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A NEW FUZZY C MEANS CLUSTERING ALGORITHM BASED ON CONSTRAINED DYNAMIC TIME WARPING DISTANCE MEASURE

[1]V KATHIRESAN, [2] Dr P SUMATHI
[1]Research Scholar, Bharathiar University, Coimbatore
[2]Assistant Professor, Department of Computer Science, Government Arts College, Coimbatore
Email: [1]kathirsujith@gmail.com , [2]sumathirajes@hotmail.com

ABSTRACT

A decade back, Dynamic Time Warping (DTW) was establishing into Data Mining neighborhood as effectiveness for different responsibilities for moments sequence evils including categorization, group, and variance discovery. The method has flourished, chiefly in the last three years, and has been useful to a multiplicity of troubles in a variety of authority. In this paper, distant intellect clustering methods that make use of a solitary position iterative modified fuzzy C-means grouping algorithm is projected based leading the preceding in sequence. This technique is able to work out the fuzzy C-means algorithm's difficulty to the clustering worth is really reproduction by the data issue and the stochastic initializing the middle of clustering. Experimental results make obvious that the Modified FCM advance create better clusters than FCM clustering algorithms.

Keywords: *Centroid, Cluster, Precision, Segmentation*

1. INTRODUCTION

In instance sequence examination, **Dynamic Time Warping** (DTW) is an algorithm for calculating the comparison among two sequential series which might differ in instance or rate. For example, comparison in walking model might be perceive with DTW, still if one individual was walking earlier than the additional, or if herebe acceleration and deceleration during the path of an inspection. DTW have been functional to sequential series of video, audio and graphics information certainly, any information which is able tocurve into a linear progression is able to investigate with DTW. A fine recognized request has been repeated language appreciation, to manage with dissimilar talking rate. Additional request contain speaker acknowledgment and online autograph respect. Moreover it is seen to facilitate it container be used in unfinished shape similar function.

In common, DTW is a technique to determine a finest competition among two known series (e.g. time series) with confidentlimits. The progression is "warped" non-linearly in the instant measurement to establish, to calculate of their comparison autonomous of confident non-linear dissimilarity in the time quantity. This progression arrangement technique is frequently utilized in time sequence categorization. Even though DTW actions a distance-like quantity among two given progression, it doesn't assure the triangle dissimilarity to hold. Dynamic Time Warping space calculation was initiated to the data mining population as an answer to this exact weakness of Euclidean distance metric. After the possibility statistics of creative information, the weights

of information attribute are calculated to alter unique illustration to the uniform allocation, and additional to the procedure of cyclic iteration, which might be fitting for the nature of Modified Fuzzy C-means algorithm so as to get better the accuracy. The remaining part of this paper is organized as follows. In Section 2, review of fuzzy, modified fuzzy clustering and Dynamic Time Warping algorithms with several popular validity indexes were discussed. An existing method of FCM discussed in Section 3, Section 4 and 5 presents a process of definition and algorithm for Dynamic Time Warping and Classical DTW. In Section 6, MFCM with Constraints Dynamic Time Warping Distance is discussed. In section 7, three real data sets of Iris, Wine and Lung Cancer is used to have more comparisons. Many motivatingexperiencecan be found in these association results.Conclusions are drawn in Section 8.

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2. LITERATURE SURVEY

Dynamic Time Warping (DTW) is frequently used in motion appreciation responsibilities in order to arrange, to undertake the sequential extent unpredictability of gesture. In the DTW structure, a situate of motion model are evaluated one by one to a unlimited test series, and a uncertainty gesture group is familiar if a warping price under a confident threshold is establish inside the test series. In this paper, a probability-based DTW for motion appreciation is planned by Mantena *et al* (2013). TarikArici *et al* (2013) show the Dynamic Time Warping is single method used in motion appreciation to discover a most favorable arrangement among two progressions. DTW computes a difference determine by time-warping the succession on a per example foundation by using the space between the present suggestion and test progression.

Consequently, this document presents the exploit of DTW to procedure the speed recent signals for distinguish and quantifying common faults in a downstream two-stage reciprocating compressor. DTW is an instant province stand process and its algorithm is simple and easy to be bounded into real-time strategy. In this study, DTW is used to repress the provide incidence constituent and underscore the sideband mechanism based on the beginning of an orientation indication which has the similar regularity module as that of the provide power by Zhen*et al* (2013).

