A NEW FUZZY POSSIBILISTIC CMEANS CLUSTERING ALGORITHM BASED ON DYNAMIC TIME WARPING DISTANCE

V. Kathiresan[1] , *S. Mythili*[2]

ABSTRACT

Most works in present field are centered on the description and make use of a distance among sequence of aspects. A measure called Dynamic Time Warping (DTW) appears to be presently the major related for a huge panel of applications. This work is about the use of DTW in data mining algorithms, and focus on the calculation of an average of a set of sequence. Averaging is an necessary tool for the investigation of data. For illustration, the K-means clustering algorithm frequently calculates such an average, and requests to offer a explanation of the group it forms. Averaging is now critical steps, which must be sound in arrange to construct algorithms work perfectly. This work performs the technique of Fuzzy Possibilistic C-Mean (FPCM) algorithm which enhances the clustering accuracy. Experimental results make obvious that the FPCM advance create better clusters than FCM and MFCM clustering algorithms.

Keywords: *Centroids, Cluster, Precision, K-Mean, Modified K-Mean, Fuzzy Possibilistic C-Mean (FPCM).*

[2]Assistant Professor-BCA, PSGR Krishnammal College for Women, Coimbatore.

I. INTRODUCTION

Dynamic Time Warping (DTW) is time sequence is a ubiquitous variety of informationhappening in almost every technicalregulation and business purpose. There is greatly latest job on adapting data mining algorithms to instance sequence databases. Starting with obtainable techniques residential around DTW, this work proposes an investigation framework to categorize averaging techniques. It then proceeds to learn the two major queries elevated by the framework. Initially, enlarge a global method for averaging a set of series. This method is creative in that it avoids using iterative pairwise averaging. It is therefore not sensitive to ordering property. Subsequent, explain a latest approach to diminish the length of the resulting standard series. This has afavorablecontact on appearance, but also on the significance of the product. Both features are designed on common datasets, and the judgment demonstrates that it compare relatively with presented techniques.

Dynamic time warping (DTW) is the name of a category of algorithms for comparesequence ofworth with each other. The motivationfollowing DTW is, given two time sequence, to extend orreduce them nearby in order to create one resemble the other as much as probable.Various types of DTW algorithms differ for the input characteristic space, the local distance implicit,attendance of local and global constraint on the alignment, and so on. This freedom composesDTW a very flexible alignment approach.

The remainingpart of this work is organized as follows. In Section 2, survey of fuzzy, modified fuzzy clustering, Fuzzy Possibilistic C-Mean and Dynamic Time Warping algorithmswith were discussed. An existing method of FCM discussed in Section 3, Section 4 presents a performance and algorithm for Dynamic Time Warping and Classical DTW. In Section 6, proposed method of FPCM with Constraints Dynamic Time Warping Distance is discussed. In section 7, three real data sets of Iris, Wine and Lung Cancerare used to have more comparisons. Many motivatingexperiencecan be found in these association results.Conclusions are drawn in Section 8.

II. 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 work, a probability-based DTW for motion appreciation is planned by Mantenaet al (2013).TarikAriciet al (2013) show the Dynamic Time Warpingis 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.

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.Myerset al (1980) demonstrate the method of dynamic programming for the instance registration of a position and anexaminationmodel has established widespread use in the region of isolated word appreciation. The maindissimilarity in the techniquesis the global path restriction, the local connectionconstraint on the path, and the space weighting and normalization used to offer the overall minimum distance.The presentation measures that were used contain: velocity of procedure, memory necessities, and recognition precision.

Consequently, this document presents the exploit of DTWto procedure the speed recent signals for distinguish and quantifying common faults in a downstream two-stage reciprocating compressor. 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 Zhenet al (2013).

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 Mantenaet al (2013). The difficulty of indexing time series has involved a great deal of attention. Dynamic Time Warping is a greatdeal 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 conservative fuzzy C-means clustering algorithm is a statement in preceding mechanism for market separation, but it might be incompetent or unbalanced particularly in large-scale power organization. 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 Raoofatet al (2013).In this study, proceeding with the objective function-based clustering (such as, e.g., fuzzy C-means), they revisit and augment the algorithm to make it applicable to spatiotemporal data given by Izakian 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 Bloemberget al (2013).

