Article

An Exhaustive Review of Bio-Inspired Algorithms and its Applications for Optimization in Fuzzy Clustering

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Abstract: In recent years, new metaheuristic algorithms have been developed taking as reference the inspiration on biological and natural phenomena. This nature-inspired approach for algorithm development has been widely used by many researchers in solving optimization problem. These algorithms have been compared with the traditional ones algorithms and have demonstrated to be superior in complex problems. This paper attempts to describe the algorithms based on nature, that are used in fuzzy clustering. We briefly describe the optimization methods, the most cited nature-inspired algorithms published in recent years, authors, networks and relationship of the works, etc. We believe the paper can serve as a basis for analysis of the new are of nature and bio-inspired optimization of fuzzy clustering.

Keywords: FUZZY; CLUSTERING; OPTIMIZATION ALGORITHMS

1. Introduction

Optimization is a discipline for finding the best solutions to specific problems. Every day we developed many actions, which we have tried to improve to obtain the best solution; for example, the route at work can be optimized depending on several factors, as traffic, distance, etc. On other hand, the design of the new cars implies an optimization process with many objectives as wind resistance, reduce the use of fuel, maximize the potency of motor, etc. These best solutions are found by adapting the parameters of the algorithm to give either a maximum or a minimum value for the solution. Therefore, in the last years many optimization methods have been developed with the aim of improving existing solutions.

Nowadays, many optimization algorithms based on nature can be found in the literature, it is calculated there are more than 150 different algorithms, and improved algorithms for finding the best results on the optimization problems [1–11]. However, it is not our aim to analyze all methods. Instead, our approach will be on the bio-inspired algorithms that are dealing with fuzzy clustering. Therefore, we have selected only a few algorithms in this review. Although, we have worked with different algorithms in different ways, for example, with parameter adaptation using fuzzy logic, original methods, the selected methods were chosen because they have demonstrated are good alternative for solving many optimization problems, and we have experience working with them. However, we focused with the applications about optimization fuzzy clustering.

Nature inspired algorithms can be classified as those based on biology and those inspired on natural phenomena. The algorithms based on biology can be further divided into those based on evolution and those based on swarm behavior. The evolutionary algorithms include the Genetic Algorithms, Differential Evolution, Cultural Evolution, Evolutionary Strategies, Genetic Programming. The swarm category includes Particle Swarm Optimization, Ant Colony Optimization [12], Artificial Bees [13], Temites [14], Bats [15], Birds [16], Cats [17], Bacterial Foraging [18], Cuckoo Search [19], Firefly algo-

rithm [20] and others. Also, there are algorithms based on the physical laws; for example,
Simulated Annealing, the Gravitational Search algorithm and the Big Bang Big Crunch algorithm.

2. Literature Review

In this section, we made a general review about the methods using optimization fuzzy clustering with different bio-inspired optimization methods. However, in the following sections a deep study is developed doing specific queries of Web of Science, and the tool VoSviewer to calculate the clusters of the analyzed works. In Table 1, is presented a list with the most popular bio-inspired optimization algorithms based on swarms, physics, populations, chemistry and evolution. This table shows many methods in chronological orders that have been used since 1975 to date. However, only are some methods but can be useful to expand the knowledge about these methods and to observe the inspiration type. We made the query in Web of Science: 'Optimization fuzzy clustering', we found a total of 2208 papers with this topic. However, in this paper only is presented a description of the most recent works, but with the query above mentioned can be seen the updated works. Figure 1, shows the countries with major number of publications.

Recently, multi-view clustering research has attracted considerable attention because of the rapidly increasing demand for unsupervised analysis of multi-view data in practical applications. In [21], was presented a novel Two-level Weighted Collaborative Multi-view Fuzzy Clustering (TW-Co-MFC) approach to address the aforementioned issues. In this method, TW-Co-MFC, a two-level weighting strategy is devised to measure the importance of views and features, and a collaborative working mechanism is introduced to balance the within-view clustering quality and the cross-view clustering consistency.

Also, in [22], authors proposed the image segmentation using Bat Algorithm with Fuzzy C Means clustering. The proposed segmentation technique was evaluated with existing segmentation techniques. On the other hand, in [23], the authors presented a hybridization of SKH and RKFCM clustering optimization algorithm for efficient moving object exploration.

Another recent study on this area is shown in [24], where the authors presented a hybrid interval type-2 semi-supervised possibilistic fuzzy c-means clustering and particle swarm optimization for satellite image analysis.

