Development of New Clustering Algorithm Based on Firefly Optimization

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Abstract—**Clustering is a grouping of data with similar characteristics in a data set. Within the same cluster, the similarities are high and the similarities between the clusters are low. Clustering algorithms often have unsupervised learning, so no prior information is given. In this article, firefly optimization algorithm has been applied to find the optimum cluster centers. This algorithm has a global search capability and generally is used to solve difficult problems. The proposed clustering algorithm was tested on 12 data sets from UCI data warehouse. For evaluation of performance of this new approach, the proposed clustering algorithm are compared with twelve other clustering algorithms (SFLA, ABC, PSO, Bayes Net, Mlp ANN, RBF, KStar, Bagging, Multi Boost, NB Tree, Ridor and VFI). As a result of this study, the proposed approach has performed better than many clustering algorithms in many datasets.**

Keywords—**Clustering, clustering by firefly, clustering methods, firefly optimization.**

I. INTRODUCTION

Clustering is the unsupervised classification of data elements or observations, data sets have not been classified in any cluster, and therefore clustering does not have any class attribute associated with them. Clustering is one of the most important steps in the analysis of exploratory data. These algorithms are used to find useful and unidentified pattern classes. Clustering is used to divide data into groups of similar objects. Objects that are not similar are placed in separate groups. Depending on the selected metric, a data object can belong to a single cluster, or it can belong to more than one cluster [1]. More than one clustering algorithm has been developed to this day, developed clustering algorithms is used in many areas such as data mining, statistics, biology and machine learning. Dekhici et al. (2012) optimized power dispatching by using Firefly Algorithm (FA). The authors adapted the Particle Swarm Optimization to the same problem as FA for evaluation. They focused on two thermal plant networks and IEEE-14. In comparison with PSO, FA algorithms show more effective result and get the best cost in below one second. Yang and He (2013) discussed a firefly algorithm and all metaheuristic algorithms. When compared to the intermittent search strategy, it concludes that meta-therapies such as the firefly algorithm are better than the optimal intermittent search strategy. In another research (Aydilek (2017)), it is proposed to consider the instantaneous changes in the environment by the firefly algorithm so that the algorithm is better. The obtained modified and improved firefly algorithm was applied for classification purposes on three sets of data such as iris, car, zoo, which have the multi-class feature used in literature studies. In order to perform rule-based classification, a rule list for each class label was obtained, and classification success was compared with other known classification methods such as C4.5, PART, Naive-Bayes. As a result, it has been seen that the proposed classification method gives very satisfactory and successful results. Two kinds of meta-heuristic methods (PSO and FA algorithms) have been implemented to get the optimal solutions for non-linear nonlinear continuous mathematical models [5]. In this work, a series of computational experiments was performed by using PSO & FA. As a result of this experiment, it was analyzed and compared to the best solutions obtained until now. The Firefly algorithm performs better for higher levels of noise. Gandomi et al. (2011) is used Firefly algorithm for solving mixed variable structural optimization problems. The FA code was applied to six optimization problems get from the literature including helical compression spring design, welded beam design, reinforced concrete beam designs, stepped cantilever beam design, pressure vessel design and car side impact design. The results of this work show that FA has better result than other metaheuristic algorithms (PSO, GA, SA and HS). Wang et al. (2017) have proposed a new type of firefly called the firefly neighborhood attraction (NaFA). In NaFA, each firefly is attracted by other bright fireflies chosen from a predefined neighborhood rather than those from the entire population. Experiments were performed using some well-known comparison functions. As a result, the proposed strategy demonstrates that solutions can effectively improve the accuracy and reduce computation time complexity. Yang (2013), suggests recently developed firefly algorithm to solve multiobjective optimization problems in his work. It is validated the proposed approach using a subset of selected test functions and then applied it to solve the design optimization criteria. As a result, when