Time series is a very popular type of data which exists in many domains. Clustering time series data has a wide range of applications and has attracted researchers from a wide range of discipline. In this work a novel algorithm for shape based time series clustering is proposed by Zhang et al (2011).Time series is an important class of temporal data objects and it can be easily obtained from scientific and financial applications are given by Fu and Chung (2011).Liuet al (2012) shows the possibilistic fuzzy clustering algorithm overcomes the problem of sensitivity to noises and coincident clusters, but it assumes the contribution of each sample is equal, which leads to strong impact from outliers or noises and too much iteration.

III. Fuzzy C-Means

Fuzzy C-Means is the mostaccepted fuzzy clustering techniques with the advance that the data points have their relationship values with the group centers that will be iteratively modernized. Fuzzy c-means clustering contains two major steps: the estimation of group centers and the task of points to these centers using a form of Euclidian distance such that the procedure is incessantlyfrequent until the cluster centers steady. The algorithm allocate a connection value to the data items for the clusters within a series of 0 to 1 and a fuzzification restriction in the series [1, n] which find out the degree of uncertainty in the clusters. The FCM algorithm offers a technique of grouping that facilitate a data item to belong to two or more clusters and this method of technique is regularly used in modelidentification applications. It is based on minimization of the subsequent objective purpose:

$$J_{m_f} = \sum_{j=1}^{N} \sum_{k=1}^{C} \mu_{jk}^{mf} \|x_j - c_k\|^2 \qquad (1)$$

Where:

m_f denotes some real number larger than 1 such that 1d"m_f<", μ_{jk} is the amount of relationship of x_j in the group j and c_k is the center of the cluster. In FCM, the membership matrix U is allowed to have not only 0 and 1 but also the elements with any values between 0 and 1, this matrix satisfying the following constraint:

$$\sum_{j=1}^{c} \mu_{jk} = 1, \forall k = 1, \ldots, n \qquad (2)$$

$$\mu_{jk} = \frac{1}{\sum_{p=1}^{c} \left[\frac{\|x_j - c_k\|}{\|x_j - c_p\|}\right]^{\frac{2}{m-1}}} \qquad (3)$$

$$C_k = \frac{\sum_{j=1}^{N} \mu_{jk}^{mf} \cdot x_k}{\sum_{j=1}^{N} \mu_{jk}^{m}} \qquad (4)$$

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{jk} and the cluster centers c_k are given.

Drawbacks of Fuzzy C-Means Algorithm

Fuzzy C-Means Algorithm suffers from certain drawbacks due to the restriction that the amount of membership worth of a data point xi in the entiregroup must be similar to one as given by equation (4):

1. Firstly, this restriction tends to give elevated membership values for the outlier position and due to this the algorithm has complexity in managing outlier points.

2. Next, in a cluster the membership of a data points depends straight on the relationship values of additionalgroup centers which may lead to undesirable results.

3. FCM also faces problems in handling high dimensional data sets and a large number of prototypes. Also FCM is sensitive to initialization and is easily trapped in local optima.

IV. Dynamic Time Warping Algorithm

For completeness, this work now review the classic DTW algorithm. The reader may skip this section without loss of continuity.

This work has two time sequence*Q* and *C*, of length *n* and *m* correspondingly, where:

$$Q = q_1, q_2, \ldots, q_i, \ldots, q_n \qquad (5)$$

$$C = c_1, c_2, \ldots, c_j, \ldots, c_m \qquad (6)$$

To make parallel these two sequences using DTW, this work construct an n-by-m matrix where the (i^{th} j^{th}) aspect of the matrix contain the space $d(q_i, c_j)$ among the two points q_i and c_j (typically the distance is used, so $d(q_i, c_j) = (q_i - c_j)^2$). each matrix attributes (i,j) correspond to the arrangementamong the points and . A warping path, W, is anadjacent set of matrix elements that describe a mapping among Q and C. The k^{th} element of W is defines as so it have:

$$W = w_1, w_2, \dots, w_k, \dots, w_K \qquad (7)$$
$$\max(m, n) \leq K < m + n - 1$$

The warping path is typically subjected to several constraints.

1. **Boundary conditions:** $w_1 = (1,1)$ and $w_K = (m,n)$. Justdeclared, this necessitates the warping path to begin and terminate in obliquelyreverseangle cells of the matrix.
2. **Continuity:** Specified $w_k = (a,b)$ then $w_{k-1} = (a',b')$, where $a-a' \leq 1$ and $b-b' \leq 1$. This contains the acceptable steps in the warping path to nearby cells (containing diagonally neighboring cells).
3. **Monotonicity:** Specified $w_k = (a,b)$ then $w_{k-1} = (a',b')$, where $a-a' \geq ?0$ and $b-b' \geq 0$.

