Technology and Health Care 23 (2015) S519–S527
DOI 10.3233/THC-150989
IOS Press

Multiple fuzzy c-means clustering algorithm in medical diagnosis

Yanping Wu[a,b,*], Huilong Duan[a] and Shufeng Du[c]
[a]*Department of Biomedical Engineering, School of Biomedical Engineering and Instrument Science, Zhejiang University, Hangzhou, Zhejiang, China*
[b]*Public Health Department, Zhejiang Medical College, Hangzhou, Zhejiang, China*
[c]*Zhejiang Dahua Technology Co., Ltd, Hangzhou, Zhejiang, China*

Abstract.
BACKGROUND: In recent years, the use of the fuzzy c-means (FCM) clustering techniques in medical diagnosis has steadily increased, because of its effectiveness in recognizing systems in the medical database to help medical experts diagnosing diseases. However, its performance is highly dependent on the randomly initialized cluster centroids which may allow the diagnosis to be trapped into the problem of the local optimum.
OBJECTIVE: This paper proposes a multiple fuzzy c-means (MFCM) algorithm for medical diagnosis.
METHODS: The new method optimizes the initial optimizing cluster centers by comparing the Euclidean distance between patient data. Further, this paper assigns a set of weights to the features of a certain disease to equalize their difference influence as a substitute for data normalization.
RESULTS: The performance of proposed MFCM algorithm was demonstrated through dividing complex primary headache data into Migraine, Tension-Type Headache (TTH), Trigeminal Autonomic Cephalalgias (TACs) and other primary headache disorders. In addition the superiority of MFCM algorithm was proven by comparing analytical results with other state-of-the-art clustering methods.
CONCLUSIONS: This MFCM method has shown a new application in medical diagnosis.

Keywords: Fuzzy c-means, medical diagnosis, primary headache

1. Introduction

Clustering is a data mining technique aimed at discovering sensible organization of objects in a given dataset by identifying and quantifying similarities or dissimilarities between the objects. Fuzzy clustering introduces the concept of membership into data partition because membership can indicate the degree to which an object belongs to the clusters definitely and better represents the data partition [1]. Fuzzy c-means (FCM), an effective clustering method developed by Bezdek [2], is one of most common instruments for the medical diagnosis. It helps many physicians to formulate a treatment plan by providing useful information based on the patient's diagnostic data. Many valuable applications have been achieved including medical image segmentation [3], medical feature selection [4,5] and disease classification [6].

*Corresponding author: Yanping Wu, Department of Biomedical Engineering, School of Biomedical Engineering and Instrument Science, Zhejiang University, Hangzhou, Zhejiang 310029, China. Tel.: +86 15858153889; Fax: +86 0571 8769 2809; E-mail: w_yp@zju.edu.cn, wyp@zjmc.net.cn.

Despite the general application of the FCM algorithm in the medical field, it still has considerable drawbacks such as the blindness of random initialization which leads lead to sub-optimization. The traditional FCM algorithm strikes optimal solutions by iteratively updating its membership function and cluster centers to minimize the dissimilarity of the target function. The target function is the weighted sum of the distance of the data from the cluster centers. The center of a cluster is the weighted mean of data represented by the membership function. The process of the cluster algorithm based on the target function entails looking for extreme data points with respect to the clustering centers. In other words, the final clustering optimum resulting from the target function is dependent on the initialization of the clustering centers. For the traditional FCM algorithm, its initial centers are always selected randomly which may causes trapping in the local optimum and convergence on the local extreme data points or saddle data points resulting in a less than comprehensive and optimum solution and effective cluster results. The weakness is particularly evident when the clustering number is very large [7].

Furthermore, variations in the medical features and characteristics of different clinical datasets combine to make clustering a difficult and challenging problem. During the clustering process to partition a set of object data into clusters, the unsupervised FCM algorithm always treats the features of the data vector of equal importance which can affect the clustering performance. From a practical viewpoint, different features contribute at various levels ways to the clustering structure. The existence of irrelevant features may even deteriorate the ability of the utilized learning model. Therefore, it is important to pay more attention to the relevant features during the clustering process to minimize the negative effects from irrelevant features. Evaluating the relevance of different features becomes a more challenging problem [8] in unsupervised learning, due to the absence of guiding information.

