Research Article
A Weight Possibilistic Fuzzy C-Means Clustering Algorithm

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Fuzzy C-means (FCM) is an important clustering algorithm with broad applications such as retail market data analysis, network monitoring, web usage mining, and stock market prediction. Especially, parameters in FCM have influence on clustering results. However, a lot of FCM algorithm did not solve the problem, that is, how to set parameters. In this study, we present a kind of method for computing parameters values according to role of parameters in the clustering process. New parameters are assigned to membership and typicality so as to modify objective function, on the basis of which Lagrange equation is constructed and iterative equation of membership is acquired, so does the typicality and center equation. At last, a new possibilistic fuzzy C-means based on the weight parameter algorithm (WPFCM) was proposed. In order to test the efficiency of the algorithm, some experiments on different datasets are conducted to compare WPFCM with FCM, possibilistic C-means (PCM), and possibilistic fuzzy C-means (PFPCM). Experimental results show that iterative times of WPFCM are less than FCM about 25% and PFPCM about 65% on dataset $X_1$. Resubstitution errors of WPFCM are less than FCM about 19% and PCM about 74% and PFPCM about 10% on the IRIS dataset.

1. Introduction

Clustering is a method of unsupervised learning and has been applied in various fields, including data mining, pattern recognition, computer vision, and bioinformatics. Cluster methods might be summarized as follows: partition-based [1, 2], hierarchical-based [3], density-based [4–6], and grid-based [7]. Partition methods included hard partition [8, 9] and soft partition [10–12]. Soft partition is represented by using fuzzy membership, and membership value lies in interval $[0, 1]$. Many fuzzy clustering algorithms had been developed and widely used in a variety of areas [13–16], such as data mining and pattern recognition. Ruspini [17] regarded fuzzy C-means (FCM) as a clustering algorithm, and DUNN [18] analyzed fuzzy exponent $m$ and determined that the value of $m$ was equal to 2. Bezdek generalized fuzzy exponent $m > 1$. The constraint of FCM ($\sum_{i=1}^{c} u_{ij} = 1$) might cause that membership conflicted with intuitive belonging degree; furthermore, it made the clustering results be sensitive to noise. In order to overcome this defect, Krishnapuram and Keller [19] relaxed the constraint and proposed a new algorithm named possibilistic C-means (PCM) [20] which reduced influence of noise on clustering and had good robustness. However, PCM relied on initialization condition and might produce coincident clusters [21]. Many algorithms were developed to overcome coincident problem. For example, studies [22, 23] modified the PCM objective function adding an inverse function of the distances between cluster centers to resolve coincident problem. The study [23] proposed a new model named the fuzzy possibilistic C-means (FPCM) which introduced membership and typicality value $t_{ij}$ subjected to $\sum_{i=1}^{c} t_{ij} = 1$ for unlabeled data. FPCM reduced sensitivity to noise in FCM and resolved coincident problem in PCM; however, typicality value became very small as dataset scale increasing for the reason of row sum constraints.
The study by Pal [24] proposed new algorithms named possibilistic fuzzy C-means (PFCM), which was a hybridization of PCM and FCM and overcame problems of PCM, FCM, and PFCM. PFCM solves the noise sensitivity. So, PFCM has been widely applied in many fields [25–27] and solved some problems well. PFCM added coefficients to FCM, and FPCM. PFCM solves the noise sensitivity. So, possibilistic fuzzy C-means (PFCM), which was a hybridization of FCM, PCM, and PCM clustering algorithm. Section 3 provides a new method on the computation of parameters and WPFCM was proposed. Section 4 experimentally demonstrates the improvement of performance of WPFCM on some UCI database. Section 5 offers conclusion.

This study is quite different from literature [28]. First, this study focussed on clustering on possibilistic fuzzy C-means, while the study by Schneider [28] aimed to the possibilistic C-means algorithm. The research algorithms were different. Second, the key point was that designing weight parameter was diverse. Algorithm in this study could allocated weight value to samples inlier and outlier automatically according to the calculation method of weight parameters, which made membership value maximizing and outlier reduce influence of estimation. Weight parameter could satisfy the optimization objective function, make it iterate faster, and avoid the coincident problem. The method in the study by Schneider [28] could not have these advantages.

Experiments on different datasets show that new algorithm not only makes clustering results obvious but also partitions overlapping data better and also reduces iterative times and speeds up convergence. The rest of this study is organized as follows: Section 2 reviews the FCM, PCM, FPCM, and PFCM clustering algorithm. Section 3 provides a new method on the computation of parameters and WPFCM was proposed. Section 4 experimentally demonstrates the improvement of performance of WPFCM on some UCI database. Section 5 offers conclusion.

