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An Adaptive Cat Swarm Optimization Based on Particle Swarm Optimization Approach (ACPSO) for Clustering

Irvan Santoso, Robin Solala Gulo, Abba Suganda Girsang

Abstract – *This paper proposes an adaptive cat swarm optimization based on particle swarm optimization for clustering, called ACPSO. Unlike the cat swam optimization that operates one cat, this algorithm uses some cats as population bases to converge the result. ACPSO employs an adaptive method by choosing a seeking mode or tracing mode based on a mixture ratio (MR). In the tracing mode, this algorithm uses a modified particle swarm optimization to increase diversity solutions. To demonstrate the performance, ACPSO was conducted to solve some datasets clustering problem. The results show that ACPSO has a good performance compared to the other methods.*

Keywords*: Cat Swarm Optimization, Data Clustering, CSO, Clustering, PSO*

Nomenclature

SMP	(Seeking Memory Pool), defines the number of copies of the cat in seeking mode CSO and ACPSO algorithm
SRD	(Seeking range of the selected dimension), the maximum difference between old and new positions of a cat in the dimensions for mutationcat in seeking modeCSO and ACPSO algorithm
CDC	(Counts of dimension to change) is mutation for dimensioncat in seeking modeCSO and ACPSO algorithm
SPC	(Self-position consideration), indicates the current position included in candidate points to movecat in seeking modeon CSO and ACPSO algorithm
MR	(Mixture Ratio) is used to choose between seeking mode and tracing mode with a constant value on CSO and ACPSO algorithm
$V_{k,d}$	Current Velocity of k-th cat on dimension $d$in tracing mode on CSO and ACPSO algorithm
r_1, r_2	Random value in tracing mode on CSO and ACPSO algorithm
c_1, c_2	Constant Value in tracing mode on CSO and ACPSO algorithm
$X_{best,d}$	Best position of cat which has the fittest value on dimension d in tracing mode on CSO and ACPSO algorithm
$X_{k,d}$	the current position of cat m on dimension d in tracing mode on CSO and ACPSO algorithm
V_{max}	Velocity maximum as a boundary in tracing mode on ACPSO algorithm
V_{min}	Velocity maximum as a boundary in tracing mode on ACPSO algorithm
SSE	(Sum Squared Error) on ACPSO algorithm is used to measure between the result of each data and dataset
$d(x,y)$	Euclidean distance for each data (x) and group all data into population according to cluster center in population (y) on ACPSO algorithm
CC_k	represents k cluster center on ACPSO algorithm
s	shifting value for updated position on ACPSO algorithm
w	Weight control variable on ACPSO algorithm
$P_{g,d}$	Position global best on dimension d on ACPSO algorithm

I. Introduction

Clustering is one of NP-hard problems that is used to find the relationship between patterns in a given set of patterns [1]. Many supervised and unsupervised techniques are used to obtain the optimal cluster centers in a given set [2]-[4]. The aim of clustering is to find groups of similar objects, which share similar characteristics. K-means algorithm is one of the popular methods. However, K-means algorithm often gets stuck in local optima and its result depends on the initial randomization of cluster centers that can be very tricky.

Due to this reason, many researchers have tried to improve K-means algorithm with various techniques. Zhang [5], proposed K-harmonic algorithm that is modified by Hammerly and Elkan [6], but it turns out to converge to local optima. Recently, some metaheuristic algorithms, such as genetic algorithms, simulated annealing, and particle swarm optimization are being applied to solve clustering problems.

A bio-inspired algorithm has been implemented in many fields, such as Particle Swarm Optimization (PSO) [7], Ant Colony [8]-[9], Cat swarm optimization (CSO) and so forth. CSO is a technique based on the behavior of cats that is proposed by Chu and Tsai [10]. These behaviors are divided into two modes; seeking mode and tracing mode.

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A cat usually spends more time in seeking modes than tracing mode. CSO shows that several various optimizing problems can be solved effectively [11]-[15]. Therefore, Santosa and Ningrum proposed the first implementation of CSO in clustering with modification [11].