As an improvement, evolutionary algorithms such as the genetic algorithm (GA) [9], ant colony optimization (ACO) [10], particle swarm optimization (PSO) [11] and features weighted fuzzy c-means (WFCM) [12] algorithms have been applied to tackle these problems. Many researchers are gradually promoting the use of the FCM algorithm in medical diagnosis with these optimal algorithms. Yeh et al. [13] introduced a novel FCM method for classifying heartbeat cases from ECG signal with the advantages of a low memory space of dataset. Gopal et al. [14] diagnosed brain tumors with an FCM optimized by GA technique. Niu [11] imported an improved FCM clustering algorithm based on PSO for lung cancer classification. Nithya and Manavalan [15] used an ACO clustering algorithm with a fuzzy set for breast cancer diagnosis. Ramathilagam [16] and Kannan et al. [17], found an extended and effective fuzzy c-means for analyzing medical data to identify the proper subtypes of lung cancer. Wang et al. [18] introduced a feature evaluation index C fuzziness and proved its performance in terms of clustering results in detecting BUPA liver disorders. Polat [19] presented an application of an FCM clustering-based feature weighted for the detection of Parkinson's disease. Zhang et al. [20] improved an interval weighted FCM for diagnosing a new-thyroid classification.

In this study, an improved Multiple Fuzzy C-Means (MFCM) algorithm proposed for primary headache diagnosis. The new method consisted of a two-layer FCM algorithm and corresponding improvement in two aspects. The first aspect was an achievement of optimization selection of initial clustering centers with comparison to Euclidean distance between patient data in first layer. The second aspect was to introduce a simple set of feature weighted parameters as a substitute to adjust feature differences of a disease in the data normalization in a second FCM clustering diagnosis layer. As a case study, a primary headache was chosen for medical diagnosis. Since primary headache diagnosis can also be formulated as a classification problem. There is no FCM algorithm available or applied in the headache determination of the origins of a headache. Hence this study will present the MFCM algorithm on primary headache classification. The experimental results of the proposed MFCM clustering method

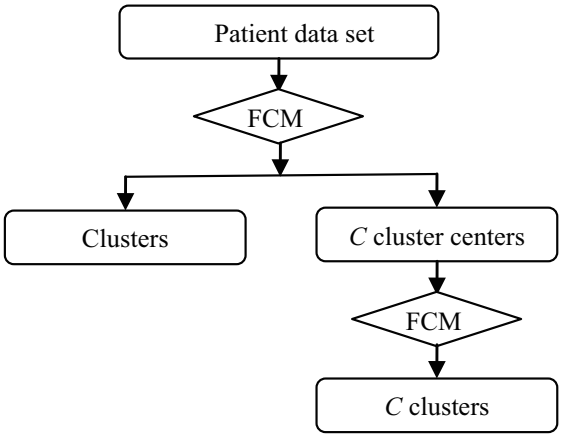

Fig. 1. Flowchart of MFCM structure.

were be compared with three well-known optimal clustering methods, traditional FCM [2] and FCM with genetic algorithm (FCM-GA) [9] and ACO clustering algorithm [10].

The remainder of the paper is organized as follows. Section 2 presents the multi-FCM algorithm in detail. The application and evaluation of the method in primary headache diagnosis is in Section 3 and final conclusion in Section 4.

2. MFCM algorithm

In this section, a medical diagnosis algorithm with a two-level FCM is proposed, the structure of which is shown in Fig. 1. As shown, the MFCM algorithm initially searches the optimal initial clustering centers by a clustering method based on comparing Euclidean distances between patients. Next, it achieves an agreeable medical diagnosis by assigning a set of weights to the features of a certain disease to equalize their difference influences as a substitute for data normalization.