2. Related Works

Since fuzzy set theory was introduced by Zadeh, this method was applied in the clustering algorithm rapidly. FCM is one of the most famous algorithms and obtains clustering results by minimizing objective function and iterating membership and centroid. The objective function of FCM is designed as follows:

\[ J_{FCM}(u, v) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m D_{ij}^2, \quad m > 1, \]  

(1)

where fuzzy exponent \( m \) is subjected to \( m > 1 \) and Euclidean distance is defined as \( D_{ij}^2 = ||x_i - v_j||^2 \). Membership can be obtained by minimizing objective function (1). The following equations are iterative functions of membership and centroid.

\[ u_{ij} = \left( \frac{\sum_{k=1}^{c} \left( \frac{D(x_j, v_k)}{D(x_i, v_k)} \right)^{(2m-1)-1}}{\Sigma_{j=1}^{n} \left( \frac{D(x_j, v_k)}{D(x_i, v_k)} \right)^{(2m-1)-1}} \right), \quad m > 1, \]  

(2)

\[ v_j = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}. \]

The clustering performance is better; however, the algorithm subjects to the following three constraints: \( u_{ij} \in [0, 1], \) \( (i = 1, 2, \ldots, c, \quad j = 1, 2, \ldots, n), \) \( \Sigma_{j=1}^{n} u_{ij} = 1, \) \( (j = 1, 2, \ldots, n), \) and \( 0 < \Sigma_{j=1}^{n} u_{ij} < n, \) \( (j = 1, 2, \ldots, n), \) which make the algorithm be sensitive to noise and usually lead to center deviation for individual anomalous data points.

The constraints of FCM require data points to consider the relation to other points in current cluster and in other clusters; therefore, membership might conflict with intuitive belonging degree and does not directly reflect real clustering results. The FCM algorithm is sensitive to noise and obtains poor clustering results in noisy data environment. Krishnapuram and Keller [19] improved FCM and proposed the possibilistic C-means algorithm which relaxed constraint. Objective function is designed as follows:

\[ J_{PCM}(t, v) = \sum_{i=1}^{c} \sum_{j=1}^{n} t_{ij}^q D_{ij}^2 + \sum_{i=1}^{c} \eta_i \sum_{j=1}^{n} (1 - t_{ij})^q, \quad q > 1, \]  

(3)

where \( \eta_i \) is the scaling parameter of the \( i^{th} \) class and defined \( \eta_i = K (\Sigma_{j=1}^{n} u_{ij} D_{ij}^2 / \Sigma_{j=1}^{n} u_{ij}^2) \) (common \( K = 1 \)), and exponent \( q \) subjects to constraint \( q > 1, \) and Euclidean distance is defined \( D_{ij}^2 = ||x_j - v_i||^2 \). Iterative functions of typicality and centroid are obtained by minimizing objective function (3). Equations (4) and (5) are the iterative functions.

\[ t_{ij} = \frac{1}{1 + \left( \frac{D^2(x_j, v_i)}{\eta_i} \right)^{(1/q-1)}} , \quad 0 < i < c, \quad 0 < j < n, \]  

(4)

\[ v_j = \frac{\sum_{j=1}^{n} t_{ij}^q x_j}{\sum_{j=1}^{n} t_{ij}^q} \]  

(5)

In equation (3), \( t_{ij} \) is not the membership but possibility, and clustering results are easy to interpret. PCM [29] relaxes the constraint \( \Sigma_{j=1}^{n} u_{ij} = 1, \) \( (i = 1, 2, \ldots, n) \) and defines the constraint \( \Sigma_{j=1}^{n} t_{ij} \leq c, \) \( (j = 1, 2, \ldots, n) \), so the rows and columns are independent, and data structure becomes loose. Therefore, the algorithm is insensitive to noise and could deal with the dataset including outlier; on the other side, there is another weakness. Experiments show that PCM’s clustering results depend on initialization and generate the coincident problem. Pal [30] held that clustering centroids
were closed to data centers due to the effect of membership.
Pal proposed a new algorithm FPCM on the basis of FCM
and PCM. FPCM used data center as the clustering center. It
is feasible to a great extent. Membership is a good method
when data points need to be marked clearly because it is
natural to assign a point to cluster whose prototype is the
nearest to the point, while possibility is important to esti-
mate clustering centers, and effectively reduces the influence
that was brought by abnormal data point. The objective
function was designed as follows:

\[ J_{\text{FPCM}}(u, t, v) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij}^{m} + t_{ij}) D_{ij}^{2}, \]  

(6)

where membership subjects to constraint \( \sum_{i=1}^{c} u_{ij} = 1, \)
\( j = 1, \ldots, n, \) and the typicality subjects to constraint \( \sum_{i=1}^{n} t_{ij} = 1 \) \( i = 1, \ldots, c, \) and other constraints are \( m > 1, \)
\( q > 1, \) and \( 0 < u_{ij}, t_{ij} < 1, \) and Euclidean distance was defined
\( D_{ij}^{2} = \|x_j - v_i\|^2. \) Iterative function of membership and
typicality and prototype can be obtained by minimizing
objective function. The equations (7)–(9) are the iterative
functions, respectively.

\[ u_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{D(x_j, v_k)}{D(x_j, v_i)} \right)^{(2/m-1)} \right]^{-1}, \]  

(7)

\[ t_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{D(x_j, v_k)}{D(x_k, v_i)} \right)^{(2/q-1)} \right]^{-1}, \]  

(8)

\[ v_i = \frac{\sum_{j=1}^{n} (u_{ij}^{m} + t_{ij}^{q}) x_j}{\sum_{j=1}^{n} (u_{ij}^{m} + t_{ij}^{q})}. \]  

(9)