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compared to other algorithms, the highly objective firefly algorithm shows that it is a multi-purpose optimizer. Khadwilard et al.(2012) have used Firefly Algorithm (FA) to solve JSS problem. They investigated parameter setting of FA algorithm, and compared FA parameter with various parameter settings. The experiment was implemented to 5 benchmarking problem obtained from JSSP datasets. An analysis of the results of the experiments was carried out using the optimized parameter settings and comparing the FA performance before parameter settings was done. The appropriately parameterized FA obtained from the test analysis produced a better program that was better than FA without accepting parameter settings. In another study (Umbarkar et al. (2017), quick sort and the bubble sort are used to reduce firefly time complexity. The dataset used in this work is unconstrained benchmark functions from CEC 2005. The comparison of FA using bubble sort and FA using quick sort is performed with respect to best, worst, mean, standard deviation, number of comparisons and execution time. As a result FA, which uses quick sort, requires less number of comparisons, but requires more execution time. While the increasing number of FAs helped to approach the optimal solution, different sizes for the algorithm showed better performance at a lower dimension than the higher dimension. Hrosik et al. (2019) presented a study focused on combination of firefly algorithm and K-means clustering for brain image segmentation. The proposed algorithm was performed on Harvard Whole Brain Atlas images. They compared the combined algorithm to other techniques. In this study, the combination of firefly algorithm and K-means clustering obtained better result on segmentation considering standard segmentation quality metrics such as peak signal to noise, normalized root square mean error and structural similarity index metric. Xie et al. (2019) improved the K-means clustering method with enhanced Firefly algorithm. The proposed algorithm tested on three database (ALL-IDB2, a skin lesion and 15 UCI data sets) to evaluate the efficiency on clustering tasks. For reducing the feature dimensionality, the minimum Redundancy Maximum Relevance (mRMR)-based feature selection method is applied. As a result of this work, the proposed FA models demonstrate statistically significant superiority in both distance and performance measures. In another study on firefly clustering, SMC-PHD multi-target tracking method has proposed by Tian et al. (2019). In this work, the improved algorithm has more stable peak extraction ability than K-Means clustering algorithm in SMC-PHD filter.

In this work, the firefly optimization algorithm is used to find optimum cluster centers. As we know, FA has a global search capability and it solves many difficult problems. Generally, firefly algorithm is focused on optimization problems and used for solving these problems. We used the firefly algorithm in clustering process for finding the cluster centers. To evaluate the performance of this algorithm, it is tested in 12 benchmark data sets from UCI machine learning and compared with three metaheuristic algorithms (SFLA, ABC and PSO) and other nine algorithms (Bayes Net, Mlp ANN, RBF, KStar, Bagging, Multi Boost, NB Tree, Ridor and VFI) in literature.

II. CLUSTERING

Clustering is the process of separating data in the data set into groups, which are called sets. Clustering is known as one of the most important operations of data mining. The clustering operation directly affects the classification success of the data set. Several clustering algorithms have been proposed by researchers. To date, there are more than one clustering algorithms in the literature by researchers. In general, clustering algorithms can be classified in four different methods, Partitioning method, Hierarchical method, Density Based and Fuzzy logic these four methods are explained below.

A. *Partitioning method*

Partitioning method divide the dataset into groups of k where each group represents a set. It is expected that the objects of the same group are similar to each other and different from the objects in the other groups. The most widely used and best known partitioning methods are those that are center-based, that is, k-means. The reason for the k-mean naming of the algorithm is that it requires a fixed number of sets before the algorithm runs. The cluster number is denoted by k and represents the number of groups to be created according to the closeness of the elements. Accordingly, k is a constant positive integer that is known in advance and does not change its value until the end of the clustering process. The clustering process is performed by placing the clusters nearest to the data or similar cluster centers. Clustering is usually done on the basis of Euclidean linkage in the working method. The number k at the beginning of the algorithm is given as the input parameter. If the number of clusters is not specified, the most suitable number is found by trial, or this value is given to the algorithm from the outside. K random cluster centers may be specified or the first element may be the center. The closeness of the elements to the centers is calculated and clustered according to the centers they are close to. New cluster centers are determined by calculating the average of the resulting clusters. This process continues until the element to be clustered is not found [12].

B. *Hierarchical method*

Hierarchical method finds clusters that follow using pre-existing clusters. Hierarchical algorithms can be adders and divisors. Aggregation algorithms start by taking each element as a separate set and combine it into larger sets. Splitter algorithms begin with the whole cluster and divide the data set into smaller clusters in subsequent steps. In hierarchical clusters, the data can not be divided into clusters in a single step. Instead, a series from one set containing all objects to a set containing one object is applied [13].