Also, in [25] a fuzzy based unequal clustering and context aware routing procedure with glow-worm swarm optimization was developed in random way point based dynamic wireless sensor networks. Based on fuzzy systems the unequal clustering is formed and the optimal cluster head is nominated to convey the information from cluster member to base station to increase the system lifespan and to decrease the energy consumption.
Table 1: Popular Bio-inspired Optimization Algorithms based on swarms, physics, populations, chemistry and evolution.

| Year | Algorithms and references |
|------|---------------------------|
| 2021 | Horse herd optimization algorithm [26] |
| 2020 | Mayfly Optimization Algorithm [27] |
| 2020 | Chimp Optimization Algorithm [28] |
| 2020 | Coronavirus Optimization Algorithm [29] |
| 2020 | Water strider algorithm [30] |
| 2020 | Newton metaheuristic algorithm [31] |
| 2020 | Black Widow Optimization Algorithm [32] |
| 2019 | Harris hawks optimization [33] |
| 2019 | Sailfish Optimizer [34] |
| 2019 | Spider Monkey Optimization [35] |
| 2017 | Grasshopper Optimisation Algorithm [36] |
| 2017 | Fractal Based Algorithm [37] |
| 2017 | Bacterial Foraging Inspired Algorithm [18] |
| 2017 | Rain-fall Optimization Algorithm [38] |
| 2016 | Dragonfly algorithm [39] |
| 2016 | Sperm Whale Algorithm [40] |
| 2015 | Water-Wave Optimization [41] |
| 2015 | Ant Lion Optimizer [42] |
| 2014 | Symbiotic Organisms Search [43] |
| 2013 | Egyptian Vulture Optimization Algorithm [44] |
| 2013 | Dolphin echolocation [45] |
| 2012 | Great Salmon Run [46] |
| 2012 | Big Bang-Big Crunch [47] |
| 2012 | Flower Pollination Algorithm [48] |
| 2011 | Spiral Optimization Algorithm [49] |
| 2011 | Galaxy-based Search Algorithm [50] |
| 2010 | Japanese Tree Frogs [51] |
| 2010 | Bat Algorithm [15] |
| 2010 | Termite Colony Optimization [14] |
| 2010 | Firefly Algorithm [20] |
| 2009 | Cuckoo Search [19] |
| 2009 | Glowworm Swarm Optimization [52] |
| 2009 | Bee Colony Optimization [53] |
| 2009 | Gravitational Search Algorithm [54] |
| 2008 | Fast Bacterial Swarming Algorithm [55] |
| 2007 | River Formation Dynamics [56] |
| 2007 | Imperialistic Competitive Algorithm [57] |
| 2008 | Roach Infestation Optimization [58] |
| 2006 | The bees Algorithm [13] |
| 2006 | Cat Swarm Optimization [17] |
| 2004 | BeeHive [59] |
| 2003 | Queen-Bee Evolution [60] |
| 2001 | Harmony Search Algorithm [61] |
| 1995 | Particle Swarm Optimization [16] |
| 1992 | Genetic Programming [62] |
| 1992 | Ant Colony Optimization [12, 63] |
| 1989 | Tabu Search [64] |
| 1975 | Genetic Algorithms [65] |
3. Bio-Inspired Optimization Methods

This section presents the algorithms used as reference in this study. After making a complete review of the methods above mentioned. We decide to include, in making our study, some important and relevant methods along the history. Though, there are many algorithms, it is impossible to include all methods. However, with these selected methods it is possible to give us an idea of the relationship of authors, citations, cluster of work networks with specific queries from high impact journals and other important information. The main aim of this section is to briefly outline the basic concepts of several bio-inspired optimization algorithms for a better comprehension of the importance of this area. The selected algorithms are presented in the following sub-sections.

