A Survey of Image Segmentation based on Evolutionary Computation and Clustering Techniques

J. Hajiram Beevi
PG and Research Department of Computer Science
Jamal Mohamed College (Autonomous)
(Affiliated to Bharathidasan University)
Trichy, Tamil Nadu, India

O.A. Mohamed Jafar
PG and Research Department of Computer Science
Jamal Mohamed College (Autonomous)
(Affiliated to Bharathidasan University)
Trichy, Tamil Nadu, India

A.R. Mohamed Shanavas
PG and Research Department of Computer Science
Jamal Mohamed College (Autonomous)
(Affiliated to Bharathidasan University)
Trichy, Tamil Nadu, India

ABSTRACT

Image segmentation is treated as the fundamental problem in image processing. Its execution has a notable impact on further analysis. However, there exist many algorithms and approaches for image segmentation. Evolutionary Computation Algorithms have been given considerable attention in the area of image segmentation due to their capability in providing optimal solutions for many practical applications. Meanwhile, Clustering is also one of the commonly used image segmentation techniques. There are rarely any exhaustive surveys on Evolutionary Computation and Clustering Algorithms based on image segmentation methods, which can entitle the researchers to obtain a quick perception of these areas and compare the existing methods. Therefore, this survey briefly discusses some of the works done by the researchers using Evolutionary Computation and Clustering Algorithms. This survey leads to the conclusion that the field of Evolutionary Computation is growing fast. The continuous advancement of Evolutionary Computation will surely help to resolve many complex image segmentation tasks in the future.

General Terms

Image Segmentation, Evolutionary Computation, Clustering

Keywords

Image Segmentation, Clustering, Evolutionary Computation, Segmentation Techniques, Performance Metrics

1. INTRODUCTION

The major objective of image processing is to fetch the essential information from the given image in a way that it will not affect the other features of that image. Image denoising/enhancement is the foremost step needed to carry out this prerequisite. After noise elimination from an image, any operation can be performed on that image. Image segmentation is the technique in which the image is split into multiple regions in the forms of pixels or broken down into dissimilar objects and regions. Each region will provide some type of information to the user in the form of color, intensity or texture. Therefore, it is essential to separate the edges of any image in the form of its segments. The main objective of image segmentation is to represent the image into a smooth and noise free one [1].

The significance of image segmentation can't be negligible because it is employed nearly in all fields of science. The segmented images are frequently provided as the input to top-level image processes, such as feature extraction, object detection, image recognition and classification. It is noticed that it is not an easy process to design a universal technique for image segmentation. Since a technique applied to one image may not be suitable to the other type of image and therefore, one may have to choose the technique, based on the needs from one's own perspective. However, segmenting an image has a computational overhead. From the list of available techniques, the two most used efficient techniques are Clustering and Evolutionary computation algorithms. Clustering is the most essential data mining process. The process of divisioning an unlabeled data set into a class of similar objects is known as Clustering. Each class comprises objects which are similar between themselves and dissimilar to objects of other classes. Clustering is applied as a data processing technique in many different areas, including Artificial Intelligence, Bio-Informatics, Information Retrieval, Image Processing, and Machine Learning and so on [2].

Evolutionary Computation is now an indivisible branch of Artificial Intelligence (AI), Machine Learning and Smart Systems. Evolutionary Computation is an almost hot and appealing area of research which employs biological evolution principles in order to resolve computational problems with different complexities [3]. The overall goal of this paper is to discuss Clustering and Evolutionary Computation Algorithms briefly and analyze the improvements over existing methods and identify the problems and challenges in image segmentation.

The rest of the paper is organized as follows. Image segmentation and important evaluation metrics are described in section 2. In section 3, Clustering techniques, and a survey about existing works on image segmentation using Clustering are presented. Section 4 presents Evolutionary Computation Algorithms and a survey about the existing works on image segmentation using Evolutionary Computation. A brief discussion is also provided in section 5. Finally, conclusions are presented in section 6.

2. IMAGE SEGMENTATION

Image segmentation is a basic processing step that splits an image into meaningful segments based on pixel properties like color, intensity, and sharpness. Two of the major categories of methods for image segmentation approaches are discontinuity-based and similarity-based. Discontinuity-based segmentation focuses on variations in intensity values, which frequently involves edge detection techniques using first or second-order derivatives. Similarity-based segmentation groups pixels into regions with similar properties and comprises two primary approaches: threshold-based segmentation, which classifies pixels according to a predetermined threshold, and region-based segmentation, which groups pixels sharing similar features like color or intensity. These approaches offer essential resources for extracting and analyzing meaningful image data [4].