The modification removed mixture ratio (MR) in order to set every cat to pass seeking mode and tracing mode correspondingly. CDC has 100% value that every dimension of the cat's copy will change.

Furthermore, Liu and Shen proposed CSO clustering and *K*-harmonic means CSO clustering (KCSOC)to refine the population and accelerate the convergence of the clustering algorithm [15]. Liu et al. proposed K-means improvement and Simulated Annealing CSO clustering (KSACSOC). *K*-means was integrated into seeking mode to improve convergences and Simulated Annealing hybridize in tracing mode is to avoid cat being trapped in local optima.

Kumar and Sahoo proposed a hybrid clustering approach based on CSO and *K*-harmonic means algorithm with few adjustments [12]. The mixture ratio was removed so that every cat would move in seeking mode and tracing mode. CDC parameters were also removed from the algorithm so that every cat's copy would change. An improvement was proposed by Kumar and Sahoo based on their previous work [12]. The modification introduced that opposition-based learning method is used to enhance the diversity of CSO algorithm, a Cauchy mutation operator implement in CSO to overcome local optima problem and to deal with data vectors trapped in local optima; the solution lies near the boundary of the datasets.

The modifications of CSO in previous studies are not aligned with the first original CSO by Chu and Tsai.

Therefore, ACPSO is proposed to adapt an original behavior of cats with adaptive MR. According to [10], the initialization of the mixture ratio is used to choose between seeking mode and tracing mode with a constant value. In this research, an adaptive mixture ratio is applied in order to control the mode that was chosen among the population, as the performance of CSO has increased by using adaptive MR [16]. In tracing mode, ACPSO adapts PSO approach in velocity formula [7], since in this research, we applied population to increase the diversity of cluster center position and use it as a global best position in order to obtain the optimal result. Further, this article is organized into several sections.

Section I discusses background and research motivation. Section II briefly outlines original CSO.

Section III explains ACPSO algorithm for clustering problem. Section IV shows an experimental result.

Finally, section V contains a conclusion of the experiment.

II. Cat Swarm Optimization

Algorithm of Cat Swarm Optimization (CSO) consists of two modes: seeking mode and tracing mode that embrace cat's characteristics.

In seeking mode, it reflects a cat's strong curiosity while resting but stay alert. In tracing mode, it represents a cat moving to a particular object.

Seeking mode is used to model the cat during a period of resting but being alert that is looking around its environment for the next move. There are four essential characteristics in seeking mode. Seeking Memory Pool (SMP) which defines a number of copies of the cat in seeking mode. Seeking range of the selected dimension (SRD) that is the maximum difference between old and new positions of a cat in the dimensions for mutation. Counts of dimension to change (CDC) is the mutation for dimension. Self-position consideration (SPC), indicates current position included in candidate points to move.

According to [10], there are five steps in seeking mode, described as follows:

Step 1: Make *j* copies of the present position of cat *m*, where $j = SMP$. If the value of *SPC* is true, let $j = (SMP - 1)$, then retain the present position as one of the candidates.

Step 2: For each copy, according to *CDC*, randomly plus or minus *SRD* the present values and replace the old ones.

Step 3: Calculate the fitness values (*FS*) of all candidate points.

Step 4: If all *FS* are not exactly equal, calculate the selecting probability of each candidate point, otherwise set all the selecting probability of each candidate point to be one.

Step 5: Randomly pick the point to move to from the candidate points, and replace the position of cat *m*.

Tracing mode is an action of cat *m* that tracing the target described as follows:

Step 1: Update the velocities for every dimension *d*, $V_{k,d}$ according to Eq. (1):

$$V_{m,d} = V_{m,d} + r_1 \cdot c_1 \cdot (X_{best,d} - X_{k,d}) \quad (1)$$

r_1 is a random value and c_1 is a constant value. $X_{best,d}$ is the best position of cat who has the fittest value on dimension *d*, while $X_{k,d}$ is the current of position cat *m* on dimension *d*

Step 2: Check if the velocities are in the range of maximum velocity. In case the new velocity is over-range, it is set equal to the limit.

