65	56.64	59.9	62.41	61.9	61.15	60.29	2.11	62.41
19	Plane	100	100	100	100	100	100	100	100.00	0.00	100.00
20	Car	88.33	85	85	83.4	81.67	73.33	73.33	81.44	5.89	88.33
21	Olive oil	77.33	56.67	53.33	48	45	40	40	51.48	13.01	77.33
22	Diatom size reduction	95.1	95.75	96.41	94.44	93.45	91.83	81.37	92.62	5.19	96.41
23	Symbol	95.08	95.88	96.28	96.88	95.48	93.97	92.46	95.15	1.50	96.88
24	Worms	44.18	45.33	45.29	48.07	51.37	51.93	54.15	48.62	3.89	54.144
25	Two pattern	93.7	99	99.6	99.6	99.2	99.2	99.2	98.50	2.13	99.60
26	Wafer	98.04	100	100	98.72	98.72	98.72	98.35	98.93	0.77	100.00
27	Faceall	56.98	73.61	78.46	84.02	88.17	93.02	93.02	81.04	12.83	93.02
28	Lighting2	70.49	73.77	77.05	78.69	78.69	78.69	77.05	76.35	3.12	78.69
29	ECGFiveday	70.73	76.77	76.77	80.02	81.42	84.21	86.53	79.49	5.28	86.53
30	Haptics	39.29	39.29	45.13	43.18	43.18	41.23	41.23	41.79	2.17	45.13
31	InLineSkate	35.45	35.8	36.4	37.27	37.27	40	38	37.17	1.54	40.00
32	Motestrain	91.05	91.05	91.29	92.09	92.81	92.65	91.53	91.78	0.74	92.81
33	SonyII	70.83	80.80	80.80	81.22	82.48	83.32	83.32	80.39	4.36	83.32
34	sonySurface	60.07	61.06	62.06	65.72	66.06	67.72	68.22	64.42	3.30	68.22
35	StarLightCurve	68.01	72.00	76.01	76.01	78.00	72.00	64	72.29	4.96	78.00
36	Two lead ECG	86.83	92.10	89.46	89.464	86.83	85.95	81.56	87.46	3.35	92.10
37	Criket X	34.62	39.23	42.05	44.36	45.90	52.56	52.56	44.47	6.63	52.56
38	Criket Y	38.97	45.38	48.46	56.41	56.41	56.41	54.87	50.99	6.90	56.41
39	U wave X	56.25	56.25	57.79	57.79	59.38	59.38	65.63	58.93	3.22	65.63
40	U wave Y	40.90	40.90	40.90	40.90	43.19	50	52.26	44.15	4.89	52.26
41	Insect wing	30.25	51.52	54.59	56.16	53.08	53.08	53.08	50.25	8.94	56.16
42	Arrow head	65.72	68.57	68.57	73.71	70.86	67.43	67.43	68.90	2.64	73.71
43	Beetle fly	80	80	80	80	80	80	80	80.00	0.00	80.00
44	Bird chicken	75	85	85	85	90	90	85	85.00	5.00	90.00
45	Ham	60	65.71	65.71	71.43	74.29	68.57	65.71	67.35	4.63	74.29
46	Phalanges O-C	66.32	68.30	69.11	70.51	71.10	71.10	68.18	69.23	1.78	71.10
47	Proximal POA	78.54	78.54	78.54	79.51	79.51	77.56	77.56	78.54	0.80	79.51
48	Proximal POC	85.57	89.00	95.88	94.85	91.75	89.35	87.97	90.62	3.73	95.88
49	Proximal PT	74.5	74.5	78.25	79	78.5	75.75	74.75	76.46	2.04	79.00
50	Toe segmentation1	76.75	76.75	78.07	82.46	87.28	82.46	80.70	80.64	3.82	87.28
51	Toe segmentation2	93.90	93.89	95.56	96.67	96.67	95.56	95.56	95.40	1.14	96.67
52	Distal POA	78	80.5	79.5	78	77.5	74.5	74	77.43	2.41	80.50
53	Distal POC	73.34	73.34	73.34	73.34	76.67	75	75	74.29	1.31	76.67
54	Distal PT	73	73.5	75.5	75.5	75.5	75.5	77.75	75.18	1.56	77.75
55	Earth quakes	62.11	62.11	65.40	65.84	68.01	71.74	71.74	66.77	4.00	71.74
56	Middle POA	65.75	65.75	68	72	67	66.5	66.5	67.36	2.19	72.00
57	Middle POC	71.17	76.67	77.17	82.83	85.33	82.83	82.83	79.83	4.99	85.33
58	Shapelet sim	73.89	73.89	86.67	88.89	91.67	92.78	92.78	85.80	8.43	92.78
59	Wine	57.41	51.85	48.15	48.15	50	50	50	50.79	3.18	57.41
60	Computers	69.2	69.2	62	62	62	62	62	64.06	3.51	69.20
61	Meat	90	93.33	66.67	53.33	48.33	45	33.33	61.43	22.94	93.33
62	Refrigeration	49.07	45.07	45.07	39.47	37.33	39.2	37.33	41.79	4.59	49.07
63	Worm two class	62.98	71.82	74.59	74.59	74.59	71.82	74.59	72.14	4.24	74.59
Mean accuracy %		69.85	73.05	74.13	74.75	**75.05**	74.14	72.90	73.41	**4.80**	79.01

2.76%, respectively. In general the mean of standard deviation for all data sets is equal to **1.94%**. It shows the lower standard deviation than that of LCSS method (**4.80%**). In summary, this method has also more stable result that LCSS method. On the other hand, the accuracy for Adiac and Olive oil datasets are more than 68% and about 46%, respectively. In general, the best situation for all data sets is equal to **76.14%**, where $\in_2 = 0.6$.

There are two top situations for accuracy under DLCSS method and this is where the highest accuracy index of this technique occurs. First, it is when $\in_1 = 0.05$ and $\in_2 = 0.6$ with 77.88% accuracy. Second, it is when $\in_1 = 0.1$ and $\in_2 = 0.6$ with 76.14% accuracy. Paired sample t-test

Table 4
Accuracy and mean accuracy of the 1-NN under DLCSS, $\in_1 = 0.05$ and different value of $\in_2$.