Although FPCM overcomes weakness of PCM and FCM,
the typicality value becomes very small with sample data
increase. Typicality is limited by FPCM. On a large
sample dataset, the typicality value is inconsistent with real
value due to constraint row sum. Pal [24] improved algo-

\[ J_{\text{FPCM}}(t, u, v) = \sum_{i=1}^{c} \sum_{j=1}^{n} (au_{ij}^{m} + bt_{ij}^{q}) D_{ij}^{2} + \sum_{i=1}^{c} \sum_{j=1}^{n} (1 - t_{ij})^{q}, \]  

(10)

where parameters subject to constraints \( m > 1, q > 1, \eta > 0, \)
\( 0 < u_{ij}, t_{ij} < 1, \) \( 1 \leq i \leq c, \) and \( 1 \leq j \leq n. \) Euclidean distance is
defined \( D_{ij}^{2} = \|x_j - v_i\|^2, \) and parameters \( a \) and \( b \) are the
constants. Iterative function of membership and typicality
and prototype can be obtained by minimizing objective
function. The equations (11)–(13) are iterative functions.

\[ u_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{D(x_j, v_k)}{D(x_j, v_i)} \right)^{(2/m-1)} \right]^{-1}, \]  

(11)

\[ t_{ij} = \frac{1}{\left( 1 + \left( \frac{bD^2(x_j, v_i)}{\eta_i} \right)^{(1/q-1)} \right)}, \]  

(12)

\[ v_i = \frac{\sum_{j=1}^{n} (au_{ij}^{m} + bt_{ij}^{q}) x_j}{\sum_{j=1}^{n} (au_{ij}^{m} + bt_{ij}^{q})}, \]  

(13)

where \( \eta_i \) is defined \( \eta_i = K \left( \sum_{j=1}^{n} u_{ij}^{m} D_{ij}^{2} / \sum_{j=1}^{n} u_{ij}^{m} \right), \) and usu-
ally, \( K \) is a constant \( (K = 1). \)

3. WPFCM Algorithm

This section includes three paragraphs. The motivation of
weight parameters was first introduced, and then, the cal-

3.1. Motivation Weight Parameters. PFCM integrates merit
of PCM with FCM, which includes membership and typi-

cality. PFCM reduces the sensitivity to noise in FCM and
overcomes coincident problem in PCM and can deal with
the problem that typicality value becomes very small with
data points increasing in FPCM. After analyzing the pa-

\[ J_{\text{WPFCM}}(t, u, v) = \sum_{i=1}^{c} \sum_{j=1}^{n} (au_{ij}^{m} + bt_{ij}^{q}) D_{ij}^{2} + \sum_{i=1}^{c} \sum_{j=1}^{n} (1 - t_{ij})^{q}, \]  

(10)

where parameters subject to constraints \( m > 1, q > 1, \eta > 0, \)
\( 0 < u_{ij}, t_{ij} < 1, \) \( 1 \leq i \leq c, \) and \( 1 \leq j \leq n. \) Euclidean distance is
defined \( D_{ij}^{2} = \|x_j - v_i\|^2, \) and parameters \( a \) and \( b \) are the
constants. Iterative function of membership and typicality
and prototype can be obtained by minimizing objective
function. The equations (11)–(13) are iterative functions.
3.2. Calculation Method of Weight Parameters. Many literatures have mentioned methods for calculating weight parameters [31–33]. The study by Fan et al. [32] assigned weights to properties according to the importance of each property to the cluster process. For example, in dataset IRIS [34], the third property and the fourth property are beneficial to get obvious clustering results, so they are assigned a high weight value and others are assigned a low weight value. The premise is that we must know which property is important and unimportant. To an unknown dataset, this method is inappropriate and cannot be applied. The study by Nock and Nielsen [33] estimated all samples’ probability density by using the analogy method. This method needs a great deal of computation. The study by Hung [29] gave a prototype-driven learning of parameter α which is based on exponential separation strength between clusters and updated each iteration to improve the performance of FCM. Equation (14) is the definition of parameter α.

$$\alpha = \exp\left(-\min_{x \in X} \left(\frac{||v_j - v_i||^2}{\beta}\right)\right), \quad (14)$$

where parameter β is defined as the distance from data point $x_i$ to sample mean. Parameter β is defined as follows:

$$\beta = \frac{\sum_{j=1}^{n}||x_j - \bar{x}||^2}{n}, \quad (15)$$

and $\bar{x}$ can be defined as sample mean:

$$\bar{x} = \frac{\sum_{j=1}^{n}x_j}{n}. \quad (16)$$

Definition 1. A given sample set to be classified is denoted by $X = \{x_1, x_2, \ldots, x_n\} \subseteq F(X)$, and $X$ is partitioned into $c (0 < c < n)$ fuzzy subsets, and $c$ is the number of clustering.

Definition 2. According to the importance of the data point $x_j (x_j \in X)$ during the clustering process, weight parameter can be defined as $y_{ij}$, which is the weight of $x_j$ w.r.t. class $i$. The following equation is the calculation method.

$$y_{ij} = \exp\left(\frac{\sum_{j=1}^{n}||x_j - \bar{x}||^2 \times c}{-||x_j - v_i||^2 \times n}\right). \quad (17)$$

Theorem 1. Distance from $x_i$ to center $v_i$ can be regarded as weight; if the distance is long, then the value of weight will be high; on the contrary, if the distance is short, then the value of weight will be low.

