World Engineering & Applied Sciences Journal 8 (4): 161-167, 2017
ISSN 2079-2204

DOI: 10.5829/idosi.weasj.2017.161.167

An Application of PSO-Based Intuitionistic Fuzzy Clustering to Medical Datasets

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Abstract: Clustering is the process of splitting data into several groups based on the characteristics of data. Fuzzy clustering assigns a data object to various clusters based on different membership values. In medical field, the diagnosis of the disease has to be done without faults and in an earlier time without any delay. Generally, the data may be imperfect. So there is a need to represent imprecise nature of the data. To solve this problem, Intuitionistic fuzzy clustering introduces a parameter called hesitancy degree that indicates the user is not aware whether the object belongs to or not belongs to a cluster. In such a case, hesitancy can very well represent the inherent noise in the data or the ignorance of the user that is given by the state 'may be'. All clustering algorithms choose the initial seed in a random fashion. But, this creates a serious impact on the convergence of the algorithm. This work utilizes Particle Swarm Optimization to initialize the centroids for the Intuitionistic fuzzy clustering algorithm. The algorithm is executed over medical datasets from UCI repository and the results indicate that optimal clusters are achieved.

Key words: Clustering · Intuitionistic Fuzzy Set · Particle Swarm Optimization · Inertia weight · Mass value · Lambda value

INTRODUCTION

Nowadays, a big burst of data is available in all fields. It is very difficult to handle and analyze all these data manually. Clustering helps in effective decision making in various fields like market analysis, business intelligence, social media analysis, medical diagnosis, opinion analysis, satellite image segmentation [1], etc.

Clustering segregates data into several groups based on their traits. Clustering algorithms can be classified as hard or soft. Hard clustering algorithms allocate an object to exactly one cluster. Soft clustering allows an object to be a part of different clusters with different membership values.

Fuzzy clustering indicates a 'yes' or 'no' state only. But Intuitionistic fuzzy clustering allows another intermediate state 'may be'. The problem with Fuzzy C-Means (FCM) [2] and Intuitionistic Fuzzy C-Means algorithms is that they tend to fall into local minima. So, an optimization algorithm can be used to select the initial seed and to reach the global optimal solution.

Optimization is an applied science which explores the best values of the parameters of a problem that may take under specified conditions [3,4]. The two main phases in optimization algorithms are exploration and exploitation where exploration deals with searching of best local solutions and exploitation concentrates on reaching a global optimum solution.

Particle Swarm Optimization (PSO) [5] is a renowned conventional technique that imitates the bird flocking behavior and uses two parameters called velocity and position which represent the speed with which the particle travels and the resulting change in the particle's position respectively.

PSO enables rapid searching and leads to fast convergence of the clustering algorithm. There are only a few numbers of works that have combined PSO with Intuitionistic Fuzzy (IF) clustering. Most of the researchers have utilized PSO for initializing the FCM algorithm and for segmentation of images.

Kumutha *et al.* [6] used Intuitionistic Fuzzy (IF) PSO to cluster gene expression datasets to yield faster

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convergence and reduce the complexity of IFCM. Nanda *et al*. [7] automatically identified the number of clusters in the dataset by combining cloning technique with PSO. Binu [8] compares PSO, Genetic Algorithm and Cuckoo search over seven newly defined objective functions and found that PSO works well for large scale data.

Izakian *et al*. [9] combined fuzzy PSO with FCM to minimize the objective function leading to a global solution. Benaichouche *et al*. [10] segmented images by considering the geometrical shape of clusters found by incorporating spatial information and Mahalanobis distance. The resulting image is reclustered using a local criterion optimization using greedy algorithm to detect the misclassified pixels.

Silva TM *et al*. [11] dynamically varied the parameters of PSO like c1, c2 and inertia weight during execution and proposed improved self-adaptive PSO for clustering data by reducing the number of parameters to be tuned. Mekhmoukh *et al*. [12] used PSO to reduce the sensitivity to noise by incorporating spatial information into Kernel Possibilistic C Means algorithm.

Chaira [13] developed a multi-objective criterion function for segmenting brain CT images by including hesitancy factor in the updation of cluster centers. Shanthi *et al*. [14] utilized this clustering to classify mammogram images and built decision tree for effective diagnosis. Chaira [15] also utilized IF divergence for edge detection of Tumor/ hemorrhage regions. Xu *et al*. [16] applied a new method for clustering numerical data like car market data, supplier data and building materials data using Lagrange multiplier method and introduced a weighted average operator to assign weights for each IFS.