Row	Database name	Accuracy %								
		$\in_2$						Mean	Std	Max
		0.20	0.25	0.30	0.40	0.50	0.60			
1	Statistical control	87.33	89	90	90.67	92.67	94	90.61	2.43	94.00
2	Gun-point	98	97.33	97.33	97.33	96.67	96.67	97.22	0.50	98.00
3	CBF	99	99.33	99.56	99.78	99.78	99.78	99.54	0.32	99.78
4	ECG	87	88	88	85	88	86	87.00	1.26	88.00
5	Face4	90.91	90.91	90.91	92.32	93.42	95.45	92.32	1.84	95.45
6	Medical	58.95	58.82	60.66	60.26	61.05	62.37	60.35	1.34	62.37
7	Sweedian	79.96	79.04	80.32	82.72	84.48	85.28	81.97	2.58	85.28
8	OSU	66.94	66.94	67.95	69.01	69.01	69.23	68.18	1.06	69.23
9	Adiac	81.82	82.47	83.12	83.77	83.12	82.47	82.80	0.68	83.77
10	Beef	63.33	63.33	66.67	66.67	66.67	70	66.11	2.51	70.00
11	Lighting	61.64	64.38	67.12	68.49	73.97	73.98	68.26	5.01	73.98
12	Fish	88.57	89.71	90.86	90.29	90.29	90.29	90.00	0.79	90.86
13	50words	70.78	71.43	73.11	74.23	76.19	77.03	73.80	2.51	77.03
14	Trace	95	96	96	97	97	97	96.33	0.82	97.00
15	Lighting7	61.64	64.38	67.12	68.49	72.6	73.97	68.03	4.72	73.97
16	Distal	74.75	73.5	73.5	74.25	75	76	74.50	0.96	76.00
17	Italy power demand	85.52	87.85	89.99	91.64	93	93.97	90.33	3.21	93.97
18	Middle-P-T	60.65	59.15	58.9	58.65	58.65	59.4	59.23	0.75	60.65
19	Plane	100	100	100	100	100	100	100.00	0.00	100.00
20	Car	91.67	91.67	93.33	91.67	90	88.33	91.11	1.72	93.33
21	Olive oil	77.33	77.33	77.33	77.33	77.33	77.33	77.33	0.00	77.33
22	Diatom size reduction	95.76	95.75	95.75	95.75	96.08	96.08	95.86	0.17	96.08
23	Symbol	96.38	96.68	96.68	96.38	96.18	96.18	96.41	0.23	96.68
24	Worms	45.28	46.41	47.51	48.07	48.07	49.75	47.51	1.53	49.72
25	Two pattern	98.5	99.2	98.5	98.5	98.3	98.3	98.55	0.33	99.20
26	Wafer	100	100	100	100	100	100	100.00	0.00	100.00
27	Faceall	77.1	79.88	82.78	87.52	91.66	93.19	85.35	6.49	93.20
28	Lighting2	75.41	75.41	75.41	77.05	80.33	83.61	77.87	3.40	83.61
29	ECGFiveday	76.77	78.16	78.16	78.63	80.02	80.02	78.63	1.25	80.02
30	Haptics	41.23	45.13	45.13	49.03	47.08	47.08	45.78	2.66	49.03
31	InLineSkate	36	36.18	36.73	37.45	39.64	40.18	37.70	1.80	40.18
32	Motestrain	91.05	91.29	91.29	92.25	92.33	92.33	91.76	0.60	92.33
33	SonyII	82.06	83.32	83.53	84.99	85.41	85.41	84.12	1.37	85.41
34	sonySurface	60.57	60.57	61.56	64.76	65.56	68.72	63.62	3.28	68.72
35	StarLightCurve	72.0	74.04	70.01	70.01	70.01	70.01	71.01	1.68	74.041
36	Two lead ECG	92.89	95.87	93.85	91.22	91.22	90.34	92.57	2.06	95.87
37	Criket X	44.36	45.90	45.90	45.90	47.44	52.56	47.01	2.89	52.56
38	Criket Y	50	50	54.62	57.69	57.69	60	55	4.23	60
39	U wave X	53.13	57.82	57.82	59.38	68.76	65.63	60.42	5.74	68.76
40	U wave Y	36.35	38.64	38.64	38.64	47.74	47.74	41.29	5.07	47.74
41	Insect wing	48.49	53.03	53.03	54.55	54.55	54.55	53.03	2.35	54.55
42	Arrow head	64	65.72	65.71	67.43	72.57	75.43	68.48	4.51	75.43
43	Beetle fly	80	80	80	80	80	85	80.83	2.04	85.00
44	Bird chicken	80	80	85	85	90	90	85.00	4.47	90.00
45	Ham	65.71	73.33	68.57	68.57	68.57	68.57	68.89	2.46	73.33
46	Phalanges O-C	70.16	71.10	71.10	72.78	71.10	71.10	71.21	0.83	72.73
47	Proximal POA	73.66	74.64	74.64	76.59	76.58	78.54	75.77	1.79	78.54
48	Proximal POC	84.54	85.57	86.6	86.6	87.63	88.66	86.60	1.46	88.66
49	Proximal PT	74.25	74.5	77.75	74	72.25	72.25	74.17	2.02	77.75
50	Toe segmentation1	76.32	78.51	78.51	82.46	87.72	87.72	81.87	4.94	87.72
51	Toe segmentation2	93.89	93.89	96.67	98.34	98.34	98.34	96.58	2.18	98.34
52	Distal POA	80	80.5	80.5	81.5	81.5	81.5	80.92	0.66	81.50
53	Distal POC	71.34	71.34	71.34	74.34	75.67	75.67	73.28	2.18	75.67
54	Distal PT	75	75	75	75	73	73	74.33	1.03	75.00
55	Earth quakes	71.74	73.6	73.6	71.74	71.74	71.74	72.36	0.96	73.60
56	Middle POA	64.25	66.5	66.5	66.5	66.5	66.5	66.13	0.92	66.50
57	Middle POC	77.67	78.34	78.34	81.17	84.5	84.5	80.75	3.15	84.50
58	Shapelet sim	83.34	85.56	86.11	91.11	93.89	96.11	89.35	5.11	96.11
59	Wine	53.7	53.7	53.7	53.7	53.7	53.7	53.70	0.00	53.70
60	Computers	68.8	71.2	71.2	71.2	66.8	66.8	69.33	2.17	71.20
61	Meat	86.67	86.67	86.67	85	86.67	85	86.11	0.86	86.67
62	Refrigeration	43.2	43.2	41.33	41.33	41.33	41.33	41.96	0.96	43.20
63	Worm two class	71.27	71.27	71.27	74.59	74.59	74.59	72.93	1.82	74.59
Mean accuracy %		74.03	75.05	75.54	76.29	77.33	**77.88**	76.02	**2.04**	78.69

is used to select the best situation between these two conditions. The assumptions in this test are as follows.