Step 3: Update the position of *cat m* according to Eq. (2):

$$X_{k,d} = X_{k,d} + V_{k,d} \quad (2)$$

III. Proposed Algorithm of ACPSO

Clustering is a process of grouping objects with similar properties [20]. This has been applied in many research fields such as image analysis, pattern recognition, data mining and medical [1]. The purpose of clustering is to ensure that every cluster contains similar data. It can be achieved by finding cluster center that represents the grouping of all data.

Generally, there is no information before about the number of cluster and grouping pattern [21]-[23].

A modified of CSO, ACPSO is proposed aiming to find the best cluster center position. ACPSO also uses an adaptive MR to control the modes chosen among the population. At last, this method uses a PSO approach to find global best cluster centers based on population. The algorithm of ACPSO is described on a flowchart presented in Fig. 1. It has several steps, which are:

Step 1: Initialization of Population

Set a number of populations randomly to create initial cluster center k for each population. Each population consists of the number of cluster center for the dataset.

Step 2: Initialization of seeking mode properties

SPC is used in seeking mode to decide whether each cluster center in population move from the current position or otherwise. Randomly set *SPC* between 0 and 1. Afterward, specify the *SRD* that declares shifting value between range 0 and 1 and *SMP*, which represents how many copies of population solution.

Step 3: Initialization of tracing mode properties

To update velocity, the setting parameters are set as follows. $c_1 = c_2 = 2$. V_{max} is set 0.5, and V_{min} is set -0.5.

These maximum and minimum velocity are set in order to set the boundary of population moves [17].

Step 4: Calculation of Sum Squared Error (SSE) of global best position

The fitness function of population is measured by *SSE* as in Eq. (3):

$$SSE = \sum_{i=1}^{k} \sum_{x \in Di} |x - m_i|^2 \tag{3}$$

X represents each of result data
m_i represents each data in dataset.

Step 5: Calculation of Euclidean Distance and SSE of population

Calculate Euclidean distance uses Eq. (4) for each data and group all data into population according to cluster center in population:

$$d(x, y) = |x - y|^2 = \sqrt{\sum_{i=1}^{n} (x - y)^2} \tag{4}$$

where x represents data and y represents cluster center in population.

Step 6: Setting of Mixture Ratio (MR)

According to [16], an adaptive MR optimal is obtained in the range between 0 and 0.3. Rand_number is generated to compare with MR.

If random number is greater than MR then enter seeking mode, otherwise enter tracing mode.

Step 6.1: Seeking Mode

Calculate shifting value s for updating position using Eq. (5) for each population:

$$s = SRD \cdot CC_k \tag{5}$$

where CC_k represents cluster center in each population.

After apply shifting value to update position of cluster center, and then *SSE* is calculated using Eq. (4) and Euclidean distance using Eq. (5). Afterward, compare the previous value of *SSE* with the current *SSE* and update the position of cluster center if the current *SSE* is less than the previous *SSE*.

Step 6.2: Tracing Mode

A velocity formula according to [7], is shown in the following Eq. (6):

$$V_{k,d} = w \cdot V_{k,d} + r_1 \cdot c_1 \cdot (P_{k,d} - X_{k,d}) + \\ + r_2 \cdot c_2 \cdot (P_{g,d} - X_{k,d}) \tag{6}$$

In this research, the initial velocity $V_{k,d}$ and weight w are not used in ACPSO to simplify the process where the cat spends most time to rest. Therefore, the initial cat moves usually equal to zero where the cat is not moving.

To implement this idea, a modified velocity formula is proposed in Eq. (7). The proposed formula a has similar parameter as follows: $c_1 = c_2$ is a constant with a value of 2; $r_1 = r_2$ is a random value between 0 to 1; $P_{mean(xk)}$ is mean of data in each cluster center, and P_{best} is the global best position of the cluster center. Then, the calculation result will be used to update a new position of cluster center using Eq. (7):

$$X_{k,d} = X_{k,d} + V_{k,d} \tag{7}$$

In Eq. (7), $X_{k,d}$ represents position of cluster centers. Furthermore, calculate new Euclidean distance using Eq. (4) and SSE using Eq. (3). Afterwards, update previous positions of cluster centers with $X_{k,d}$ and update global best positions P_{best} if global best *SSE* greater than minimal current *SSE* of each cluster center, otherwise keep previous global best positions $P_{best.}$

Step 7: Stopping Criteria

The stopping criteria usually use a number of iteration. For each dataset, a different number of iteration is operated according to their properties. The greater number of dataset usually requires more iteration to get the best result and vice versa.