Image segmentation techniques are widely used in various areas, namely document processing, object detection, remote sensing, and health care. In medical imaging, image segmentation involves separating organs, disease regions, tumors, or anomalies to help in diagnosis, identify pathology, and monitor the advancement of diseases. Medical Image Segmentation is an extremely difficult task due to the slow grayscale variation in medical images, making it difficult to distinguish objects. Various image segmentation methods have been presented over the last few decades. As new segmentation methods have emerged, a number of evaluation metrics have been used to provide accurate comparisons with existing methods. These metrics also play an important role in the validation of the model. Over the years, a wide range of evaluation metrics has been proposed in the literature. The details of some of these metrics are discussed below. Accuracy - The percentage of correct predictions (both true positives and true negatives) among every case is measured as accuracy. Formula might be stated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision - It measures the proportion of true positive predictions out of all positive predictions made by the model. The formula is as follows:

$$Precision = \frac{TP}{TP + FP}$$

Sensitivity - It is commonly referred to as true positive rate, calculates the proportion of true positives correctly identified. The formula can be expressed as follows:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity - It is commonly referred to as the true negative rate, calculates the proportion of true negatives correctly identified [5]. Formula might be stated as follows:

$$Specificity = \frac{TN}{TN + FP}$$

Peak Signal-to-Noise Ratio (PSNR) - It is used to measure the quality of reconstructed or compressed images. It compares the maximum possible signal power to the power of distorting noise. The formula is stated as follows:

$$PSNR = 10 \cdot \log_{10}\left(\frac{I_{\max}^2}{MSE}\right)$$

Mean Squared Error (MSE) - It is a common metric used to measure the average squared difference between the original values and the predicted values. It is frequently used to assess the quality of reconstruction or the performance of a model in regression tasks [6]. Formula for MSE for a segmentation task:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2$$

Structural Similarity Index Measure (SSIM) - It is a perceptual metric that compares the structural similarity between two images. It considers luminance, contrast, and structure to evaluate segmentation quality. Formula might be stated as follows:

$$SSIM(X,Y) = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)}$$

Feature Similarity Index Measure (FSIM) - It evaluates image quality by comparing low-level features such as gradient magnitude and phase congruency. It measures feature preservation in segmentation [7]. The formula is as follows:

$$FSIM(X,Y) = \frac{\sum_{i=1}^{N} S_L(i) \cdot PC_m(i)}{\sum_{i=1}^{N} PC_m(i)}$$

3. CLUSTERING

Clustering is an unsupervised technique, in which objects are grouped into similar groups; objects in the same cluster are identical, while objects in different clusters are different. It plays a significant role in examining patterns by grouping them into similar groups. Efficient clustering based on factors such as initial conditions, similarity measures, and criteria functions. It consists of four steps: feature selection, design of clustering algorithm, cluster validity analysis, and result interpretation, which guarantee precise data partitioning. It is categorized into two types: hard clustering, where each element belongs exclusively to one cluster, and fuzzy clustering, where elements have partial memberships in multiple clusters. In image processing, it is used to discover similar image primitives for efficient segmentation. Several clustering techniques, like hard and fuzzy methods, have been implemented to increase segmentation efficiency, each offering specific advantages for various applications [8]. It is more flexible than classification and helps identify features in diverse groups. Even so, it may face challenges like fragmented or dispersed segments, which can be resolved by using pixel coordinates, though this might divide large areas. K-Means is valued for its simplicity and speed but struggles with random centroid selection and high computational costs in image segmentation. Fuzzy C-Means (FCM) effectively handles ambiguities and retains more detail but is sensitive to noise and outliers. Despite their limitations, both methods are efficient and serve as a foundation for advanced image segmentation research [9].

3.1 K-Means Algorithm

K-Means algorithm divides a dataset of n objects into K clusters with the goal of increasing intra-cluster similarity and decreasing inter-cluster similarity. The algorithm depends on the predefined value of K, with clustering results varying according to the chosen value. Later, K centroids are randomly selected, and objects are assigned to clusters according to their Euclidean distance to the centroids. The cluster centroids are then updated iteratively by recalculating the mean value of the objects in each cluster, repeating the process until convergence is achieved. Although the algorithm is easy to understand, it has shortcomings, including sensitivity to noise, outliers, and the risk of being trapped in local minima. Researchers have developed several improved versions of K-Means to overcome these challenges [10].

3.2 Fuzzy C-Means Algorithm

The Fuzzy C-Means algorithm was initially introduced by Joe Dunn in 1974 and modified by Jim Bezdek in 1981, is a highly effective clustering technique. In contrast to hard clustering, FCM allows objects to belong to several clusters with partial membership values ranging from 0 to 1, assuring the total membership sum for each object equals 1 [11]. It operates iteratively by calculating centroids and membership measures, adjusting these values after each step until convergence criteria or a fixed number of iterations are met. It is popularly used in image segmentation because of its robustness in handling uncertainty and its ability to preserve additional information. However, it is sensitive to noise and artifacts, as it lacks spatial context in its computations [12].

3.3 Literature Survey on Clustering

This section provides a detailed survey of prior works on K-Means Clustering and Fuzzy C-Means Clustering used for image segmentation, showcasing their methodologies, performance metrics, dataset used, and purpose of the work. These are summarized in Table 1 and 2. Both algorithms, known for their effectiveness in clustering, have been extensively used in segmenting images into meaningful regions using pixel similarities.