$H_0 : A_{First} = A_{Second}$ (The accuracy of two situations is statistically the same)

$H_1 : A_{First} > A_{Second}$ (The accuracy of first situations is better than the accuracy of second situation)

The results of this test are presented in Table 6. These results represent that paired differences of first situation and second situation with 99.5% confidence is greater than zero. So it can be claimed that the accuracy of first situation is better than that of second situation with **99.5%** confidence. Therefore, in the following, the best value for these similarity thresholds would be $\in_1 = 0.05$ and $\in_2 = 0.6$.

Table 5
Accuracy and mean accuracy of the 1-NN under DLCSS, $\in_1 = 0.1$ and different value of $\in_2$.

Row	Database name	Accuracy %								
		$\in_2$						Mean	Std	Max
		0.20	0.25	0.30	0.40	0.50	0.60			
1	Statistical control	87.33	88.33	90	91.67	93.67	94	90.83	2.76	94.00
2	Gun-point	98	98	98	98	98	98	98.00	0.00	98.00
3	CBF	99.33	99.67	99.78	99.78	99.78	99.89	99.71	0.20	99.89
4	ECG	90	89	90	88	87	89	88.83	1.17	90.00
5	Face4	92.05	93.18	93.18	93.18	93.18	95.45	93.37	1.11	95.45
6	Medical	59.47	60.79	61.45	60.39	62.89	63.95	61.49	1.66	63.95
7	Sweedian	80.64	81.28	82.72	84.12	84.96	85.44	83.19	1.97	85.44
8	OSU	69.42	68.6	68.6	69.42	70.25	69.42	69.29	0.62	70.25
9	Adiac	68.18	66.23	68.83	69.48	68.83	68.83	68.40	1.14	69.48
10	Beef	73.33	76.67	76.33	73.33	73.33	73.33	74.39	1.64	76.67
11	Lighting	67.12	71.23	71.23	73.97	73.97	73.97	71.92	2.71	73.97
12	Fish	90.29	89.14	90.29	90.29	89.71	88.57	89.72	0.73	90.29
13	50words	72.83	73.67	74.23	75.35	76.47	77.31	74.98	1.71	77.31
14	Trace	99	99	98	99	98	97	98.33	0.82	99.00
15	Lighting7	67.12	71.23	71.23	73.97	73.97	73.97	71.92	2.71	73.97
16	Distal	75.25	74.5	74.25	74.75	73.5	74	74.38	0.61	75.25
17	Italy power demand	87.56	89.6	90.28	92.32	92.91	94.17	91.14	2.43	94.17
18	Middle-P-T	57.89	58.15	59.15	58.9	57.39	57.14	58.10	0.80	59.15
19	Plane	100	100	100	100	100	100	100.00	0.00	100.00
20	Car	90	91.67	91.67	90	83.33	83.33	88.33	3.95	91.67
21	Olive oil	46.67	46.67	46.67	46.67	46.67	46.67	46.67	0.00	46.67
22	Diatom size reduction	96.08	96.41	96.41	96.73	96.73	96.73	96.52	0.26	96.73
23	Symbol	95.05	95.35	95.74	96.35	96.66	96.05	95.87	0.61	96.66
24	Worms	45.28	47.53	47.53	48.07	48.07	49.17	47.61	1.29	49.17
25	Two pattern	98.5	98.5	98.5	99	99.2	99.2	98.82	0.35	99.20
26	Wafer	99.35	99.35	99.35	99.35	100	100	99.57	0.34	100.00
27	Faceall	81.25	83.32	83.32	88.88	91.66	92.31	86.79	4.76	92.31
28	Lighting2	77.05	77.05	78.67	78.67	80.33	80.33	78.68	1.47	80.33
29	ECGFiveday	78.63	80.02	81.42	81.42	81.42	82.35	80.88	1.33	82.35
30	Haptics	43.18	43.18	47.08	47.08	45.13	41.23	44.48	2.36	47.08
31	InLineSkate	38.18	38.73	38.73	39.09	39.27	39.27	38.88	0.42	39.27
32	Motestrain	91.05	91.05	91.29	91.45	92.01	92.01	91.48	0.44	92.01
33	SonyII	80.06	80.80	83.32	85.62	85.83	86.25	83.65	2.70	86.25
34	sonySurface	59.24	61.06	61.56	64.56	67.77	67.22	63.57	3.49	67.77
35	StarLightCurve	74.01	78	76.01	72.001	68.01	68.01	72.67	4.13	78.00
36	Two lead ECG	92.98	92.1	92.1	90.34	89.46	87.71	90.78	1.98	92.98
37	Criket X	44.36	44.36	45.90	45.90	47.18	49.23	46.15	1.85	49.23
38	Criket Y	51.54	53.08	54.62	56.41	56.41	54.62	54.44	1.90	56.41
39	U wave X	56.25	56.25	57.82	60.92	64.60	65.61	60.24	4.15	65.61
40	U wave Y	40.90	38.64	38.64	38.64	45.45	45.45	41.28	3.34	45.45
41	Insect wing	48.48	50	51.52	57.58	57.58	57.58	53.79	4.26	57.58
42	Arrow head	68.57	70.86	72	72	75.43	75.43	72.38	2.67	75.43
43	Beetle fly	80	80	80	80	80	85	80.83	2.04	85.00
44	Bird chicken	80	80	80	85	85	85	82.50	2.74	85.00
45	Ham	65.71	65.71	65.71	68.57	68.57	68.57	67.14	1.57	68.57
46	Phalanges O-C	69.70	69.70	69.11	69.11	68.65	68.18	69.08	0.59	69.70
47	Proximal POA	73.66	73.66	73.66	73.66	74.63	74.63	73.98	0.50	74.63
48	Proximal POC	90.72	91.75	91.75	90.72	89.69	89.69	90.72	0.92	91.75
49	Proximal PT	72.75	72.75	72.75	73	73	73.5	72.96	0.29	73.50
50	Toe segmentation1	78.51	78.51	82.46	82.46	80.70	80.70	80.56	1.77	82.46
51	Toe segmentation2	95.56	96.67	96.67	98.34	98.34	98.33	97.32	1.19	98.33
52	Distal POA	79.5	79.5	79.5	79.5	79.5	79	79.42	0.20	79.50
53	Distal POC	72.17	72.17	71.17	71.17	71.17	68.33	71.03	1.41	72.17
54	Distal PT	77	77	73.25	73.25	71.5	71.5	73.92	2.51	77.00
55	Earth quakes	67.70	67.70	67.70	69.88	71.43	71.43	69.31	1.85	71.43
56	Middle POA	65.5	65.5	67.25	64.75	63.25	63.25	64.92	1.53	67.25
57	Middle POC	78.33	78.67	78.67	77.17	77.17	77.67	77.94	0.70	78.67
58	Shapelet sim	83.33	86.67	87.78	92.22	95	96.67	90.28	5.18	96.67
59	Wine	51.85	51.85	51.85	46.3	51.85	51.85	50.93	2.27	51.85
60	Computers	64	64.5	64.5	59.2	59.2	59.2	61.77	2.82	64.50
61	Meat	93.33	80	93.33	56.67	93.33	93.33	85.00	14.87	93.33
62	Refrigeration	43.2	41.33	41.33	37.33	37.33	37.33	39.64	2.62	43.20
63	Worm two class	74.59	74.59	74.59	74.59	71.27	74.59	74.03	1.35	74.59
Mean accuracy %		74.42	74.77	75.40	75.17	75.98	**76.14**	75.33	**1.94**	77.36

