K-harmonic means Data Clustering using Combination of Particle Swarm Optimization and Tabu Search

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Abstract

Clustering is one of the widely used techniques for data analysis. Also it is a tool to discover structures from inside of data without any previous knowledge. K-harmonic means (KHM) is a center-based clustering algorithm which solves sensitivity to initialization of the centers which is the main drawback of K-means (KM) algorithm, but, both KM and KHM converge to local optimal. In this paper, a hybrid data clustering algorithm based on KHM is proposed called PSOTSKHM, using Particle Swarm Optimization (PSO) algorithm as a stochastic global optimization technique and Tabu Search (TS) algorithm as a local search method. This algorithm makes full use of the advantages of three algorithms. The proposed algorithm has been compared with KHM, PSOKHM and IGSAKHM algorithms on four real datasets and the obtained results show the superiority of suggested algorithm in most cases.

Keywords: Data clustering, K-harmonic means, Particle Swarm Optimization, Tabu Search.

1. Introduction

Clustering is a method of unsupervised learning. It organizes data instances into disjointed clusters such that the objects in the same cluster are similar to each other and objects in different clusters are as dissimilar as possible [3]. It has been widely used in
various fields and many applications such as machine learning, data mining, pattern recognition, image analysis and bioinformatics [14, 19]. The existing clustering algorithms can be basically classified into two categories: hierarchical clustering and partitional clustering. Hierarchical clustering approach aims at grouping data through repeated cluster separation or agglomeration. Partitional clustering approach attempts to directly decompose data into disjoint clusters based on an objective function such as minimizing the distance between data points and cluster centers [5].

The classic K-means algorithm (KM) is the most popular clustering algorithm due to it’s simplicity and efficiency but it is very sensitive to initialization, and is easily trapped in local optimal. Recently much work was done to overcome these problems [7, 9]. As an improved version of KM, the K-harmonic means (KHM) algorithm was first proposed by Zhang et al [4] and modified by Hammerly and Elkan [8]. Similar to KM, KHM partitions data objects into k clusters while KHM uses the harmonic average of the distances from each data point to all cluster centers to find the clusters. Therefore, KHM is insensitive to the initialization of the centers, however it runs into local optima [14].

In more references, for solving this problem, some heuristic clustering algorithms have been used. A method is suggested based on genetic algorithm called Genetic K-means algorithm (GKA) to solve the problem of clustering which defines a basic mutation operator to clustering. Using finite Markov chain theory, it has been proved that GKA converge to the global optimum. It is also observed that GKA searches faster than some of the other evolutionary algorithms used for clustering [12].

Shelokar et al an algorithm is provided based on ant colony algorithm. Results of this algorithm compared with other metaheuristics algorithms such as GA, TS and SA which showed that the performance of the proposed algorithm was better than other algorithms [16]. Hua et al was proposed a new algorithm using the Ant clustering algorithm with K-harmonic means clustering called ACAKHM [9]. A new hybrid data clustering algorithm based on KHM And IGSA, called IGSAKHM, was proposed by Minghao et al [14]. Gangor and Anler proposed a hybrid method with SA algorithm to solve the problem of
convergence to local optima of KHM [22], also they suggested other hybrid algorithm using KHM and TS method called TABUKHM [23].

A new algorithm based on PSO and KHM was proposed by Yang et al to optimize KHM algorithm called PSOKHM. This algorithm helps the KHM clustering escape from local optima and overcomes the shortcoming of the slow convergence speed of the PSO algorithm [7]. Zhang et al proposed a Tabu Search Particle Swarm Optimization (TSPSO) algorithm. They proved that the TSPSO is superior to GA, TS, and PSO [20]. Also they will apply the TSPSO algorithm to cluster analysis problem [19].

In this paper a hybrid clustering algorithm based on KHM is suggested using the PSO and TS algorithms which uses the global search ability of PSO and local search ability of TS and enables to counterract the weaknesses of each three algorithms and find better performance in less time. Four real-life data sets and three algorithms were used for experiment and the results illustrate the superiority of the proposed clustering algorithm in most cases.

The rest of article is classified followed as: overall description of clustering problem is presented in section 2. A description of KHM algorithm is given in section 3. In section 4 and 5 PSO and TS algorithms are briefly reviewed and our proposed algorithm is introduced in section 6, then experimental studies are presented in section 7 and in section 8 conclusions are provided and look at ideas about the proposed algorithm.