Prabhjot kaur *et al*. [17] presented a robust IFCM and kernel version of IFCM with a new distance metric incorporating the distance variation of data-points within each cluster. Rohan Bhargava *et al*. [18] hybridized rough set with IFS in order to describe a cluster by its centroid and its lower and upper approximations.

Balasubramaniam [19] segmented nutrition deficiency in incomplete crop images using IFCM. The missing pixels in the incomplete images were imputed using IFCM algorithm. V.P. Ananthi *et al*. [20] segmented gray scale images using IFS. The entropy is calculated to find the threshold. The value that minimizes the entropy is taken as the threshold for segmenting the image.

Many researchers [6,7,8,9,11,12] have proved that PSO suits well for obtaining global optimal solutions because of its intuitiveness, ease of implementation and the ability to effectively solve highly nonlinear problems.

This paper is organized as follows: Section 2 gives an overview of fuzzy set and Intuitionistic fuzzy sets, Section 3 focuses on IFCM clustering, Section 4 throws light on PSO, Section 5 explains the proposed IFPSO_IFCM algorithm and Section 6 provides the experimental results and discussion.

Fuzzy Set and Intuitionistic Fuzzy Set: Fuzzy sets are designed to manipulate data and information possessing non-statistical uncertainties[21]. A fuzzy set is represented by Zadeh [22] as follows

$$FS = \{< x, \mu_{FS}(x) > | x \circledcirc X\}$$

where $\mu_{FS}: X \rightarrow [0, 1]$ and $\nu_{FS}: X \rightarrow [0, 1]$ and $\nu_{FS}(x) = 1 - \mu_{FS}(x)$. Here μ_{FS} is the membership value and ν_{FS} is the non-membership value.

An Intuitionistic Fuzzy Set proposed by Atanassov [23] can be symbolized as below

$$IFS = \{< x, \mu_{IF}(x), \nu_{IF}(x) > | x \circledcirc X\}$$

where $\mu_{IF}: X \rightarrow [0, 1]$ and $\nu_{IF}: X \rightarrow [0, 1]$ define the degree of membership and non-membership, respectively and

$$\pi_{IF}(x) = 1 - \mu_{IF}(x) - \nu_{IF}(x) \text{ such that } 0 < \mu_{IF}(x) + \nu_{IF}(x) < 1$$

where π_{IF} is the hesitancy value used to represent the uncertainty. Use of this soft computing approach in clustering leads to a valuable decision making in solving real time problems.

Intuitionistic Fuzzy C-means Clustering: The first and foremost task for IFCM algorithm [15] is to convert crisp data into fuzzy data which in turn would be converted to Intuitionistic fuzzy data. This process involves the task of fixing the lambda value which is a value that varies for each dataset. The value of lambda is chosen as the one which maximizes the entropy value. Entropy [24] is the amount of fuzziness present in any given dataset and it is calculated as

$$IFE = \frac{1}{N X M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \frac{2\mu_i(d_j)\nu_i(d_j) + \pi_i^2(d_j)}{\pi_i^2(d_j) + \mu_i^2(d_j) + \nu_i^2(d_j)} \quad (1)$$

The crisp data is converted into fuzzy data using the following equation

$$\overline{\mu_i}(d_j) = \frac{d_{ij} - \min(d_j)}{\max(d_j) - \min(d_j)} \quad (2)$$

Then the fuzzy data is converted to Intuitionistic fuzzy data as follows:

$$\mu_i(d_j;\lambda) = 1 - (1 - \overline{\mu_i}(d_j))^{\lambda} \quad (3)$$

$$v_i(d_j;\lambda) = (1 - \overline{\mu_i}(d_j))^{\lambda(\lambda+1)} \quad (4)$$

where $\lambda \in [0,1]$

The intuitionistic fuzzification converts the intermediate fuzzy dataset to intuitionistic fuzzy dataset $Dd_j'(d_{ij}, \mu_i(d_j, v_i(d_j))$.

The hesitancy factor is calculated by summing up the membership and non-membership degrees and subtracting the sum from one.