The summary of the best results of 1-NN technique under DTW, LCSS and DLCSS and the Mean accuracy of 1-NN under these methods have been presented in Tables 7 and 8, respectively.

It is time to answer the following question:

• Is the accuracy of 1-NN under DLCSS method better than that of under DTW and LCSS methods?

In order to answer the above question, paired sample t-test was used. The results of this test are presented in Table 9. The following assumptions were used to compare the DLCSS and DTW methods.

$$H_0 : A_3 = A_1$$

Table 6
Paired samples t-Test of two top situations for accuracy under DLCSS.

	Paired differences			T	df	Sig. (2-tailed)	Correlation
	Mean	Std. deviation	Std. error mean				
$A_{First} - A_{Second}$	1.73498	4.89790	0.61708	2.812	62	0.007	A_{First} & $A_{second} = 0.959$

	Confidence interval of the difference				
	95% Lower	**97.5%** Lower	**99%** Lower	**99.5%** Lower	**99.95%** Lower
$A_{First} - A_{Second}$	0.70459	0.50146	0.26140	0.09511	−0.39670

A_{First} : Accuracy of 1-NN under DLCSS method when $\in_1 = 0.05$ and $\in_2 = 0.6$.
A_{Second} : Accuracy of 1-NN under DLCSS'method when $\in_1 = 0.10$ and $\in_2 = 0.6$.

Table 7
Best accuracy of 1-NN technique under DTW, LCSS and DLCSS methods.

Row	Database name	Accuracy %			Row	Database name	Accuracy %		
		DTW	LCSS	DLCSS			DTW	LCSS	DLCSS
		A_1	A_2	A_3			A_1	A_2	A_3
1	Statistical control	97.33	93	94	33	SonyII	84.58	82.48	85.41
2	Gun-point	90.67	92.67	96.67	34	sonySurface	65.23	66.06	68.72
3	CBF	99	99.67	99.78	35	StarLightCurve	66.1	78	70.01
4	ECG	79	90	86	36	Two lead ECG	89.465	86.831	90.34
5	Face4	81.82	94.5	95.45	37	Criket X	69.99	45.90	52.56
6	Medical	65.39	62.33	62.37	38	Criket Y	56.4	56.41	60
7	Sweedian	72.16	84.62	85.28	39	U wave X	65.605	59.38	65.63
8	OSU	46.28	69.83	69.23	40	U wave Y	40.927	43.19	47.74
9	Adiac	74.03	42.7	82.47	41	Insect wing	27.271	53.08	54.53
10	Beef	63.33	73	70	42	Arrow head	70.31	70.86	75.43
11	Lighting	68.49	75.34	73.98	43	Beetle fly	70	80	85
12	Fish	75.43	81.69	90.29	44	Bird chicken	75	90	90
13	50words	66.39	73.95	77.03	45	Ham	42.86	74.29	68.57
14	Trace	100	98	97	46	Phalanges O-C	69.23	71.10	71.10
15	Lighting7	68.49	75.34	73.97	47	Proximal POA	74.64	79.51	78.54
16	Distal	70.5	75.5	76	48	Proximal POC	87.63	91.75	88.66
17	Italy power demand	93.97	91.74	93.97	49	Proximal PT	74.5	78.5	72.25
18	Middle-P-T	58.4	62.41	59.4	50	Toe segmentation1	76.31	87.28	87.72
19	Plane	100	100	100	51	Toe segmentation2	86.11	96.66	98.34
20	Car	71.67	81.67	88.33	52	Distal POA	83	77.5	81.5
21	Olive oil	83.33	45	77.33	53	Distal POC	71.83	76.67	75.67
22	Diatom size reduction	96.41	93.45	96.08	54	Distal PT	72.75	75.5	73
23	Symbol	94.27	95.48	96.18	55	Earth quakes	62.42	68.01	71.74
24	Worms	45.33	51.37	49.72	56	Middle POA	64.50	67	66.5
25	Two pattern	100	99.2	98.3	57	Middle POC	79	85.33	84.5
26	Wafer	98.04	98.72	100	58	Shapelet sim	56.11	91.67	96.11
27	Faceall	84.74	88.17	93.19	59	Wine	57.4	50	53.7
28	Lighting2	86.9	78.69	83.61	60	Computers	54.80	62	66.8
29	ECGFiveday	75.84	81.42	80.02	61	Meat	93.33	48.33	85
30	Haptics	41.23	43.18	47.08	62	Refrigeration	33.33	37.33	41.33
31	InLineSkate	38.9	37.27	40.18	63	Worm two class	71.27	74.59	74.59
32	Motestrain	81.16	92.81	92.33					

A_1: Accuracy under DTW, A_2: Accuracy under LCSS and A_3: Accuracy under DLCSS.

$$H_1 : A_3 > A_1$$

The results show that accuracy differences of this technique under DLCSS and DTW methods with 99.95% reliability are greater than zero. So, it can be claimed that the accuracy of 1-NN under DLCSS is better than that of this technique under DTW with **99.95%** confidence. The following assumptions were used to compare the DLCSS and LCSS methods.

$$H_0 : A_3 = A_2$$

$$H_1 : A_3 > A_2$$

The results show that the accuracy differences of this technique under DLCSS and LCSS methods with 99.5% reliability is greater than zero. So, it can be claimed that the accuracy of 1-NN under DLCSS is better than that under LCSS with **99.5%** confidence.

