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K-HARMONIC MEANS DATA CLUSTERING WITH IMPERIALIST COMPETITIVE ALGORITHM

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Data clustering is one of the most important tasks of data mining. This paper aims to describe an integrated data clustering method based on Imperialist Competitive Algorithm (ICA) and K-Harmonic Means (KHM) algorithm. The proposed method is called ICA-KHM. KHM is a well-known clustering method and its main drawback is to converge to local optimums. Imperialist competitive algorithm is an evolutionary global search and optimization algorithm inspired by socio-political process of imperialistic competition. ICA has high convergence rate and can be used to solve optimization problems with multiple local minima. The proposed method combined the advantageous aspects of ICA and KHM in data clustering process. The proposed method is evaluated on five well-known datasets from different domains, and compared with KHM, and ICA. The experimental results indicate that the ICA-KHM provides better results than the two other methods.

Keywords: Data Clustering, K-Harmonic Means Algorithm, Imperialist Competitive Algorithm, Optimization

1. Introduction

Clustering is an unsupervised method and there is not any training data with class labeling. The goal of data clustering is to group data objects into a number of clusters based on similarities and differences among the data objects. Clustering is a main task of explorative data mining, and a common technique for statistical data analysis used in many domains, including machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics [1][2][3].

K-means (KM) [4] which is an iterative distance-based clustering method and has linear time complexity attempts to minimize a criterion function (e.g. a squared error function) in an iterative fashion. KM has some drawbacks; firstly different initial cluster centers may lead KM to produce different final clustering, each one corresponding to a different local optimum. Secondly, the number of

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clusters is required as a priori knowledge. Thirdly, KM is sensitive to outliers and noise. Fourthly, KM is not suitable for data with nominal (categorical) coordinates. In summary, the main weakness of KM is that it often trapped in local optimum and its efficiency depends on the initialization of cluster centers [1].

K-Harmonic Means (KHM) algorithm [2][5] like KM, is a center-based and iterative algorithm which objective function uses the harmonic average of distances from each data object to the centroids and the aim of the KHM algorithm is to minimize this objective function. The KHM algorithm solves the problem of initialization of cluster centers in the KM algorithm, but it also easily get stuck at local optimum. Unlike KM, KHM assigns dynamic weights to each data objects based on a harmonic average in the every iteration of algorithm.

In this paper, to solve the problem of convergence to local optimum in KHM, we used Imperialist Competitive Algorithm (ICA) [6]. ICA is an optimization strategy that has high convergence rate and can achieve to global optimum. Hence in this paper, we proposed a hybrid data clustering algorithm based on KHM and ICA, called the ICA-KHM. The proposed algorithm has high efficiency compared to other algorithms have recently been proposed for data clustering. We compared the result of ICA-KHM algorithm with those of KHM and ICA algorithms. The numerical results by applying ICA-KHM on different datasets indicate that this algorithm is very better than KHM and ICA.

2. Data Clustering

Data clustering is an active research direction in the field of data mining [7]. Data clustering, which is an NP-complete problem, is the process of grouping data objects into some clusters by minimizing some dissimilarity measures, so that the data objects within a class are highly similar to one another and dissimilar with the data objects in other clusters. Clustering is one of the major tools in data mining, machine learning and pattern classification solutions. We describe here the KHM clustering algorithm that is widely used in various applications.

A. K-Harmonic Means (KHM) Algorithm

As mentioned before, the main weakness of the KM algorithm is that it often is trapped in local optima (i.e. it does not necessarily find the global minimum of the objective function) and its performance depends on the initialization of cluster centers. K-Harmonic Means (KHM) algorithm [2][8] is a center based and iterative partitioned clustering algorithm. KHM is an approach to overcome the problem of dependency to center initialization of KM (i.e. KHM is essentially insensitive to the initialization of the centers). Unlike KM, the KHM algorithm uses the harmonic averages of the distances from each data point to the centers as its performance function. KHM assigns dynamic weights to each data objects based on a harmonic average. Like KM, KHM algorithm may be get stuck at local optimums. To solve this problem and improving clustering quality some researchers have used hybrid methods that combine KHM and other global optimization algorithms. Therefore, in this paper, we used ICA to improve KHM. The formal description of KHM clustering algorithm is shown in Fig. 1.