Proof: $\bar{x}$ is the mean value of sample, and the difference between $x_i$ and $\bar{x}$ is reflected by the distance from data point $x_i$ to $\bar{x}$, which is constant. The smaller the value of $D_{ij}$, the shorter the distance from $x_i$ to class $i$. We can deduce that the larger the value of $||x_j - v_i||^2$, the smaller the value of $(\sum_{j=1}^{n}||x_j - \bar{x}||^2 / c) \times n$, and value of $\exp(-||x_j - v_i||^2 \times n / \sum_{j=1}^{n}||x_j - \bar{x}||^2 / c)$ will be small; on the contrary, the long the distance from $x_i$ to class $i$, the larger the value of $\exp(-||x_j - v_i||^2 \times n / \sum_{j=1}^{n}||x_j - \bar{x}||^2 / c)$. Optimization of objective function requires a minimum value. Weight parameter should satisfy the optimization objective; so long distance should get large $y_{ij}$ It is appropriate to use $y_{ij}$ as the weight parameter. □

3.3. Design Objective Function. According to the rule of classification, there is little difference among all data in the same class and great difference in different classes. During the process of designing objective function, in order to assign data point, the nearest distance from data point to center should be selected, which is denoted by the maximizing membership value. The typicality value can be used to reduce influence of estimation caused by outlier. New objective function should meet two requirements: on the one hand, role of membership in objective function should be increased when the sample is inlier; on the other hand, the role of the typicality value should be increased in objective function when the sample is outlier. Therefore, the objective function is designed as in the following equation, which include two parts: the first part is fuzzy function denoted by fuzzy weight parameter and the second part is typicality function denoted the by typicality weight parameter.

$$J_{WPFCM}(U, T, V) = \sum_{j=1}^{n} \sum_{i=1}^{c} \left[(1 - y_{ij})u_{ij}^m + y_{ij}t_{ij}^q\right]D_{ij}^2 + \frac{\sum_{i=1}^{c} \sum_{j=1}^{n} (1 - t_{ij})^q}{\sum_{i=1}^{c} \sum_{j=1}^{n} t_{ij}^q}, \quad (18)$$

where $y_{ij} (0 < y_{ij} < 1)$ denotes the weight between data point $x_i$ and class $i$, which comes from equation (17). Different data points have various weight values, and then, clustering results are more reasonable by using different weight parameters and avoid the coincident problem. $U$, $T$, and $V$ denote membership matrix ($c \times n$), typicality matrix ($c \times n$), and centroid matrix ($c \times 1$), respectively. Here, $u_{ij} (0 < u_{ij} < 1)$ is the membership of feature point $x_j$ in cluster $c_i$ and $t_{ij} (0 < t_{ij} < 1)$ is the typicality of $x_j$ in cluster $c_i$. $D_{ij}^2 = ||x_j - v_i||^2$ is the Euclidean distance between data point $x_j$ and $v_i$. The parameters $m (m > 1)$ and $q (q > 1)$ are the fuzzy exponents. The parameter $\eta_1 (\eta_1 > 0)$ is a constant, which is defined by $\eta_1 = K(\sum_{j=1}^{n}u_{ij}^mD_{ij}^2(x_j, v_i) / \sum_{j=1}^{n}u_{ij}^m)$, where $K$ usually is fixed at 1.

According to the analysis of the preceding context, we know that the nearer the distance between data point $x_j$ and cluster $c_i$, the smaller the value of weight parameter $y_{ij}$. The
distance from data point $x_j$ to cluster $c_i$ is near, which shows that data point $x_j$ belongs to the $i^{th}$ cluster. The weight parameter value of membership should be increased and be set as $(1−γ_{ij})$. On the contrary, the further the distance between $x_j$ and the $i^{th}$ cluster, the greater the difference between $x_j$ and the $i^{th}$ cluster, and $x_j$ may be an anomalous point. Typicality weight parameter should be increased to reduce the effect of $x_j$ on clustering. The typicality weight parameter is set as $γ_{ij}$. With increase (decrease) of weight parameter of membership, typicality weight parameter will be decreased (increased). The weight parameter is calculated on the basis of different sample data points, which overcomes the unreasonable value of $a$ and $b$ in PFCM and resolves coincident problem which is caused by small value of $a$ and poor initialization centroid.

According to Definition 3, the Lagrangian multiplier method was used to construct the Lagrange equation. In order to minimize equation (18), the partial derivatives of $u_{ij}$ and $t_{ij}$ were computed according to constraints $\sum_{i=1}^{n}u_{ij} = 1$ and $\sum_{j=1}^{m}t_{ij} = 1$ and acquired the membership $u_{ij}$ and typicality $t_{ij}$ and centroid $v_i$ as follows:

$$u_{ij} = \left[ \sum_{k=1}^{c} \left( \frac{D(x_j, v_j)}{D(x_j, v_k)} \right)^{(2(m-1))/q-1} \right], \quad (19)$$

$$t_{ij} = \left( \frac{1}{1 + \left( \frac{\gamma_{ij}}{\gamma_{ij}} \right)^2 \left( x_j, v_j \right)^{(1/q-1)}} \right), \quad (20)$$

$$v_i = \frac{\sum_{j=1}^{m} \left( 1 - \gamma_{ij} \right) u_{ij} x_j + \gamma_{ij} t_{ij} x_j}{\sum_{j=1}^{n} \left( 1 - \gamma_{ij} \right) u_{ij} + \gamma_{ij} t_{ij}}. \quad (21)$$