Table 8
Mean accuracy of the 1-NN under DTW, LCSS and DLCSS methods.

	DTW	LCSS	DLCSS
Mean accuracy %	**72.38** (A_{DTW})	**75.05** (A_{LCSS})	**77.88** (A_{DLCSS})

Table 10 shows the comparison of the accuracy of 1-NN under DLCSS with that of under DTW and LCSS. The accuracy under DLCSS is more than or equal to accuracy under DTW in **80.95%** of cases. The accuracy under DLCSS is more than or equal to accuracy under LCSS in **68.25%** of cases.

In summary, DLCSS is more likely to identify the class of a time series than LCSS and DTW methods in 1-NN technique.

4.2. K-medoids clustering results

In this research, k-medoids clustering technique was used to discover the clusters in the data set. This means that how many meaningful clusters the data set can be divided into? How many members and

Table 9
Paired samples t-test the accuracy of 1-NN under DLCSS with that of under DTW and LCSS.

	Paired differences			T	df	Sig. (2-tailed)	Correlation
	Mean	Std. deviation	Std. error mean				
$A_3 - A_1$	5.48940	8.85645	1.11581	4.92	62	0.000	DLCSS & DTW = 0.864
$A_3 - A_2$	2.83014	8.22857	1.03670	2.73	62	0.008	DLCSS & LCSS = 0.883

	Confidence interval of the difference				
	95% Lower	**97.5%** Lower	**99%** Lower	**99.5%** Lower	**99,95%** Lower
$A_3 - A_1$	3.62622	3.25893	2.82483	2.52416	1.63485
$A_3 - A_2$	1.09905	0.75781	0.35449	0.07513	−0.75113

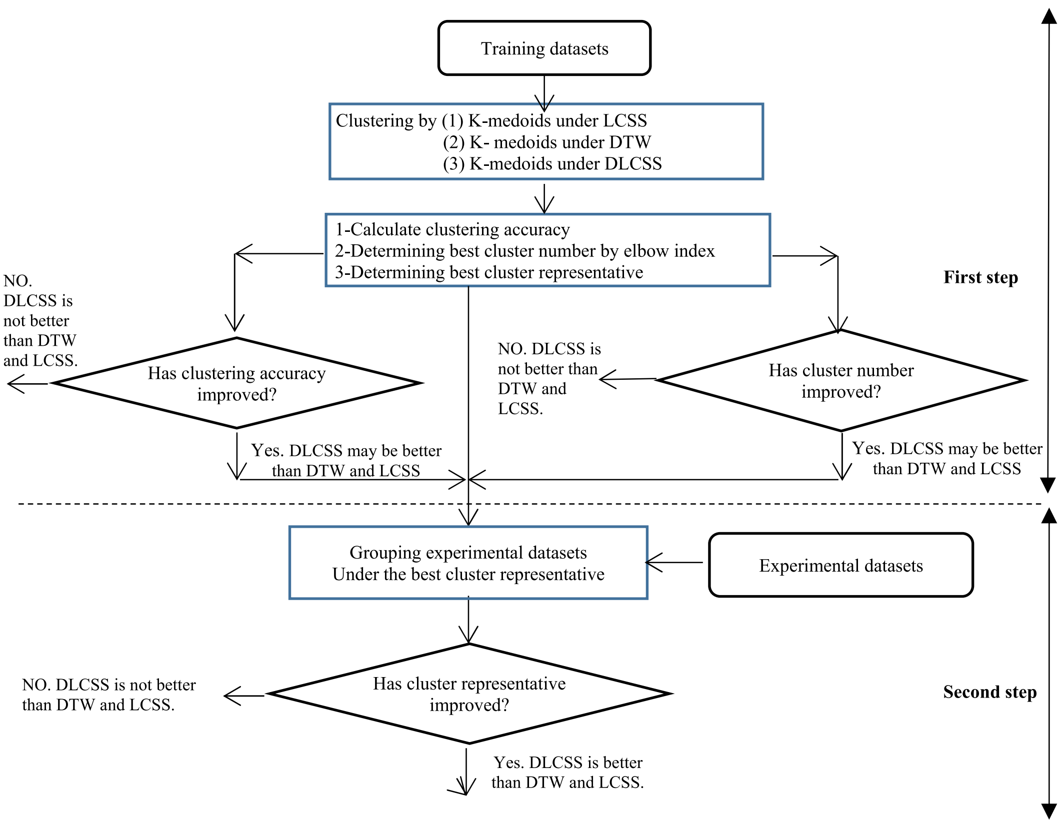

Fig. 4. Evaluation process by k-medoids clustering technique.

Table 10
Comparison of the accuracy of 1-NN under DLCSS with that of under DTW and LCSS.

Row	Description	Number	Percent	Row	Description	Number	Percent
1	$A_3 > A_1$	49	77.78	1	$A_3 > A_2$	39	61.90
2	$A_3 = A_1$	2	3.17	2	$A_3 = A_2$	4	6.35
3	$A_3 < A_1$	12	19.05	3	$A_3 < A_2$	20	31.71

which members are in each cluster? And who are the representatives in each cluster? Objective function of k-medoids is $\min \sum_{i=1}^{k} \sum_{x \in S_i} \|x - C_i\|^2$, where k is the number of clusters, S_i is elements of cluster i ($i = 1, 2, \ldots, k$) and C_i is the representative of cluster i. The evaluation process has been illustrated in Fig. 4. This process has two steps.

In the first step, the training data sets are clustered by k-medoids algorithm for different cluster numbers. The best clustering for any cluster numbers are selected based on the **objective function**. The best number of clusters for any data sets was selected based on angle method. The **elbow method** is a heuristic method of interpretation and validation of consistency within cluster analysis designed to help find the appropriate number of clusters in a dataset and it is a two-dimensional graph, the x-axis denotes the number of clusters and the y-axis represents the sum of the squares of all elements of the center of the cluster of that element. According to this method, the best number of clusters is when the changes of sum of the squares of all elements of the center of the cluster of that element are very small. Finally, the **clustering accuracy** is calculated. The clustering accuracy is the ratio of the number of time series of training data set that have correctly assigned to the right cluster to the total number of time series of the training data set.

In the second step, the experimental data sets were grouped based on the best number of clusters and the representative cluster obtained from the first step. The**n, the grouping accuracy** was calculated as the ratio of the number of time series of experimental data set that had correctly assigned to the right cluster to the total number of time series of the experimental data set. This accuracy illustrates the effect of the similarity measurement method on determining cluster representation at the clustering step.