2. Clustering problem

As it is pointed, clustering is organizing similar objects in the same cluster based on a similarity metric between two objects. The total clustering process include following steps [2]:

1. Pattern preparation which include feature extraction and/or selection,
2. Definition of a similarity measure appropriate to the data domain,
3. Clustering or grouping process,
4. Data abstraction and cluster analysis (if needed),
5. Validation of output.

Because of the variety of feature types and scales, the similarity measure must be chosen carefully. The most used distance metric is Euclidean distance. It is a special case (p=2) of the Minkowski metric which is defined as [2]:

\[
d_p(x_i, x_j) = \sqrt[p]{\sum_{k=1}^{d} |x_{i,k} - x_{j,k}|^p} = \|x_i - x_j\|_p
\]

(1)

Where \(d_p(x_i, x_j)\) shows dissimilarity measure between object i and object j, and \(x_{i,k}\) denotes the value of kth attribute of object i. Thus, the number of an object’s attributes are denoted by d.

3. K-Harmonic means algorithm

As noted previously, dependency of KM clustering results to the clusters initialization is a primary problem of this algorithm. KHM clustering can solve this problem by replacing the minimum distance from a data point to the centers, used in KM, by the harmonic mean of the distance from each data point to all centers [14]. Also in contrast to the KM algorithm which gives equal weight to all of the data points, KHM gives dynamic weight to each data point every time and uses from membership function. The following notations (modes) are used for KHM algorithm:

\(X = (x_1, ..., x_n)\): the data should be clustered.

\(C = (c_1, ..., c_k)\): the cluster centers set.

\(m(c_j|x_i)\): the membership function which define the proportion of data point that belongs to c_j center.

\(w(x_i)\): the weight function which define the amount of xi effects in re-computing of the center parameters in the next iteration.

Steps of basic algorithm for KHM is following as [9, 14]:

1. Initialize the algorithm by random selection of the centers.
2. Calculation of objective function value which is following to:

\[
KHM (X,C) = \sum_{i=1}^{n} \frac{K}{\sum_{j=1}^{K} \| x_i - c_j \|^{p}}
\]  

(2)

Where harmonic means is used to measuring distances and \( p \) is an input parameter \((p>2)\).

3. For each data point \( x_i \), membership function is calculated in each center \( c \) according to:

\[
m(c_j \mid x_i) = \| x_i - c_j \|^{-p-2} \sum_{j=1}^{K} \| x_i - c_j \|^{-p-2}
\]

(3)

4. For each data point \( x_i \), it’s weight \( w(x_i) \) calculated as:

\[
w(x_i) = \frac{\sum_{j=1}^{K} \| x_i - c_j \|^{-p-2}}{\left( \sum_{j=1}^{K} \| x_i - c_j \|^{-p} \right)^{2}}
\]

(4)

5. For each center \( c_j \), re-compute it’s location from all data points \( x_i \) according to their memberships and weights:

\[
c_j = \frac{\sum_{i=1}^{n} m(c_j \mid x_i) w(x_i) x_i}{\sum_{i=1}^{n} m(c_j \mid x_i) w(x_i)}
\]

(5)

6. Repeat steps 2 to 5 until it reaches the predefined number of iterations or \( KHM (X,C) \) does not change significantly.

7. Allocate the point \( x_i \) to the cluster \( j \) with the biggest \( m(c_j \mid x_i) \).
4. Particle Swarm Optimization

PSO is a population-based stochastic optimization technique developed by Eberhart and Kennedy [17]. PSO was inspired by social behavior of bird flocking or fish schooling. Each single solution is considered as a particle and each particle has fitness value, position and velocity that attempts to move toward a better solution [15]. PSO algorithm procedure is described as follows [5]:

1. Particle initialization: An initial swarm of particles is generated in search space. Usually, the population size is decided by the dimension of problems.
2. Velocity and position update: In every iteration, a new velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position by equation (6). Then the new position of the particle is calculated using the new velocity value by equation (7).

\[
V_{id}^{new} = \omega \times V_{id}^{old} + c_1 \times rand_1 (P_{id} - x_{id}^{old}) + c_2 \times rand_2 (P_{gd} - x_{id}^{old})
\]  

(6)

\[
x_{id}^{new} = x_{id}^{old} + V_{id}^{new}
\]  

(7)