The clustering procedure given by Xu [16] is followed. The distance matrix is calculated based on the Intuitionistic fuzzy Euclidean distance. Then, the membership matrix is calculated as follows:

$$U_{ij} = \frac{1}{\sum_{r=1}^{c}\left(\frac{dis(d'.v_i)}{dis(d'.v_r)}\right)^{\left(\frac{2}{m-1}\right)}}, 1 \le i \le c, 1 \le j \le n, m = 2 \quad (5)$$

This membership value is used to calculate non-membership and hesitancy values. Using these values, the mass (weight) factor given to each attribute t is calculated as follows

$$ma_{i(k+1)} = \left\{\frac{u_{i1}(k)}{\sum_{j=1}^{n} u_{ij}(k)}, \frac{u_{i2}(k)}{\sum_{j=1}^{n} u_{ij}(k)}, \dots, \frac{u_{in}(k)}{\sum_{j=1}^{n} u_{ij}(k)}\right\}, 1 \le i \le c \quad (6)$$

Using these mass values, the new centroids are calculated as

$$V_i = \{ |d_s, \textstyle\sum_{j=1}^{n} ma_j u_{Aj}(d_s), \sum_{j=1}^{n} ma_j v_{Aj}(d_s)|, 1 \le s \le n \}, 1 \le i \le c \quad (7)$$

The objective function of IFCM can be given as

$$J_m(x,y) = \sum_{i=1}^{c} \sum_{j=1}^{p} U_{ij}^{m} \|X'_j - C_i\|, \quad 1 \le m \le \infty \quad (8)$$

Particle Swarm Optimization: Particle swarm optimization (PSO) [5,25] is a population-based stochastic optimization technique inspired by bird flocking and fish schooling which is based on iterations/generations. Each particle has an initial position and it moves towards a better position with a velocity. The positions represent the solutions for the problem. Initially, the position and velocity matrices are assigned random values.

Consider the population or swarm size as m and the particle dimension as n. Let Velocity be represented as $Velo_i = \{v_1, v_2, \dots, v_n\}$ and position be represented as $Xpos_i = \{x_1, x_2, \dots, x_n\}$ where i= 1 to n. For every iteration, these two vectors are updated using the following equations.

$$Velo(k+1) = wt.Velo(k) + (c1.rand1).(p_{best}(k) - Xpos(k)) + (c2.rand2).(g_{best}(k) - Xpos(k)) \quad (9)$$

$$Xpos(k+1) = Xpos(k) + Velo(k+1) \quad (10)$$

where c1 and c2 are user-defined constants, wt denotes the inertia weight, rand1 and rand2 are the random values from 0 to 1.

The fitness is evaluated by calculating the objective function for each particle in the swarm. The individual best performance is termed as p_{best} and it is updated by comparing fitness values of each iteration with that of the previous iteration. The overall best position attained by any particle with the overall minimum fitness (in case of minimization problems like clustering) is chosen as the g_{best}.

The inspiring feature of PSO is that it exempts the possibility of the solution getting stuck in the local optima and tries to reach the global optima by converging in less number of iterations.

Proposed Methodology: The outcome of a clustering algorithm is essentially determined by the choice of initial cluster centers. In such a case, there arises a need to optimize the way in which initial clusters are chosen. This is achieved with the help of optimization algorithms like PSO or CSA. This work introduces two novel algorithms IFPSO_IFCM and CS_IFCM which leads to effective clustering of benchmark data sets.

IFPSO_IFCM algorithm: All the existing approaches work well for datasets which do not possess any noise. The need for Intuitionistic fuzzy clustering to be combined with Intuitionistic Particle Swarm Optimization comes into picture when there are abnormalities in the features of a data. This abnormality or error factor can be very well represented as the hesitancy value in IFS. This results in a consistent state of the particle's position.

Algorithm IFPSO_IFCM

Step 1: Initialize the parameters like population size, c1, c2, inertia weight and the maximum number of iterations, the number of clusters c, the problem dimension D and the fuzziness parameter m
Step 2: Convert the data into IFS representation using Eq. 1, 4 and 5
Step 3: For IFS conversion, fix the parameter lambda using Eq.3. The lambda value which maximizes the entropy is fixed for each dataset
Step 4: Create a swarm with P particles
Step 5: Initialize the position xpos, velocity velo, pbest and gbest as n x c matrices
Step 6: For each particle, compute the distance measure and thus calculate membership values of each object to various clusters using Eq. 6
Step 7: Evaluate the fitness of each particle using Eq. 9
Step 8: Calculate the personal best value pbest for each particle and the overall best performance gbest for the entire swarm
Step 9: Update the particle velocity and position using Eq. 10 and Eq. 11 respectively
Step 10: Repeat steps 6 to 9 until IFPSO converges i.e. gbest attains stability
Step 11: Obtain the particle that has the global best value with minimum cost and keep it as the initial set of centroids for the execution of the IFCM algorithm
Step 12: Compute the membership values using Eq. 6
Step 13: In order to update the centroids, a mass is to be calculated for each attribute in the dataset using Eq. 7
Step 14: As a function of mass, the centroids are updated using Eq. 8
Step 15: Evaluate the fitness using Eq. 9
Step 16: Repeat steps 12 to 15 until IFCM converges i.e. until the objective function converges
Step 17: if IFPSO_IFCM has met the stopping criterion to reach the maximum iterations, then stop. Otherwise, go to Step 6.
Step 18: Find the index value of the cluster for each object. The cluster center which has the maximal membership will be the corresponding index.