Generally, the purpose of this process is to answer the following questions:

Question 1: Is the clustering accuracy under DLCSS better than that of under DTW and LCSS?

Table 11
Clustering accuracy and expected cluster number of training data set by K-medoids under DTW, LCSS and DLCSS.

Row	Database name	DTW		LCSS		DLCSS		Row	Database name	DTW		LCSS		DLCSS	
		K	A_1%	K	A_2%	k	A_3%			K	A_1%	K	A_2%	k	A_3%
1	Statistical control	**6**	97.67	**6**	87.33	**6**	91.33	33	SonyII	4	74.07	**2**	92.59	**2**	96.296
2	GP	**2**	56	4	56	**2**	56	34	SonySurface	$\underline{3}$	60	**2**	65	$\underline{3}$	65
3	CBF	**3**	96.67	**3**	96.67	**3**	96.67	35	StarLightCurve	$\underline{4}$	66.07	**3**	75	$\underline{4}$	72.62
4	ECG	**2**	60	**2**	73	**2**	72	36	Two lead ECG	4	60.58	**2**	78.26	**2**	82.77
5	Face4	$\underline{3}$	66.67	$\underline{5}$	83.33	$\underline{5}$	87.5	37	Criket X	$\underline{13}$	41.79	$\underline{11}$	29.23	$\underline{11}$	37.18
6	Medical	6	32.29	6	31.76	8	32.28	38	Criket Y	$\underline{11}$	39.23	$\underline{13}$	32.82	15	35.13
7	Sweedian	19	52.4	13	66.4	13	65	39	U wave X	6	49.89	$\underline{7}$	45.86	$\underline{7}$	48.77
8	OSU	$\underline{5}$	43	10	47.5	$\underline{7}$	48	40	U wave Y	5	48.05	11	41.90	$\underline{9}$	41.34
9	Adiac	30	42.31	33	37.17	34	46.15	41	Insect wing	**11**	25.46	7	41.82	5	42.73
10	Beef	$\underline{6}$	43.33	7	46.67	$\underline{4}$	43.33	42	Arrow head	$\underline{2}$	61.11	$\underline{2}$	63.89	$\underline{2}$	63.89
11	Lighting	$\underline{6}$	55.71	10	60	$\underline{8}$	57.1	43	Beetle fly	2	65	$\underline{2}$	85	$\underline{2}$	80
12	Fish	9	59.57	$\underline{6}$	72.57	$\underline{7}$	82.86	44	Bird chicken	4	55	$\underline{3}$	65	$\underline{3}$	60
13	50words	48	44.89	45	48.22	45	50	45	Ham	**2**	44.95	**2**	52.29	**2**	53.21
14	Trace	$\underline{3}$	78	2	52	**4**	71	46	Phalanges O-C	**2**	33.83	4	42.11	**2**	54.28
15	Lighting7	$\underline{6}$	55.71	**7**	55.71	$\underline{8}$	55.71	47	Proximal POA	**3**	78.25	$\underline{2}$	74.75	$\underline{2}$	81.75
16	Distal	3	59	3	67.63	3	61.15	48	Proximal POC	**2**	38.33	**2**	38.33	**2**	38.33
17	Italy power demand	$\underline{3}$	73.14	$\underline{3}$	67.16	$\underline{3}$	68.66	49	Proximal PT	4	53.17	2	67.81	3	78/05
18	Middle-P-T	2	55.85	2	55.85	2	55.85	50	Toe segmentation1	**2**	35	$\underline{3}$	52.5	$\underline{3}$	55
19	Plane	**7**	100	**7**	100	**7**	100	51	Toe segmentation2	**2**	80.56	**2**	77.78	**2**	77.78
20	Car	$\underline{5}$	56.67	**4**	70	**4**	73.33	52	Distal POA	7	46.04	6	48.92	$\underline{2}$	68.35
21	Olive oil	**4**	86.67	$\underline{3}$	65	**4**	83.33	53	Distal POC	**2**	43.84	**2**	43.48	**2**	43.48
22	Diatom size reduction	**4**	100	**4**	100	**4**	100	54	Distal PT	3	58.99	3	68.35	3	67.65
23	Symbol	**6**	96	**6**	100	**6**	100	55	Earth quakes	**2**	48.20	**3**	43.88	**2**	48.92
24	Worms	2	22.08	$\underline{6}$	28.57	$\underline{6}$	32.47	56	Middle POA	**3**	37.01	$\underline{2}$	53.25	$\underline{2}$	53.87
25	Two pattern	**4**	97.5	**4**	60.3	**4**	61.8	57	Middle POC	**2**	62.89	**2**	66.67	**2**	62.20
26	Wafer	**2**	62.35	**2**	70.48	**2**	68.37	58	Shapelet sim	**2**	30	**3**	60	**3**	75
27	Faceall	$\underline{15}$	67.86	**14**	78.39	**14**	84.82	59	Wine	**2**	47.37	**2**	57.89	4	38.59
28	Lighting2	6	41.67	4	48.33	4	48.33	60	Computers	**2**	40.4	**2**	62	$\underline{3}$	48
29	ECGFiveday	**2**	65.22	$\underline{3}$	60.87	**2**	78.26	61	Meat	**3**	78.33	$\underline{2}$	56	$\underline{2}$	71.67
30	Haptics	$\underline{4}$	28.39	7	42.58	**5**	39.36	62	Refrigeration	$\underline{4}$	44.80	$\underline{4}$	53.60	**3**	55.20
31	InLineSkate	**7**	38	$\underline{8}$	38	**7**	38	63	Worm two class	**4**	24.68	**2**	42.86	**2**	45.45
32	Motestrain	$\underline{3}$	55	**2**	90	**2**	80								

K: Expected cluster number from the clustering.
A_1: Accuracy under DTW, A_2: Accuracy under LCSS and A_3: Accuracy under DLCSS.
Note: bold number means the correct cluster number and underline number is cluster number with 1 error.

Table 12
Mean clustering accuracy under DTW, LCSS and DLCSS.

	DTW	LCSS	DLCSS
Mean clustering accuracy %	56.55 (A_{DTW})	60.89 (A_{LCSS})	63.03 (A_{DLCSS})

Question 2: Is the effect of DLCSS in determining the cluster number better than that of under DTW and LCSS?
Question 3: Is the effect of DLCSS in determining the cluster representative better than that of under DTW and LCSS?