3. Imperialist Competitive Algorithm (ICA)

The ICA is one of the evolutionary population based optimization and search algorithms. The source of inspiration of this algorithm is the imperialistic competition. So far, the ICA has been used in various optimization and engineering applications [6][9]. ICA has good performance in both convergence rate and better global optimum achievement. The ICA formulates the solution space of a problem as a search space. This means each point in the search space is a potential solution of the problem. The ICA aims to find the best points in the search space that satisfy the problem constraints. A flowchart of the working principle of the origin ICA is presented in Fig. 2.

An ICA begins its search and optimization process with an initial population. Each individual in the population is called a country. Then, the cost of each country is evaluated according to a predefined cost function. The cost values and their associated countries are ranked from lowest to highest cost. Some of the best countries are selected to be the imperialist states and the remaining form the colonies of these imperialists. All colonies of the population are divided among the imperialists based on their power. Obviously more powerful imperialists will have the more colonies. The colonies together with their relevant imperialists form some empires in the solution space. The ICA contains two main steps that are assimilation policy and imperialistic competition. During assimilation step, colonies in each empire start moving toward their relevant imperialist and change their current positions. The assimilation policy causes the powerful empires are reinforced and the powerless ones are weakened. Then imperialistic competition occurs and all empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful empires. In the ICA, the imperialistic competition is modeled by just picking some of the weakest colonies of the weakest empire and making a competition among all empires to possess these colonies. The assimilation and imperialistic competition are performed until some predefined termination conditions are satisfied.

Step1: *Initialize the algorithm with guessed centers* $C = \{C_1, C_2, ..., C_K\}$ *(i.e. select the K initial cluster centers randomly from n data points* $X = \{x_1, x_2, ..., x_n\}$*);*

Step 2: *Calculate objective function value as below:*

$$KHM(X, C) = \sum_{i=1}^{N} \frac{K}{\sum_{j=1}^{K} \frac{1}{\|x_i - c_j\|^p}} \tag{1}$$

Where p is an input parameter for KHM algorithm and typically $p \geq 2$ *;*

Step 3: *For each data point* x_i *compute its membership function* $m(c_j|x_i)$ *in which each center* c_j *as below:*

$$m(c_j|x_i) = \frac{\|x_i - c_j\|^{-p-2}}{\sum_{j=1}^{k} \|x_i - c_j\|^{-p-2}} \tag{2}$$

Step 4: *For each data point* x_i *compute the* $w(x_i)$ *as below:*

$$w(x_i) = \frac{\sum_{j=1}^{k} \|x_i - c_j\|^{-p-2}}{\left(\sum_{j=1}^{k} \|x_i - c_j\|^{-p}\right)^2} \tag{3}$$

Step 5: *For each center* c_j*, re-compute its location from all data points* x_i *according to their membership* $m(c_j|x_i)$ *and weights* $w(x_i)$ *:*

$$c_j = \frac{\sum_{i=1}^{n} m(c_j|x_i) \times w(x_i) \times x_i}{\sum_{j=1}^{k} m(c_j|x_i) \times w(x_i)} \tag{4}$$

Step 6: *Repeat step 2-5 until the predefined stopping criteria is satisfied;*

Step 7: *Assign data point* x_i *to cluster j with the biggest* $m(c_j|x_i)$.

Fig. 1. K-harmonic means clustering algorithm [2][10].