Let the data set of patients be $P = \{p_1, p_2, \ldots, p_N\}$. Each patient p_k, called a patient vector with m-dimensional symptoms, is represented by $p_k = \{s_{k1}, s_{k2}, \ldots, s_{km}\}, k = 1, 2, \ldots, N$, where $s_{kj} (j = 1, 2, \ldots, m)$ is the j-th symptom of the k-th patient vector. A set of $W = \{w_1, w_2, \ldots, w_m\}$ denotes as feature weights for symptoms of disease to balance the patient data vectors as mentioned. Each parameter w_j $(j = 1, 2, \ldots, m)$ is the corresponding weight value to the j-th symptom.

Let $D = \{D_1, D_2, \ldots, D_C\}$ denote the disease clusters with corresponding membership function $U = \{\mu_{D1}, \mu_{D2}, \ldots, \mu_{DC}\}$, A matrix $U \in R^{C \times N}$ contains the membership values of the objects in clusters and a fuzzy c-partition $\tilde{U} \in [\mu_{Di}(p_k)]_{i=1,2,\ldots,c,k=1,2,\ldots,N}$ if it satisfies the following conditions.

$$\sum_{i=1}^{C} \mu_{Di}(p_k) = 1, \quad k = 1, 2, \ldots, N$$

$$0 \leqslant \sum_{k=1}^{N} \mu_{Di}(p_k) \leqslant N, \quad i = 1, 2, \ldots, C$$

Condition (1) claims that each patient vector p_k has its total number of members value 1 divided among all disease clusters. Condition (2) states that the sum of the membership degrees of patient vectors in a given disease cluster does not exceed the total number of patient vectors.

