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Performance Analysis of Whale optimization based Data Clustering

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Abstract

Data clustering is the method of gathering of data points so that the more similar points will be in the same group. It is a key role in exploratory data mining and a popular technique used in many fields to analyze statistical data. Quality clusters are the key requirement of the cluster analysis result. There will be tradeoffs between the speed of the clustering algorithm and the quality of clusters it produces. Both the quality and speed criteria must be considered for the state-of-the-art clustering algorithm for applications. The Bio-inspired technique has ensured that the process is not trapped in local minima, which is the main bottleneck of the traditional clustering algorithm. The results produced by the bio-inspired clustering algorithms are better than the traditional clustering algorithms. The newly introduced Whale optimization-based clustering is one of the promising algorithms from the bio-inspired family. The quality of clusters produced by Whale optimization-based clustering is compared with k-means, Kohonen self-organizing feature diagram, Grey wolf optimization. Popular quality measures such as the Silhouette index, Davies-Bouldin index, and Calianski-Harabasz index are used in the evaluation.

Keywords

Clustering, Whale optimization, Quality metrics

1. Introduction

The job of grouping several data points in such a way that data points in the same category are more similar than those in other classes is cluster analysis or clustering [1]. The different shapes and sizes of the data clusters make data clustering a challenging problem. There will be tradeoffs between the speed of clustering algorithm and the quality of the clusters it produces. Recently, bio-inspired computation has become a more promising optimization technique in the field of data clustering. The bio-inspired computation has become popular for various studies and applications. Bio-inspired methods are evolved from biological evolution. The bio-inspired optimization refers to a wide range of biological systems-based approaches. The adaptive features of the bio-inspired techniques have attracted researchers to apply to many optimization issues. The main subset of naturally inspired optimization strategies is bio-inspired computation and optimization. Bio-inspired optimization techniques are the subsets of naturally inspired optimization techniques that are most commonly used. Most of the bio-inspired optimization technique can be used for any optimization problems [2]. The optimization process is about finding the optimal solution to a particular problem. The selection of right algorithm for a particular application is a critical issue. Several algorithms found in the literature are developed to imitate the behavior of animals or insect families by enforcing procedures to be applied to various applications.

Due to the convincingly promising result outcome, researchers are more focused on bio-inspired clustering than traditional clustering techniques. The key problem in the traditional approach is getting struck in local minima, can be solved in bio-inspired approach. The bio-inspired optimization technique is robust and Provides better solutions. A comparative study is conducted on k-means clustering, fuzzy c-means clustering and particle swarm optimization based clustering (pso) [3].

The experimental results show better quality clusters for pso clustering. The difference in execution time is negligible. For clustering large-scale data sets, the mapreduce-based enhanced grey wolf optimizer is provided as an efficient clustering technique [4].

to improve the prey search efficiency, the grey wolf optimizer is combined with binomial crossover and levy flight steps. The well-known tabu-search (ts) method is integrated with the grey wolf optimization (gwo) [5].

while stochastic operators help this algorithm, it is still susceptible to local optima stagnation and premature convergence when dealing with problems involving a large number of variables.

to improve the constraint, the gwo algorithm is combined with the ts process.

The results of the experiments show that the suggested approach outperforms grey wolf optimization and tabu search clustering.

The different metaheuristic optimization technique whale optimization is presented [6]. The nature motivated algorithm mimics the social activities of humpback whales.

This algorithm is inspired by the technique bubble-net feeding in humpback whales.

Bio-inspired optimization results show that the woa algorithm shows more promising results as compared to state-of-the-art metaheuristic algorithms and conventional approaches.

This paper proposes the grey wolf optimizer (gwo), modern optimization algorithm inspired by grey wolves [7].

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The gwo algorithm is based on the natural hierarchy of leadership and hunting method of grey wolves. To simulate the leadership hierarchy, four types of grey wolves are used, such as alpha, beta, delta and omega. The three primary hunting stages of grey looking for prey, surrounding the prey and attacking prey are introduced. The findings show that gwo produces results that are very competitive as compared to other well-known metaheuristic algorithms. The proposed algorithm is applicable to difficult problems with uncertain search spaces, as shown by its application to three classic engineering designs and implementation.