A computerized system for Magnetic Resonance Imaging (MRI) brain segmentation is designed. The MRI image space is corresponding to high-dimensional distinguishing spaces that contain multimodal greatness features as well as spatial features are given by Mayer *et al* (2009). Hyper powerful white material indicator abnormalities, also called Diffuse Excessive High Signal Intensity (DEHSI) are shown by He *et al* (2013).Segmentation techniques supports on fuzzy advance have been inhabited to increase further than the ambiguity explanation by this property is given by Ghasemi *et al* (2013).In this paper obtainable by Sivaperumal, and Sundhararajan (2013), they analysis the characteristic withdrawal of brain representation disease like brain growth segmentation by means of the method called seeded area & PCNN. These theory papers examine two algorithms to section brain tissues and to execute the capable one during reproduction by MATLAB software.

Soleimani *et al* (2013), using medical imaging strategy is necessary for disease analysis and medical inspect. Surrounded by these plans, Magnetic Resonance Imaging has the major position. Segmentation of these images is additional hard than natural images since their practical compassion is advanced than additional images. Up to now, a lot of dissimilar algorithms contain be not compulsory for segmentation of this type of images. In this paper, they suggest an advance in arrange to get enhanced ant colony algorithm effectiveness.

By means of the enlarge in multi-media information over the Internet, inquiry by illustration verbal expression uncovering (QbE-STD) has be converted into significant in providing a look for instrument to discover verbal queries in verbal audio. In common, advance consequential from the healthy identified Dynamic Time Warping (DTW) algorithm suffers from scalability evils. To defeat such troubles, an Information Retrieval-based DTW (IR-DTW) algorithm has been planned freshly by Mantena *et al* (2013). The difficulty of indexing time series has involved a great deal of attention. The majority algorithms used to index time sequence consume the Euclidean expanse or several variations. Nevertheless, it has been powerfully exposed that the Euclidean expanse is an extremely delicate expanse quantify. Dynamic Time Warping is a great deal of robust distance measure for time series; allocate related shapes to competition even if they are out of stage in the time axis are given by Keogh *et al* (2005)

The method of Dynamic Time Warping for time registration of a suggestion and test expression has establish widespread use in the area of discrete statement appreciation. As initially planned, the algorithm located burly restriction on the probable set of active paths—namely, it was understood that the early and last surround of both the test and orientation expression were in exact time synchrony. Myers *et al* (1980), shows the technique of dynamic programming for the time registration of a reference and a test pattern has found widespread use in the area of isolated word recognition. The major differences in the methods are the global path constraints, the local continuity constraints on the path, and the distance weighting and normalization used to give the overall minimum distance.The performance measures that were used include: speed of operation, memory requirements, and recognition accuracy.

The conservative fuzzy C-means clustering algorithm is a statement in preceding mechanism for market separation, but it might be incompetent

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or unbalanced particularly in large-scale power organization. To improve the obstruction organization, the proposed algorithm obtains directly the outcome of crowded lines using an appropriate index. In this advance, the fuzzy C-means is use in a new way to steady and get better the efficiency of the algorithm and to moderate the reported insufficiency of beforehand market separation technique are given by Raoofat *et al* (2013).

Warping technique is a significant group of process that can be accurate for misalignments in substance capacity. Their use in preprocessing of chromatographic, spectroscopic and spectrometric information has developed quickly over the last decade. This study evaluation aims to give a serious introduction to the most significant warping technique, the place of warping in preprocessing and recent views on the connected matters of situation collection, optimization and assessment are shown by Bloemberg *et al* (2013).

In this study, proceeding with the objective function-based clustering (such as, e.g., fuzzy C-means), we revisit and augment the algorithm to make it applicable to spatio temporal data given by Izakian *et al* (2013).