This services the points in W to be monotonically spaced in time.

There are exponentially numerous warping paths that assure the beyondcircumstances, thoughthis works are concerned only in the path which diminish the warping cost:

$$DTW(Q, C) = min\left\{\frac{1}{K}\sqrt{\sum_{k=1}^{K} w_k}\right\} \qquad (8)$$

The K in the denominator is utilized to balance for the fact that warping paths may containdissimilar lengths. This path can be establishextremelypowerful using dynamic programming to calculate the subsequentreappearance which describe the growingspace $\gamma(i,j)$ as the distance $d(i,j)$ establish in the present cell and the least amount of the increasing distances of the neighboring elements:

$$\gamma(i, j) = d(q_i, c_j) + \min\{\gamma(i-1, j-1), \gamma(i, j-1 \qquad (9)$$

The space between two series can be seen as a particular case of DTW, where the k^{th} elements of W is controlled such that Note that it is simplydistinct in the particular case where the two series have the similar length. The time difficulty of DTW is $O(nm)$.

V. FPCM with Constraints Dynamic Time Warping Distance (FPCM)

In this segment, anoriginalFPCM algorithm is plannedfor conquer the disadvantages of other techniqueexpressedabove. The FPCMalgorithm is initial proposed and an image denoising technique. It tries to take advantageof the elevated degree of idleness in image. The experiments showthat the FPCM algorithm can contract with the distance between two methods can be calculatedperfectly.To overcome difficulties of the FCM, the process of combine the features of both Fuzzy C-Means and Possibilistic C-Means by using the fuzzy standards of the FCM as well as the typicality standards of the PCM in arrange to attain a improved clustering technique. This work named this advancemethod as Fuzzy Possibilistic C-Means or FPCM. Relationship and Typicality are very important for the accurate and fixed characteristic of data foundation in clustering form and FPCM uses an objective purpose that depends on both membership and typicality features and is specified as below by Mohamed (2009).

$$J_{FPCM}(U,T,V) = \sum_{i=1}^{c}\sum_{j=1}^{N}\left(\mu_{ij}^{m} + t^{\eta}\right) d^{2}(x_j, v_i) \tag{10}$$

The algorithm also follows following constraints

$$\sum_{i=1}^{c} \mu_{ij} = 1, \forall j \varepsilon \{1, \ldots, n\} \tag{11}$$

$$\sum_{i=1}^{c} t_{ij} = 1, \forall j \varepsilon \{1, \ldots, c\} \tag{12}$$

The initial order essentialcircumstances for great of $J_{FPCM}(U,T,V)$ in conditions of Lagrange multiplier theorem can be characterize as follows

$$t_{ik} = \frac{1}{\sum_{j=1}^{N}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m}-1}}, \forall i,k \tag{13}$$

$$v_i = \frac{\sum_{k=1}^{N}(\mu_{ik}^{m} + t_{ik}^{\eta})x_k}{\sum_{k=1}^{N}(\mu_{ik} + t_{ik}^{\eta})}, \forall i \tag{14}$$

Where d_{ik} is the space of the information point X_k to the examplev$_i$, calculate as:

$$d_{ik} = \|x_k - v_i\| = (x_k - v_i)^T A\,(x_k - v_i) \tag{15}$$

Here, A is symmetric optimisticspecific matrix. FPCM generate Memberships and potential at the similarinstance, jointly with the standard point prototypes or cluster center for everygroup.

By an optimization way alike to the FCM, J_m^{Φ}can be diminish below the restriction of U. purposely, if this task 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

$$u_{ij} = \frac{\left(1 - DTW(x_k, v_i)\right) - \frac{1}{(m-1)}}{\sum_{j=1}^{c}\left(1 - DTW(x_k, x_j)\right) - \frac{1}{(m-1)}} \tag{16}$$

$$v_i = \frac{\sum_{k=1}^{n} U_{ik}^{m} DTW(x_k, v_i) xk}{\sum_{k=1}^{n} U_{ik}^{m} DTW(x_k, v_i)} \tag{17}$$

It is obviousto the achieve centroids or prototypes {vi} still lie in the uniquebreak and not in the changed higherdimensional characteristic space, thus, the computational minimalism is still preserve. In totaling, it is shown that the FPCM resulted are healthy to outliers and noise according to Huber's robust statistics. This quality can furthermore give an perceptiveclarificationthat 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.