Table 1. Research Contributions by different authors based on K-Means Clustering.

Author	Method	No of images / Name of datasets	Purpose	Performance Metrics
Debelee et al., 2019 [14]	Modified Adaptive K-Means	13 images	To improve image segmentation quality and computational cost	Q-value, Computation time, PSNR
Febrinanto et al., 2019 [15]	K-Nearest Neighbor and K-Means	136 leaf images	To identify diseases on citrus leaves	Accuracy
Basar et al., 2020 [16]	Enhanced K-Means	Berkeley Segmentation Dataset (BSDS) 500	To optimize K-means clustering initialization parameters	MSE
Kumar et al., 2020 [17]	Membership K-Means	11 images	To enhance color separation of satellite images	Computational Cost
Islam et al., 2021 [18]	K-Means	BSDS300	To improve image segmentation accuracy	Probabilistic Rand Index
Saifullah et al., 2021 [19]	K-Means	Fish Image dataset	To improve image quality through preprocessing techniques	SSIM

4. EVOLUTIONARY COMPUTATION

Evolutionary Computation (EC) is a branch of Artificial Intelligence. It usually tackles the problems of continuous optimization or combinatorial optimization. It has received much attention in image processing because of their ability to manage numerous optimization tasks simultaneously and their intelligent features including self-organization, adaptation, and self-learning. It has been efficiently used for problems such as image segmentation, edge detection, and object detection, particularly in scenarios where conventional methods are ineffective or produce poor results. Inspired from biological processes, EC algorithms resolve challenges including high partitioning costs and large search spaces by using natural selection-based search methods. It makes EC-based image segmentation a well-known and highly researched area in modern image processing.

When using EC techniques to conduct image segmentation, most of the existing works incorporate them with other traditional segmentation approaches. In hybrid types of approaches, EC takes the role of optimizing parameters or minimizing/maximizing objective function [13].

Image segmentation requires a universal method as each image has distinct foreground and background features, and traditional approaches depending on texture information are not always successful. Evolutionary Computation approaches stand out in image segmentation because of their independence from critical parameters, threshold values, or prior image knowledge, coupled with their robust search capabilities. These techniques have been efficiently used to multilevel thresholding and optimization tasks, avoiding local minima and providing effective solutions. Common EC-based segmentation algorithms are Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Bacterial Foraging Optimization (BFOA), Genetic Algorithm (GA) and so on. In this section, state-of-the-art algorithms are discussed.

4.1 Ant Colony Optimization Algorithm (ACO)

ACO algorithm was introduced by Dorigo et al., is a meta-heuristic technique designed to solve complex combinatorial optimization problems effectively. Inspiration from the behavior of real ants during food searching, it uses their social communication system using pheromones?chemical trails left by ants. Ants tend to choose paths with higher pheromone concentrations. Over time, pheromone levels on longer paths decrease because of evaporation, while shorter paths keep higher concentrations, leading ants more effectively. Initially, ants explore randomly, but as pheromone patterns form, they increasingly prefer shorter paths [20]. In the ACO Algorithm, artificial ants use a pheromone model to construct solutions. Pheromone levels are updated iteratively depending on the quality of previous solutions, and it continues until a predefined

Table 2. Research Contributions by different authors based on Fuzzy C-Means Clustering.

Author	Method	No of images / Name of datasets	Purpose	Performance Metrics
Li et al., 2019 [21]	Fuzzy Clustering with Cellular Automata and Feature Weighting	Berkeley image segmentation dataset	To address FCM's sensitivity to initial clustering centers	PSNR, Precision, Kappa Coefficient
Nayak and Bhoi, 2019 [22]	FCM and Normal Shrink Denoising and Membership Filtering	Weizmann dataset	To reduce noise impact in images	Accuracy, Sensitivity, F-measure, Precision, Dice, Jaccard, Specificity
Shang et al., 2020 [23]	Thumbnail based Hierarchical FCM	2 Simulated Synthetic Aperture Radar (SAR) images, 4 Real SAR images	To improve segmentation accuracy and computational efficiency	Accuracy
Wang et al., 2021 [24]	Residual driven FCM	Brain Web, BSDS, Near Earth Object	To enable accurate noise estimation in image clustering	Accuracy
Mohammdian khoshnoud et al., 2022 [25]	FCM and Gray Wolf	Breast Cytology images	To overcome FCM's limitations in cytology image analysis	Variance Partition Coefficient (Vpc), Variance Partition Entropy (Vpe), Davies Bouldin, Calinski Harabasz
Vikraman and Afthab, 2023 [26]	FCM and Raindrop Optimization Algorithm	Brain Tumor Segmentation 2018	To improve lesion detection and diagnosis accuracy	Partition Entropy, Partition Coefficient

stopping criterion is met. The pheromone model is central to ACO's success in optimization tasks. ACO algorithms are more efficient because the construction graph applied in the ACO algorithm can reduce the amount of redundant information in the search space represented. It also has fewer parameters and a high level of reliability. Another advantage of ACO is that it just requires small tweaks when it is used to address a different problem [27].