IV. Experimental Result

In this research, ACPSO was implemented for clustering and searching the optimal value in each dataset.

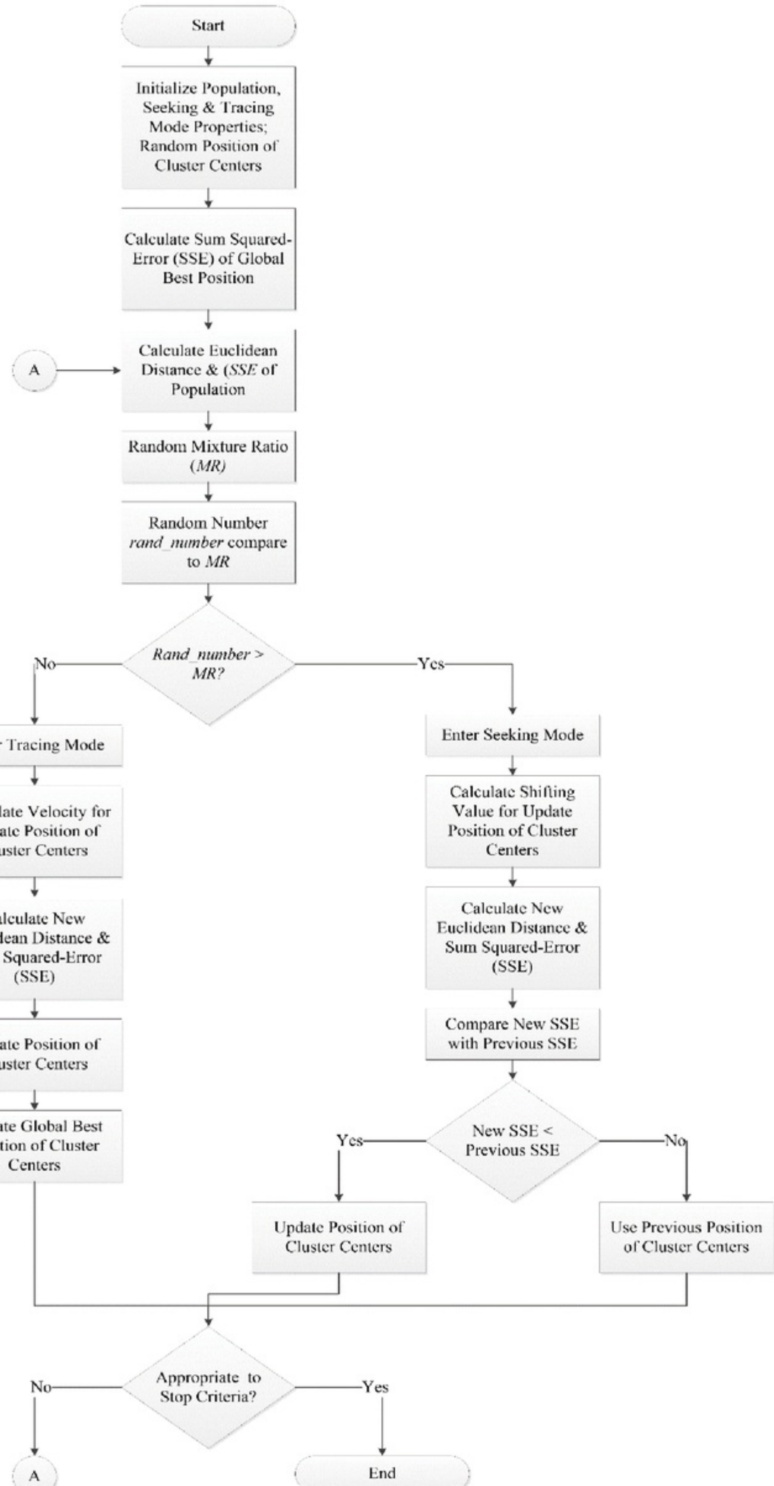

Fig. 1. ACPSO Algorithm Flowchart

The experiment was conducted to examine the experiment of proposed algorithm to prove the correctness of algorithm to find a solution.