Advantages of FPCM are shown by Suganya and Shanthi (2012):

1) FPCM is a hybridization of possibilistic c-means (PCM) and fuzzy c-means (FCM) and gives solution todifferenttroubles of PCM and FCM.

2) FPCM allowsovercoming the concurrent clusters difficulty of FCM, MFCM.

3) It also resolves the noise sensitivity absence of MFCM but the noisy data might have anmanipulate on the judgment of centroids.

VI. Experimental Results

In this section, the experimental results are discussed by three clustering techniques FCM, MFCM and FPCM. The proposed method of FPCM is used to measure the distance time warping in accurate manner.

Experiments were behavior on three datasets from the UCI repository: *Iris*, *Wine*, and *lung cancer*. These courses were selectedbecauseitcharacterizehard visual favoritismtroubles. 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	150	178	32
D	4	13	56
K	3	3	3

This workhave used pair wise F-Measure to estimate the grouping results support on the fundamentalmodules. F-Measure relies on the conventionalinse quencerepossessionevents, adapted for estimate clustering by consider same-cluster pairs:

$$\text{Precision} = \frac{\#\text{PairsCorrectlyPredictedInSameCluster}}{\#\text{Total Pairs PredictedInSameCluster}}$$

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

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

TABLE 2

PRECISION AND RECALL FOR DATASETS

	Precision			Recall		
	FCM	MFCM	FPCM	FCM	MFCM	FPCM
Iris	45	63	86	72	68	53
Wine	72	85	93	85	79	67
Lung cancer	85	92	97	96	82	71

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

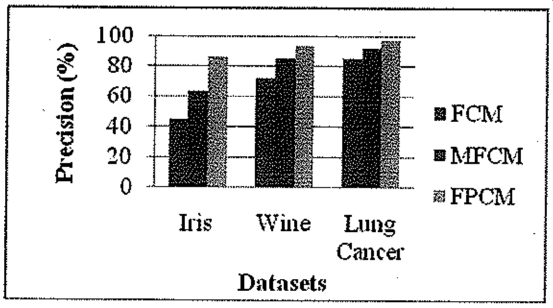

Figure 1: Precision

Figure 1 shows the proposed method of FPCM may have high accuracy when compared with existing approaches and lesser in execution time by using IRIS, Wine and Lung Cancer Datasets.

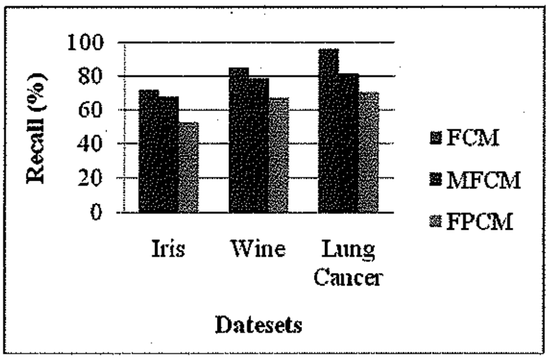

Figure 2: Recall

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

TABLE 3

F-MEASURE

Datasets	F-Measure		
	FCM	MFCM	FPCM
Iris	0.49	0.52	0.68
Wine	0.53	0.65	0.82
Lung cancer	0.71	0.83	0.96

Table 3 shows the F-Measure for the proposed method with three datasets.

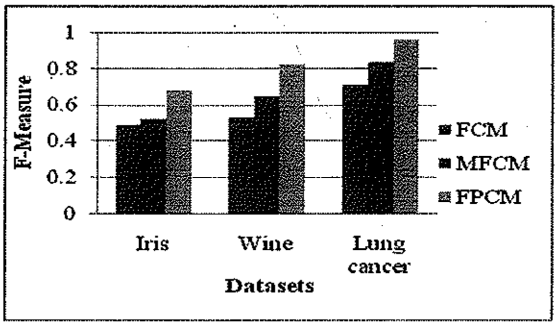

Figure 3: F-Measure

Table 3 and Figure 3 show the F-Measure for the FCM, MFCM and proposed FPCM.

Conclusion

The Fuzzy clustering advances defeat the disadvantage of the conventional clustering techniques used previous. FCM algorithm is the most accepted fuzzy based clustering algorithm that has largevariety of submission in dissimilarareas of learning. Furthermore, a variety of algorithms have been planned and residential by numerous authors with Fuzzy C-Means algorithm as their foundation and the objective of clustering more common datasets. Even though the robustness of the FPCM algorithm is improved, the convergence rate of it is lower. In this work, to conquer the problem in FCM and MFCM algorithm is time consuming, a proposed FPCM algorithm with constraints is proposed. Experiments on the reproduction and real-world datasets show that the proposed method offers accurate result with less execution time.

