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A Novel Hybrid Approach for Global Optimization

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ABSTRACT

In this paper we tend to gift application of hybrid clustering algorithms .Data cluster helps one recognize the structure of and alter the quality of huge quantities of information. It a typical technique for applied mathematics knowledge analysis and is employed in several fields, as well as machine learning, data processing, pattern recognition, image analysis, and bioinformatics. The well-known K-means algorithm, which has been successfully applied to many practical clustering problems, has several disadvantages due to its initialization selection. However, its performance depends on the initial centroid state and can be trapped in the local optima. Genetic algorithms are an evolutionary algorithm that is inspired by nature and used in the clustering field. In this paper, we propose a hybrid method. A hybrid technique based on the combination of the K-means algorithm, the genetic algorithm, the Nelder–Mead simplex search and the K–GA-NM–PSO particle swarm optimization is proposed. The KM-GA–NM–PSO searches for cluster centres of an arbitrary data set as well as the K-means algorithm, but the global optima can be found effectively and efficiently. The new KM–GA-NM–PSO algorithm is tested on UCI repository data sets and compared to K means and KM-GA clustering algorithms. This algorithm can be improved, such as image segmentation and university time tabling."The new technique K-mean–GA–NM-PSO algorithm is tested on datasets, and its performance is compared with those of k-mean, GA, NM, PSO and K-means clustering. Results show that K–GA–NM-PSO are better than other cluster."

Keywords:- K-means clustering, Genetic algorithm, Nelder-Mead search method, Particle swarm optimization;

I. INTRODUCTION

Clustering is a very important unattended classification technique. once used on a collection of objects, it helps determine some inherent structures gift within the objects by classify-ing them into subsets that have some that means within the context of a selected drawback. additional specifically, objects with attributes that characterize them, sometimes repre-sented as vectors during a multi-dimensional house, are sorted into some clusters. Clustering is of many types and in operation varied. The fundamental variations in clustering are hierarchical and partitional clustering. There are many algorithms for performance.

Many algorithms have been suggested for clustering. However, due to a wide variety of applications, different data types and different clustering purposes, we can not find a unique algorithm that can meet all requirements simultaneously. Clustering algorithms can generally be divided into two groups:Algorithms and partitional algorithms of hierarchy. Hierarchical clustering algorithms find clusters recursively either in agglomerated mode (bottom-up) or in divisive mode (top-down). Agglomerative methods begin with each data object in a separate cluster and merge the most similar pairs successively until the end criteria are met. All data objects begin with divisive methods In one cluster, divide each cluster into smaller clusters repeatedly, even until the termination criteria have been met. In contrast, partitional clustering algorithms simultaneously find all clusters without forming a hierarchical structure. A well-known class of partitional clustering algorithms is the clustering method based on the center and the most commonly used. This class algorithm is an algorithm of k-means. K-means are easy to implement and efficient in most cases [1–2]. suffers from several drawbacks due to its choice of initializations. However, its performance depends on the initial state of centroids and may trap in local optima. The gentic algorithm (GA) is one effective method for find optimal solution. But GA algorithms with other algorithms can provide sufficient results, while some clustering algorithms, while working very well, provide fairly good results, are bound by a constraint/condition that needs to be met and satisfied for their precise and successful operation.

Genetic algorithms typically begin with some candidate optimization solutions and these candidates evolve towards a better solution through selection, cross- over and mutation. The basic idea is to simulate nature's evolution process and develop solutions from one generation to the next.These genetic algorithms, which could converge to a local optimum, are insensitive to the initialization process and eventually converge to the global optimum. Particle swarm optimization (PSO), a population-based algorithm has a slow convergence rate. This problem can be resolved using the local line search method Nelder Mead (NM). In this paper, we explore the applicability of the hybrid K-means algorithm, Gentic algorithm ,Nelder-Mead simplex search method, and particle swarm optimization (K– GA-NM–PSO) to clustering data vectors.build a new hybird apporach that enhances the quality of the clustering (reduces the upcoming error).

K-Mean Algorithm

K-mean introduce by MacQueen, 1967 [8] . K-Means clustering aims to divide n objects into k clusters in which each object belongs to the nearest mean cluster. This method produces different clusters of difference exactly k. The best number of clusters k that lead to the greatest distance is not known as a priori and must be calculated from the data. The aim of the K- means that agglomeration is to cut back the overall intra-cluster variance or the sq. error function [10]. The objective function is

$$J = \sum_{j=1}^{k} \sum_{i=1}^{k} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (1)$$

Where $\left\| x_i^{(j)} - c_j \right\|^2$ is a distance measurement chosen between this data point and the cluster centre, is a display of the distance of n(number of data points) data points from their respective cluster canters The algorithm is composed of the following steps[11]: Given K, the K-mean algorithm

1. Randomly choose the initial "K" centroids.

2. Assign each object to the closest centroid cluster.

3. Calculate every centroid as the mean of assigned objects.

Repeat the last 2 steps without alteration.