Hybrid clustering is performed using artificial bee colony clustering and whale optimization in this paper [8].

The simulation results showed that increasing the number of iterations of the proposed solution maintained the degree of convergence. The combination of whale optimization for data clustering with tabu-search is proposed [9].

The clustering algorithm was created based on humpback whale hunting behavior [10]. Many defence and commercial applications uses vehicular ad-hoc networks (vanets). The complex topology and frequent disconnections make vanet difficult to use in efficient communication. Vnaet see clustering as one of the potential solutions for efficient communication.

However, minimizing the number of clusters with an increasing number of interacting nodes is one of the main problems.

The suggested metaheuristic clustering algorithm is based on the swarm-foraging behaviour of humpback whales [11].

The modified clustering algorithm is compared with k-means, particle swarm optimization, artificial bee colony and genetic algorithm clustering. Seven benchmark datasets from uci machine learning repository and one artificial dataset are used to evaluate the suggested clustering algorithm. The results show that the suggested technique can be used for data clustering effectively. WOA is a metaheuristic algorithm with the right ability to solve complex problems with numerical function optimization [12] [13]. a novel constitutional assessment method based on woa was set out to strengthen woa's convergence compliance. The simulation results suggest that the suggested scenario is more effective, with statistical significance in terms of woa convergence efficiency. The same approach is used for the clinical dataset of an anemic pregnant woman and optimized clusters are obtained. Simulation tests with the differential evolution algorithm, pso, abc, and cuckoo search algorithm with grey wolf optimizer are performed using regular benchmark functions. Experimental findings show that the algorithm achieved fastest speed of convergence and precision of optimization [14] [15] [16] [17]. The grey wolf optimization-based clustering algorithm [18] has been proposed for vanets. the approach for cluster analysis is based on the social behavior and hunting mechanism of grey wolves. The method has a higher degree of convergence as well as the other clusters.

The results show that the proposed method produces the best results, resulting in a stable routing protocol for clustering vanets that is more appropriate for highways and can achieve quality communication, ensuring efficient information transmission to each vehicle.

The algorithm randomly deploys search agents in the search space and uses delta difference and distance neighbor as objective functions to find the optimum number of clusters in the search space.

The results show that the proposed method improves the development of vehicular clusters and outperforms the existing optimization approach in terms of touch end-to-end delays [21].

Particle swarm optimization (pso) and grey wolf optimization (gwo) are combined in a hybrid algorithm [19].
gwo is simplified, and a novel differential perturbation technique is embedded in the simplified gwo's search method to improve global search ability while retaining gwo's strong exploitation ability. A large number of tests on complex functions taken from the test sets show that it has higher optimization performance than a number of state-of-the-art algorithms. According to experimental results on k-means clustering optimization, the hybrid approach has strong advantages over the other algorithms.
The bio-inspired optimization is gaining poplarity because of its flexibility to adapt for various domains of application. in recent years, the field of bio-encouraged computing has steadily gained traction.
As a result of the increasing complexities associated with research procedures, both the process of acquiring meaningful contents and collecting information with the aid of standard algorithms has become a difficult task.
The bio-inspired optimization techniques proved to be more promising method for various kinds of optimization problems [20].
The aim of this paper is to create a multi-stage automatic classifier for beaked whales [22].
The proposed method is validated using acoustic data and a manually annotated workshop dataset. The blocks are divided into appropriate and unsuitable watermarking regions using the optimized fcm clustering. For initial cluster center selection, the optimized fcm with least favorable-based whale optimization algorithm enabled makes the decision about the regions where the watermark can be inserted [23]. There are several methods are proposed on fuzzy logic and neural network. Inorder to Achieve the more optimized result whale optimization algorithm is used. The outcome of the proposed method is evaluated against numerous benchmark functions [24]. The memetic fuzzy whale optimization (mfwo) algorithm is a fuzzy clustering algorithm that has been proposed for data clustering. Uci benchmark data sets are used to assess the productivity of the suggested method. fcm and particle swarm optimization are compared to this approach [25].