4.2 Particle Swarm Optimization Algorithm (PSO)

PSO algorithm is a popular Swarm Intelligence technique which is used to solve optimization problems by mimicking bird flocking behavior. According to this example, birds search for food collectively, and the best way to find food is to follow the bird that is closest to it. Likewise, in PSO, possible solutions are given as particles in an n-dimensional search space, where every particle's fitness value is calculated by the objective function. Particles change their position and velocity iteratively, controlled by two key values: pbest (the particle's best position so far) and gbest (the best position found by any particle in the swarm). It adjusts particle velocities and positions depends on these values, allowing them to converge toward the optimal solution through collaboration and exploration. This iterative process guarantees efficient exploration of the solution space [28]. The key advantage of the PSO algorithm is that it converges faster than many other global optimization algorithms. When compared to mathematical algorithms and other heuristic optimization techniques, PSO algorithms offer many advantages, including: simple concept, easy implementation, robustness to control parameters which avoids unnecessary local convergence, less sensitivity to the nature of the objective function, less dependence on set of initial points, and computation efficiency [29].

4.3 Artificial Bee Colony Algorithm (ABC)

ABC Algorithm is a swarm intelligence-based algorithm presented by Karabaga in the year 2015, which is influenced by the functioning of honey bees. In the ABC Algorithm, three types of bees are listed. They are (i) employed bees – The bees who give out the information regarding food sources to the onlooker bees (ii) onlooker bees – The main task of these type of bees is to choose the best food sources from those identified by the employed bees (iii) The scout bees – These are actually the employed bees which have given up their food sources and then are transformed to scout bees. In the ABC Algorithm, the foremost half of the swarm comprises employed bees and the other half comprises the onlooker bees. The number of solutions in the swarm should be equal to either the number of employed bees or the onlooker bees [30]. The ABC algorithm offers less sensitivity to initial conditions. Another advantage of using this algorithm is the faster convergence and less computation cost. In addition, the ABC algorithm offers better convergence rate, segmentation accuracy, time complexity and robustness [31].

4.4 Bacterial Foraging Optimization Algorithm (BFOA)

BFOA was introduced by Passino, and is motivated by the movement behavior of E. Coli bacteria. It moves by means of flagella, which revolve either counterclockwise or clockwise. It uses three main processes to function: Chemotaxis: Combines swimming and tumbling to recreate bacterial movement, Reproduction: Bacteria with better health are likely to survive and reproduce, Elimination and Dispersal: To explore a wider search space, some bacteria are randomly eliminated, while others are dispersed to new regions, improving global optimization. These processes collectively enable local and global searches, making BFOA effective for optimization problems [32]. The main advantages of BFOA are parallel distributed processing, insensitivity to initial value and global optimization. The reproduction operator of BFOA is conducive to improve the convergence speed of the algorithm. BFOA is used in the field of image segmentation because of its high robustness and good global search capability [33].

4.5 Genetic Algorithm (GA)

GA works on the basis of natural selection and genetics, which was proposed by John Holland in the year 1970 and influenced by the biological advancement of existence. GA interprets the specific problem as a sample of the population and tries to uncover the fittest single by creating generations repeatedly. In the course of all generations, three elementary genetic operators are subsequently used on every single person with specific probabilities i.e., selection, crossover and mutation. The search space in GA comprises strings, each of which can be represented as a possible solution to the issue and are called chromosomes. Each chromosome has a fitness value which is the result of its objective function value. A collection of chromosomes together with their related fitness is called a population. The population generated in each iteration of GA is known as generations [34]. Genetic algorithms are a straightforward and effective approach for image segmentation, especially for managing complex color images. It has advantages include non-arbitrariness, minimal dependence on the initial population, and faster convergence to optimal solutions without the need of threshold values. They are particularly suitable for optimization problems, as they do not require differentiating the fitness function, only its evaluation. Additionally, with a sufficiently large population relative to the search space, they guarantee the optimal value of the fitness. This adaptability has led to growing interest in combining genetic algorithms with other methods for improved segmentation outcomes [35].

4.6 Literature Survey on Evolutionary Computation

Algorithm, Particle Swarm Optimization Algorithm, Artificial Bee Colony Algorithm, Bacterial Foraging Optimization Algorithm, Genetic Algorithm for image segmentation are surveyed. The key contributions and improvements offered by each of these algorithms are summarized in Table 3. Hybrid algorithms are significant in image segmentation as they combine the powers of various techniques. They enhance accuracy and robustness, especially for complex images with various properties like textures, edges, and regions, which a single technique may not be so effective to process in detail. The key contributions and improvements offered by hybrid algorithms are summarized in Table 4. Both tables highlight the methodologies, performance metrics, dataset used, and the purpose of the work in image segmentation. This comprehensive overview helps in understanding the comparative effectiveness of different optimization techniques for image segmentation tasks.