\(V\) is particle’s velocity, \(x\) is particle’s position, \(c_1\) and \(c_2\) are acceleration coefficients that are conventionally set to a fixed value between 0 and 2. \(P_{id}\) is the previous individual best position of a particle and \(P_{gd}\) is the current global best position. \(\omega\) is an inertia weight that larger inertia ensures a more effective global search of particles and smaller inertia weight means a more efficient local search [11]. According to this theory, Shi and Eberhart proposed a strategy which inertia weight linearly decreases with the increase number of iterations. Expressed as follows [21]:
\[ \omega = \omega_{\text{max}} - k \times (\omega_{\text{max}} - \omega_{\text{min}}) / \text{gen} \]  

(8)

Which \( \omega_{\text{max}} \) calls as the maximum inertia weight, \( \omega_{\text{min}} \) calls the minimum inertia, \( \text{gen} \) calls the total number of iterations for the algorithm, \( k \) calls the current number of iterations for the algorithm.

3. Evaluation and update of best locations: The fitness value of each particle is calculated by the objective function. The values of \( P_{pd} \) and \( P_{gd} \) are then evaluated and replaced if better particle best position or global best position is obtained.

4. Termination: Repeat steps 2 and 3 until the termination condition is met.

5. Tabu Search

Tabu Search is a search method for combinatorial optimization problems which is proposed by Glover in 1989 [6]. TS uses a local or neighborhood search procedure to iteratively move from a solution \( S \) to a solution \( S_1 \) in the neighborhood of \( S \) until some stopping criterion has been satisfied. Perhaps the most important aspect of TS is its memory structure which is called “Tabu List”. In its simplest form, a tabu list contains the solutions that have been visited less than \( n \) moves ago, where \( n \) is the length of tabu list.

The basic components of the TS algorithm as follows [13]:

1. Configuration is an assignment of values to variables. It is a solution to the optimization problem.
2. Move is a specific procedure for getting a trial solution Which is feasible to the optimization problem that is related to the current configuration.
3. Neighborhood is the set of all neighbors, which are the “adjacent solutions” that can be reached from any current configuration. It may also include neighbors that do not satisfy the given customary feasible conditions.
4. Candidate subset is a subset of the neighborhood. It is to be examined instead of the entire neighborhood, especially for large problems where the neighborhood have many elements.

5. Tabu restrictions are constraints that prevent the chosen Moves to be reversed or repeated. They play a memory Role for the search by making the forbidden moves as tabu. The tabu moves are stored in a list, called tabu list.

6. Aspiration criteria are rules that determine when the tabu restrictions can be overridden, thus removing a tabu classification otherwise applied to a move. If a certain move is forbidden by some tabu restrictions then the aspiration criteria, when satisfied, can make this move allowable.

6. The proposed algorithm

The KHM algorithm converges faster than the PSO algorithm but usually it trapped in local optimum. Although PSO could be effective to solving this problem but it converges too slow or even converges to local optimal [18].

In this research we develop an algorithm by combining PSO and TS called PSOTSKHM to speed up the convergence of PSO and finding the good result in a minimum time. In PSO function of our algorithm, firstly amount of particle’s step length is considered to be high to increase ability of global search. After executing PSO function we select the best particle then we apply TS function to search it’s neighbor carefully to obtaining the best results. Considering that our algorithm conducts both global search and local search in each of iterations, the probability of finding the better solution increases.

A particle is a vector of real numbers with k×d dimension, so that k is the clusters number and d is the dimension of data to be clustered. In Figure 1 a model of particle is represented.

\[
\begin{array}{ccccccc}
    x_{11} & x_{12} & \cdots & x_{1d} & \cdots & x_{k1} & x_{k2} & \cdots & x_{kd} \\
\end{array}
\]

Figure 1: The representation of a particle
Two following swap strategy are used to creating neighborhood in TS function:

1. A center of cluster is selected randomly representative \( c_j \), then we choose the closest pattern \( x_j \) to the \( c_j \) and assign the \( x_j \) as a new cluster replace to \( c_j \). Remaining centers are the same.
2. A center of cluster is selected randomly representative \( c_j \), then we choose the pattern \( x_j \) randomly and assign the \( x_j \) as a new cluster replace to \( c_j \). Remaining centers are the same.

Steps of suggested algorithm are following as:

1. Set the initial parameters
2. Initialize the population in the number of \( p_{\text{size}} \) randomly
3. Calculating the fitness function of each particle using KHM function
4. Executing PSO and update the position and velocity of each particle in a considered number.
5. Executing TS for the best particle of PSO
6. Updating the “\( p_{\text{best}} \)” and “\( g_{\text{best}} \)” particles
7. Apply KHM for the best particle in the result.
8. Repeat Step 3 to Step 7 until the final criterion was met.
9. Output representation of obtained results.