2. Background

2.1 Cluster analysis

The method for partitioning a set of similar data objects into subsets is cluster analysis. Each subset is a cluster, and the objects in the cluster are identical, but the objects in the other cluster are different. The important application of clustering is used to identify the previously unknown patterns in the given database [1]. The following three properties need to be satisfied by the clusters formed [3]. There must be at least one data point in each cluster i.e.

$$ci \neq \emptyset, \forall i \epsilon \{1,2,\ldots\ldots k\} \quad (1)$$

All the clusters must have mutually exclusive data points, i.e.

$$ci \cap cj = \emptyset,\ \forall i \neq j \text{ and } i,\ j \epsilon \ \{1,2,\ldots\ldots k\} \quad (2)$$

The data point must belong to the one of the clusters, i.e

$$\cup_{i=1}^{k} C_i = X \quad (X = \{x_1, x_2, \ldots \ldots \ldots x_n\}) \quad (3)$$

2.2 clustering based on whale opimization

One of the recent metaheuristic algorithms is the whale optimization based clusteringthis technique of optimization mimics humpback whales' social behavior.
The smart hunting activity of humpback whales is imitated by this approach. This form of food quest is seen only in the bubble-net feeding technique of humpback whales.

While encircling prey during hunting, the whales generate the usual bubbles along a circular course.

Bubble-net feeding is a special and complex feeding activity that humpback whales are involved in. it is one of the few activities of surface feeding that humpback whales are known to participate in. in communities, this form of feeding is always performed. The size of the group will range from minimum of two or three participating whales and up to sixty at once. The humpback whales dive approximately 12 meters and swim upwards to the surface after the bubbles to form a spiral around the prey.

2.2.1 Encircling prey

Humpback whales can find out where they are by encircling their food. The woa considers the current best search agent's location to be target prey or close to the best possible solution, and other search agents may try to match the best search agent's position. The following equations reflect this action.

$$\vec{D} = |\vec{C}\vec{X}\text{-}\vec{X}(t)| \quad (4)$$

$$\overrightarrow{X}(t+1) = |\overrightarrow{X^*}(t) - \vec{A}\vec{D} \quad (5)$$

In the above equation, $\overrightarrow{X^*}$ represents the position of the best solution so far. $\vec{X}$ is the search agent location and t is the current iteration. In equations (3) and (4), the coefficient vectors a and c are computed.

$$A = 2.\ a.\ \mathrm{r} - a \quad (6)$$

$$C = 2\mathrm{r} \quad (7)$$

Over the progress of iteration, a is linearly reduced from 2 to 0 and r is an arbitrary value.

2.2.2. Bubble-net attack technique

The social activity of a humpback whale's bubble net is mathematically represented Using the following two techniques.

2.2.3 Shrinking encircling mechanism

The shrinking encircling process can be accomplished by lowering the value of a. a is an arbitrary value between [-a, a], with a decreasing from 2 to 0 as the iteration continues. The value of a is selected from the range [-1,1]. The new location of a search agent can be set somewhere between the original position and the current best agent's position. by comparing the original agent position to the current best agent position, the new search agent position can be determined.

2.2.4 Spiral updating position

The method first calculates the distance between the whale at (x, y) and the prey at (x*, y*). Then, to simulate the helix-shaped movement of humpback whales between the position of whale and prey, a spiral equation is developed as follows:

$$\vec{D} = |\overrightarrow{X^*(t)}\text{-}\overrightarrow{X(t)}| \quad (8)$$

$$\vec{X}(t+1) = \vec{D}.\, e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \quad (9)$$

Where b is the constant describes logarithmic shape, l is a random value between [-1,1] and $\vec{D}$ is the distance between the whale and prey.

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*(t) -}\ \vec{A}\,\vec{D} & \text{If } p<0.5 \\ \vec{D}.\, e^{bl}.\cos(2\pi l) + \overline{X^*(t)} & \text{If } p\geq 0.5 \end{cases} \quad (10)$$

Where p is random number in between 0 and 1.

2.2.5. Search for prey (exploration phase)

To find the best solution, the metaheuristic algorithm employs random selection. The location of the best solution in the bubble-net system is not known in advance. The humpback whales begin their hunt for prey in an unexpected area.

Consider the exploitation process, where $\vec{A}$ is in the range [1, 1]. The search agent would be able to move farther away from a reference whale if the above claim were true. Meanwhile, instead of using the best search agent found so far, the search agent's location is changed based on an arbitrarily chosen search agent.