3.1. Genetic Algorithms

John Holland, from the University of Michigan initiated his key work on genetic algorithms at the beginning of the 1960s. His first achievement was the publication of Adaptation in Natural and Artificial Systems in 1975, developing a popular method in the evolutionary computation field, known as genetic algorithm. In the simple genetic algorithm, the representation used is a bit string. Each position in the string is assumed to represent a particular feature of an individual, and the value stored in that position represents how that feature is coded in the solution. Usually, the string is “evaluated as a collection of structural features of a solution that have little or no interactions”. The analogy may be drawn directly to genes in biological organisms. Each gene represents an entity that is structurally independent of other genes. The main reproduction operator used is bit-string crossover, in which two strings are used as parents and new individuals are formed by swapping a sub-sequence between the two strings. Another popular operator is bit-flipping mutation, in which a single bit in the string is flipped to form a new offspring string. A variety of other operators have also been developed, but are used less frequently. A primary distinction that may be made between the various operators is whether or not they introduce any new information into the population. Crossover, for example, does not while mutation does. All operators are also constrained to manipulate the string in a manner consistent with the structural interpretation of genes. For example, two genes at the same location on two strings may be swapped...
The system is initialized with a random population distribution from a large (positive) A, depending on the
that are created replace the parents. For example, if N parents are selected, then N offspring are generated which replace the parents in the next generation [65].

3.2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as the Genetic Algorithms (GA). The system is initialized with a random population of solutions and searches for optima by updating generations. However, unlike the GA, the PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current best particles [1,11,66].

Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

3.3. Cuckoo Search Algorithm

Cuckoo Optimization Algorithm is based on the life of a bird called ‘cuckoo’. The basis of this novel optimization algorithm is specific breeding and egg laying of this bird. Adult cuckoos and eggs are used in this modeling. The cuckoos which are adult lay eggs in other birds’ habitat. These eggs grow and become a mature cuckoo if they are not found and not removed by host birds. The immigration of groups of cuckoos and environmental specifications hopefully lead them to converge and reach the best place for reproduction and breeding. The objective function is in this best place [19]. CSA is a new continuous over all aware search based on the life of a cuckoo bird. Similar to other meta heuristic, CSA begins with a main population, a group of cuckoos. These cuckoos lay some eggs in the habitat of other host birds. A random group of potential solutions is generated that are considered to represent the habitat in CSA.

3.4. Bat Algorithm

Bat algorithm (BA) is a bio-inspired algorithm inspired on bat behavior and BA has been found to be very efficient. If we idealize some of the echolocation characteristics of, we can develop various bat-inspired algorithms or bat algorithms. For simplicity, we now use the next idealized rules:

1. All bats use echolocation to sense distance, and they also ‘know’ the difference between food/prey and background barriers in some unknown way.
2. Bats fly randomly with a fixed frequency, varying wavelength and loudness A0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r [0, 1], depending on the proximity of their target.
3. Although loudness can vary in many ways, we assume that the loudness varies from a large (positive) A0 to a minimum constant value Amin.

For simplicity, the frequency f is in [0, {max}], the new solutions and velocity at a specific time step t are represented by a random vector drawn from a uniform distribution [15].

4. Experimental Results

In this section, is presented the obtained results with the different tools available in the literature for building the networks clusters, relationships, citations, with the analyzed methods. To validate the queried information of Web of Science, the VosViewer
tool [67] was used. However, this type of studies can be made by other similar tools to make bibliometric analysis. For example, Bibliometrix [68] is a free tool that provides various routines for importing bibliographic data from SCOPUS and Clarivate Analytics' Web of Science databases; Bibliotool [69], is a set of python scripts written by Sebastian Grauwin. They can read ISI data in CSV format and do some studies including co-occurrence map and bibliographic coupling; finally, CiteSpace [70] is a free Java-based software for visualizing and analyzing trends and patterns in the scientific literature. It is designed as a tool for progressive knowledge domain visualization.

4.1. Study with Genetic Algorithms

In this section, is presented the obtained results of the queries in Web of Science with the topic ‘optimization fuzzy clustering with genetic algorithms’. First, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc. Figure 2, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 92 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, if the keyword ‘genetic algorithm’ is selected, we can appreciate the number of clusters is 7 for this selection, with 88 links, and 141 occurrences.

Figure 3, represents the selection of the keyword ‘genetic algorithm’ that corresponding to the information obtained from Figure 2.

Figure 4, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 2 and Figure 3. It can be seen how the number of citations and papers with the analyzed topic has been increasing in recent years.

Also, with this information was possible to observe, the record by authors, where in Figure 5, it can be appreciated that two authors are the leaders in this area with the topic ‘optimization fuzzy clustering with genetic algorithms’.

4.2. Study with Particle Swarm Optimization

In this section, is presented the obtained results of the queries in Web of Science with the topic ‘optimization fuzzy clustering with genetic algorithms’. First, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc. Figure 6, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 116 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, if the keyword ‘particle swarm optimization’ is selected, we can appreciate the number of cluster is 8 for this selection, with 108 links, and 234 occurrences.