6.1. Parameter tuning

According to section 4 about \( \omega \) parameter In PSO algorithm, with setting \( \omega \), a balance could be created between local and global search. Larger inertia affords a more effective global search of particles [11]. In this article, it is tried to increase the ability of global searching of PSO. After of three iterations for PSO we run TS with one iteration then use KHM with four iterations. The PSO parameters set in our algorithm show in table 1:
Table 1: The parameters set in PSO function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{\text{size}}$</td>
<td>18</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.9</td>
</tr>
<tr>
<td>$\omega_{\text{max}}$</td>
<td>0.6</td>
</tr>
<tr>
<td>$\omega_{\text{min}}$</td>
<td>0.4</td>
</tr>
<tr>
<td>$c_1$</td>
<td>1.496</td>
</tr>
<tr>
<td>$c_2$</td>
<td>1.496</td>
</tr>
</tbody>
</table>

The abbreviations of parameters which are used in the TS function are following as:

MTLS: Maximum size of tabu list
NTS: Number of trial solutions
P: Probability threshold
TLL: Tabu list length

The TS parameters set in our algorithm show in table 2:

Table 2: The parameters set in TS function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p$</td>
<td>0.95</td>
</tr>
<tr>
<td>MTLS</td>
<td>10</td>
</tr>
<tr>
<td>NTS</td>
<td>20</td>
</tr>
</tbody>
</table>

7. Experimental studies

We test our proposed algorithm on four real data sets and compared with three algorithms. These data sets include Iris, Glass, Breast-Cancer-Wisconsin (denoted as Cancer), and Contraceptive Method Choice (denoted as CMC), which in [7] and [14] have been applied. Table 3 lists the details of the data sets. The experimental results are averages of 10 runs. The algorithms are implemented using matlab software and ran on a CPU 2.3 GHz with 4.00 GB RAM memory.
Table 3: Characteristics of data sets considered.

<table>
<thead>
<tr>
<th>Name of data set</th>
<th>No. of classes</th>
<th>No. of features</th>
<th>Size of data set (size of classes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris</td>
<td>3</td>
<td>4</td>
<td>150 (50, 50, 50)</td>
</tr>
<tr>
<td>Cancer</td>
<td>2</td>
<td>9</td>
<td>683 (444, 239)</td>
</tr>
<tr>
<td>CMC</td>
<td>3</td>
<td>9</td>
<td>1473 (629, 334, 510)</td>
</tr>
<tr>
<td>Glass</td>
<td>6</td>
<td>9</td>
<td>214 (70, 17, 76, 13, 9, 29)</td>
</tr>
</tbody>
</table>

7.1. Data sets

1. Fisher’s iris data set (n =150, d =4, k =3), which consists of three different species of iris flower: Iris Setosa, Iris Versicolour and Iris Virginica. For each species, 50 samples with four features (sepal length, sepal width, petal length, and petal width) were collected.

2. Glass (n =214, d =9, k =6), which consists of six different types of glass: building windows float processed (70 objects), building windows non-float processed (76 objects), vehicle windows float processed (17 objects), containers (13 objects), tableware (9 objects), and headlamps (29 objects). Each type has nine features, which are refractive index, sodium, magnesium, aluminum, silicon, potassium, calcium, barium, and iron.

3. Wisconsin breast cancer (n =683, d =9, k =2), which consists of 683 objects characterized by nine features: clump thickness, cell size uniformity, cell shape uniformity, marginal adhesion, single epithelial cell size, bare nuclei, bland chromatin, normal nucleoli, and mitoses. There are two categories in the data: malignant (444 objects) and benign (239 objects).

4. Contraceptive Method Choice (n =1473, d =9, k =3): This data set is a subset of the 1987 National Indonesia Contraceptive Prevalence Survey. The samples are
married women who either were not pregnant or did not know if they were at the
time of interview. The problem is to predict the choice of current contraceptive
method (no use has 629 objects, long-term methods have 334 objects, and short-
term methods have 510 objects) of a woman based on her demographic and
socioeconomic characteristics.

7.2. Experimental results

In this part, we compare the performances of KHM, PSOKHM, IGSAKHM methods
with proposed algorithms. The following two criteria have used to measuring The quality
of algorithms [7, 14].

1. The value of KHM function, as defined in equation (2). Clearly, the smaller the
sum is, the higher the quality of clustering is.