C. Density Based

Density-based clustering methods find clusters of high and low density areas in the data set. This method find arbitrary shaped clusters and noises effectively when provided with correct parameters [12].

D. Fuzzy logic

Fuzzy logic can be defined as a rigid mathematical order for working with uncertainties and uncertainties. As is known, statistical and probability theory is strictly examined instead of uncertainty. The main difference between fuzzy logic and mathematics is that it allows only extreme mathematical values in a known sense. Modeling and controlling complex systems with classical mathematical methods is difficult because the data must be complete. In fuzzy logic, logic rules are applied in a flexible and fuzzy way. As is known from classical logic, there are " true and false " or " 1 " and " 0 ", whereas in fuzzy logic, propositions and expressions can be accepted. If an expression in the fuzzy logic system is completely false, it will be 0 as it would be in a classical logic, or 1 if it is completely correct (but most fuzzy logic applications do not allow 0 or 1 in one statement or only in very special cases). Except these, all expressions are less than 1 and greater than 0 in actual values [14].

III. OPTIMIZATION AND OPTIMIZATION ALGORITHMS

Optimization is the process of obtaining the most appropriate solution by providing certain constraints for the given purpose or purposes. In mathematical terms; optimization can be defined as simply minimizing or maximizing a function.. For example, $f(x) = x^2$ function, $-\infty < x < \infty$has a minimum $f_{min} = 0$ value of 0 from x = 0 over all value ranges.In general, if a function is simple enough, the first derivative $\acute{f}(x) = 0$and the second derivative of the function $a(x) = 0$ is used to verify whether the solution is a $f\acute{\acute{}}(x)$ (maximum or minimum). However, for nonlinear, multimodal, multivariable functions, this is not an easy task. In addition, there may be discontinuity in some functions, and thus derived information is not easy to obtain. There are many optimization algorithms developed by researchers in the literature. In the following section, firefly optimization algorithm is explained from these optimization algorithms.

A. Firefly Optimization Algorithm

The Firefly algorithm is a metasequential optimization algorithm developed by Xin-she Yang (2009) and based on the social behavior of fireflies. The firefly algorithm operates based on the principle that the fireflies which has less bright is directed towards the more bright fireflies in nature. The complex biochemical process in the production of flashing lights is still discussed in the world of real-world science. Flashing lights help firebug's friends find their prey and protect them from their hunters. In order to obtain efficient optimal solutions in the firefly algorithm, the target function of a given optimization problem is related to the intensity of the flashing light or light which helps to go to the bright and attractive places of the firefly motion. It makes some of the flashing features of fireflies ideal for developing Firefly-inspired algorithms [15]. To make it easier to identify our new Firefly Algorithm (FA), three ideal rules are used:

1. All fireflies are considered as a single genus and form the basis of this algorithm.
2. Appeal is proportional to the brightness; so for any two flashing fireflies the less bright person will move towards the bright one, and as the distance increases, both decrease. If there is nothing brighter than a certain firefly, it moves randomly.
3. The brightness of a firefly, the objective function is influenced or determined by the landscape [16]. The pseudo code of the firefly algorithm is given below [17].

Definition of objective function: f(x), $x = (x_1, \dots, x_d)^T$
Generation of initial population: x_i ($i = 1,2, \dots, n$)
The intensity of light I_i, x_i (determined by $f(x_i)$)
Definition of absorption coefficient of the light (defined as γ)
While (t < max Generation)
    For i=1:n (for all fireflies)
        For j=1:i (for all fireflies)
            if (Ii <Ij), (Move firefly i towards j)
$$x_i = x_i + \beta_0 e^{-\gamma r^2{}_{ij}}(x_j - x_i) + \alpha(rand - 0.5)$$
      End if
        The variety of attractiveness varies with the distances (r) exp $(-\gamma r^2)$
        Evaluation of the new results & updation of the light intensity
        End for j
        End for i
Rank the fireflies and find the current best (g)*
End while
Postprocess results and visualization

In some sense, there are some conceptual similarities between the FA and the bacterial adder algorithm (BFA). The interaction between bacteria in BFA is based, in part, on their suitability and partly on their distances, whereas in the FA it depends on the objective functions of attraction and on the monotonous decay of distance of attraction. However, agents in the FA are usually more visibly adjustable and more versatile in attractiveness variations leading to higher mobility, and are therefore being explored more efficiently [17].