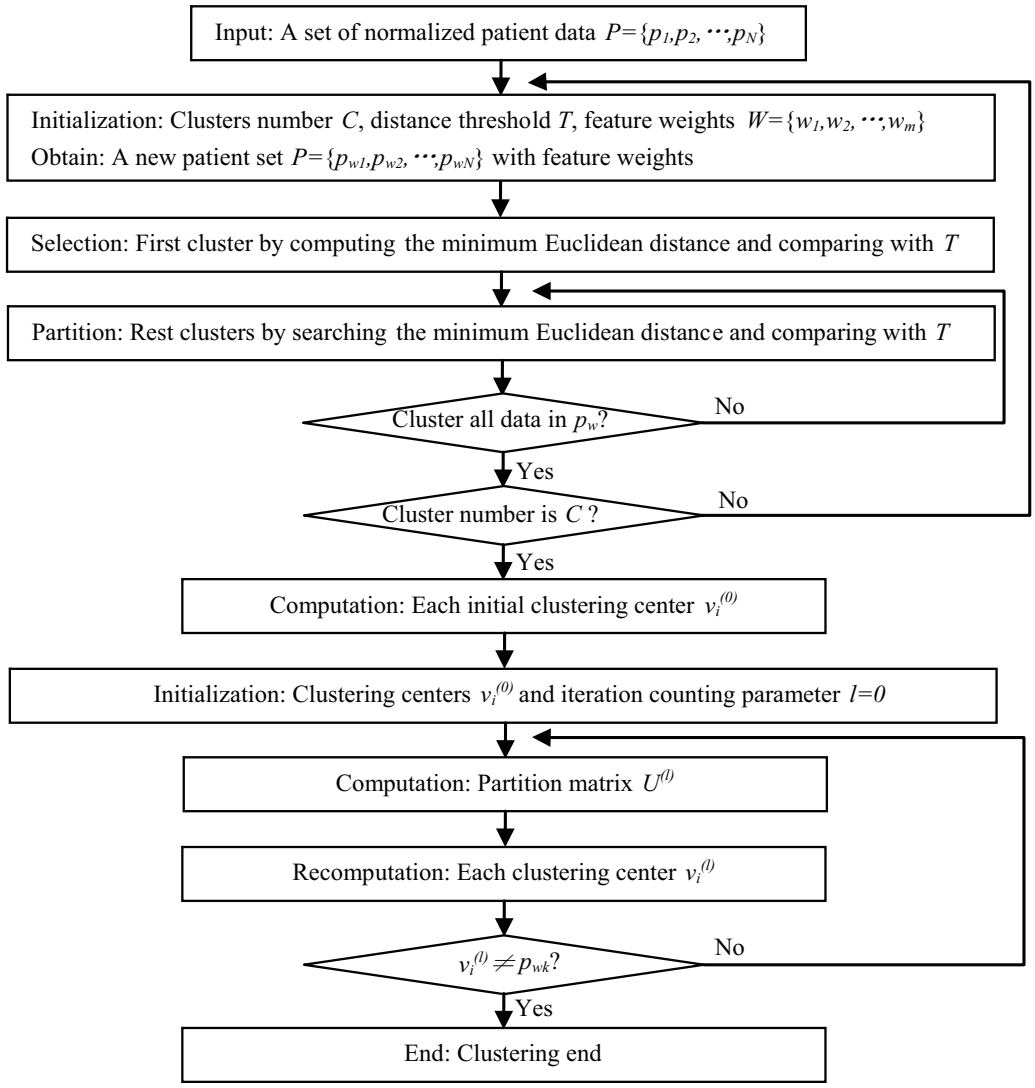

Fig. 2. Flow chart of the MFCM algorithm.

The algorithm of the proposed MFCM includes steps shown below and its algorithm flow chart in Fig. 2.

Step 1: Preprocess and normalize patient information to a set data of $P = \{p_1, p_2, \ldots, p_N\}$.

Step 2: Define clusters number $C(2 \leqslant C \leqslant N)$, distance threshold T and calculation vector norm $\|\|$, where generally the norm is defined by the Euclidean distance. Give values to the set of feature weights $W = \{w_1, w_2, \ldots, w_m\}$ according to preprocessed data results in Step 1 and obtain a new patient set $P_w = \{p_{w1}, p_{w2}, \ldots, p_{wN}\}$ where the k-th patient $p_{wk} = \{w_1 s_{k1}, w_2 s_{k2}, \ldots, w_m s_{km}\}$.

Step 3: Calculate the Euclidean distance d_{Vxy} between any two $p_{wx}, p_{wy}(x, y = 1, 2, \ldots, N)$ using as formula (1). Choose two patients having the minimum distance as a cluster. Partition other $p_{wk}(k = 1, 2, \ldots, N, k \neq x, y)$ whose distance to any one of $p_{wx}, p_{wy}(x, y = 1, 2, \ldots, N)$

is less than threshold value T to this cluster.

$$d_{Vxy} = \|p_{wx} - p_{wy}\| = \sqrt{\sum_{j=1}^{m} (w_j s_{xj} - w_j s_{yj})^2}, x, y = 1, 2, \ldots, N; j = 1, 2, \ldots, m \tag{1}$$

Step 4: Search continuously the minimum distance d_{Vxy} among the rest data that do not belong to the first cluster with formula (1) and classify them to different clusters by threshold value T according to the following rules.
- If $d_{Vxy} \succ T$, classify patients p_{wx}, p_{wy} into two different new clusters.
- If $d_{Vxy} \prec T$, select other remainder patients whose distance with any one of p_{wx}, p_{wy} below threshold T to the same new group of patients p_{wx}, p_{wy}.

Step 5: Repeat Step 4 until every patient vector $p_{wk}(k = 1, 2, \ldots, N)$ has been partitioned into a disease cluster. If a patient vector does not belong to any cluster, let it be a cluster.

Step 6: Modify threshold values T and go back to Step 2 to ensure all patients are partitioned into C clusters of disease.

Step 7: Compute each initial center $v_i(i = 1, 2, \ldots, C)$ of disease cluster using formula (2) below.

$$v_i^{(0)} = \frac{1}{|D_i|} \sum_{k, p_{wk} \in D_i} p_{wk}, \quad i = 1, 2, \ldots, C;\ k = 1, 2, \ldots, N \tag{2}$$

Step 8: Initialize clustering centers $v_i^{(0)}(i = 1, 2, \ldots, C)$ and set iteration counting parameter $l = 0$.