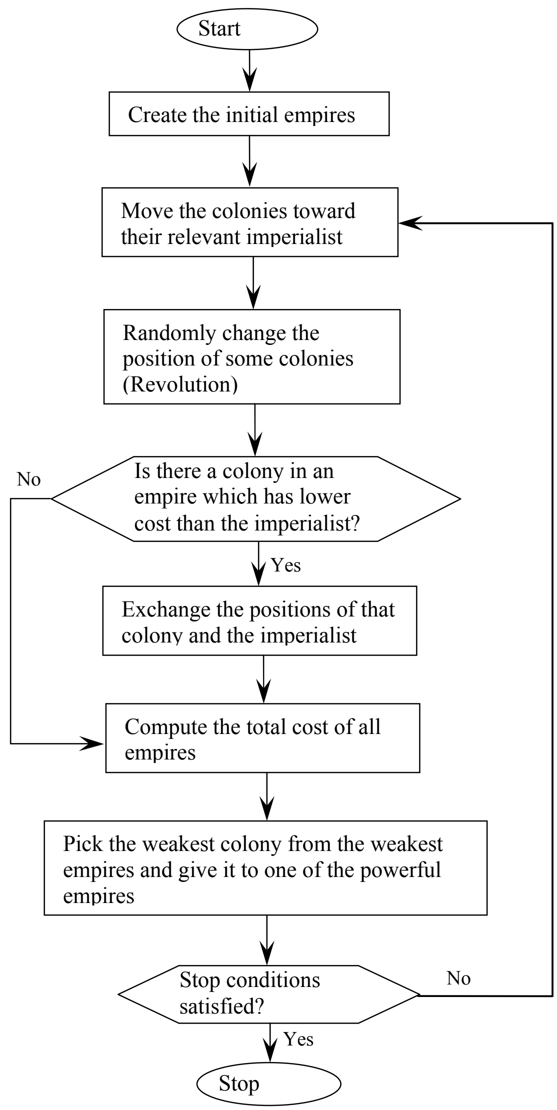

Fig. 2. Flowchart of the Imperialist Competitive Algorithm

3. Related Works

As mentioned before, the KHM algorithm has some drawbacks that one of the most important of them is the local optima problem. In the recent years, to overcome the local optima problem and improving quality of solutions, researchers have been proposed several techniques. These algorithms achieved encouraging results in the area of data clustering. Of the clustering techniques developed in recent years several major of them are described in the follow.

Selim and Al-Sultan proposed a clustering approach based on the simulated annealing algorithm [11]. The authors theoretically proved that their proposed method can reach to global optimum in solving clustering problem. Krishna and Murty to overcome the shortcomings of K-means algorithm proposed a hybrid approach called genetic K-means algorithm [12]. In the algorithm, a new distance based mutation operator was introduced specific to clustering. Sung and Jin proposed a clustering method using Tabu search algorithm [13]. Two complementary functional procedures, called packing and releasing procedures were combined with the Tabu search. Another example is the genetic based clustering approach proposed by Mualik and Bandyopadhyay [14]. The performance of the algorithm is tested on real-life and synthetic datasets. Also in recent years, many researchers have been used swarm intelligence technique to solve clustering problem. For instance, Shelokar *et al* proposed an evolutionary algorithm based on ACO algorithm for clustering problem [15]. Falco el al. used PSO algorithm to solve the clustering problem [16], Karaboga and Ozturk [17] and Zhang et al. [18] used Artificial Bee Colony (ABC) algorithm to solve the problem.

Kezhong, et al. [19] proposed a hybrid clustering algorithm combining quantum-behaved particle swarm optimization and KHM (HQPSO) for help to KHM to escape from local optima. They showed that HQPSO clustering algorithm has the advantages of global searching, fast convergence and less sensitive to initial conditions. Cheung and Huang [20] have presented an agglomerative fuzzy K-means clustering algorithm for numerical data, an extension to the standard fuzzy K-means algorithm by introducing a penalty term to the objective function to make the clustering process not sensitive to the initial cluster centers. The new algorithm can produce more consistent results from different sets of initial clusters centers. Tian et al. [2] proposed a hybrid data clustering algorithm, DEKHM based on Differential Evolution (DE) and KHM, which makes full use of the advantages of both DE and KHM algorithms. The DEHKM algorithm not only helps KHM clustering escape from local optima but also overcomes the shortcoming of the slow convergence speed of the DE algorithm. Yang et al. [1] presented a hybrid data clustering method based on K-harmonic means and Particle Swarm Optimization called PSOKHM in which they used PSO algorithm that helps the KHM escape from local optimums. They used seven datasets for evaluating their proposed algorithm. One drawback of their proposed algorithm is that it requires more runtime than KHM. Also PSOKHM algorithm is not applicable when the runtime is quite critical. Thangavel et al. [21]