Attractiveness: The exchange of light intensity and the formulation of its attractiveness are important topics in the FA. The attractiveness of a firefly is determined by the brightness associated with the encoded target function.

For maximum optimization problems, the brightness of I can be selected from the firefly at $I(x)\alpha f\ (x)$ at a specific location. However, the attractiveness is relative, must be seen or judged by the other FA. Thus, the fire will vary with the distance rij between the firefly i and firefly j. Also, as the distance increases, the intensity of the light decreases and the light is absorbed in the media, so the attractiveness changes according to the degree of absorption. In the simplest case, the intensity of $I(r)$ changes according to the inverse square law $I\ (r)\ =\ Is\ /\ r^2$. HereIs is the intensity at the source. the light absorption coefficient γ and the light intensity vary with the distance r. This is $I\ =\ I_0 e^{-\gamma r}$, where I_0 is the original light intensity. To avoid singularity at r = 0 in the expression $Is\ /\ r^2$, the combined effect of both inverse square law and absorption is approximately estimated using the following Gaussian form

$$I(r) = I_0 e^{-\gamma r^2} \quad (1)$$

Sometimes we need a function to monotonically slow down, in which case we can use the following approximation

$$I(r) = \frac{I_0}{1+\gamma r^2}. \quad (2)$$

For a shorter distance, the above two forms are basically the same. This is why the expansion of the series with r = 0.

$$e^{-\gamma r^2} \approx 1 - \gamma r^2 + \frac{1}{2}\gamma^2 r^4 + \cdots, \frac{1}{1+\gamma r^2} \approx 1 - \gamma r^2 + \gamma^2 r^4 + \cdots, \quad (3)$$

the attractiveness of the firefly is proportional to the intensity of light seen by the adjacent fireflies, we can expression the attractiveness of the firefly by

$$\beta(r) = \beta_0 e^{-\gamma r^2}, \quad (4)$$

at r = 0 the attractiveness is β_0. It is usually faster to calculate 1 / (1 + r^2) than an exponential exponential function, the above function can easily be replaced by the function $\beta = \frac{\beta_0}{1+\gamma r^2}$ if necessary. Equation (4) defines the characteristic distance $\Gamma = 1\sqrt{\gamma}$, over where the attractiveness changes significantly from β_0 to $\beta_0 e^{-1}$.

In the implementation, the actual function (r) of the attractiveness may be any monotonically decreasing function, such as the following generalized form.

$$\beta(r) = \beta_0 e^{-\gamma r m},\ (m \geq 1) \quad (5)$$

For a fixed γ, the characteristic length becomes $\Gamma = \gamma^{-1/m}$as $m \to \infty$. Conversely, for a given length scale Γ in an optimization problem, the parameter γcan be used as a typical initial value. That is $\gamma = \frac{1}{\Gamma^m}$ [17].

Distance: The distance between i and j of the two fireflies in xi and xj is Cartesian distance.

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (6)$$

Where $x_{i,k}$ is the kth component of the xi spatial coordinates of i firefly. In the case of two-dimensional, we have [18];

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (7)$$

Movement: The movement of a firefly i is attracted to another more attractive (brighter) firefly j is defined by

$$x_i = x_i + \beta_0 e^{-\gamma r^2 ij}(x_j - x_i) + \alpha\left(rand - \frac{1}{2}\right) \quad (8)$$

The second term refers to the attraction and the third term is randomization with α as a random parameter.rand is a random number it takes a random value between [0, 1]. We can take $\beta_0 = 1$ and $\alpha \epsilon\, [0,1]$. The parameter γ characterizes the variation of the attractiveness and its value is important in determining the speed of convergence and how the FA algorithm behaves [19].