3. FUZZY C-MEANS

There is a large multiplicity of clustering algorithms used for time series clustering such as Hierarchal based, separation based and concentration based. The Fuzzy C-Means (FCM) focuses mostly due to the gain of the degree of association of a time series to the group in clustering procedure. It is used to make possible the discovery of modify in prototypes. In addition, fuzzy situate include a additional sensible advance to address the impression of comparison than traditional position. A fuzzy set is a set with fuzzy restrictions wherever every module is agreed a degree of association to every set. The FCM mechanism by division a gathering of n vectors into c fuzzy groups and discovers a cluster middle in each group such that the cost task of distinction calculate is decreased. Bezdek bring in the idea of a "Fuzzification Parameter" (m) in the variety [1, n]which decide the amount of uncertainty (weighted coefficient) in the clusters. Usually m is in the range [1.25.2] inclusively and manages the permeability of the cluster possibility which can be sight as an n-dimensional cloud moving out from cluster middle. The Fuzzy C-means (FCM) has been functional to time series to discover the group in some works in journalism. For illustration, authors use FCM to cluster time sequence for lecture confirmation. Authors use fuzzy substitute to cluster a like thing motions that were experimental in a video gathering. They use the perception of FCM with time-series data using LCSS as distance measure and a new prototype bring up to date advances. Let the centers be $vj = \{v_1,..,v_c\}$ and each time series F_i that I = $\{1,..,n\}$and *DLCSS* (F_i,vj) as distances between centers and time series. Therefore, the membership values $\mu_i j$ are obtained with:

$$\mu_j(X_i) = \frac{\left(\frac{1}{(D_{LCSS}(F_i,V_j))}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{p}\left(\frac{1}{(D_{LCSS}(F_i,V_j))}\right)^{\frac{1}{m-1}}} \quad (1)$$

Where the sum of cluster memberships for a time series equals 1. Then, the FCM objective function (standard loss) that is attempted to be diminishing takes the form:

$$j = \sum_{j=1}^{c} J_j = \sum_{j=1}^{c} [\mu_{ij}] m_{D_{LCSS}}(F_i, v_j) \quad (2)$$

Whereμ_{ij} is a mathematical rate among [0; 1]; *DLCSS* (F_i,vj) is the LCSS reserve among the j_{th} sample and the i_{th} time series; and m is the exponential load which authority the degree of uncertainty of the association medium. Indifferent iterations, the membership principles of the time series are intended, and then the prototypes (cluster centers) are recomputed. The iterations will sustained to a expire standard. Finally, with the application of the fuzzy clustering algorithm to time series, a set of clusters is created so that each cluster, C_i includes a subset of time series with similar patterns (general subsequence).

4. DYNAMIC TIME WARPING DISTANCE MEASURE

Complete accomplishment of Dynamic Time Warping algorithms in R. Supports un informed restricted (Example: symmetric, asymmetric, and slope-limited) and comprehensive (windowing) restriction, fast resident code, numerous plot fashion, and more. The R Package DTW offer the most absolute, freely-available (GPL) accomplishment of Dynamic Time Warping-type (DTW) algorithms up to date. The package is explained in a attendant document, together with exhaustive directions and extensive surroundings on

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effects like multivariate corresponding, open-end variation for real-time use, interaction among recursion kind and duration normalization, times past, etc.

4.1 Definition

An (N,M)-Warping Path (or purely referred to as warping path if N and M are obvious beginning the framework) is a series p = (p1. . .pL) with Pl= (n_l, ml) ∈[1 : N] × [1 : M] for l∈[1 : L] rewarding the subsequent three situations.

(i) **Boundary condition**: p1 = (1, 1) and pL= (N,M).
(ii) **Monotonicity condition**: n1 ≤ n2 ≤ . . . ≤ nL and m1 ≤ m2 ≤ . . . ≤ mL.
(iii) **Step size condition**: p_+1 − p_ ∈ {(1, 0), (0, 1), (1, 1)} for _ ∈[1:L −1

Note to facilitate the step size situation (iii) implies the monotonicity situation (ii), which nevertheless has been quoted unambiguously for the sake of precision. An (N, M)-warping path p = (p1, . . . ,pL) characterize an association among two succession X= (x1, x2, . . . , xN) and Y = (y1, y2, . . . , yM) by transmission the component x_{nl} of X to the aspect y_{ml} of Y. The edge situation implement that the first elements of X and Y as well as the last elements of X and Y are associated to every other. In other words, the arrangement refers to the whole sequence X and Y. The monotonicity situation reproduces the constraint of accurate timing: if a constituent in X leads to a second one this be supposed to further more grip for the equivalent elements in Y, and vice versa. Finally, the step size situations communicate a kind of stability state: no element in X and Y can be absent and there is no duplication in the arrangement (in the intelligence that all catalog pairs controlled in a warping path p are pair wise separate).