5. DISCUSSION

Over the last decade, there has been an increasing attention in image segmentation for which various algorithms and approaches have been proposed. Among these approaches and algorithms, evolutionary computation and clustering algorithms are the most important techniques for image segmentation. They have gained outstanding attention among the researchers due to their simplicity, flexibility and effectiveness. They have found success in resolving image segmentation problems with promising results. Researchers have brought in novel approaches, refinements and concepts in order to enhance the performance and quality of image segmentation techniques. In image processing, clustering identifies groups of similar image elements. K-Means Clustering is popular because of its fast convergence and simplicity. It is used in tasks such as object detection, pre- processing, noise reduction, and increasing clustering accuracy. Research has also focused on enhancing its objective function and resolving issues like random initial cluster assignments.

Fuzzy C-Means Clustering is a popular technique for image segmentation, and has the benefit of keeping more data compared to hard clustering methods. Research advancements include changes to the objective function, nearest-neighbor interpolation, similarity measures, and enhanced cluster center calculation. Even so, traditional FCM has challenges like noise sensitivity, computational complexity, and dependence on initial cluster centers, which might result in local minima.

Evolutionary Computation is emerging as an alternative to traditional image segmentation techniques. ACO efficiently manages incomplete, complex, and nonlinear data. It is useful for tasks like image segmentation, scheduling and routing because of its simplicity and standard procedures. In image segmentation, ACO has been enhanced with features like pheromone evaporation, new picking and dropping functions, entropy-based metrics, and multiple ant colony approaches. Although ACO is simple and easy to implement, its performance depends highly on input parameters, which results in lower segmentation quality and longer processing times for large image datasets [36]. PSO, inspired by social behavior, is a widely used Evolutionary Computation technique for systematic search and optimization. It needs minimal information about the function being optimized and uses common mathematical operations. Researchers have improved PSO for image segmentation with enhanced fitness functions, improved local and global optimization, adaptive heuristics, multi-level thresholds, and entropy metrics. PSO is simple to implement, has few configurable parameters, and provides strong optimization capabilities [37]. ABC algorithm is a powerful optimization technique known for its simplicity, low sensitivity to noise, and robust exploration capabilities. But whereas ABC is excellent in exploration, it performs less effectively in exploitation. To increase its efficiency in image segmentation, researchers have implemented advancements like improved objective functions using PSNR, enhanced global minima achievement, automatic multi-threshold selection, less noise sensitivity, increased segmentation accuracy, stronger local search capabilities, optimal threshold values, centroid verification for clusters, and entropy-based methods.

The BFO algorithm has gained attention for its biological inspiration and structured layout. BFO has given to improvements such as better thresholding, improved local search capabilities, and refined objective functions. However, its limitations include a fixed step size, which makes it difficult to balance exploration and exploitation, and weak interactions between bacteria, increasing the risk of converging to a local rather than a global optimum.

GA is a powerful optimization technique widely used in image processing due to its ability to handle complex problems and its parallelism. In image segmentation, GA can identify the maximum number of regions in a segmentation result. However, its performance depends heavily on factors like the fitness function, population size, mutation and crossover rates, and selection criteria. Poor choices can lead to meaningless results. To enhance GA?s efficiency in image segmentation, researchers have introduced improvements such as better segmentation accuracy, automatic threshold detection, improved fitness functions, and evaluation criteria.

For image segmentation, using a single algorithm often fails to deliver the optimal results. Although they work well separately, evolutionary computation and clustering algorithms are more

Table 3. Research Contributions by different authors based on Evolutionary Algorithms.

Author	Method	No of images / Name of datasets	Purpose	Performance Metrics
Asgari et al., 2018 [38]	ACO	Document Image Binarization Contest dataset	To automate threshold selection	PSNR
Chouhan et al., 2019 [33]	BFOA	240 images	To improve image segmentation efficiency	Jaccard Coefficient
Kumari et al., 2019 [39]	Threshold GA	5 images	To improve Genetic Algorithm suitable for multi-level thresholding	PSNR, Normalized Absolute Error
Dahiya et al., 2022 [40]	Modified ABC	Brain Tumor Segmentation dataset	To improve accuracy in tumor detection and delineation	Precision, Accuracy, Specificity, Sensitivity, F-measure
Su et al., 2022 [41]	Improved ABC	COVID-19 chest X-rays and CT images	To enhance multilevel thresholding image segmentation for COVID-19 X-ray images	PSNR, SSIM, FSIM
Holland et al., 2023 [42]	Hybrid GA	Ultrasound Nerve dataset	To enhance medical image segmentation performance	Intersection over Union
Murinto et al., 2023 [43]	Modified PSO	Multispectral images	To improve multispectral image segmentation	Execution time, MSE, PSNR, SSIM, Variation of Information, Probability Rand Index
Huang et al., 2024 [44]	Improved GA	522 Breast Cancer Pathological images	To increase segmentation accuracy and efficiency	Sensitivity, Specificity, Accuracy, Dice Coefficient
Wang and Zhang, 2024 [45]	Ant Colony Algorithm	2 images	To enhance visual quality and accuracy of segmented images	Precision, Recall, F1-score, Intersection over Union

Table 4. Research Contributions by different authors based on Hybrid Approach.