Step 9: Calculate the new partition matrix $U \in R^{C \times N}$ with formulas (3)–(5).

$$U^{(l)} = \left[\mu_{Di}^{(l)}(p_{wk})\right]_{i=1,2,\ldots,C; k=1,2,\ldots,N} \tag{3}$$

$$\mu_{Di}^{(l)}(p_{wk}) = \frac{1}{\sum_{j=1}^{C} \left(\frac{d_{ki}^{(l)}}{d_{kr}^{(l)}}\right)^{\frac{2}{q-1}}}, i, r = 1, 2, \ldots, C; k = 1, 2, \ldots, N \tag{4}$$

$$d_{ki}^{(l)} = \left\|p_{wk} - v_i^{(l)}\right\| = \sqrt{\sum_{j=1}^{m} (w_j\, s_{xj} - v_{ij})^2},$$
$$k = 1, 2, \ldots, N; j = 1, 2, \ldots, m; i = 1, 2, \ldots, C \tag{5}$$

where, the parameter $d_{ki}^{(l)}$ is the distance between every $p_{wk}(k = 1, 2, \ldots, N)$ and cluster centers $v_i^{(l)}$, s_{kj} is the j-th symptom of the k-th patient vector, v_{ij} is the j-dimensional centre of the the i-th disease cluster, parameter $q \in [1.5, 2.5]$ [21] is a weighting exponent to control the fuzzy degree of partition matrix $U \in R^{C \times N}$. If $p_{wk} = v_j^{(l)}$, stop classification and get the medical diagnosis results.

Step 10: Recalculate the fuzzy cluster centers $\{v_i^{(l+1)}\}_{i=1,2,\ldots,C}$ using formula (6).

$$v_i^{(l+1)} = \frac{\sum_{k=1}^{N} \left(\mu_{Di}^{(l)}(p_{wk})\right)^q p_{wk}}{\sum_{k=1}^{N} \left(\mu_{Di}^{(l)}(p_{wk})\right)^q}, \quad i = 1, 2, \ldots, C; k = 1, 2, \ldots, N \tag{6}$$

Table 1
Feature parameters for primary headache diagnosis

Definition	Feature name	Definition	Feature name
S_1	History	S_{11}	Pain site
S_2	Monthly days	S_{12}	Aura
S_3	Whether or not a new headache	S_{13}	Conjunctival injection and/or lacrimation
S_4	Attack duration	S_{14}	Nasal congestion and/or rhinorrhoea
S_5	Attack Frequency	S_{15}	Eyelid dropping
S_6	Sensory pain	S_{16}	Vomiting
S_7	Pain intensity	S_{17}	Phonophobia
S_8	Attack season	S_{18}	Nausea
S_9	Attack daily time	S_{19}	Sensation of fullness in the ear
S_{10}	Movement worsen	S_{20}	Photophobia

Step 11: Judge the values of cluster center $v_i^{(l+1)}(i = 1, 2, \ldots, C)$. If $v_j^{(l+1)} \neq p_{wk}$, return to Step 9. Otherwise, stop at some iteration count l^*.

3. Case study

Headaches, a generally chronic disease, are broadly divided into primary and secondary classes. A primary headache is a common, painful and debilitating disorder that constitutes the vast majority of headache disorders, including four main categories. These include: Migraine, Tension-Type Headache (TTH), Trigeminal Autonomic Cephalalgias (TACs) and other primary headache disorders. Migraine and TTH are the most prevalent and affect 75%–95% of the total headache population while the TACs headache is uncommon, but often misdiagnosed and mismanaged [22].

To date, the diagnosis of the p relies on classifying self-reported headache characteristics using the criteria of International Classification of Headache Disorders, 3rd edition (beta version) (ICHD, 3rd) [23] by the International Headache Society (IHS). These criteria were developed for standardizing headache definition and have improved headache diagnosis. However, the diagnosis of the primary headache is still difficult for physicians due to its complex symptoms. None of the symptom features occur in all patients who meet a strict definition of the HIS primary headache and no single symptom is required for diagnosis. In other words, the primary headache is a complex mixture of symptoms with variable symptom profiles [24]. There are only a few studies that describe [25,26] expert systems or intelligent technologies used for primary headache diagnosis. The diagnosis of the primary headache, as an important classification problem, is partitioned into its four subtypes by the MFCM algorithm in Section 2.