Genetic Algorithm (GA):

GAs was developed by Holland [12] and more delineate by Goldberg [13] as improvement approaches to find a near-global optimal solution.

GA starts with a group of potential solutions (chromosomes). Next, genetic rule are used kinds of operators (selection, mutation and crossover) are applied one once another to get a brand new generation of chromosomes. This method is recurrent till the termination criterion is met.

Genetic rule could be a population-based probilistic search and improvement techniques, wich work supported the mechanisms of natural genetic science and netural evolution.

Algorithmically the basic steps given that, [14]-[15]:

Step I [Start]: random population of chromosomes is generated, that is, suitable solutions for the problem.

Step II [Fitness]: the fitness of each chromosome in the population is evaluated.

Step III [New population]: a new population is created by repeating the following

steps: 1) Selection: Select two parents (chromosomes) from a population according to their fitness value. The chance for each chromosome to be selected, as a parent, is determined according to its fitness.

2) Crossover: According to the crossover probability (Pc), new offspring (children) is generated from parents.

It is used to generate two new individuals (offspring) using two exiting one (parents) who have been chosen from the current population. Crossover methods vary in number. In general, the integer and binary methods based on the single point over of the individual are popular

In the uniform crossover bits the second's parent is randomly copied from the first.

Parent1	11001011	Offspring1	11011111
Parent2	11011101	Offspring2	11000100

(2)

Uniform Crossover

3) **Mutation: According to mutation probability (Pm), new offspring at each locus (position in chromosome) is mutated.**

	Mutation Point
Offspring	1010010010

MutatedOffspring	1010110010

(3)

MutationOperator

4) Accepting: new offspring is placed in the new population.

Step IV [Replace]: Use new generated population for a furtherrunofthealgorithm.

Step V [Test]: If the end condition is satisfied, return the bestsolutionincurrentpopulationandstop.

Step VI [Loop]: Go to step II. The Flowchart of Simple GAsisshowninFigure1

Nelder-MeadAlgorithm:

This simple search method, first developed by Spendley,Hext and Himsworth (1962) [16] and subsequently refined by Nelder and Mead (1965)[17], is a derivative-free line search method used to find the minimum or maximum objective function. See, for example, Olsson and Nelson (1975)[18] The fitness function value at (N+1) of the initial simplex is evaluated. In this, the function's value is high and new, andthenreplacedbyagoodpoint.Whichcanbelocated in a negative gradient form (direction). These are considered a direct line search technique as one of the best resources. Four basic practices in this process Processing per- soil is applicable. Reflecting, diversifying, storing and reducing these local surface points can be more intensive and the general can make greatprogressinitself.Thus,intheexamplebelow,the functionoftwovariablesisminimized(N=2)

2) The basic NM procedure is shown. Starting with point B and the initial step size, an initial simple design isconstructedasA,BandC,asshowninFig.1.

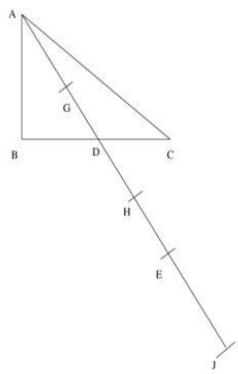

Fig.1.NMDual-dimensionalcasealgorithm operations.

1. Sort the A, B, and C function values. Assume if(C) < f(B) < f(A) is the highest of the three function values and must be replaced. In this case, a reflection is made in pointDtopointEthroughthecentreofBC.

2. If f(E) < f(C) is expanded to point J. Then we replace E or J with r for A, depending on which function value is lower.

3. If f(E) > f(C), there is a contraction to point G or H as a substitute for A, depending on which of f(A) and f(E) is lower, provided that f(G) or f(H) is lower than f(C). If either f(G) or f(H) is greater than f(C), the contraction failed and a shrinkage operation is carried out. The shrinkage procedure reduces the size of the simplex by moving everything but the best point C halfway to the best point C. We've got new points A and B. Return to step1.