2. The F-Measure value, it is a quality measure which uses the ideas of precision
and recall from information retrieval [1, 10]. Each class of i as shown by the
class labels in the data set is considered as the desired set of $n_i$ items for a query,
each cluster $j$ which produced by the algorithm is considered as the set of $n_j$ items
retrieved for a query, $n_j$ is the numbers of class i members inside cluster j. For
each class i and cluster j precision and recall are defined as equation (9) and (10)
and the value of corresponding F-Measure is given by equation (11) where set
b=1 to have equal weighting for $p(i, j)$ and $r(i, j)$. Equation (12) shows the
value of total F-Measure for the data set with the size of n. It is clear that, the
bigger value of F-Measure is, the higher the quality of clustering is.

\[
p(i, j) = \frac{n_j}{n_i} \quad (9)
\]

\[
r(i, j) = \frac{n_j}{n_i} \quad (10)
\]
Results of experiments on the KHM algorithm show that p is a key parameter to reaching to good objective function values. For this reason in this research our experiments conducted with various p values. Tables 4 - 6 are results of implementation of algorithms for different value of 2.5, 3, 3.5 and the average of KHM fitness functions, F-Measures and runtimes in 10 independent runs of each algorithm have been compared. Also the runtimes of the algorithms are shown in tables and standard deviations is represented in brackets. The best results are shown bold and the second best results are shown italic.

Table 4: Results of KHM, PSOKHM, IGSAKHM, and the proposed algorithm (PSOTSKHM) when p=2.5

<table>
<thead>
<tr>
<th></th>
<th>KHM</th>
<th>PSOKHM</th>
<th>IGSAKHM</th>
<th>PSOTSKHM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>149.333 (0.000)</td>
<td>149.058 (0.074)</td>
<td>149.058 (0.000)</td>
<td>148.890 (0.011)</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.750 (0.000)</td>
<td>0.753 (0.005)</td>
<td>0.763 (0.000)</td>
<td>0.8859 (0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td><strong>0.192 (0.008)</strong></td>
<td><strong>1.842 (0.005)</strong></td>
<td><strong>1.577 (0.002)</strong></td>
<td><strong>1.373 (0.210)</strong></td>
</tr>
<tr>
<td>Cancer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>60189 (0)</td>
<td>59844 (22)</td>
<td>59844 (0)</td>
<td>57010 (35)</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.829 (0.000)</td>
<td>0.829 (0.000)</td>
<td>0.829 (0.000)</td>
<td>0.9617 (0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td><strong>2.017 (0.009)</strong></td>
<td>9.525 (0.013)</td>
<td>7.509 (0.007)</td>
<td>5.878 (0.955)</td>
</tr>
<tr>
<td>CMC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>96520 (0)</td>
<td>96193 (25)</td>
<td>96193 (52)</td>
<td>96174 (10.17)</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.335 (0.000)</td>
<td>0.333 (0.002)</td>
<td><strong>0.488 (0.000)</strong></td>
<td>0.462 (0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td><strong>8.639 (0.009)</strong></td>
<td>39.825 (0.072)</td>
<td>31.563 (0.012)</td>
<td>14.317 (2.291)</td>
</tr>
<tr>
<td>Glass</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>1203.554 (16.231)</td>
<td>1196.789 (0.439)</td>
<td><strong>1180.756 (0.134)</strong></td>
<td>1193.328 (0.262)</td>
</tr>
<tr>
<td>F-Measure</td>
<td>0.421 (0.011)</td>
<td>0.424 (0.003)</td>
<td><strong>0.454 (0.000)</strong></td>
<td><strong>0.703 (0.002)</strong></td>
</tr>
<tr>
<td>Runtime</td>
<td><strong>4.064 (0.010)</strong></td>
<td>17.669 (0.018)</td>
<td>15.910 (0.010)</td>
<td><strong>3.489 (0.552)</strong></td>
</tr>
</tbody>
</table>
Table 5: Results of KHM, PSOKHM, IGSAKHM, and the proposed algorithm (PSOTSKHM) when p=3