proposed a novel ensemble based distributed clustering algorithm using KHM. The distributed clustering algorithm is used to cluster the distributed datasets without necessarily downloading all the data to a single site. Similarly, distributed clustering algorithm based on KM is also sensitive to centroids initialization. Guo and Peng [7] proposed a clustering algorithm based on dimensional reduction approach and KHM. They claimed that their proposed algorithm has advantages in the computation time, iteration numbers and clustering results in most cases, and it is also an algorithm which is suitable for large scale datasets. Shen et al. [22] proposed a detailed overview of hybrid algorithms combining PSO with k-Means algorithm for solving clustering problem. Runkler worked on a partially supervised clustering [23]. Partially supervised clustering finds clusters in datasets that contain both unlabeled and labeled data. The author in this paper review partially supervised k-means, partially supervised fuzzy K-means, and introduces a partially supervised extension of k-harmonic means. The author showed that partially supervised k-harmonic means inherits the advantages of its completely unsupervised variant. Chang et al. [24] developed a fuzzy k-means clustering algorithm using the cluster center displacement between successive iterative processes to reduce the computational complexity of conventional fuzzy k-means clustering algorithm. Their proposed method which is called CDFKM, first classifies cluster centers into active and stable groups. This method skips the distance calculations for stable clusters in the iterative process. To speed up the convergence of CDFKM, they also present an algorithm to determine the initial cluster centers for CDFKM. Compared to the standard fuzzy k-means clustering algorithm, this method is reduced computing time. Kalam et al. presented an enhancing k-means algorithm for image segmentation [25]. Image segmentation is typically used to locate objects and boundaries in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. The presented method, tries to develop k-means algorithm to obtain high performance and efficiency.

In general, each of these researchers attempted to improve the quality of clustering by using different methods. Some of these researchers used hybrid algorithms that combine one of the evolutionary optimization algorithms with KHM algorithm to improve the result of clustering, and some others used simple and complex learning methods, fuzzy logic, mathematical and other existing methods to improve the result of KM and KHM clustering algorithms. As other researchers, in this paper, we introduced a new hybrid algorithm for data clustering. The proposed algorithm is tested on five well-known datasets obtained from the UCI repository [26]. The performance of the proposed algorithm is compared with the ICA [6], and K-harmonic means algorithms [8]. The experiments show that the proposed method achieved better results than the other algorithms on datasets.

4. The Proposed Algorithm

Fig. 3 shows an overview of the proposed hybrid clustering algorithm. In this paper we used ICA which helps the KHM algorithm to escape from local optima and improves the quality of solutions. It is important to say that the ICA can work better by itself. ICA has the high convergence speed and has shown great performance in global optimal achievement. We integrate ICA with KHM to form a hybrid data clustering algorithm called ICA-KHM, which maintains the advantages of ICA and KHM.

In summary, the main steps of the ICA-KHM are as follows. First, an initial population of countries which contains K number of cluster centers is generated randomly. Then ICA algorithm begins its optimization process by forming initial empires. After forming initial empires in the solution space, the colonies in each empire start moving toward their relevant imperialists. During these movements, powerful imperialists are reinforced and the weak ones are weakened. Then by using revolution operator some colonies randomly change their position in the solution space. The revolution increases the exploration power of the algorithm and prevents the early convergence of countries to local optimums. Also similar empires collate together and make a new empire. Afterwards imperialistic competition begins among empires and improves the cost of countries.