These two measures are written as follows:

$\vec{D} = \vec{C}.|\overrightarrow{X_{rand}} - \vec{X}|$ (11)

$\vec{X}(t+1) = |\overrightarrow{X_{rand}} - \vec{A}.\vec{D}|$ (12)

Where $\overrightarrow{X_{rand}}$ is a arbitrarily selected search agent.

The WOA procedure begins with an initial collection of random solutions. WOA is found to be a best global optimizer. The position of the search agent is modified according to above conditions at each iteration. Dynamic variation of the vector $A^{\rightarrow}$ permits the woa algorithm switches between discovery and exploitation. Furthermore, the woa only needs to change two main internal parameters. The woa's high exploration potential can be attributed to the whales' position updating scheme (9). High manipulation and convergence are emphasized as a result of (6) and (2).

These formulas demonstrate that the woa algorithm can provide high local optima prevention and convergence speed over iteration. Whale optimization is a modern meta-heuristic optimization method that mimics humpback whales' bubble-net intelligence hunting activity. The algorithm is robust and swarm-driven, and it is based on the behavior of humpback whales.

The algorithm achieves a global optimal solution and can escape local optima. These benefits make woa a suitable algorithm for solving variety of applications without any structural modifications.

A swarm represents the number of possible solutions achieved from optimization techniques. Every search agent is a potential solution in the swarm. The woa's main objective is to find the position of the search agent that produces the best solution.

The WOA based clustering is discussed. in bio-inspired approach, there are n search agents and each search agent represents k cluster centers. Every search agent xi holds 'k' cluster centers as shown below:

$x_i=(z_{i1}, z_{i2}, z_{i3} \dots \dots z_{ik})$ (13)

where zij corresponds to ith search agent's jth cluster center in cluster cij.

The swarm is the 'n' number of potential solutions to the clustering problem. The intra-distance measure which shows the compactness of clusters is considered as the fitness function. The intra-distance of the cluster can be computed as:

$E = \sum_{i=1}^{k} \sum_{j} (P_j - C_i)$ (14)

Below is the pseudocode of the woa clustering according to the above assumptions.

Algorithm – the whale optimization-based clustering algorithm create k cluster centers at random for each search agent.

Repeat
  Repeat for every probable solutions
    Repeat for every data point do
      Find the distance between data points and cluster centers
      Allot data point to the nearest cluster such that

$$|x_p - z_{ij}| = \min_{c=1,2\dots k} |x_p - z_{ic}|$$

      Calculate the fitness using the equation:

$$\text{Fitness} = \sum_{i=1}^{k} \sum_{j=1}^{n} w_{ij} \, |x_{ij} - z_{ij}|$$

      Where

$$\begin{cases} 1 & if\ |x_{ij} - z_{ij}| = \min_{1\le i\le n} |x_i - z_{im}| \\ 0 & Otherwise \end{cases}$$

  Until all the data points covered
  Until all the probale solutuions covered
  Identify x* best potential solution
    For each probable solutions
      Modify a, a, c, i and p
      If p less than 0.5 then
        If |a| less than 1 then
          Update potential solution by eq. (5)
        Else if |a| ≥ 1 then
          Arbitrarily select a potential solution

Modify the potential solution by eq. (12)
End if
Else if p≥0.5 then
Modify the position of potential solution by eq. (9)
End of if
Until all the probable solutions coverered
t=t+1
Until t > tmax
return x*
End

3. Experimental analysis

The discussion and analysis of performance of the clustering algorithm is done in this section. The four algorithms such as k-means, ksofm, grey wolf optimization, and whale optimization based clustering are implemented on matlab.

The performance of the clustering algorithm is evaluated based on the cluster quality and time taken for the execution. Five datasets are used for the evaluation of clustering algorithms.

Table-1: datasets used

data set	instances #	features #	source
glass	214	9	uci repository
iris	150	4	
haberman	306	3	
wine	178	13	
census	10764	12	census india

Table-1 shows the five data sets used for clustering algorithm validation. Four datasets were taken from the uci benchmark datasets source [https://archive.ics.uci.edu/ml/datasets .php]

iris, glass, haberman, and wine are the real benchmark datasets from the repository. The fifth dataset is census data from the government census data [https://censusindia.gov.in/2011-common/censusdata2011. html].