Author	Method	No of images / Name of datasets	Purpose	Performance Metrics
El-Khatiba et al., 2019 [46]	Hybrid ACO-K-Means	Ossirixx image dataset	To apply drift analysis for complexity estimation	Accuracy
Dhanachandra and Chanu, 2020 [47]	Dynamic PSO and FCM	Synthetic and MRI images	To enhance noise reduction in image processing	Sensitivity, Specificity, Accuracy, Vpe, Vpc, MSE, PSNR, Correlation Coefficient
Zhi and Liu, 2020 [48]	FCM and ABC	3 images	To enhance accuracy and efficiency in image segmentation	Effectiveness index
Lu et al., 2020 [49]	Hybrid ACO and Snake Algorithm	lung CT scan images	To automate lung CT image segmentation	Accuracy, Computation Time
Verma et al., 2020 [50]	Hybrid FCM-PSO	Triangular dataset, IBSR normal brain dataset	To enhance clustering analysis of brain images	Accuracy, Recall, Precision, Similarity measure, Average Similarity Measure
Kulkarni, 2022 [51]	Hybrid Multiobjective GA	Multisensor RGB and Gray images, Multisensor medical images, Multifocus RGB images	To enhance image fusion techniques	Mutual Information, Image Quality Index, Spatial Frequency
Kanadath et al., 2023 [52]	PSO, Darwinian PSO, Fractional Order Darwinian PSO	Colonoscopy tissue segment data set	To segment lesion regions in colonoscopy images	Dice, Jaccard, Accuracy, Sensitivity, Precision, F-measure, Specificity
Sabha et al., 2023 [53]	PSO, Grey Wolf Optimizer, and Harris Hawks Optimization	CT scan images	To improve segmentation quality using meta-heuristic algorithms	PSNR, SSIM, Universal Quality Image Index

powerful when combined. Hybrid approaches have emerged as a promising area of research, offering enhanced capabilities for handling complex, imprecise, and uncertain real-world problems. Researchers have introduced innovative techniques in this domain, making it a preferred choice for complex segmentation tasks.

6. CONCLUSION

This survey highlights how clustering algorithms and evolutionary techniques for image segmentation have advanced significantly, especially in terms of their ease of use, ability to search globally, and less reliance on prior knowledge. These approaches have demonstrated potential in addressing issues such as segmentation accuracy, initialization settings, and noise reduction. Key challenges still need to be solved, yet, such as improving initialization parameters, refining autonomous cluster center selection, and increasing adaptability to various imaging conditions. Due to the complex relationships between color, texture, brightness, coherence, and image information, no single approach can effectively handle the wide range of requirements for image segmentation, despite its advantages. Consequently, combining multiple techniques or developing hybrid approaches has emerged as a promising direction to achieve better outcomes. But it produces additional costs and complexity, requiring a balanced analytical perspective. Future studies should focus on developing efficient approaches that combine evolutionary-clustering techniques, especially for use in real world applications. There is also an increasing need for approaches that can adjust their parameters to achieve better performance. These improvements could make it easier to use in important areas like medical diagnosis. The insights provided in this paper aim to guide researchers toward innovative solutions that bridge the existing gaps, ultimately advancing the field of image segmentation and broadening its applicability to diverse and complex imaging challenges.

7. REFERENCES

[1] Zaitoun, N. M., and Aqel, M. J. 2015. Survey on Image Segmentation Techniques. Procedia Computer Science, 65, 797–806.

[2] Dubey, S. K., Vijay, S., and Pratibha. 2018. A Review of Image Segmentation using Clustering Methods. International Journal of Applied Engineering Research, 13(5), 2484–2489.

[3] Liang, Y., Zhang, M., and Browne, W. N. 2014. Image Segmentation: a survey of methods based on evolutionary computation. In Lecture notes in computer science pp. 847–859.

[4] Saini, S., and Arora, K. 2014. A Study Analysis on the Different Image Segmentation Techniques. International Journal of Information & Computation Technology, 4(14), 1445–1452.

[5] Rajalakshmi, N. T. and Senthilnathan, N. R. 2023. Dataset and Performance Metrics towards Semantic Segmentation. International Journal of Engineering and Management Research, 13(1):40–49.

[6] Vlasceanu, G. V., Tarba, N., Voncila, M. L., Boiangiu, C. A., and Teodor, D. F. 2024. Selecting the right metric: A detailed study on image segmentation evaluation. Brain Broad Research in Artificial Intelligence and Neuroscience, 15(4):295.

[7] Sara, U., Akter, M., and Uddin, M.S. 2019. Image Quality Assessment through FSIM, SSIM, MSE and PSNR A Comparative Study. Journal of Computer and Communications, 07(03):8–18.