Once the ICA algorithm is over, the next step is devoted to executing the standard KHM algorithm on the empires. For each empire the standard KHM algorithm executes to update cluster centers. KHM algorithm reevaluates membership function and updates weight value of data points. As shown in Figure 3, in each empire, the KHM algorithm only applies on the half number of colonies. To do this, we used $randi\ (1,2)$ function that generates either 1 or 2 value. The result of this function determines the set of colonies that KHM algorithm applies on them. If the output of $randi\ (1,2)$ function is “1” then the selected colonies are colonies with odd index and if the outcome of this function is “2” then in question population is equal to the colonies with even index.

The proposed algorithm executes alternatively the KHM and ICA algorithms until termination condition is satisfied. In the implementation of this paper the termination condition is set to maximum iteration number.

***Algorithm**: hybrid ICA-KHM Algorithm*
***Input**: a dataset, with n data point and d dimensions.*
***Output**: global clusters of input dataset*
Procedure:
***Step 1:** set algorithm parameters such as iteration count ($AlgItr$) and maximum iteration numbers (maxItr);*
***Step 2:** Initialize an initial population of size N_{Pop} ;*
***Step 3:** set iterative count $AlgItr = 0$;*
***Step 4:** Execute ICA algorithm on population*

```
// Create initial empires
Costs= KHM_Objective_Function(Population);
Empires = CreateInitialEmpires (Population, Costs);
// Assimilate colonies
Empires = AssimilateColonies (Empires);
// Revolution
Empires = RevolveColonies (Empires);
// Compute total cost of empires
Empires.TotalCost = ComputeTotalCost(Empires);
// Collate similiar empires
Empires = UniteSimilarEmpires(Empires);
// Imperialistic competition
Empires = ImperialisticCompetition(Empires);
```

***Step 5:** For each empire apply standard KHM algorithm on the half number of its colonies*
***Step 5.1:** generate a random number from {1, 2} and select colonies*

```
k = randi(1, 2);
if ( k == 1 ) then
    colPop=select the colonies with odd index
else
    colPop=select the colonies with even index
```

Fig. 3. The proposed hybrid ICA-KHM algorithm.

5. Experiments and Results

All experiments took place on a Personal Computer with 3.00 GHz CPU and 512MB RAM for run the proposed method. Also we used MATLAB language for coding all the algorithms. The algorithms contain the KHM, the ICA and the ICA-KHM.

The performance of the algorithms is compared using five well-known datasets from different domains. Characteristics of these datasets are represented in Table 1. These datasets are Iris, Wine, Glass, Contraceptive Method Choice (CMC), and Breast-Cancer-Wisconsin or shortly Cancer. These datasets are real datasets and there exist in the UCI repository [26]. The same parameters for ICA and ICA-KHM algorithms are shown in Table 2. In KHM algorithm, variable *p* is a key factor in order to get good objective function value. In the implementation of this paper, *p* is set to 2.5.

In order to measure the potential of the algorithms and the quality of results, the following criterions are used.

- The objective function value of KHM algorithm:

$$KHM(X,C)=\sum_{i=1}^{N}\frac{K}{\frac{1}{\left\|x_i-c_j\right\|^{p}}} \tag{5}$$

How much this criterion is the smaller, the quality of clustering is the higher.

- Processing time: shows the run time of the algorithms. This is used to measure the speed of each algorithm.

The results found from applying the three algorithms for CMC, Cancer, Iris, Glass and Win datasets are summarized in Tables 3-7. In these tables min, mean, and max are the minimum, average and maximum cost values found over 10 independent simulation runs, *Sigma* is the standard deviation of results, and *runtime* is the processing time of the algorithms. In this paper, the unit of processing time is second.