Table-2: silhouette index

silhouette index	interpretation of the outcome
range 0.71 to 1	compact clusters
range 0.51 to 0.70	moderate clusters
range 0.26-0.5	weak cluster
range 0- 0.25	random/no cluster

[Ref: “efficient and effective clustering methods for spatial data mining”- Raymond t. ng, jiawei Han]

Table-2 shows the silhouette index and its interpretations. The vital role of quality measures is used to check “how good is the clustering generated by a method?” There are a number of methods for assessing the consistency of clustering. Depending on whether or not ground truth is available, these approaches are divided into two groups. Where a ground truth is usable, extrinsic approaches may be used. When the ground truth is inaccessible, the intrinsic methods may be used.

The intrinsic techniques evaluate clustering by looking at how well clusters are isolated from one another.

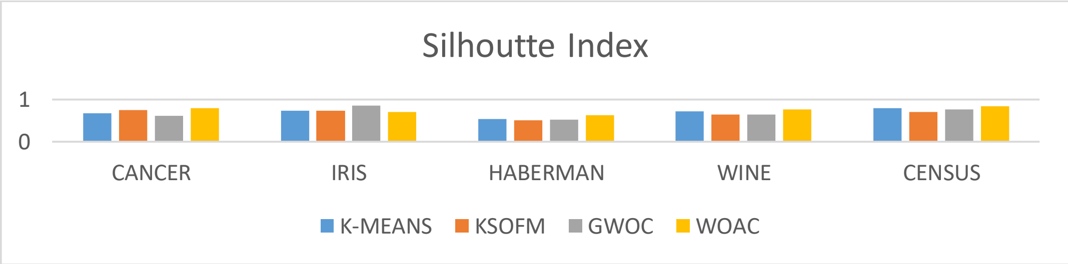

Figure 1: cluster quality analysis-silhouette index

The figure1 shows the bar graph of the quality of clusters using silhouette index. Whale optimization-based clustering outperforms the other three clustering. A lgorithms, according to the findings of the experiments.

Table 3: quality of clusters

Data Set	quality criteria	k-means	ksofm	gwoc	woc
iris	silhouette coefficient	0.74	0.74	0.85	0.69
	davies-bouldin index	0.66	0.66	0.78	0.65
	calianski-harabasz index	560	560	583	481
cancer	silhouette coefficient	0.67	0.75	0.58	0.78
	davies-bouldin index	1.58	0.76	0.85	0.74
	calianski-harabasz index	676	867	275	1041
wine	silhouette coefficient	0.73	0.45	0.60	0.72
	davies-bouldin index	0.55	0.49	0.58	0.57
	calianski-harabasz index	496	280	408	568
haberman	silhouette coefficient	0.6	0.50	0.48	0.54
	davies-bouldin index	0.86	0.87	1.0	1.12
	calianski-harabasz index	233	181	196	247
census data	silhouette coefficient	0.79	0.7	0.76	0.84
	davies-bouldin index	0.64	0.86	1.0	0.39
	calianski-harabasz index	633	349	428	502

The output measure of the four benchmark datasets and census data is shown in table 3. The whale optimization based clustering outfperforms the other clustering methods.

4. Conclusion

This study investigates the performance of a newly introduced bio-inspired clustering algorithm- Whale optimization based clustering. Whale optimization is an optimization inspired by nature that belongs to the swarm intelligence family, focused on the hunting behavior of humpback whale by constructing bubble nets.

This algorithm's outcome is contrasted with K-Means, Kohonen self-organizing feature map and Grey wolf optimization based clustering.

The cluster quality evaluation is done using Silhouette coefficient index, Davies-Bouldin index and calianski-Harabasz Index. The algorithm is tested with 4 benchmark data sets and census data (around 10000 records and 12 features).

Most of the evaluation Whale optimization based clustering outperformed other algorithms.

From the results obtained, it was proved that whale optimization based clustering outperforms other clustering algorithms for the four bench mark data sets considered.

The researchers have introduced more than thirty cluster quality measures. In the future, the obtained results can be checked with more quality indices. Still there are a lot of scope for tuning the basic parameters and fitness function.

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