3.4. WPFCM Algorithm. According to the objective function, steps of algorithms were provided as following:

4. Experiments

In order to validate the algorithm efficiency, some experiments on different datasets were carried out. The initial value of parameters is set as follows: $ε = 0.000001$, the maximum iterative times $\text{max}_\text{iter} = 100$, constant $K = 1$, the number of class $\text{Cluster}_n = 2$ for dataset $X_{12}$, and the number of class $\text{Cluster}_n = 3$ for dataset IRIS [34].

Experiment 1. Dataset $X_{12}$ [35]; algorithm: FCM, PCM, PFCM, and WPFCM; initialization:

$$V_0 = \begin{bmatrix} 0.2722 & 0.0153 \\ 0.1988 & 0.7468 \end{bmatrix}. \quad (22)$$

Table 1 presents centroids which are generated by running FCM, PFCM, and WPFCM on $X_{12}$. Suppose distance equation $\text{Dist}_X = ||V_{X12} - V_X||^2$, which denotes the distance from real centroid to centroid $V_X$ generated by algorithms. The following are the centroids:

$$V_{\text{FCM}} = \begin{bmatrix} 2.9854 \\ -2.9853 \end{bmatrix},$$

$$V_{\text{PCM}} = \begin{bmatrix} 2.8367 \\ -2.8367 \end{bmatrix},$$

$$V_{\text{WPFCM}} = \begin{bmatrix} 3.0059 \\ -3.0059 \end{bmatrix}. \quad (23)$$

The real centroid of $X_{12}$ is $V_{X12} = \begin{bmatrix} 3.34 \\ -3.34 \end{bmatrix}$. We compute distance of each algorithm by using distance equation as follows: $\text{Dist}_{\text{FCM}} = 0.4212$, $\text{Dist}_{\text{PFCM}} = 0.3860$, and $\text{Dist}_{\text{WPFCM}} = 0.1537$. Comparing three distances, although each algorithm can get good result, $\text{Dist}_{\text{WPFCM}}$ has the minimum distance, that is, to say $V_{\text{WPFCM}}$ is nearer to real centroid than other $V_X$. $V_{\text{WPFCM}}$ reflects real cluster center better.

![Figure 1: Coordinate distribution of dataset $X_{12}$](image-url)
Table 2: Prototypes of FCM, PFCM, and WPFCM on X_{12}.

| Algorithm | FCM (m = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 5) |
|-----------|-------------|----------------------------------|------------------------|
|           | 2.9854 0.5435 | 2.8367 0.3643                    | 3.0059 0.2052          |
|           | -2.9853 0.5435 | -2.8367 0.3643                   | -3.0059 0.2052         |

Table 3: Iterative times of FCM, PFCM, and WPFCM on X_{12}.

| Algorithm | FCM (m = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 5) |
|-----------|-------------|----------------------------------|------------------------|
| Iterative times | 12 | 26 | 9 |

Table 4: Membership of FCM, PFCM, and WPFCM on X_{12}.

| Dataset | FCM (m = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 5) |
|---------|-------------|----------------------------------|------------------------|
|         | U_1 | U_2 | U_1 | U_2 | U_1 | U_2 |
| X_{1}  | 0.0636 | 0.9364 | 0.0725 | 0.9275 | 0.0039 | 0.9961 |
| X_{2}  | 0.0327 | 0.9673 | 0.0468 | 0.9532 | 0.0028 | 0.9972 |
| X_{3}  | 0.0103 | 0.9897 | 0.0100 | 0.9900 | 0.0000 | 1.0000 |
| X_{4}  | 0.1006 | 0.8994 | 0.0941 | 0.9059 | 0.0068 | 0.9932 |
| X_{5}  | 0.0844 | 0.9156 | 0.0681 | 0.9319 | 0.0069 | 0.9931 |
| X_{6}  | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |
| X_{7}  | 0.9156 | 0.0844 | 0.0391 | 0.0681 | 0.9931 | 0.0069 |
| X_{8}  | 0.9673 | 0.0327 | 0.9532 | 0.0468 | 0.9972 | 0.0028 |
| X_{9}  | 0.9897 | 0.0103 | 0.9900 | 0.0100 | 1.0000 | 0.0000 |
| X_{10} | 0.8994 | 0.1006 | 0.9059 | 0.0941 | 0.9932 | 0.0068 |
| X_{11} | 0.9364 | 0.0636 | 0.9275 | 0.0725 | 0.9961 | 0.0039 |
| X_{12} | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 | 0.5000 |

Table 5: Typicality values of PFCM and WPFCM on X_{12}.