Table 1: Parameters for IFPSO_IFCM

Parameter	Value
Fuzziness parameter m	2
Lambda	0 to 1 (based on the value that maximizes entropy)
Mass vector	1/n, where n is the number of attributes in dataset
Population	10
Max Iterations	100
Algorithm-specific parameters	C1=C2=1.4, Inertia weight =0.72

RESULTS AND DISCUSSIONS

The algorithms are implemented using MATLAB. In order to quantitatively evaluate the performance of the proposed algorithm, the results are compared with FCM-PSO and IFCM algorithms. Experiments are conducted in two aspects: the first one with respect to the objective function value and the second one with respect to the validity indices namely the Rand Index and DB index.

Cluster validation is the predominant way of judging the performance of a clustering algorithm. Rand index is external validity measure and DB index is an internal measure. A greater value closer to one indicates good performance in Rand index. Lesser value results in good clusters in case of DB index.

Six medical datasets from UCI data repository [26] are considered for evaluating the performance. The datasets include Breast tissue, Bupa liver disorders, Contraceptive Method Choice (CMC), Dermatology, Haberman survival and Wisconsin Breast Cancer. The dataset details are given in Table 2.

Table 2: Details of the Dataset

Dataset	Number of clusters	Number of attributes	Number of Instances
Breast tissue	6	9	106
Bupa liver disorders	2	7	345
CMC	3	9	1473
Dermatology	6	34	366
Haberman survival	2	3	306
Wisconsin Breast Cancer	2	32	569

Table 3 shows the fitness values obtained as a result of the proposed method and compares it with the IFCM and FCM-PSO algorithms. It is evident from the table that the proposed IFPSO-IFCM algorithm gives an overwhelming response in terms of the fitness values for all the six datasets. The IFCM algorithm produces a high value for all the datasets and takes more time to converge.

Also, only local optimum solutions are achieved in many cases. But PSO is utilized in the other two methods for rapid searching of the optimal solution. By exploiting both the cognitive component of the relative particle and the social component generated by the swarm, PSO can reach the global optimum solutions.

The datasets have different scales with respect to their variables. Generally, Euclidean distance is sensitive to this variation in scales and this difference can be eliminated by normalizing the variables in the range 0 to 1. Due to the fact that PSO algorithm maintains its stochastic behavior capacity, it provides high quality solutions.

Table 3: Comparison of objective function values

Dataset	Values	IFCM	FCM-PSO	IFPSO-IFCM
Breasttissue	Mincost	3.15	1.87	0.55
	Maxcost	4.25	1.94	0.60
	Avgcost	3.21	1.91	0.59
Bupa liver disorders	Mincost	26.81	9.36	8.61
	Maxcost	27.06	9.83	8.99
	Avgcost	26.92	9.38	8.77
CMC	Mincost	175.18	112.5	71.19
	Maxcost	224.17	124.2	86.99
	Avgcost	183.21	113.1	72.44
Dermatology	Mincost	131.23	119.25	108.12
	Maxcost	174.54	121.38	128.15
	Avgcost	132.35	120.11	113.41
Haberman survival	Mincost	39.07	8.95	6.88
	Maxcost	51.01	9.45	7.42
	Avgcost	40.26	8.98	6.90
Wisconsin Breast Cancer	Mincost	58.62	21.29	13.56
	Maxcost	76.10	24.60	15.19
	Avgcost	60.76	22.58	14.82

Rand Index: A true positive (TP) decision assigns two similar documents to the same cluster; a true negative (TN) decision assigns two dissimilar documents to different clusters. There are two types of errors we can commit. A (FP) decision assigns two dissimilar documents to the same cluster. A (FN) decision assigns two similar documents to different clusters. The Rand index [27] measures the percentage of decisions that are correct.

$$RI = \frac{TP + TN}{TP + FP + FN + TN} \quad (11)$$

Davis-Bouldin Index: The Davis-Bouldin index (Davies and Bouldin, 1979) is based on a ratio of within cluster and between cluster distances. This shows good performance when the value is less.