[8] Berkhin, P. 2006. A Survey of Clustering Data Mining Techniques. In: Kogan J, Nicholas C, TeboulleM (eds) Grouping Multidimensional Data, pp. 25–71.

[9] Aslam, Y., N, S., N, R., and K, R. 2020. A Review on Various Clustering Approaches for Image Segmentation. Proceedings of the Fourth International Conference on Inventive Systems and Control (ICISC 2020) IEEE Xplore Part Number: CFP20J06-ART; ISBN: 978-1-7281-2813-9.

[10] Shukla, S., Naganna, S. 2014. A Review on K-Means Data Clustering Approach. International Journal of Information & Computation Technology, vol 4, number 17, pp. 1847–1860, ISSN 0974-2239.

[11] Aneja, D., Rawat, T.K. 2013. Fuzzy Clustering Algorithms for Effective Medical Image Segmentation. International Journal of Intelligent Systems and Applications, 11, 55–61.

[12] Suganya, R., and Shanthi, R. 2012. Fuzzy C- Means Algorithm - A Review. International Journal of Scientific and Research Publications, 2(11).

[13] Larabi-Marie-Sainte, S., Alskireen, R., and Alhalawani, S. 2021. Emerging applications of Bio-Inspired Algorithms in image Segmentation. Electronics, 10(24), 3116.

[14] Debelee, T. G., Schwenker, F., Rahimeto, S., and Yohannes, D. 2019. Evaluation of modified adaptive k-means segmentation algorithm. Computational Visual Media, 5(4):347–361.

[15] Febrinanto, F. G., Dewi, C., and Triwiratno, A. 2019. The implementation of K-Means algorithm as image segmenting method in identifying the citrus leaves disease. IOP Conference Series Earth and Environmental Science, 243:1–11.

[16] Basar, S., Ali, M., Ochoa-Ruiz, G., Zareei, M., Waheed, A., and Adnan, A. 2020. Unsupervised color image segmentation: A case of RGB histogram-based K-means clustering initialization. PLoS ONE, 15(10), e0240015.

[17] Kumar, J., Nanda, R., Rath, R. K., and Rao, G. T. 2020. Image Segmentation using K-means Clustering. International Journal of Advanced Science and Technology, 29(6S), 3700–3704.

[18] Islam, M. Z., Nahar, S., Islam, S. S., Islam, S., Mukherjee, A., and Ali, L. E. 2021. Customized K Means Clustering Based Color Image Segmentation Measuring PRI. pp. 1–4.

[19] Saifullah, S., Suryotomo, A. P., and Yuwono, B. 2021. Fish detection using morphological approach based-on k-means segmentation. Compiler, 10(1).

[20] Pei, Y., Wang, W., and Zhang, S. 2012. Basic Ant Colony Optimization. International Conference on Computer Science and Electronics Engineering.

[21] Li, C., Liu, L., Sun, X., Zhao, J., and Yin, J. 2019. Image segmentation based on fuzzy clustering with cellular automata and features weighting. EURASIP Journal on Image and Video Processing, 2019(1).

[22] Nayak, T. N., and Bhoi, N. 2024. Robust fuzzy C-Means clustering algorithm based on normal shrink and membership filtering for image segmentation. CLEI Electronic Journal, 27(1).

[23] Shang, R., Chen, C., Wang, G., Jiao, L., Okoth, M. A., and Stolkin, R. 2020. A thumbnail-based hierarchical fuzzy clustering algorithm for SAR image segmentation. Signal Processing, 171, 107518.

[24] Wang, C., Pedrycz, W., Li, Z., and Zhou, M. 2021. Residual-driven fuzzy C-Means clustering for image segmentation. IEEE/CAA Journal of Automatica Sinica, 8(4), 876–889.

[25] Mohammdian-Khoshnoud, M., Soltanian, A. R., Dehghan, A., and Farhadian, M. 2022. Optimization of fuzzy c-means (FCM) clustering in cytology image segmentation using the gray wolf algorithm. BMC Molecular and Cell Biology, 23(1), 2.

[26] Vikraman, B. P., and Afthab, J. 2023. Fuzzy C-Means Approach Optimized using Raindrop Algorithm for Image Segmentation. In Atlantis Highlights in Computer Sciences/Atlantis highlights in computer sciences, pp. 33–44.

[27] Ticala, C., Pintea, C., and Matei, O. 2021. Sensitive ANT algorithm for edge detection in medical images. Applied Sciences, 11(23), 11303.

[28] Ab Wahab, M. N., Nefti-Meziani, S., and Atyabi, A. 2015. A Comprehensive Review of Swarm Optimization Algorithms. PLoS ONE, 10(5), e0122827.

[29] Kaur, A., and Singh, M. D. 2012. An Overview of PSO- Based Approaches in Image Segmentation. International Journal of Engineering and Technology, 2(8), 1349–1357.

[30] Xu, Y., Fan, P., and Yuan, L. 2012. A simple and efficient artificial bee colony algorithm. Mathematical Problems in Engineering, 2013:1–9.