| Dataset | FCM (m = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 5) |
|---------|-------------|----------------------------------|------------------------|
|         | T_1 | T_2 | T_1 | T_2 | T_1 | T_2 |
| X_{1}  | 0.1142 | 0.6225 | 0.4160 | 0.9271 |
| X_{2}  | 0.1660 | 0.8021 | 0.4598 | 0.9891 |
| X_{3}  | 0.1717 | 0.9536 | 0.4659 | 1.0000 |
| X_{4}  | 0.1580 | 0.6437 | 0.4561 | 0.9438 |
| X_{5}  | 0.2796 | 0.8416 | 0.5527 | 0.9961 |
| X_{6}  | 0.4924 | 0.0492 | 0.7383 | 0.7383 |
| X_{7}  | 0.8416 | 0.2796 | 0.9961 | 0.5527 |
| X_{8}  | 0.8021 | 0.1660 | 0.9891 | 0.4598 |
| X_{9}  | 0.9536 | 0.1717 | 1.0000 | 0.4659 |
| X_{10} | 0.6437 | 0.1580 | 0.9438 | 0.4561 |
| X_{11} | 0.6225 | 0.1142 | 0.9271 | 0.4160 |
| X_{12} | 0.0729 | 0.0729 | 0.3730 | 0.3730 |

Table 6: Centroids and iteration times by running WPFCM on dataset X_{12} with different parameters. Clustering results of WPFCM are better than FCM and PFCM as a whole. Iteration times of WPFCM are a bit less than FCM and PFCM. When the value of m keeps unchanged and value of q varied from 2 to 5, there is an increasing tendency of membership values, but not obvious; however, typicality values have an evident decreasing tendency. Clustering centers also have great changes, and the values are increasing and nearer to real centroid. Iteration times are decreasing. With increase of q, the influence of weight parameter γ_{ij} on clustering results is increasing. Weight parameter γ_{ij} is generated in iterative procedure, and initial centroid is generated randomly, so WPFCM overcomes the defect of random selection a and b and improves the vulnerability of uncertain clustering results. Clustering results in Table 7 are better than in Table 6; however, we find that membership values greatly reduce but iteration times increase. Comprehensive consideration suggests that the value of m and q are 1.5 and 5, respectively.

Experiment 2. Dataset: IRIS; algorithm: FCM, PCM, PFCM, and WPFCM.
IRIS is a four-dimensional dataset including three classes: setosa, versicolor, and virginica. Each cluster has 50 data points, adding up to 150 data points. The first cluster setosa has good separation from the other two clusters without overlapping. There are some overlaps between versicolor and virginica.

Data in Tables 8 and 9 were acquired by running FCM, PCM, PFCM, and WPFCM many times on IRIS. Each algorithm got good clustering centroid. Compared with other algorithms, WPFCM acquired more obvious membership and typicality values and better separation. The two centroids of versicolor and virginica got by running the PCM algorithm almost overlap. It is difficult to find separation between clusters in Tables 8 and 9. In order to compare separation between different classes, we defined the distance between classes as \( \text{Dist}_{ij} = \|V_i - V_j\|^2 \), which denotes the distance from \( i \)th cluster to the \( j \)th cluster.

Table 10 provides distance values between different centroids generated by FCM, PCM, PFCM, and WPFCM with IRIS. \( \text{Dist}_{12} \) and \( \text{Dist}_{13} \) that are calculated by using \( \text{Dist}_{ij} = \|V_i - V_j\|^2 \) in WPFCM, FCM, and PFCM reflect the fact that setosa separates from the other two classes versicolor and virginica. However, in PCM, \( \text{Dist}_{12} \) and \( \text{Dist}_{13} \) have almost identical results and \( \text{Dist}_{23} \) is nearly zero, so the results do not reflect the features of dataset which is caused by coincidence of PCM. Although FCM, PCM, and WPFCM all reflect separation of setosa from other two class and overlapping between versicolor and virginica, by comparing \( \text{Dist}_{23} \), we find that \( \text{Dist}_{23} \) in WPFCM is the nearest to the real value. We conclude that WPFCM reflects the characteristic of dataset better than other algorithms and easily get good partition especially for class versicolor and class virginica.

Table 11 provides the distance values between different centroids and real centroid generated by FCM, PCM, PFCM,
Table 11: Distance between different centroids and real centroid of FCM, PCM, PFCM, and WPFCM on IRIS.

|                | FCM (m = 2) | PCM (m = 2, q = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 1.5) |
|----------------|-------------|--------------------|-----------------------------------|--------------------------|
| Dist$_{X_1}$  | 0.0011      | 1.4262e-004        | 0.0014                            | 0.0010                   |
| Dist$_{X_2}$  | 0.0186      | 0.4055             | 0.0284                            | 0.0016                   |
| Dist$_{X_3}$  | 0.0554      | 0.9650             | 0.0140                            | 0.0022                   |
| Dist$_{X}$    | 0.0750      | 1.3706             | 0.0437                            | 0.0049                   |

Table 12: Iterative times of four algorithms on IRIS.

|                | FCM (m = 2) | PCM (m = 2, q = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 1.5) |
|----------------|-------------|--------------------|-----------------------------------|--------------------------|
| Iterative times| 23          | 75                 | 74                                | 27                       |

Table 13: Resubstitution errors of four algorithms on IRIS.