IV. DATA CLUSTERING APPLING BY FIREFLY OPTIMIZATION ALGORITHM

In the clustering process finding the best cluster centers is an NP-hard problem. To solve this problem, researchers have proposed more than one method. Due to the success of the firefly algorithm, many problems have been solved. In this work, the fire algorithm is proposed to find the optimum cluster centers in the clustering process. In the proposed clustering algorithm Classification Error Percentage (CEP) evaluation criterion is used as a fitness function.

$$\text{CEP} = \frac{\text{\#of misclassified examples}}{\text{size of test data set}} \times 100 \quad (9)$$

The firefly algorithm can achieve global solutions from a wider search space. The steps of the proposed firefly algorithm based clustering algorithm are given below.

Proposed clustering algorithm steps

*Step 1:*Read the data set.

*Step 2:*Set parameters of firefly algorithm (alpha, beta, gamma, number of firefly, number of iteration).

Step 3: Generate random start cluster centers up to the number of firefly and calculate the fitness function Classification Error Percentage (CEP) according to these cluster centers.

*Step 4:*Update cluster centers according to equations 1 and 2up to the number of iterations.

*Step 5:*Sort the solutions and get the best solution, cluster the data according to this solution.

V. EXPERIMENTAL RESULTS

As an experiment, the proposed FA clustering method is tested on 12 data sets from the UCI data set [20], the properties of the data sets are given in table 1. The results were compared with the clustering methods of SFLA, ABC, PSO, Bayes Net, Mlp ANN, RBF, KStar, Bagging, Multi Boost, NB Tree, Ridor and VFI.

Table 1: Properties of the data sets used

NO	Datasets Name	# Samples	# Attributes	# Classes
1	Balance	625	4	3
2	Cancer	569	30	2
3	Cancer-Int	699	9	2
4	Credit	690	51	2
5	Dermatology	366	34	6
6	Diabetes	768	8	2
7	E. coli	327	7	5
8	Glass	214	9	6
9	Heart	303	35	2
10	Iris	150	4	3
11	Thyroid	215	5	3
12	Wine	178	13	3

The parameters of the FA clustering method are set to (α= 0.7,β=1 and γ = 1).P-FA was used as the CEP function in the clustering method and the best CEP value of 1000 iterations was obtained. The results obtained from our experiment compared with other methods are given in table 2. As can be seen from the table, the firefly algorithm is compared with 12 other algorithm for clustering 12 data sets. The first coloumn of the table includes data sets and the results belong to Firefly algorithm are given in the second coloumn. In the second coloumn, both the clustering percentage and ranking, given in parenthesis, of the FA are shown.

Table 2: Results for FA clustering method compared with other methods

Data Set	Firefly Clustering Algorithm	SFLA	ABC	PSO	Bayes Net	Mlp ANN	RBF	KStar	Bagging	Multi Boost	NB Tree	Ridor	VFI
Balance	14,24 (3)	28,33	15,38	25,47	19,74	9,29	33,6	10,25	14,77	24,2	19,7	20,63	38,85
Cancer	4,241 (9)	6,42	2,81	5,8	4,19	2,93	20,3	2,44	4,47	5,59	7,69	6,36	7,34
Cancer-Int	5,4 (5)	4,01	0	2,87	3,42	5,25	8,17	4,57	3,93	5,14	5,71	5,48	5,71
Credit	16,015 (6)	13,77	13,37	22,96	12,13	13,81	43,3	19,18	10,68	12,71	16,2	12,65	16,47
Dermatology	2,53 (5)	3,93	5,43	5,76	1,08	3,26	34,7	4,66	3,47	53,26	1,08	7,92	7,6
Diabetes	26,56 (5)	28,81	22,39	22,5	25,52	29,16	39,2	34,05	26,87	27,08	25,5	29,31	34,37
E. Coli	14,98 (5)	14,15	13,41	14,63	17,07	13,53	24,4	18,29	15,36	31,7	20,7	17,07	17,07
Glass	23,11 (2)	43,35	41,5	39,05	29,62	28,51	44,4	17,58	25,36	53,7	24,1	31,66	41,11
Heart	28,5 (11)	20,92	14,47	17,46	18,42	19,46	45,3	26,7	20,25	18,42	22,4	22,89	18,42
Iris	3,334 (11)	7,22	0	2,63	2,63	0	9,99	0,52	0,26	2,63	2,63	0,52	0
Thyroid	4,094 (3)	5,08	3,77	5,55	6,66	1,85	5,55	13,32	14,62	7,4	11,1	8,51	11,11
Wine	2,36 (6)	2,88	0	2,22	0	1,33	2,88	3,99	2,66	17,77	2,22	5,1	5,77
Mean Value	**12,11**	**14,90**	**11,04**	**13,90**	**11,70**	**10,69**	**25,98**	**12,96**	**11,89**	**21,63**	**13,25**	**14,00**	**16,98**