References

[1]. Mantena, Gautam, and Xavier Anguera. *"The probability-based DTW for motion appreciation."Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on.* IEEE, 2013.

[2]. TarikArici, SaitCelebi, Ali S. Aydin, Talha T. Temiz. *"Robust gesture recognition using feature pre-processing and weighted dynamic time*

warping." Multimedia Tools and Applications (2013): 1-18.

[3]. Myers, Cory, Lawrence Rabiner, and Aaron E. Rosenberg. *"Performance tradeoffs in dynamic time warping algorithms for isolated word recognition."Acoustics, Speech and Signal Processing, IEEE Transactions on* 28.6 (1980): 623-635.

[4]. Zhen, Dong, T. Wang, F. Gu, A.D. Ball, *"Fault diagnosis of motor drives using stator current signal analysis based on dynamic time warping." Mechanical Systems and Signal Processing* 34.1 (2013): 191-202.

[5]. Mantena, Gautam, and Xavier Anguera. *"Speed improvements to information retrieval-based dynamic time warping using hierarchical k-means clustering."Acoustics, Speech and Signal Processing (ICASSP), 2013IEEE International Conference on.* IEEE, 2013.

[6]. Keogh, Eamonn, and Chotirat Ann Ratanamahatana. *"Exact indexing of dynamic time warping."* Knowledge and information systems 7.3 (2005): 358-386.

[7]. Rabiner, Lawrence R., Aaron E. Rosenberg, and Stephen E. Levinson. *"Considerations in dynamic time warping algorithms for discrete word recognition." The Journal of the Acoustical Society of America* 63.S1 (2005): S79-S79.

[8]. Raoofat, Mahdi, and NavidEghtedarpour"A modified fuzzy clustering algorithm for market zonal partitioning in electricity markets." *International Transactions on Electrical Energy Systems* 23.4 (2013): 526-538.

[9]. Bloemberg, Tom G., Jan Gerretzen, Anton Lunshof, Ron Wehrens, Lutgarde M.C. Buydens. *"Warping methods for spectroscopic and chromatographic signal alignment: A tutorial." Analyticachimicaacta* 781 (2013): 14-32.

[10]. Izakian, Hesam, WitoldPedrycz, and Iqbal Jamal. *"Clustering Spatiotemporal Data: An Augmented Fuzzy C-Means." Fuzzy Systems, IEEE Transactions on*21.5 (2013): 855-868.

[11]. Zhang, Xiaohang, Jiaqi Liu, Yu Du, and Tingjie Lv. *"A novel clustering method on time series data." Expert Systems with Applications* 38, no. 9(2011): 11891-11900.

[12]. Liu, Bing, Shi-Xiong Xia, Yong Zhou, and Xu-Dong Han. *"A sample-weighted possibilistic fuzzy clustering algorithm." DianziXuebao(Acta Electronica Sinica)* 40, no. 2 (2012): 371-375.

[13]. Fu, Tak-chung. *"A review on time series data mining." Engineering Applications of Artificial Intelligence* 24, no. 1 (2011): 164-181.

[14]. R.Suganya, R.Shanthi,"*Fuzzy C- Means Algorithm- A Review*", International Journal of Scientific and Research Publications, Volume 2, Issue 11, November (2012) 1 ISSN 2250-3153

[15]. Mohamed FadhelSaad and Adel M. Alimi, *"Modified Fuzzy Possibilistic C-means"*, Proceedings of the International MultiConference of Engineers and Computer Scientists 2009 Vol I IMECS 2009, March 18 - 20, 2009, Hong Kong.

AUTHORS' BIOGRAPHY

Kathiresan.Vreceived his B.Sc., in 2003 and MCA in2006 from Bharathiar University, Coimbatore. He obtained his M.Phil. in the area of Data mining from Periyar University, Salem in 2007. At present he is working as a Assistant Professor, Department of Computer Applications (MCA) in RVS College of Arts and Science, Coimbatore. His research interest lies in the area of Data mining. He got Faculty Excellence Award from RVS College of Arts & Science for the Academic year 2007-08, 2008-09, 2009-10, 2010-11, 2011-12 and 2012-13 consecutively.

S.Mythili, Assistant Professor-BCA, PSGR Krishnammal College for Women, Coimbatore.