PSOAlgorithm:

PSOstandsforparticleswarmsoptimization(PSO)itis most popular evolutionary optimization techniques developed by Kennedy and Eberhart (1995)[19,20]in this algorithm population based and evolutionary in nature.

It is inspired by the collective behavior of birds flying around in the sky - those who are engaged in search of their food and are same as fish schooling [21]. This search space is applied to a fitness function to reach good results. The particles swarm through the fitness function solved to search space to find the maximum value return by the objective function. That a used a number of particles constitute a swarm moving award in search space locking for the best solution. each particle in search space adjusts its "swarm" according to own swarm experience as well as the swarm experience of the other particle.PSO is same as a genetic algorithm, but the main difference is that they cannot apply filtering. This means that all the members of the population Survive through the entire search process. The followingstepsofthePSOalgorithm:

1.initialization process. Randomly generate 5N potential solutions called" particles',' N being the number of parameters to be optimized and a randomized velocity is assigned to each particle.

2. velocity Update . The particles then' fly' through hyperspacewhileupdatingtheirownvelocity,whichis achieved by taking into account their own past flight andthatoftheircompanions.'Thevelocityandposition of the particle is dynamically updated with the

following equations[22].

.

$$V_{id}^{New}=(W*V_{id}^{old})+c_1*r1*(p_{id}-x_{id}^{old})+c_{2}*r2*(p_{gd}-x_{id}^{old}) \quad (4)$$

$$X_{id}^{New}=x_{id}^{old}+V_{id}^{New} \quad (5)$$

Where c_1 and c_2 are two positive constants, w is an inertia weight, and r1 and r2 are random number generated[23,24].

II. HYBRID IAPPROACH I I IKM-GA-NM-PSO

An improvement over the algorithm is a hybrid technique based on combining the K-means algorithm with various other algorithms. The combined approach of different algorithms therefore provides better performance using the goodness of the whole algorithm to overcome the disadvantage of any particular algorithm. Genetic algorithm is one of the most commonly used evolutionary algorithm techniques to solve a clustering problem. Therefore, a hybrid data clustering algorithm based on GA and k-means (GA-KM), which uses the advantages of both algorithms. The GA-KM algorithm helps the k-means algorithm to escape local optimum. GA has been shown to be able to determine the best cluster initialization and to optimize initial parameters. .GA defines a randomly generated population of people. These people are involved in the generation of new and better offspring by mutation / crossover. Decision on better offspring/individuals is achieved by fitness. The greatest benefit of genetic algorithms is that the fitness function can be changed to change the algorithm's behaviour. There is a wide variety of representations of individual or chromosomes. The solutions are traditionally represented using fixed length strings, in particular binary strings, but alternative encoding has been developed. The main focus of the GA-based algorithm was to generate high-quality clusters in optimized time. The focus of the current research was to use GA as an initial centroid selection tool and to study the performance of improved clustering of k-means. The applications of GA-based k means have been tested in literature on standard data sets, but educational data set specifically from the problem of school children has not been investigated. Current research has focused on developing an appropriate system to study school children's problems using basic k-means and improved k-means (GA with k-means). Consequently, the approach to the development of a new algorithm was problematic and the selection criteria or initial centroid influenced the nature of the domain. In short, according to the problem area, the fitness function in GA has been defined. Apart from identifying preferable technique for out of school children problem, there is always a need to analyze quality of clusters. There will be good method to measure the quality of the better clusters and performance of clustering. The hybrid (KM-GA-NM-PSO) algorithms contain all the best features of the existing algorithm that overcome the limitations of the individual algorithm when combined. The improvement of this combined approach will lead to even better results. This will be requires a minimum number of evaluations of functions to achieve the optimum solution. Compared to other methods, the hybrid approach will be produces high-quality clusters with small standard deviations on selected data sets. It is proposed to combine KM-GA with NM-PSO. This combination of hybrids improves the quality of data clustering and improves the algorithm.

Experimental results

Step1: K-mean method apply
Randomly choose “k” centroids from dataset for desired clusters
Assign to each data object to the cluster with the closet centroids
Update the centroids by calculating the mean value of object within clusters
repate step 1.2, and 1.3 until termination certroids are met.
Step2: Generate initial population of size i({j1,j2, j3,......,ji}).
J1=k-mean(dataset)
J2=min(dataset)
J3=mean(dataset)
J4=max(dataset)
J5=Ji=random value of(dataset)
Step3: GA algorithm apply
Apply crossover operator on N particle(GA).
Apply mutation operator on update N particle(GA).
Step4: NM simplex method apply
Initialization: Generate a population of size 3N+1.
Evaluation and Ranking: Evaluate the fitness of each particle rank them on the basis of fitness.
Apply NM operator to the top N+1 particle and replace the (N+1)
Particle with the update.
Step PSO algorithm apply
Apply PSO operator for updating the remaining 2N particles.
Selection: from the population select the global best particle and the neighbourhood best particles.
Velocity Update: apply update to the 2N particle with worst fitness according equations (3)&(4);
Step5: If the termination conditions are not meet then go to back 4.2.