3.1. Experimental design

Based on previous research [27], 20 headache features (Table 1) were considered as diagnostic variables for a primary headache. We considered 379 patients from a certain hospital in China for primary headache diagnostic tests. The class numbers of instances of migraine, TTH, TACs and others are 213, 127, 35 and 4. All data sets for the patients were preprocessed in floating vectors using a normalization method [28].

For the MFCM algorithm, parameter T is influenced by the values in normalized patient vectors since cluster centers are classified by their distance which leads to different medical diagnosis results. Hence, we first determined the optimal value of parameter T which leads to the same clustering number as the number of clustering centers and the number of each cluster should be nearest to the true number in each group. When selecting the optimal value of parameter T, all original values of feature weights should be set to "1" and treating each feature equally helps to find the best value. For the primary headache,

Table 2
Experimental results of numbers in each four clusters with different values of parameter T

Clusters	$T = 1$	$T = 2.5$	$T = 5$
Cluster one	221	207	192
Cluster two	135	135	118
Cluster three	23	23	54
Cluster four	0	14	15

Table 3
Accuracies of cluster results in primary headache diagnosis with different feature weight values when $T = 2.5$

Clusters	$w_{10} = 5$ $w_{13} = 10$	$w_{10} = 12$ $w_{13} = 5$	$w_{10} = 12$ $w_{13} = 10$	$w_{10} = 15$ $w_{13} = 10$	$w_{10} = 20$ $w_{13} = 10$
Migraine	0.727	0.901	0.972	0.901	0.953
TTH	0.260	0.929	0.941	0.941	0.929
TACs	0.857	0.648	0.657	0.657	0.829
Others	0.174	0.267	0.286	0.138	0.138

the optimum objective of the parameter is to classify the initial patient into four groups and the number of each group should be 213, 127, 35 and 4. Then according to the selected optimal value of T, the best feature weight values will be found based on combination of primary headache data normalization and its experimental clustering results. For weighting exponent, select weighting exponential parameter $q = 2$ based on previous experience [21].

In order to measure and compare the results among the clustering algorithms, the diagnosis accuracy is imported from Eq. (7). The proportion of true results was determined by the accuracy calculation. All experiments were performed using C language on a personal computer with Windows XP, Intel(R) Core(TM) Dual CPU 3.1 GHz, and 4 GB memory.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Where *TP* is number of true positive, *TN* is number of true negative, *FP* is number of false positive, and *FN* is number of false negative.

3.2. Experimental results

To analyze the selection for parameter T with no weighting difference on features, select experimental results are presented in Table 2. As can be seen, that $T = 2.5$ was optimum for partitioning patients into four clusters in comparison with three clusters when $T = 1$. The numbers in each class are respectively 207, 135, 23 and 14 when $T = 2.5$ and are nearest to the real numbers 213, 127, 35 and 4 in primary headache dataset compared with the resulting numbers when $T = 5$.

As a second case, setting $T = 2.5$ with different values for weights of symptoms in the headache searched to achieve the best medical diagnosis yielded the following. From the preprocessed data for primary headache diagnosis, values of features Movement worsen (S_{10}) and Conjunctival injection and/or lacrimation (S_{13}) are too small to be distinguished in comparison with measure of other values. Therefore, we initialized the weight set as following.

$$W = \{w_1, w_2, \ldots, w_m\} = \{1, 1, 1, 1, 1, 1, 1, 1, 1, w_{10}, 1, 1, w_{13}, 1, 1, 1, 1, 1, 1, 1\}$$

Where, different weight values for w_{10} and w_{13} could be adjusted to obtain the best classifying results when $T = 2.5$ their experimental accuracies are shown in Table 3. According to the data in Table 3, it is obvious that best medical diagnosis accuracies were attained when $w_{10} = 12$ and $w_{13} = 10$. The corresponding optimal initial cluster centers values are shown in Table 4. Due to the small number cluster sampling of other headache disorders, clustering is difficult. Therefore, it can be inferred that the number of samples has direct influence on clustering results.