The formula for DB Index can be given as

$$\frac{1}{k}\sum_{i=1}^{k} max_j \frac{s(C_i)+s(C_j)}{d_C(C_i,C_j)} \quad (12)$$

where k is the number of clusters, s(c) is the average distance among the instances in cluster C, d_c (C_i,C_j) measures the distance between the centers of C_i and C_j.

Table 4 shows the Rand Index and DB Index values for the six datasets. It can be noticed that the highest Rand index value is obtained for Wisconsin Breast Cancer (WBC) dataset as 0.8123 and the least value is for liver disorder dataset. In case of DB index, the best value is obtained again for WBC and the least value is for Haberman survival dataset.

Table 4: Comparison of Rand Index and DB Index values

Algorithm	IFPSO			IFPSO	FCM	FCM
----------------	-IFCM	IFCM	FCM-PSO	-IFCM	IFCM	-PSO
Dataset	--------- Rand Index ----------			---------- DB Index ------		
Breasttissue	0.7461	0.7269	0.7218	0.3629	0.3624	0.3724
Liver disorders	0.6026	0.5031	0.5583	0.1315	0.2971	0.1882
CMC	0.6457	0.5637	0.5812	0.3178	0.3216	0.4113
Dermatology	0.7421	0.6560	0.6976	0.1207	0.3979	0.2095
Haberman survival	0.6127	0.5128	0.6003	0.3767	0.5586	0.3942
WBC	0.8123	0.7512	0.7994	0.0145	0.2952	0.1094

The results of the tests lead to the conclusion that IFPSO-IFCM is really better than the other two algorithms. PSO is also capable of memorizing the solutions. This helps in retaining the best individuals. Figure 1 shows the comparative results of IFPSO-IFCM, IFCM and FCM-PSO for the Rand Index and Figure 2 compares the DB Index values obtained. The proposed methodology shows a superior performance for all the datasets.

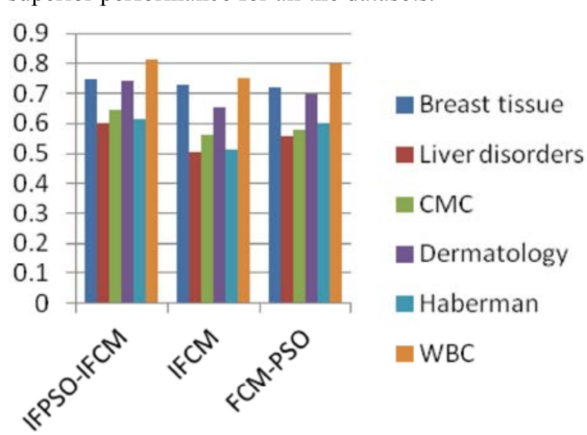

Fig. 1: Rand Index comparison

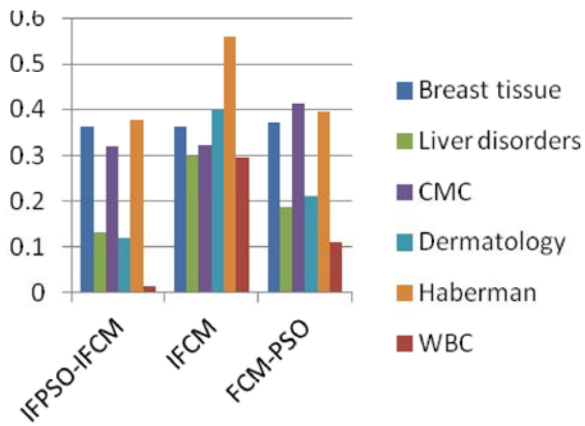

Fig. 2: DB Index comparison

CONCLUSION

The FCM and IFCM algorithms tend to fall into local minima and also the convergence is delayed due to random selection of initial seeds. The IFCM algorithm is hybridized with PSO which is based on intelligence in this work. This method results in fast convergence to the sub optimal solution. Also, the performance of the algorithm is evaluated in terms of fitness function and validity indices. The results prove that the IFPSO-IFCM converges to a minimum objective function value and efficient cluster structures are obtained.

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