|                | FCM (m = 2) | PCM (m = 2, q = 2) | PFCM (m = 2, q = 2, a = 1, b = 1) | WPFCM (m = 1.5, q = 1.5) |
|----------------|-------------|--------------------|-----------------------------------|--------------------------|
| U$_{CX}$       | 16          | 50                 | 14                                | 13                       |
| T$_{CX}$       | -----       | 50                 | 13                                | 10                       |

(1) Initializing parameters $m (m > 1), q (q > 1)$, and $c, c (0 < c < 1)$, setting the maximum cycle number max_iter, setting the initial value of cycle number as 1, and randomly generating centroid $V_0$.
(2) Computing distance according to $D_{ij}^c = |x_j - y_i|^2$
(3) Computing the weight parameter $y_{ij}$ and $(1-y_{ij})$ by using equation (18)
(4) Computing membership value $u_{ij}$ and typicality value $t_{ij}$ by using equations (19) and (20)
(5) Computing the objective function obj_fcn
(6) If $|obj_fcn (i)-obj_fcn (i-1)| < \varepsilon$ or iterative times are less than max_iter, then stop

$\text{Else } \text{obj}_f \text{cn} (i) \longrightarrow \text{obj}_f \text{cn} (i-1)$
(7) Computing centroid $v_i$ by using equation (21) and going to step 2

Algorithm 1: Weight possibilistic fuzzy c-means clustering algorithm.

Dist$_{X} = \sum_{i=1}^{c} \left\| V_{IRIS_i} - V_X \right\|^2. \quad (24)$

5. Conclusions

A new possibilistic fuzzy C-mean based on weight parameters was proposed according to the importance of membership and typicality in the clustering process. First, aiming at unreasonable parameters $a$ and $b$, we designed weight parameter $y_{ij}$ based on literature [23] and provided the concrete calculation method. Weight parameters $(1-y_{ij})$ and $y_{ij}$ were assigned to membership and typicality. Objective function (equation (18)) was improved, and then, new algorithm idea (Algorithm 1) was provided. Experiment on different datasets show that the new algorithm has good performance in dealing with noisy data and gets better clustering results. WPFCM resolves the coincident problem and overcomes defect of sensitivity to noisy data. New algorithm discusses the influence on membership values, typicality values, and centroids with different values of exponent parameters $m$ and $q$. Exponent parameters are determined by comprehensively comparing membership
values, typicality values, and centroids. Experiments compare iterative times in different algorithms. WPFCM has less iterative times and fast convergence speed. Resubstitution errors of WPFCM are near to FCM and PFCM, but far less than PCM. Comprehensively, many performance indexes suggest that WPFCM overcomes weakness of sensitivity of FCM and resolves the coincident problem of PCM and unreasonable weight parameters of PFCM. The next work is to extend the new algorithm to the nonpoint prototype clustering model such as the spherical prototype, the quadric prototype, and the shell prototype.