The results for accuracies of the optimal primary headache diagnosis using MFCM algorithm com-

Table 4
Initial cluster centers results when $T = 2.5$

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
Primary	0.89324	1.02802	0.98551	0.98261	0.97923	1.05411	0.91015	0.98068	1.01401	1.30435
TTH	1.10222	1.03630	0.98222	1.03259	1.01482	1.03407	1.09926	0.98667	1.02000	28.88000
TACs	0.99565	0.99565	0.88696	0.78696	0.95652	0.79130	1.37391	0.71304	0.83044	14.03478
Others	0.78571	0.85000	1.45714	0.85714	0.85000	0.81429	1.17143	0.94286	1.10000	3.08571
	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}	S_{19}	S_{20}
Primary	1.01981	0.02995	0.00000	0.00000	0.00610	0.00916	0.00000	0.00153	0.00167	0.00000
TTH	1.00444	1.42370	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TACs	0.51304	0.00000	165.00000	0.16500	0.10983	0.08239	0.16487	0.15113	0.15000	0.16478
Others	1.00714	12.84286	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Table 5
Clustering accuracies of MFCM clustering, traditional FCM, FCM-GA and ACO clustering algorithm on primary headache diagnosis

	MFCM	FCM	FCM-GA	ACO
Migraine	0.972	0.636	0.598	0.892
TTH	0.941	0.220	0.181	0.843
TACs	0.657	0.400	0.005	0.857
Others	0.286	0.300	0.001	0.154

pared with traditional FCM, FCM-GA and ACO algorithms are shown in Table 5. It can be seen from Table 5 that the proposed MFCM algorithm performs better than the other methods. The significant improvement in clustering accuracy can be attributed to the improved search by optimizing the initial centriods of the clusters and the feature weights as a substitute to data normalization. As a result of the refined initial centroids and efficient assignment of the data points to the different clusters, the MFCM algorithm yields better clusters.

4. Conclusion

Accurate clustering has a very crucial influence on accurate disease diagnosis. The traditional fuzzy c-means clustering techniques do not generally provide sufficiently acceptable results. The MFCM algorithm in combination with the optimum initial cluster centers and simple set of feature weights as proposed in this study improves the performance of the FCM. The primary headache, a common complicated chronic disease, was examined using the proposed MFCM algorithm. Study results showed that the MFCM algorithm exhibited better performance in diagnosing the primary headache in comparison to other clustering algorithms.

Acknowledgments

The work was supported by the Health and Family Planning Commission of Zhejiang Province under Grant Zhejiang medical and health science and technology project (No. 2013KYA050). The authors are especially thankful for the positive support received from Zhejiang University staff involved.

References

[1] Albayrak S, Amasyali F. Fuzzy c-means clustering on medical diagnostic systems. Turkish symposium on Artificial