IV.1. Datasets and Parameters

The experiment of ACPSO clustering using four real-world datasets is shown in Table I.

TABLE I
DATASETS

Datasets	Number of Data	Number of Attributes	Number of Class
Iris	150	4	3
Haberman	306	4	2
Wine	178	13	3
Parkinsons	197	23	2

Each dataset represents the different case. Haberman has a higher number of data while Parkinsons has a higher number of attributes. In order to evaluate the proposed algorithm, we define several parameters for both seeking mode and tracing mode as shown in Table II.

TABLE II
PARAMETERS

Parameters	ACPSO
SRD	0.1
SMP	4
SPC	between 0 and 1
MR	rand(0,0.3)
c_1, c_2	2
r_1, r_2	rand(0,1)
V_{max}	0.5
V_{min}	-0.5

The values of parameters were obtained from several experiments and show an optimal result. An adaptive MR value was used as proposed in [13]. Constant value c1 and c2 equal to 2 adapt the original PSO in [14] as an optimal value.

IV.2. Experiment with Iterations

The experiment was conducted to find the correlation between the numbers of iteration with the performance of ACPSO. The experiment was conducted ten times for each dataset. The result is shown in Table III.

TABLE III
CLUSTERING SUCCESS RATE

Dataset	Number of Iteration	Success rate
Iris	500	70%
	1000	100%
Haberman	500	60%
	1000	100%
Wine	1500	70%
	2000	90%
Parkinsons	1500	80%
	2000	90%

In Iris and Haberman's dataset, the result is good under 1000 iteration and obtains optimal value in 1000 iteration.

In the dataset of Wine and Parkinsons, a higher number of iteration achieved above 1000 iterations.

The difference between these datasets is the number of attributes, which is greater than Iris and Haberman as shown in Table I.

The correlation number of iteration with datasets is shown as the success rate of each dataset, which depends on the higher number of iteration, as shown in Figure 2.

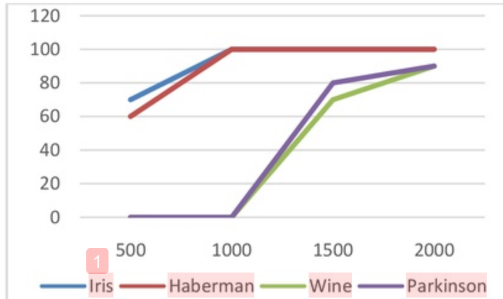

Fig. 2. Comparison Number of Iteration (in percent)

IV.3. Experiment with Population

In this research, the number of cat in each population depends on the number of cluster.

The number of population plays the important role in the experimental result, as shown in Table IV.

TABLE IV
EXPERIMENT WITH POPULATION

Dataset	Number of Population	Result with 1000 Iterations
Iris	5	80%
	10	100%
Haberman	5	80%
	10	100%
Wine	5	30%
	10	50%
Parkinsons	5	40%
	10	60%

As shown in Table IV, using five populations does not increase the number of diversity of solutions while using ten populations, show the diversity of solutions.

Therefore, in this research, we set the number of population pop = 10. As shown in Fig. 3, with ten populations (P-1, P-2, P-3,…, P-10), the optimal solutions (B-P) of clustering were obtained based on the diversity of solutions. In this research, local optima are never shown during iterations. The adaptiveness of MR prevents algorithm stuck in local optima where ACPSO tends to enter seeking mode to search candidate solutions.

IV.4. Comparison with Different Method

To ensure the performance of ACPSO, a comparison was conducted between proposed algorithm and different algorithm shown in Table V.