The total cost cp(X, Y) of a warping path p among X and Y with reference to the local cost measure C is distinct as

$$C_p(X,Y) := \sum_{l=1}^{L} C(x_{n1}, y_{m1}) \qquad (3)$$

Furthermore, a most favorable warping path among X and Y is a warping path p ∗hold smallest total cost among all possible warping paths. The DTW distance DTW(X, Y) between X and Y is then distinct as the total cost of p∗:

DTW(X, Y):= cp∗(X, Y) = min{cp(X, Y) | p is an (N,M)-warping path} (4)

4.2 Algorithm

The algorithm for Optimal Warping Path can be discussed below

```
path[] ← new array
i = rows(dtw)
j = columns(dtw)
while(i > 1) & (j > 1)do
  ifi == 1then
      j = j –1
   else ifj == 1then
      i = i – 1
   else
      if dtw(i–1; j) == min {dtw(i – 1; j); dtw(i; j – 1); dtw(i – 1; j – 1)}
then
        i = i – 1
        else ifdtw(i; j–1) == min {dtw(i – 1; j); dtw(i; j – 1); dtw(i – 1; j – 1)}
then
        j = j – 1
      else
        i = i – 1; j = j – 1
      end if
      path.add((i, j))
   end if
end while
return path
```

Algorithm 4.2.1 optimal warping path (DTW)

Once the accrue cost matrix built the warping path could be established by the simple backtracking from the point P_{end} = (M, N) to the P_{start} = (1, 1) subsequent the greedy approach as illustrated in the Algorithm 4.2.1.

5. CLASSICAL DTW

The purpose of DTW is to compare two (time-dependent) progression X: = (x1, x2. . .xN) of length N ∈ N and Y: = (y1, y2, . . . , yM) of length M∈N. These succession might be separate signal (time-series) or, more normally, characteristic series model at equidistant points in time. In the subsequent, they fix a characteristic break indicated by F. Then xn, ym∈ F for n ∈[1 :N] and m ∈[1 : M]. To compare two dissimilar features x, y ∈ F, one needs a local cost measure, sometimes also

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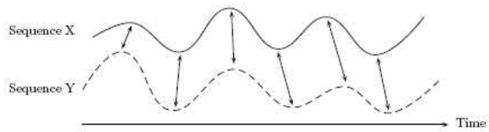
referred to as local distance calculate, which is distinct to be a function c:F ×F →R≥0.



Time alignment of two time-dependent sequences. Aligned points are indicated by the arrows.

Classically, c(x, y) is tiny (low cost) if x and y are alike to each other, and or else c(x, y) is huge (high cost). Estimating the local cost determine for each pair of elements of the sequence X and Y , one gain the cost matrix C ∈RN×M definite by C(n,m) := c(xn, ym). Then the target is to discover a placement among X and Y containing smallest largely cost. Instinctively, such a best arrangement runs beside a “valley” of low cost within the cost matrix C. The next definition formalizes the concept of an alignment.

6. MFCM WITH CONSTRAINTS DYNAMIC TIME WARPING DISTANCE (MFCM)

In this segment, an original Modified FCM algorithm is planned for conquer the disadvantages of other technique expressed above. The MFCM algorithm is initial proposed and an image denoising technique. It tries to take advantage of the elevated degree of idleness in image. In other words, they understood that for each pixel in an image, they can discover a set of illustration with a comparable neighborhood pattern of it. Then the pixel below deliberation might be subjective by the weighted averaging over this model. The experiments show that the modified FCM algorithm can contract with the distance between two methods can be calculated perfectly. Some problem facts are able to smooth out by the MFCM algorithm. In our planned algorithm, the expanse dimension predisposed by local and non-local information is modified as follow:

By an optimization way alike to the FCM, J_m^{Φ}can be diminish below the restriction of U. purposely, if they take its primary unoriginal with respect to u_{ik} and v_i, and zero them, correspondingly, two essential but not enough circumstances for $J_m^{\Phi}$to be at local smallest amount will be achieved as

$$uik = \frac{(1 - DTW(xk, vi)) - \frac{1}{(m-1)}}{\sum_{j=1}^{c}(1 - DTW(xk, xi)) - \frac{1}{(m-1)}} \quad (5)$$

$$vi = \frac{\sum_{k=1}^{n} U_{ik}^{m} DTW(xk, vi)xk}{\sum_{k=1}^{n} U_{ik}^{m} DTW(xk, vi)} \quad (6)$$

It is obvious to the achieve centroids or prototypes {vi} still lie in the unique break and not in the changed higher dimensional characteristic space, thus, the computational minimalism is still preserve. In totaling, it is shown that the MFCMs resulted are healthy to outliers and noise according to Huber’s robust statistics. This quality can furthermore give an perceptive clarification that the information point x_k is brilliant with an added weight $k(x_k,v_i)$, which procedures the resemblance between x_k and v_i, and while x_k is an outlier, i.e., x_k is far from the other data points $k(x_k,v_i)$, will be very little, so the prejudiced sum of information position shall be concealed and therefore result in strength. Our experiments also confirm that new algorithms are indeed more robust to outliers and noise than FCM.