To answer these questions, the clustering technique was implemented on 63 training datasets under DTW, LCSS and DLCSS. The assumptions of this clustering are as follows:

1. For each number of clusters, the clustering operation was repeated 500 times.

2. The representative of clusters a maximum of 500 times could be moved, in each iteration.

The clustering results are presented in next section.

Table 14
Comparison of the clustering accuracy under DLCSS with that of under DTW and LCSS.

Row	Description	Number	Percent	Row	Description	Number	Percent
1	$A_3 > A_1$	39	61.90	1	$A_3 > A_2$	33	52.38
2	$A_3 = A_1$	9	14.29	2	$A_3 = A_2$	14	22.22
3	$A_3 < A_1$	15	23.81	3	$A_3 < A_2$	16	25.40

4.2.1. Clustering results

Table 11 represents the results of implementing k-medoids clustering technique under DTW, LCSS and DLCSS methods. Based on these results and as an example, for "Statistical control" data set, the best result under DTW would be in cluster number of 6 with 97.67% accuracy. It means that 97.67% of the time series of this data set have been correctly clustered in correct place. The best result under LCSS with $\in = 0.25$ is in 6 clusters with 87.33% accuracy and the best result under DLCSS with $\in_1 = 0.05$ and $\in_2 = 0.6$ is in 6 clusters with 91.33% accuracy.

Table 13
Paired samples t-test the clustering accuracy under DLCSS with that of under DTW and LCSS.

	Paired differences			T	df	Sig. (2-tailed)	Correlation
	Mean	Std. deviation	Std. error mean				
$A_3 - A_1$	6.48584	11.77789	1.48387	4.371	62	.000	DLCSS & DTW = 0.813
$A_3 - A_2$	2.13929	7.10946	0.89571	2.388	62	.020	DLCSS & LCSS = 0.926

	Confidence interval of the difference				
	95%	**97.5%**	**99%**	**99.5%**	**99.95%**
	Lower	Lower	Lower	Lower	Lower
$A_3 - A_1$	4.00806	3.51962	2.94233	2.54248	1.35982
$A_3 - A_2$	0.64363	0.34879	0.00033	−0.24104	−0.95492

Table 15
The number of correct predictions of cluster number for 63 data sets.

Row	Description	DTW	LCSS	DLCSS
1	Correct prediction of cluster number	28	25	30
2	Prediction cluster number with 1 error	17	19	21
3	Not correct prediction of cluster number	18	19	12

In general, the mean clustering accuracy for all training datasets is **56.55%** under DTW, **60.89%** under LCSS and **63.03%** under DLCSS (Table 12).

To answer first question, the paired sample t-test was used. The results of this test are presented in Table 13. The following assumptions were used to compare the DLCSS and DTW methods.

$H_0 : A_3 = A_1$

$H_1 : A_3 > A_1$

The results show that paired differences of DLCSS and DTW with 99.95% confidence is greater than zero. So it can be claimed that the clustering accuracy of DLCSS is better than that of DTW with **99.95%** confidence. Also, the following assumptions were used to compare the DLCSS and LCSS methods.

$H_0 : A_3 = A_2$

$H_1 : A_3 > A_2$

The results show that paired differences of DLCSS and LCSS with 99% confidence is greater than zero. So it can be claimed that the clustering accuracy of DLCSS is better than that of LCSS with **99%** confidence.

Table 14 shows a summary of comparing the clustering accuracy under DLCSS with the clustering accuracy under DTW and LCSS methods. The clustering accuracy under DLCSS is more than or equal to that under DTW in **76.19%** of cases. Also, the clustering accuracy under DLCSS is more than or equal to that of under LCSS in **74.60%** of cases.

Table 17
The mean grouping accuracy of the experimental data sets.

	DTW	LCSS	DLCSS
Mean grouping accuracy %	54.35 (GA_{DTW})	56.06 (GA_{LCSS})	60.20 (GA_{DLCSS})

To answer the second question, look at Table 15. This table shows the influence of DTW, LCSS and DLCSS on determining the right number of clusters for data sets. Based on these results and using these methods, the correct number of clusters could be determined for 28, 25 and 30 data sets, respectively. This means that the effect of the DLCSS method has been better or more pronounced than the other methods in determining the correct number of clusters.

In summary, DLCSS is more likely to better identify the clusters and correct number of clusters of the datasets than the LCSS and DTW methods.

4.2.2. *Grouping results*

After clustering the training data sets and determining the best cluster number and cluster representatives for each of them, the experimental data sets was grouped. These results are presented in Table 16. Based on these results and as an example, the "Statistical Control" data set could be grouped with 96%, 85.57% and 87.33% accuracies under DTW, LCSS and DLCSS methods, respectively.

In general, for all data set, the mean grouping accuracy under DTW, LCSS and DLCSS of experimental dataset is **54.35%, 56.06%** and **60.20%**, respectively (Table 17).

To answer third question, the paired sample t-test was used. The results of this test are presented in Table 18. The following assumptions were used to compare the effect of DLCSS and DTW methods in

Table 16
Grouping accuracy the experimental data sets with cluster centers obtained from training data clustering.