Experimental result

Iris Data Set We used the Iris data set to bring our algorithms a pragmatic result. In this case, each data set in the Iris Data Set has the number of their own distributions that these items of clusters and data are important to. Iris is used to set up a good comparison and algorithm for data sets. In this data set (n=150, d=4, k=3) it has three equal squares of 50 squares. In this data set we have 150 samples. It covers each class type of a class iris Flowers, in which four-digit properties are also included. These data sets are such that the length of the sepal in cm, width and height of the petals Widths are in centi-meters. There is no missing value in this dataset.

III. PERFORMANCE MEASURE

The Iris data set has been used in separate different different algorithms, a predominantly KM algorithm, GA, NM,PSO Algorithm and K-GA-NM-PSO Algorithm have been developed in a table. In which good results have been found and the individual's best performance has been received. That compares to other clustering algorithms. K-mean algorithm in some cases there are problems. Just as in the beginning, there may be a set of solutions for the K-GA matching solution to the problem of a satellite base and its solutions. So, we are using the PSO algorithm. With the help of algorithms, it helps to maintain the integrity of all algorithms and simultaneously solve their problems. This is how the NM algorithm has been defeated again. NM algorithm helps us to provide a lot of efficient local research process from algorithms. But the NM algorithm is dependent on the starting point and this convergence is sensitive to choose the randomly the starting point and this can also be an algorithms increase percentage in algorithm.

Table 1 shows the comparison of intra cluster distance.

K value	k-mean	GA	NM	PSO	k-mean+ GA+NM +PSO
K=1	68.6166	66.0783	60.0123	70.2568	35.1443
K=2	82.6219	68.635	59.3256	94.2564	50.6701
K=3	129.5325	92.3585	91.6584	135.2567	20.3042
K=4	203.5256	150.1065	149.2569	278.2547	48.0000
K=5	355.2576	121.4141	360.5698	396.4567	91.2340
K=6	328.016	198.7141	365.1245	421.2584	68.2677
K=7	432.2051	268.4564	456.2584	547.1234	48.8133
K=8	516.0121	339.368	591.4568	621.5487	16.2100
K=9	645.2582	367.8258	679.2465	754.2547	54.5613
K=10	766.1073	241.8844	790.4658	875.2547	33.0444

Table 2 shows the efficiency comparison.

K value	k-mean	GA	NM	PSO	k-mean +GA+NM+PSO
K=1	41.0214	43.1249	42.2547	43.5684	40.2547
K=2	57.2167	53.2647	54.2555	55.2658	52.5802
K=3	25.2365	24.1257	64.2347	65.1235	22.3043
K=4	52.15465	53.1234	53.1236	55.2584	50.0000

K=5	95.2547	97.2547	92.1547	94.2547	93.2324
K=6	80.2547	79.2547	76.2648	75.4578	78.2354
K=7	56.5684	56.2314	49.2547	48.8945	51.8233
K=8	19.2547	18.2145	19.2654	14.2354	16.3212
K=9	59.2500	58.2564	57.1265	54.2588	56.6481
K=10	35.2648	38.2654	35.1567	31.1572	32.0147

Fig.2 comparsion of intra cluster distances.

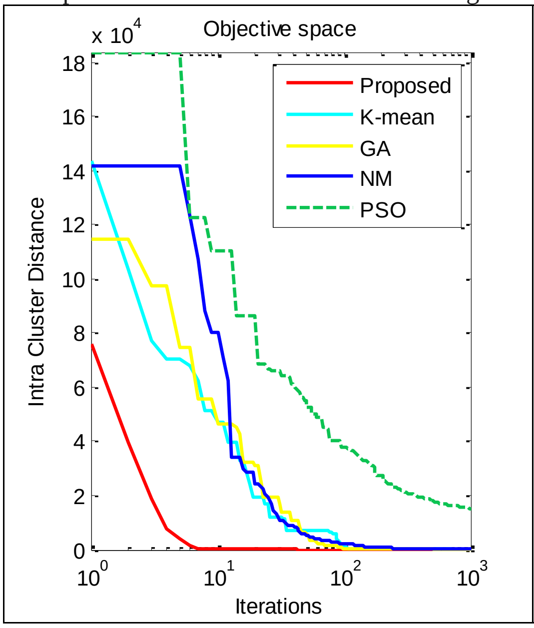

Fig.3 efficiency comparison.