6.1 Corresponding Description of MFCM Algorithm

In this section, they will build the consequent kernelized description of the MFCM algorithm. Alike to the origin of MFCM, they kernelize standard and achieve the subsequent new purpose function during the newly-induced distance calculate replacement

$$JSm^{\Phi} = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m}(1 + DTW(xk, vi)) + \frac{a}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m}\sum_{r\in N_k}(1 + DTW(x_k, v_i)) \quad (7)$$

Where k(x,y) is still taken as GRBF,N_k,X_k,α and N_R are distinct as before. An iterative algorithm of reduce with deference to u_{ik} and can likewise be resultant, as shown in (8) at bottom of the page. In practical realization of the algorithm, we use (9b) to replace (9a), as shown at the bottom of the page, so as to further reduce the computation of (9a). In fact, such a simplification is not able to cause bad effective to clustering results as shown in our experiments.

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$$u_{ik} = \frac{\left(\left(1 - DTW(x_k, v_i)\right) + \frac{a}{N_R}\sum_{r \in N_k}(1 - DTW(x_r, v_i))m\right)^{-\frac{1}{(m-1)}}}{\sum_{j=1}^{c}\left(\left(1 - DTW(x_k, v_i)\right) + \frac{a}{N_R}\sum_{r \in N_k}(1 - DTW(x_r, v_i))m\right)^{-\frac{1}{(m-1)}}} \quad (8)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m}\left(DTW(x_k, v_i) + \frac{a}{N_R}\sum_{r \in N_k} DTW(x_r, v_i)\right)x_k}{\sum_{k=1}^{n} u_{ik}^{m}\left(DTW(x_k, v_i) + \frac{a}{N_R}\sum_{r \in N_k} DTW(x_R, v_i)\right)} \quad (9b)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m}\left(DTW((x_k, v_i)x_k + \frac{a}{N_R}\sum_{r \in N_k} DTW(x_r, v_i)x_r\right.}{\sum_{k=1}^{n} u_{ik}^{m}\left(DTW((x_k, v_i)x_k + \frac{a}{N_R}\sum_{r \in N_k} DTW(x_r, v_i)\right)} \quad (9a)$$

Similarly, a kernelized modification to (7) is

$$JSm^{\Phi} = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m}(1 + DTW(xk, vi))$$
$$+ a\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m} \sum_{r \in N_k} u_{ik}^{m}(1 + DTW(x'_k, v_i)) \quad (10)$$

Where x'k is distinct as previous to and frankly viewed a data point in the original space to be drawing by Φand thus can be calculate in progress and stored. And the objective function in (10) is minimized using the following alternate iterations:

$$u_{ik} = \frac{\left(\left(1 - DTW(x_k, v_i)\right) + a\left(1 - DTW(x'_k, v_i)\right)\right)^{-\frac{1}{(m-1)}}}{\sum_{j=1}^{c}\left(\left(1 - DTW(x_k, v_i)\right) + a\left(1 - DTW(x'_k, v_i)\right)\right)^{-\frac{1}{(m-1)}}} \quad (11)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{m}^{ik}\left(DTW((x_k, v_i)x_k + a\,DTW(x'_k, v_i)x'_k\right.}{\sum_{k=1}^{n} u_{m}^{ik}\left(DTW(x_k, v_i) + aK(x'_k, v_i)\right)} \quad (12)$$

7. EXPERIMENTL RESULTS

In this section, the experimental results on several synthetic and real processes are discussed. There are a total of two algorithms used in this section, i.e., standard FCM, MFCM. The proposed method of MFCM is used to measure the distance time warping in accurate manner. Then the precision and recall values can be shown below in these experimental results.