Row	Database name	DTW	LCSS	DLCSS	Row	Database name	DTW	LCSS	DLCSS
		GA_1%	GA_2%	GA_3%			GA_1%	GA_2%	GA_3%
1	Statistical control	96	85.57	87.33	33	SonyII	66.32	74.19	79.23
2	Gun point	48	46.67	48	34	sonySurface	44.59	43.26	53.08
3	CBF	93.33	91	91.33	35	StarLightCurve	67.59	75.41	76.24
4	ECG	54	71	65	36	Two lead ECG	60.58	66.37	73.93
5	Face4	44.32	86.34	87.5	37	Criket X	38.46	19.74	31.28
6	Medical	32.76	26.45	28.55	38	Criket Y	36.67	28.20	28.98
7	Sweedian	55.04	63.84	64.64	39	U wave X	54.10	47.63	50.56
8	OSU	35.54	39.67	41.74	40	U wave Y	45.09	36.68	47.26
9	Adiac	37.85	35.29	43.22	41	Insect wing	18.33	42.68	41.31
10	Beef	46.67	50	46.67	42	Arrow head	48	52.57	48.57
11	Lighting	51.43	50.49	52.06	43	Beetle fly	60	80	85
12	Fish	52	72.57	80.57	44	Bird chicken	40	45	45
13	50words	40.66	45.49	49.23	45	Ham	45.72	41.91	46.67
14	Trace	72	48	63	46	Phalanges O-C	44.99	31.35	62.82
15	Lighting7	52.01	49.32	52.06	47	Proximal POA	76.10	85.37	85.37
16	Distal	73.25	78.25	74.75	48	Proximal POC	36.43	36.43	36.43
17	Italy power demand	73.86	64.34	65.69	49	Proximal PT	52.5	72.25	77.75
18	Middle-P-T	61.16	61.16	61.16	50	Toe segmentation1	41.67	56.14	57.02
19	Plane	99.05	99.05	100	51	Toe segmentation2	82.31	74.62	79.23
20	Car	43.33	51.67	70	52	Distal POA	65.75	69	80.75
21	Olive oil	86.67	56.67	80.33	53	Distal POC	37.17	37.17	37.17
22	Diatom size reduction	84.64	91.83	94.77	54	Distal PT	73.25	77.25	77.25
23	Symbol	91.76	94.17	94.88	55	Earth quakes	47.52	41.31	47.52
24	Worms	23.76	34.25	34.25	56	Middle POA	68.75	25.5	64
25	Two pattern	97.17	59.32	60.37	57	Middle POC	44.17	48.5	45.83
26	Wafer	59.38	68.58	64.54	58	Shapelet sim	29.44	48.89	54.44
27	Faceall	58.81	63.67	69.17	59	Wine	48.15	50	44.36
28	Lighting2	32.79	36.07	44.26	60	Computers	38.40	65.20	54.78
29	ECGFiveday	60.86	53.66	65.62	61	Meat	71.67	46.67	60
30	Haptics	19.16	29.22	32.14	62	Refrigeration	41.60	46.13	48
31	InLineSkate	18.00	17.26	21.08	63	Worm two class	34.25	56.91	58.70
32	Motestrain	69.57	88.58	80.19					

GA_1: Accuracy under DTW, GA_2: Accuracy under LCSS and GA_3: Accuracy under DLCSS.

Table 18
Paired samples t-test the grouping accuracy under DLCSS with that of under DTW and LCSS.

	Paired differences			T	Df	Sig. (2-tailed)	Correlation
	Mean	Std. deviation	Std. error mean				
$GA_3 - GA_1$	5.84492	12.09644	1.52401	3.835	62	0.00	DLCSS & DTW = 0.809
$GA_3 - GA_2$	4.14048	8.22417	1.03615	3.996	62	0.00	DLCSS & LCSS = 0.912

	Confidence interval of the difference				
	95% Lower	**97.5%** Lower	**99%** Lower	**99.5%** Lower	**99,95%** Lower
$GA_3 - GA_1$	3.30013	2.79847	2.20557	1.79490	0.58026
$GA_3 - GA_2$	2.41031	2.06925	1.66614	1.38694	0.56112

Table 19
Comparison of the grouping accuracy under DLCSS with that of under DTW and LCSS.

Row	Description	Number	Percent	Row	Description	Number	Percent
1	$GA_3 > GA_1$	44	68.75	1	$GA_2 > GA_1$	47	73.44
2	$GA_3 = GA_1$	6	9.38	2	$GA_2 = GA_1$	7	10.94
3	$GA_3 < GA_1$	14	21.88	3	$GA_2 < GA_1$	10	15.63

determining the representative clusters quality of clusters.

$H_0 : GA_3 = GA_1$

$H_1 : GA_3 > GA_1$

The results show that paired differences of DLCSS and DTW with 99.95% confidence is greater than zero. So it could be claimed that the grouping accuracy under DLCSS is better than that of under DTW with **99.95%** confidence. This means that the quality of the representative clusters determined by DLCSS method is better than that of by DTW method. Also, the following assumptions were used to compare the effect of DLCSS and LCSS methods in determining the representative clusters quality of clusters.

$H_0 : A_3 = A_2$

$H_1 : A_3 > A_2$

The results show that paired differences of DLCSS and LCSS with 99.95% confidence is greater than zero. So it could be claimed that the grouping accuracy under DLCSS is better than that of under LCSS with **99.95%** confidence. This means that the quality of the representative clusters determined by DLCSS method is better than that of by LCSS method.

Table 19 shows the comparison of the grouping accuracy under DLCSS with that of under DTW and LCSS. The grouping accuracy under DLCSS is more than or equal to that of under DTW in **77.78%** of cases. Also, the grouping accuracy under DLCSS is more than or equal to that of under LCSS in **84.13%** of cases

In summary, DLCSS is more likely to better identify the representative of clusters than the LCSS and DTW methods.

5. Conclusion

In this research, a new method for measuring the similarity of time series has been presented. This new method is based on LCSS and used two similarity thresholds. It named Developed Longest Common Subsequence (DLCSS). The reason for using two similarity thresholds is the high fluctuation in the results of data mining technique under LCSS method.

In DLCSS method, first and second similarity thresholds are the basis for recognizing the definite similarity between two data and the basis for recognizing the conditional similarity of the two data, respectively. According to the investigations the best value for them are $\in_1 = 0.05$ and $\in_2 = 0.60$, respectively. By implementation the 1-NN technique under DLCSS, LCSS and DTW methods, the accuracies of 77.88%, 75.05% and 72.38% were determined, respectively. Using paired sample t-test, it was shown that the accuracy of the 1-NN technique under DLCSS was better than that of DTW and LCSS methods with at least 99.5% confidence.

In the k-medoids clustering technique, the clustering accuracy of the training datasets under DTW, LCSS and DLCSS were 56.55%, 60.89% and 63.03%, respectively. The paired sample t-test showed that the clustering accuracy under DLCSS is better than that of under DTW and LCSS with at least 99% confidence. Also, DLCSS is more likely to better identify correct number of clusters of the data sets than the LCSS and DTW methods. By using the best cluster number and cluster representative obtained from the clustering step, the experimental dataset members were grouped under DTW, LCSS and DLCSS. They have the grouping accuracy of 54.35%, 56.06% and 60.20%, respectively. Then, using paired sample t-test t, it can be claimed that DLCSS has better performance in determining the cluster representatives than that of DTW and LCSS with at least 99% confidence.

In general, it could be claimed that the DLCSS has a better performance in time series data mining compared to the performance of DTW and LCSS methods with at least 99% confidence. Since there are no similarity measurement methods that are suitable for all types of datasets, therefore, it is possible to investigate the feasibility of applying fuzzy logic and meta-heuristic methods to measure the similarity of time series in the future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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