Figure 7, represents the selection of the keyword ‘genetic algorithm’ that corresponding to the information obtained from Figure 6.

Figure 8, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 6 and Figure 7. It can be seen how the number of citations and papers with the analyzed topic has been increasing in recent years.
Figure 2. Total cluster obtained with the search ‘optimization fuzzy clustering with genetic algorithms’ from VOS viewer.

Also, with this information was possible to observe, the records by authors, where in Figure 9, it can be appreciated that two authors are the leaders in this area with the topic ‘optimization fuzzy clustering with particle swarm optimization’.

4.3. Study with Cuckoo Search Algorithm

In this section, we present the obtained results of the queries in Web of Science with the topic ‘optimization fuzzy clustering with Cuckoo Search Algorithm’. The main difference with the other analyzed algorithms was that only 23 papers were found with the reviewed topic. Also, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc. Figure 10, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 3 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, we can appreciate the number of clusters is 2 as can be seen in Figure 10 with only 1 link. With these results, it can be seen that this method has not been widely used or combined with fuzzy clustering.

Figure 11, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 10. It can be seen how the number of citations and papers are less than the other analyzed methods.

Also, with this information was possible to observe, the records by authors, where in Figure 9, it can be appreciated that two authors are the leaders in this area with the topic ‘optimization fuzzy clustering with cuckoo search algorithm’.
In this section, is presented the obtained results of the queries in Web of Science with the topic 'optimization fuzzy clustering with Bat Algorithm'. The main difference with the other analyzed algorithms was that only 23 papers were found with the reviewed topic. Also, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc. Figure 13, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 3 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, we can appreciate the number of clusters is 1 as can be seen in Figure 13 with only 1 link.
**Figure 4.** Citation report for 369 results from Web of Science Core Collection

**Figure 5.** Record by authors for TOPIC: (optimization fuzzy clustering with genetic algorithms)
With these results, it can be seen that this method has not been widely used or combined with fuzzy clustering.

Figure 14 shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 13. It can be seen how the number of citations and papers are less than the other analyzed methods.

Also, with this information was possible to observe, the record by authors, where in Figure 15, it can be appreciated that two authors are the leaders in this area with the topic ‘optimization fuzzy clustering with bat algorithm’.

4.5. Analysis by authors

In this section is presented an analysis by authors, considering the total cites from web of science, we can appreciate that the author with more works in this area with the analyzed algorithms in this paper is Witold Pedrycz from the University of Alberta, Canada. According with the information collected of Web of Science, Figure 16 shows the total of the publications of this author.

Figure 17, was calculated in Vos Viewer and represents the relationship authors with Witold Pedrycz in the area of fuzzy clustering. The graph, was made considering the global work with a total of 1001 works collected from Web of Science.
Figure 7. Representing the selection of the keyword 'particle swarm optimization'.
Figure 8. Citation report for 508 results from Web of Science Core Collection

Figure 9. Record by authors for TOPIC: (optimization fuzzy clustering with particle swarm optimization)
Figure 10. Total cluster obtained with the search ‘optimization fuzzy clustering with cuckoo search optimization’ from VOS viewer.

Figure 11. Citation report for 23 results from Web of Science Core Collection.
Figure 12. Record by authors for TOPIC: (optimization fuzzy clustering with cuckoo search algorithm)

Figure 13. Total cluster obtained with the search ‘optimization fuzzy clustering with cuckoo search optimization’ from VOS viewer
Figure 14. Citation report for 23 results from Web of Science Core Collection

Figure 15. Record by authors for TOPIC: (optimization fuzzy clustering with bat algorithm)
Figure 16. Citation report for 1,001 results from Web of Science Core Collection by the author Witold Pedrycz.

Figure 17. Clusters by authors on Vos Viewer
5. Conclusions

After reviewing the state of the art about area optimization fuzzy clustering with optimization methods. We decided to make an analysis, considering four optimization methods, which we have used in the last year. With all collected information of Web of Science, Vos Viewer tool, we can observe that Genetic Algorithms and Particle Swarm Optimization are two very popular methods that the authors have been using in the last years. On the other hand, Cuckoo Search and Bat Algorithm, are two methods newer than the other two. However, not many authors have attempted to make fuzzy clustering using these two methods. Also, we were able to review the author with more works in this area. As a future work, this review can be extended analyzing other optimization methods with fuzzy clustering. The type of queries can be made by authors, keywords, occurrences, etc. However, with the paper can be reviewed the software and tools used and can be extracted all the information here presented.

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