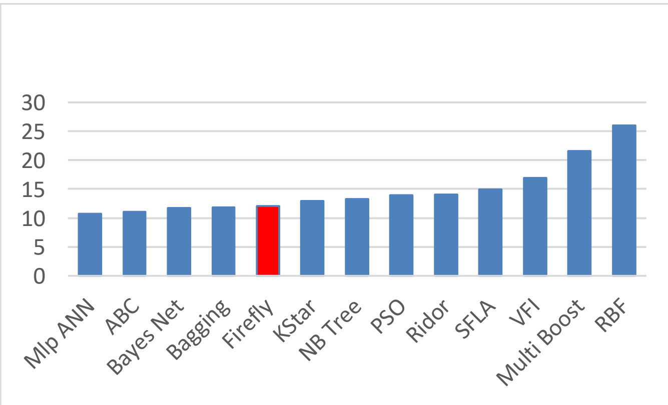

Fig. 1. The mean values of the results.

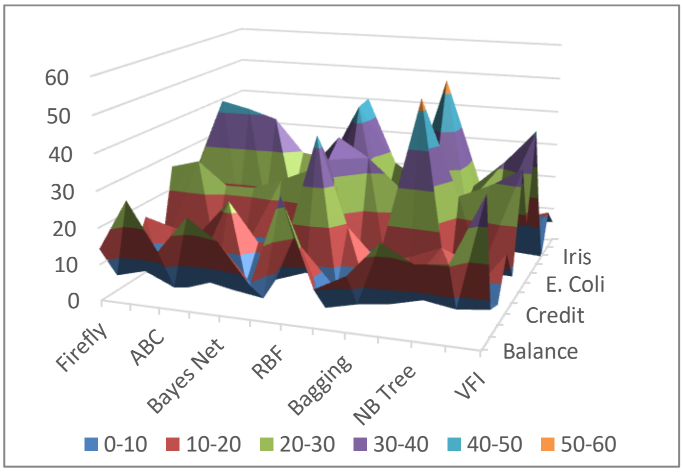

Fig. 2. The surface graph of the results belong to clustering algorithms.

For the result of the study, the error rates and the ranking number are presented above. When we look at table 2, ABC obtained best results in Cancer-Int, Diabetes, E.coli, Heart datasets; The Bayes Net method obtained the best results in

Dermatology and Wine data sets; the MLP-ANN method obtained the best CEP results in Balance, Iris and Thyroid data sets; the Kstar method obtained the best results in Cancer and Glass data sets; the Bagging method obtained the best result in Credit data set; the NB Tree method obtained the best CEP result in Dermatology dataset; the VFI method obtained the best result in the Iris dataset.

The proposed FA clustering method obtained better results in all data sets compared with RBF method, better results in 9 data sets with VFI method, better results in 8 data sets with Ridor method, 7 data sets with PSO, SFLA and Multi Boost method, better results in 6 data sets with Bagging method, better results in 3 data sets with Bayes Net, Mlp ANN and NB Tree method.

VI. CONCLUSION

In this study, clustering, clustering methods, optimization and firefly optimization algorithm are explained. FA is used as the clustering algorithm to find the optimal cluster centers. As FA clustering algorithm, it is tested in 12 data sets from UCI machine learning on benchmark problem and compared with three metaheuristic algorithms (SFLA, ABC and PSO) and other nine algorithm given in literature. Proposed FA clustering algorithm performed better than many clustering algorithms.

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