Intelligence and Neural Networks. 2003; 1-3.
[2] Bezdek JC, Ehrlich R, Full W. FCM: The fuzzy c-means clustering algorithm. Computers & Geosciences. 1984; 10(2): 191-203.
[3] Naz S, Majeed H, Irshad H. Image segmentation using fuzzy clustering: A survey. Sixth International Conference on Emerging Technologies. 2010.
[4] Xu JC, Sun L, Gao YP, Xu TH. An ensemble feature selection technique for cancer recognition. Bio-medical Materials and Engineering. 2014; 24: 1001-1008. doi: 10.3233/BME-130897.
[5] Sun L, Xu JC. Feature selection using mutual information based uncertainty measures for tumor classification. Bio-medical Materials and Engineering. 2014; 24: 763-770. doi: 10.3233/BME-130865.
[6] Azar AT, El-Said SA, Hassanien AE. Fuzzy and hard clustering analysis for thyroid disease. Computer Method and Programs in Biomedicine. 2013; 111: 1-16. doi:10.1016/j.cmpb.2013.01.002.
[7] Xia KJ, Wu Y, Ren XG. Research in clustering algorithm for disease analysis. Journal of Networks. 2013; 8(7): 1632-1639. doi: 10.4304/jnw.8.7.1632-1639.
[8] Jia H, Cheung YM. Feature weighted kernel clustering with application to medical data analysis. Conference on Brain and Health Informatics. 2013. p. 496-505.
[9] Bandyopadhyay S, Maulik U. Genetic clustering for automatic evolution of clusters and application to image classification. Pattern Recognition. 2002; 35: 1197-1208.
[10] Shelokar PS, Jayaraman VK, Kulkarni BD. An ant colony approach for clustering. Analytica Chimica Acta. 2004; 509: 187-195. doi:10.1016/j.aca.2003.12.032.
[11] Niu Q, Huang XJ. An improved fuzzy c-means clustering algorithm based on PSO. Journal of Software. 2011; 6(5): 873-879. doi:10.4304/jsw.6.5.873-879.
[12] Frigui H, Nasraoui O. Unsupervised learning of prototypes and attribute weights. Pattern Recognition. 2004; 37: 567-581. doi: 10.1016/j.patcog.2003.08.002.
[13] Yeh YC, Wang WJ, Chiou CW. A novel fuzzy c-means method for classifying heartbeat cases from ECG signals. Measurement. 2010; 43: 1542-1555. doi:10.1016/j.measurement.2010.08.019.
[14] Gopal NN, Karnan M. Diagnose brain tumor through MRI using image processing clustering algorithms such as fuzzy c means along with intelligent optimization techniques. IEEE International Conference on Computational Intelligence and Computing Research. 2010.
[15] Nithya S, Manavalan R. An ant colony clustering algorithm using fuzzy logic. International Journal of Soft Computing and Software Engineering. 2012; 2(5): 13-24. doi: 10.7321/jscse. v2.n5.2.
[16] Ramathilagam S, Devi R, Kannan SR. Extended fuzzy c-means: an analyzing data clustering problems. Cluster Computing-The Journal of Networks Software Tools and Applications. 2013; 16: 389-406. doi: 10.1007/s10586-012-0202-2.
[17] Kannan SR, Ramthilagam S, Devi R, Hong TP. Fuzzy c-means in finding subtypes of cancers in cancer database. Journal of Innovative Optical Health Sciences. 2014; 7(1): 1-20. doi: 10.1142/S1793545814500187.
[18] Wang LJ, Guan SY, Wang XL, Wang XZ. Fuzzy c-mean algorithm based on feature weights. Chinese Journal of Computers. 2006; 29(10): 1797-1803.
[19] Polat K. Classification of Parkinson's disease using feature weighting method. International Journal of Systems Science. 2012; 43(4): 597-609. doi: 10.1080/00207721.2011.581395.
[20] Zhang LY, Pedrycz W, Lu W, Liu XD, Zhang L. An interval weighted fuzzy c-means clustering by genetically guided alternating optimization. Expert Systems with Application. 2014; 41: 5960-5971. doi: 10.1016/j.eswa.2014.03.042.
[21] Pal NR, Bazdek JC. On clusters validity for the fuzzy c-means mode. IEEE Trans. On Fuzzy Systems. 1995; 3(3): 370-379.
[22] Fayyaz A. Headache disorders: differentiating and managing the common subtypes. The British pain society. 2012; 6(3): 124-132. doi: 10.1177/2049463712459691.
[23] Headache Classification Committee of the International Headache Society. The International Classification of Headache Disorders (3rd edition, beta version). 2013. doi: 10.1177/0333102413485658.
[24] Chen CCM, Mengersen KL, Keith JM, Martin NG, Nyholt DR. Linkage and heritability analysis of migraine symptom groupings: a comparison of three different clustering methods on twin data. Journal of Human Genetics. 2009; 125: 591-604. doi: 10.1007/s00439-009-0652-7.
[25] Svetlana S, Dragan S, Petar S. Computer-assisted diagnosis of primary headache. HAIS. 2008. p. 314-321.
[26] Jeong Y, Kyung SH, Sun YO. An application of interval-valued intuitionistic fuzzy sets for medical diagnosis of headache. International Journal of Innovative Computing Information and Control. 2011; 7(5): 2755-2762.
[27] Lora A, Hasse P, Neal R, Robert S. Quantifying headache symptoms and other headache features from chart notes. Headache. 2004; 44: 873-884.
[28] Zhuang HY, Shen XP, Lu JF, Huang LF. Theoretical analyses of the computing method of fuzzy cluster. Journal of Jiangsu Agriculture College. 1998; 19: 37-41.