Data Availability

The data used to support the findings of this study are available at http://archive.ics.uci.edu/ml/datasets/iris.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] S. S. Wang, A. Gittens, and M. W. Mahoney, “Scalable kernel $k$-means clustering with nystrom approximation: relative-error bounds,” Journal of Machine Learning Research, vol. 20, pp. 1–49, 2019.
[2] K. Zhao, X. Zhao, C. Peng et al., “Partition level multiview subspace clustering,” Neural Networks, vol. 122, pp. 279–288, 2020.
[3] D. Fogli, G. Giovanni, M. Redolfi, and R. Tonoli, “A knowledge-based approach to hierarchical classification: a voting metaphor,” Expert Systems with Applications, vol. 161, no. 15, Article ID 113737, 2020.
[4] Y.-A. Geng, Q. Li, R. Zheng et al., “RECOME: a new density-based clustering algorithm using relative KNN kernel density,” Information Sciences, vol. 436–437, pp. 13–30, 2018.
[5] R. M. Mahboobeh, A. A. Ahmad, B. Nasersharihi, and B. Raahemi, “A new density-based subspace selection method using mutual information for high dimensional outlier detection,” Knowledge-Based Systems, vol. 216, Article ID 106733, 2021.
[6] M. Lia, X. H Bi, L. M. Wang, and X. M. Han, “A method of two-stage clustering learning based on improved DBSCAN and density peak algorithm,” Computer Communications, vol. 167, pp. 75–84, 2021.
[7] B. Liu, Y. Y. Xia, and P. S. Yu, Clustering through Decision Tree Construction, pp. 20–29, CIKM2000, NewYork, NY, USA, 2000.
[8] H. Liu, J. Wu, T. Liu, D. Tao, and Y. Fu, “Spectral ensemble clustering via weighted $k$-means: theoretical and practical evidence,” IEEE Transactions on Knowledge and Data Engineering, vol. 29, no. 5, pp. 1129–1143, 2017.
[9] N. Gornitz, L. A. Lima, K.-R. Muller, M. Kloft, and S. Nakajima, “Support vector data descriptions and $k$-means clustering: one class?” IEEE Transactions on Neural Networks and Learning Systems, vol. 29, no. 9, pp. 3994–4006, 2018.
[10] F. A. T. Carvalhoa, Y. Lechevallierb, and F. M. Meloab, “Partitioning fuzzy clustering algorithms based on multiple dissimilarity matrices,” Fuzzy Sets and Systems, vol. 215, no. 16, pp. 1–28, 2013.
[11] F.-Q. Li, S.-L. Wang, and G.-S. Liu, “A Bayesian Possibilistic C-Means clustering approach for cervical cancer screening,” Information Sciences, vol. 501, pp. 495–510, 2019.
[12] H. Yazdani, “Bounded fuzzy possibilistic method,” Fuzzy Sets and Systems, vol. 389, no. 15, pp. 51–65, 2020.
[13] P. D. Pantula, S. S. Miriyala, and K. Mitra, “An Evolutionary Neuro-Fuzzy C-means Clustering Technique,” Engineering Applications of Artificial Intelligence, vol. 89, Article ID 103435, 2020.
[14] A. Singh and A. K. P. Upadhayay, “A novel approach to incorporate local information in possibilistic c-means algorithm for an optical remote sensing imagery,” The Egyptian Journal of Remote Sensing and Space Science, vol. 24, 2020.
[15] D. S. Mai, L. T. Ngo, L. H. Trinh, and H. Hagras, “A hybrid interval type-2 semi-supervised possibilistic fuzzy c-means clustering and particle swarm optimization for satellite image analysis,” Information Sciences, vol. 548, pp. 398–422, 2021.
[16] S. Askari, “Fuzzy C-Means clustering algorithm for data with unequal cluster sizes and contaminated with noise and outliers: review and development,” Expert Systems with Applications, vol. 165, Article ID 113856, 2021.
[17] E. R. Ruspini, “A new approach to clustering,” Information Control, vol. 15, no. 1, pp. 22–32, 1969.
[18] J. C. Dunn, “A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters,” Journal of Cybernetics, vol. 3, no. 3, pp. 32–57, 1973.
[19] R. Krishnapuram and J. Keller, “A possibilistic approach to clustering,” IEEE TFS, vol. 1, no. 2, pp. 88–110, 1993.
[20] R. Krishnapuram and J. M. Keller, “The possibilistic C-means algorithm: insights and recommendations,” IEEE Transactions on Fuzzy Systems, vol. 4, no. 3, pp. 385–393, 1996.
[21] M. Barni, V. Cappellini, and A. Mecocci, “A possibilistic approach to clustering,” IEEE Transactions on Fuzzy Systems, vol. 4, no. 3, pp. 393–396, 1996.
[22] H. Timm, C. Borgelt, and R. Kruse, Fuzzy Cluster Analysis with Cluster RepulsionEUNITE, Tenerife, Spain, 2001.
[23] Q. Zhang, L. T. Yang, Z. Chen, and F. Xia, “A high-order possibilistic $\delta$C$\delta$-means algorithm for clustering incomplete multimedia data,” IEEE Systems Journal, vol. 11, no. 4, pp. 2160–2169, 2017.
[24] N. R. Pal, K. H. Pal, and M. K. James, “A possibilistic fuzzy c-means clustering algorithm,” IEEE TFS, vol. 13, no. 1, pp. 517–530, 2005.
[25] C. L. Chowdhary and D. P. Acharya, “Segmentation of mammograms using a novel intuitionistic possibilistic fuzzy c-mean clustering algorithm,” Nature Inspired Computing, vol. 652, pp. 75–82, 2018.
[26] S. Askari, N. Montazerin, M. H. F. Zarandi, and E. Hakimi, “Generalized entropy based possibilistic fuzzy C-Means for clustering noisy data and its convergence proof,” Neurocomputing, vol. 219, pp. 186–202, 2017.
[27] C. L. Chowdhary, M. Mittal, P. A. Pattanaik, and Z. Marszalek, “An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-mean clustering and fuzzy SVM algorithm,” Sensors, vol. 20, no. 14, 2020.
[28] A. Schneider, “Weighted possibilistic C-means clustering algorithms,” in Proceedings of the Ninth IEEE International
Conference on Fuzzy Systems, pp. 176–180, San Antonio, TX, USA, May 2000.

[29] W. L. Hung, M. Yang, and D. Chen, "Parameter selection for suppressed fuzzy c-means with an application to MRI segmentation," Pattern Recognition Letters, vol. 27, no. 5, pp. 424–438, 2005.

[30] N. R. Pal, K. Pal, and J. C. Bezdek, "A mixed c-means clustering model," in Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, pp. 11–21, Barcelona, Spain, July 1997.

[31] L. T. Cheng, S. G. Wang, and X. Wei, "New fuzzy c-means clustering model based on the data weighted approach," Data & Knowledge Engineering, vol. 69, pp. 881–900, 2010.

[32] J. Fan, M. Han, and J. Wang, "Single point iterative weighted fuzzy C-means clustering algorithm for remote sensing image segmentation," Pattern Recognition, vol. 42, no. 11, pp. 2527–2540, 2009.

[33] R. Nock and F. Nielsen, "On weighting clustering," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 8, pp. 1223–1235, 2005.

[34] E. Anderson, "The IRIS of gasp peninsula," Bulletin of American IRIS Society, vol. 59, pp. 2–5, 1935.

[35] N. R. Pal, K. Pal, and J. C. Bezdek, "A new hybrid c-means clustering model," in Proceedings of the 2004 IEEE International Conference on Fuzzy Systems, pp. 179–184, Piscataway, NY, USA, July 2004.