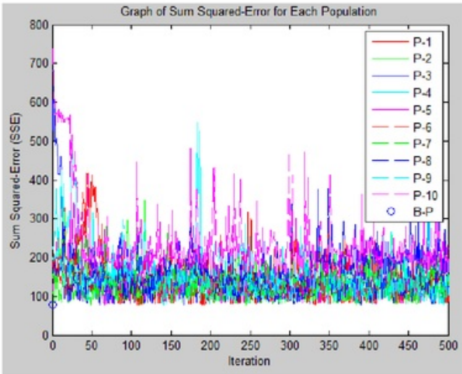

Fig. 3. Iris SSE result with 10 populations

TABLE V
COMPARISON WITH DIFFERENT METHODS

Dataset	Parameter	ACPSO	CSO	GA*K*-means
Iris	Best	7.89e+01	7.90e+01	7.89e+01
	Average	7.89e+01	8.03e+01	8.16e+01
	Worst	7.89e+01	8.29e+01	8.44e+01
Haberman	Best	3.05e+04	3.06+e04	3.05e+04
	Average	3.05e+04	3.07e+04	3.05e+04
	Worst	3.05e+04	3.08e+04	3.05e+04
Wine	Best	2.37e+06	2.37e+06	2.37e+06
	Average	2.37e+06	2.37e+06	2.42e+06
	Worst	2.38e+06	2.38e+06	2.63e+06
Parkinsons	Best	1.16e+06	1.34e+06	1.34e+06
	Average	1.16e+06	1.35e+06	1.34e+06
	Worst	1.17e+06	1.35e+06	1.34e+06

Several algorithms of optimization were used in this experiment: ACPSO, CSO [8], and GA *K*-means [21].

Each algorithm was conducted one by one from ACPSO to other algorithm. The results show that ACPSO is able to gain the best solution of SSE with 100 percent for Iris and Haberman's datasets.

For Wine and Parkinsons' datasets, ACPSO is able to gain the best solution, but not always. Otherwise, CSO algorithm unable to gain the best solution but the difference is not significant. Moreover, GA *K*-means algorithm is able to gain the best solution. However, GA *K*-means often get stuck in local optima. Therefore, it can be concluded that the proposed algorithm can obtain a better solution than CSO and GA K-means algorithm.

V. Conclusion

Clustering problem is still popular; many researchers have proposed different techniques for solving the clustering problem, such as PSO, CSO, *K*-means, etc. *K*-means is one popular method for solving clustering problem; yet it often gets stuck in local optima.

Therefore, an ACPSO is proposed to avoid local optima and increase the diversity of solutions. The proposed algorithm was adapted from CSO with adaptive MR in order to prevent local optima where algorithm tends to enter seeking mode than tracing mode. This characteristic is adapted from the behavior of cats, which spend most of the time resting but stay alert.

The value of MR between 0 and 0.3 is proven [11] to increase the tendency of population to choose seeking mode. A population was also added to increase the diversity of solutions of each cluster center. Through experiments, the number of population which has the correlation with the number of best solutions was found with the limited number of iteration. It proves that using ten populations will affect the result of SSE although the computation time is increasing.

In tracing mode, a modification in velocity formula as in CSO, there is a probability that the cat is not moving as part of the solution. Then the initial velocity is equal to zero. After the solution has been found, an update of global best position was applied into each cluster center in population. In this clustering problem, four datasets were used, as shown in Table I.

In each dataset, several experiments were conducted with a certain number of iteration, the number of population and comparison with the different technique.

In the experiment with iteration, the dataset of Iris and Haberman shows 100 percent that the best solution was found under 1000 iterations, while the dataset of Wine and Parkinsons achieved the best solution in a higher number of iteration. The different number of iteration depends on a number of attributes in each dataset. To achieve best solutions in datasets with higher attributes, increasing number of iteration is needed.

The experiment with population shows that using ten populations is better than using five populations. The higher number of population will increase the diversity of solution obtained in iteration. However, it also increases the computation time.

Compared to different techniques such as CSO and GA *K*-means, the result of ACPSO is superior where best, average and worst solutions have a small number of differentiations. In the CSO, the boundary value of SSE is often higher than the best solutions and stuck in local optima, as well as GA K-means.

For future research, a fast algorithm combined with ACPSO should be used to cut unnecessary processes to obtain minimal computation time.

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