<table>
<thead>
<tr>
<th></th>
<th>KHM</th>
<th>PSOKHM</th>
<th>IGSAKHM</th>
<th>PSOTSKHM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>126.517(0.000)</td>
<td>125.951(0.052)</td>
<td>125.951(0.000)</td>
<td>125.940(0.043)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.744(0.000)</td>
<td>0.744(0.000)</td>
<td>0.751(0.000)</td>
<td>0.891(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>0.190(0.007)</td>
<td>1.826(0.009)</td>
<td>1.650(0.004)</td>
<td>1.349(0.206)</td>
</tr>
<tr>
<td>Cancer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>119458(0)</td>
<td>117418(237)</td>
<td>117418(55)</td>
<td>112562(275)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.834(0.000)</td>
<td>0.834(0.000)</td>
<td>0.847(0.000)</td>
<td>0.964(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>2.027(0.007)</td>
<td>9.594(0.023)</td>
<td>7.91(0.002)</td>
<td>5.952(0.970)</td>
</tr>
<tr>
<td>CMC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>187525(0)</td>
<td>186722(111)</td>
<td>186722(94)</td>
<td>186840(54)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.303(0.000)</td>
<td>0.303(0.000)</td>
<td>0.472(0.000)</td>
<td>0.4617(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>8.627(0.009)</td>
<td>39.485(0.056)</td>
<td>32.107(0.034)</td>
<td>15.164(2.502)</td>
</tr>
<tr>
<td>Glass</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>1535.198(0.000)</td>
<td>1442.847(35.871)</td>
<td>1400.950(0.630)</td>
<td>1394.753(0.697)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.422(0.000)</td>
<td>0.427(0.003)</td>
<td>0.442(0.000)</td>
<td>0.713(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>4.042(0.007)</td>
<td>17.609(0.015)</td>
<td>15.958(0.001)</td>
<td>3.982(0.630)</td>
</tr>
</tbody>
</table>

Table 6: Results of KHM, PSOKHM, IGSAKHM, and the proposed algorithm (PSOTSKHM) when p=3.5

<table>
<thead>
<tr>
<th></th>
<th>KHM</th>
<th>PSOKHM</th>
<th>IGSAKHM</th>
<th>PSOTSKHM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>113.413(0.085)</td>
<td>110.004(2.260)</td>
<td>110.004(0.004)</td>
<td>109.819(0.175)</td>
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<tr>
<td>F-measure</td>
<td>0.770(0.024)</td>
<td>0.762(0.004)</td>
<td>0.766(0.000)</td>
<td>0.891(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>0.194(0.008)</td>
<td>1.873(0.005)</td>
<td>1.587(0.004)</td>
<td>1.310(0.198)</td>
</tr>
<tr>
<td>Cancer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>243440(0)</td>
<td>235441(696)</td>
<td>236125(15)</td>
<td>228387(906)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.832(0.000)</td>
<td>0.835(0.003)</td>
<td>0.862(0.000)</td>
<td>0.966(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>2.072(0.008)</td>
<td>9.859(0.015)</td>
<td>31.521(0.009)</td>
<td>5.596(0.914)</td>
</tr>
<tr>
<td>CMC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>381444(0)</td>
<td>379678(247)</td>
<td>380183(16)</td>
<td>380048.191(220)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.332(0.000)</td>
<td>0.332(0.000)</td>
<td>0.506(0.000)</td>
<td>0.459(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>8.528(0.012)</td>
<td>42.701(0.250)</td>
<td>31.521(0.009)</td>
<td>16.632(2.645)</td>
</tr>
<tr>
<td>Glass</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KHM</td>
<td>1871.812(0.000)</td>
<td>1857.152(4.937)</td>
<td>1857.152(0.035)</td>
<td>1843.133(4.107)</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.396(0.000)</td>
<td>0.396(0.000)</td>
<td>0.420(0.000)</td>
<td>0.663(0.000)</td>
</tr>
<tr>
<td>Runtime</td>
<td>4.056(0.008)</td>
<td>17.651(0.013)</td>
<td>15.799(0.003)</td>
<td>3.502(0.555)</td>
</tr>
</tbody>
</table>
Conclusions

In this article, an algorithm of data clustering was developed based on KHM algorithm using combination of PSO and TS, called PSOTSKHM. Four well-known standard data sets, three algorithms namely KHM, IGSAKHM and PSOKHM and two quality measurement criteria were used to evaluate the algorithm. Experimental results show that the proposed algorithm for reaching to the best solution, has more convergence speed than other algorithms and doesn’t trapped in local optimal. The improvement of two evaluation criteria, in most cases, represents the more efficiency of proposed algorithm than three other algorithms. Also the time of running compared with IGSAKHN and PSOKHM has been improved. To completing done work, various researches could be proposed such as Apply a method for determining the number of clusters automatically, use from other metaheuristics algorithms to combining with KHM and apply the PSOTSKHM to use in applications such as image processing, data mining and crime prediction.

References