[31] Ma, M., Liang, J., Guo, M., Fan, Y., and Yin, Y. 2011. SAR image segmentation based on Artificial Bee Colony algorithm. Applied Soft Computing, 11:5205–5214.

[32] Sahib, M. A., Abdulnabi, A. R., and Mohammed, M. A. 2018. Improving bacterial foraging algorithm using non-uniform elimination-dispersal probability distribution. Alexandria Engineering Journal, 57(4), 3341–3349.

[33] Chouhan, S. S., Kaul, A., and Singh, U. P. 2019. Plants Leaf Segmentation using Bacterial Foraging Optimization algorithm. pages 1500–1505.

[34] Haldurai, L., Madhubala, T., and Rajalakshmi, R. 2016. A Study on Genetic Algorithm and its Applications. International Journal of Computer Sciences and Engineering, 4(10):139–143.

[35] Kale, A., and Jain, A. 2014. A Review: Image Segmentation Using Genetic Algorithm. International Journal of Scientific & Engineering Research, 5(2).

[36] Khanna, K., and Arora, S. M. 2016. Ant Colony Optimization towards Image Processing. Indian Journal of Science and Technology, 9(48).

[37] Lee, KY., Park, JB. 2006. Application of Particle Swarm Optimization to Economic Dispatch Problem: Advantages and Disadvantages. In: 2006 IEEE PES Power Systems Conference and Exposiiton, Atlanta, GA, pp. 188–192.

[38] Asgari, M., Pirahansiah, F., Shahverdy, M., Fartash, M. 2017. Using an Ant Colony Optimization Algorithm for Image Edge Detection as a Threshold Segmentation for OCR System. Journal of Theoretical and Applied Information Technology, vol. 95, no. 21.

[39] Kumari, R., Gupta, N., and Kumar, N. 2019. Image Segmentation using Improved Genetic Algorithm. International Journal of Engineering and Advanced Technology, 9(1), 1784–1792.

[40] Dahiya, P., Kumar, A., Kumar, A., and Nahavandi, B. 2022. Modified Artificial Bee Colony Algorithm-Based Strategy for Brain Tumor Segmentation. Computational Intelligence and Neuroscience, 2022:1–13.

[41] Su, H., Zhao, D., Yu, F., Heidari, A. A., Zhang, Y., Chen, H., Quan, S. 2022. Horizontal and vertical search artificial bee colony for image segmentation of COVID-19 X-ray images. Computers in Biology and Medicine, 142, 105181.

[42] Holland, J., Djenouri, Y., Laidi, R., and Yazidi, A. 2023. Hybrid Genetic U-Net Algorithm for medical segmentation. Proceedings of the 14th International Conference on Agents and Artificial Intelligence, 558–564.

[43] Murinto, Prahara, A., and Ujianto, E. I. H. 2023. An Improved Segmentation Technique of Multispectral Image Using Modified Particle Swarm Optimization Algorithm. Int. J. Advance Soft Compu. Appl, 15(2).

[44] Huang, T., Yin, H., and Huang, X. 2024. Improved genetic algorithm for multi-threshold optimization in digital pathology image segmentation. Scientific Reports, 14(1).

[45] Wang, X. and Zhang, J. 2024. Image segmentation technology based on Ant Colony algorithm. J. Electrical Systems, 20(7s):1038–1042.

[46] El-Khatib, S., Skobtsov, Y., and Rodzin, S. 2019. Theoretical and experimental evaluation of hybrid ACO-K-Means image segmentation algorithm for MRI images using drift-analysis. Procedia Computer Science, 150, 324–332.

[47] Dhanachandra, N., and Chanu, Y. J. 2020. An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm. Multimedia Tools and Applications, 79(25?26), 18839–18858.

[48] Zhi, H., and Liu, S. 2020. Gray image segmentation based on fuzzy c-means and artificial bee colony optimization. Journal of Intelligent & Fuzzy Systems, 38(4), 3647–3655.

[49] Lu, M., Xu, B., Qin, W., and Shi, J. 2020. Hybrid Ant Colony Optimization-Based Method for focal of a disease segmentation in lung CT images. In Lecture notes in computer science, pp. 215–222.

[50] Verma, H., Verma, D., and Tiwari, P. K. 2020. A population-based hybrid FCM-PSO algorithm for clustering analysis and segmentation of brain image. Expert Systems with Applications, 167, 114121.

[51] Kulkarni, J. S. 2022. Image fusion by a hybrid multiobjective genetic algorithm technique. International Journal of Recent Technology and Engineering (IJRTE), 11(1), 123–128.

[52] Kanadath, A., Jothi, J. a. A., and Urolagin, S. 2023. Multilevel colonoscopy histopathology image segmentation using particle swarm optimization techniques. SN Computer Science, 4(5).

[53] Sabha, M., Thaher, T., and Emam, M. M. 2023. Cooperative swarm Intelligence algorithms for adaptive multilevel thresholding segmentation of COVID-19 CT-Scan images. JUCS - Journal of Universal Computer Science, 29(7), 759–804.