From the reported experimental results it can be seen that the values of $KHM(X, C)$ obtained by ICA-KHM is often better than those two others. For all datasets the KHM algorithm has the minimum processing time; the ICA takes the second place. The main drawback of the ICA-KHM is that it requires a little more processing time than two other algorithms and this due to the combination of ICA and KHM algorithms. With the exception of two case (iris and glass datasets), the standard deviation of the KHM algorithm is better than that of ICA-KHM and ICA is relatively bad.

In summary, for all datasets the ICA-KHM finds better results in terms of solution quality than two others. This indicates the capability of ICA-KHM to overcome the problem of convergence to local optimum of the KHM algorithm.

Table 1

Characteristics of Datasets

No.	***Dataset name***	***Instances***	***No. of features***	***No. of classes***	***Class distribution***
1	CMC	1473	9	3	(629,334,510)
2	Cancer	683	9	2	(444,239)
3	Iris	150	4	3	(50,50,50)
4	Glass	214	9	6	(70,17, 76, 13,9,29)
5	Wine	178	13	3	(59, 71,48)

Table 2

The Parameters of ICA and ICA-KHM algorithms

Algorithm Parameter	***Value***
No. of Countries	30
No. of Initial Imperialists	4
No. of All Colonies	26
No. of Decades	10
Revolution Rate	0.25
Uniting Threshold	0.02
Assimilation Coefficient	2
Assimilation Angle Coefficient	0.45
Damp Ratio	0.90

Table 3

Results of KHM, ICA, and ICA-KHM on CMC datasets

Algorithm	***min***	***mean***	***max***	***sigma***	***runtime***
KHM	96195.0850	96200.730	96203.599	3.685	1.523
ICA	137405.154	158342.242	*178932.839*	*12701.219*	*19.265*
ICA-KHM	96164.981	96188.508	*96207.058*	*8.568*	*20.827*

Table 4

Results of KHM, ICA, and ICA-KHM on Cancer datasets

Algorithm	***min***	***mean***	***max***	***sigma***	***runtime***
KHM	57168.901	57168.954	57169.000	0.029	1.221
ICA	78658.488	83631.554	91971.580	3555.389	6.471
ICA-KHM	56986.116	57040.636	57101.574	20.857	6.677

Table 5

Results of KHM, ICA, and ICA-KHM on Iris datasets

Algorithm	*min*	*mean*	*max*	*sigma*	*runtime*
KHM	148.904	148.976	149.038	0.0352	0.066
ICA	212.228	263.900	296.240	23.982	1.672
ICA-KHM	148.869	148.886	*148.913*	*0.0150*	*1.836*

Table 6

Results of KHM, ICA, and ICA-KHM on Glass datasets

Algorithm	*min*	*mean*	*max*	*sigma*	*runtime*
KHM	1167.716	1214.626	1292.736	39.418	1.005
ICA	1849.916	2059.818	2328.047	151.652	5.036
ICA-KHM	1115.009	1192.581	*1226.441*	*27.482*	*5.989*

Table 7

Results of KHM, ICA, and ICA-KHM on Wine datasets

Algorithm	*min*	*mean*	*max*	*sigma*	*runtime*
KHM	7.53385e+7	753386e+7	753387e+7	28.156	0.891
ICA	7.66079e+7	8.57634e+7	1.001502e+8	8.00337e+6	2.558
ICA-KHM	7.53377e+7	7.53391e+7	7.53410e+7	1050.195	3.129

In this paper, we proposed a data clustering algorithm based on ICA and KHM algorithms which is called ICA-KHM. Our proposed algorithm takes the advantage of globally searching capability of ICA to overcome the problem of convergence to local optimum of the KHM algorithm. The numerical experiments are performed on five well-known datasets. The objective function for KHM, ICA and ICA-KHM algorithms is the $KHM(X, C)$ of the KHM algorithm. Experimental results showed that ICA-KHM is better than KHM and ICA in terms of the minimum and the average value of $KHM(X, C)$ objective function. ICA-KHM is an efficient and feasible algorithm and is also suitable for large scale datasets .we are working on the new evolutionary algorithm and our future work focused on presenting a new efficient data clustering algorithm using this new algorithm.

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