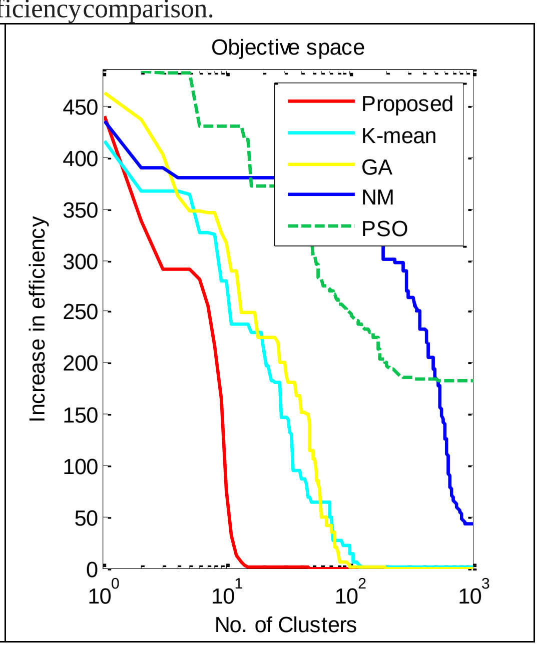

Table2 & fig3 show the efficiency comparison.

The comparison performance shown in the table is making it show as KM, GA, NM, PSO vs k-mean-GA-NM-PSO people have been reproduced and individual clusters are made in and between them. And calculation of performance details etc. Thus all the sets of KM-GA-NM-PSO algorithms are tested and as well as solutions of high-quality clusters have been developed. Which are designed in the form of distance of the best inter cluster. Also discovered are the storms standard deviation and the smallest found to near optimal solution of the run other algorithm may trap local optima in some of run. It is found to better results, thus KM-GA-NM-PSO keeps Algorithm a stronger one. This K-MEAN algorithm requires a smaller number compared to other algorithms and it is in relation to the functional visits. In this way we can say that by using the result of K-MEAN in KM-GA-NM-PSO, the GA is in a good way, which is a great way to get access to a great tool from a single GA Is of algorithm produces new generation population from traffic for generation of pig production and the environment is resolved to a new baby environment. In this way a child's solution has many features of his measurement which can be created from new parents to newborn babies. But still there is not a good start with GA, a good start with the combination of KM-GA to overcome its shortage can be started and new parents from new parents can be produced, And a suitable population size can also be made. Thus, KM-GA can be better equipped with algorithmic combination than PSO, meaning that the new population can be created at the onset of the cluttering process and can be speeded up in this situation and the health status can be discarded because it Less cluttering needs lesser working people, After we have done all the procedure, we can say that the outcome of PSO and NM-PSO clustering can be revised. With the K-MEAN algorithm, this hybrid algorithm ends with the first K-MEAN algorithm and if there is no change in this cluster's satire rayon vector, in the case of K-PSO, K-MEAN algorithm results in one particle used in the form. The 5N-1 particles start randomly, so this hybrid is used in K-GA-NM-PSO. The 3N-1 angle creates the points continuously and NM-PSO then forms this form to complete the process. Overall, the results show that the proposed algorithm is an efficient approach and open some research directions in the field of optimization [25–48].

IV. CONCLUSION

The clustering of data objects uses a hybrid method (coded as GA-KM) based on a genetic algorithm (GA) and k-means algorithm. It attempts to simultaneously exploit the merits of two algorithms, where the k-means are used to generate the initial solution and the GA is used as an algorithm for improvement. The existing algorithm's performance is compared to other approaches. The comparisons of how the existing algorithm overcomes k-means and GA's shortcomings alone. To achieve the optimal solution, it requires a minimum number of function evaluations. In addition, the proposed approach will combine the existing algorithm with NM-PSO that can produce high-quality clusters with a small standard deviation on selected datasets compared to other methods. The proposed method can be applied to other applications in future research, such as image segmentation and college time tabling. Another direction of research is the combination of the KM-GA-NM-PSO with other heuristic approaches and their application to data clustering.

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