7.1. Methodology and Datasets

Experiments were behavior on three datasets from the UCI repository: *Iris*, *Wine*, and *lung cancer*. These courses were selected because they characterize hard visual favoritism troubles. Table 1 recapitulates the belongings of the datasets: the number of instances N, the number of dimensions D, and the number of classes K. Table 1. Datasets used in experimental evaluation

Table 1
Datasets Used In Experimental Evaluation

	Iris	Wine	Lung Cancer
N	250	570	1100
D	5	19	25
K	3	3	1

They have used pair wise F-Measure to estimate the grouping results support on the fundamental modules. F-Measure relies on the conventional in sequence repossession events, adapted for estimate clustering by consider same-cluster pairs:

Precision= $\frac{\text{\#PairsCorrectlyPredicted InSameCluster}}{\text{\#Total Pairs Predicted In Same Cluster}}$

Recall = $\frac{\text{\#PairsCorrectlyPredictedInSameCluster}}{\text{\#TotalPairsInSameCluster}}$

F-Measure = $\frac{2 - \text{Precision} - \text{Recall}}{\text{Precision} + \text{Recall}}$

They created knowledge curves with 5-fold cross-validation for every dataset to find out the result of make use of the pair wise control. Each point on the knowledge curve corresponds to an exacting number of arbitrarily chosen pair wise constraints given as input to the algorithm. Unit restriction costs W and W were used for all restriction, innovative and incidental, since the datasets did not offer individual weights for the restraint. The clustering algorithm was run on the entire dataset, but the pair wise F-Measure was designed only on the test set. Results were averaged over50 runs of 5 folds.

Table 2: Precision and Recall for Dataset

	Precision		Recall	
	FCM	MFCM	FCM	MFCM
Iris	40	85	35.51	25.23
Wine	77	90	28.54	20.56
Lung cancer	80	98	20.34	12.43

Table 2 shows the values of precision and recall for different types of datasets.

When compared to existing K-Means algorithm, the proposed technique is higher in accuracy and lesser in execution time by using IRIS, Wine and

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Lung Cancer Datasets. The Proposed Clustering Algorithm is the methods which are more realistic approach to calculate accurate value and time completion. The processes of those existing and proposed approaches in datasets are compared in table 2.

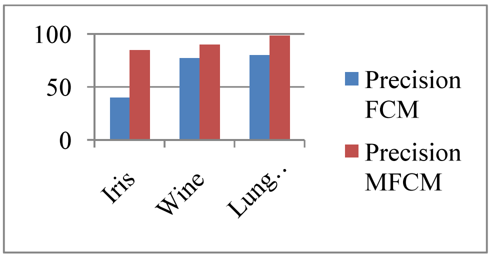

Figure 1: Precision

Figure 1 shows the accuracy by comparing three dataset. The proposed method of MFCM may have high accuracy when compared with existing approaches.

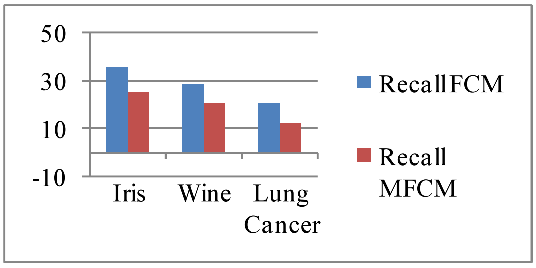

Figure 2: Recall

Figure 2 shows the recall for the datasets of Iris, Wine and Lung Cancer. Proposed approaches of MFCM have less recall value.

The Proposed Clustering Algorithm is the advanced one to overcome those problems in existing techniques. A Proposed Clustering Algorithm is enough and too attractive. The IRIS, Wine and Lung Cancer datasets are used to calculate and evaluate both existing and proposed procedure for accuracy in figure 1 and execution time shows in figure 2.

8. CONCLUSION

Fuzzy C-Means clustering (FCM) with restriction is asuccessful algorithm appropriate for Distance Time Warping. Its usefulness donates not only to the introduction of uncertainty for belongingness of each pixel but also to utilization of spatial appropriate in sequence. The backgroundin sequence can increase its insensitivity to noise to some level. Even though the robustness of the MFCM algorithm is improved, the convergence rate of it is lower. In this paper, to conquer the problem in FCM algorithm is time consuming, a Modified Fuzzy C-Means clustering algorithm with constraints is proposed. To speed up FCM calculations, MFCM algorithm adapted the degree of memberships. Experiments on the reproduction and real-world datasets show that our proposed algorithm is more efficient.

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