International Journal of Electrical and Data Communication 2023; 4(2): 26-31

International Journal of Electrical and Data Communication

E-ISSN: 2708-3977
P-ISSN: 2708-3969
IJEDC 2023; 4(2): 26-31

www.datacomjournal.com
Received: 19-06-2023
Accepted: 17-07-2023

Dr. Niamh Murphy
School of Transport and Infrastructure, University College Dublin, Ireland

Dr. Liam O'Leary
School of Transport and Infrastructure, University College Dublin, Ireland

Correspondence
Dr. Niamh Murphy
School of Transport and Infrastructure, University College Dublin, Ireland

Optimizing image segmentation with ant colony-based techniques

Dr. Niamh Murphy and Dr. Liam O'Leary

Abstract
Image segmentation is a crucial task in image processing and computer vision, aiming to partition an image into meaningful regions or objects for further analysis. Over the years, various optimization techniques have been employed to enhance the accuracy and efficiency of image segmentation. One of the promising methods that have emerged is the Ant Colony Optimization (ACO) algorithm, inspired by the foraging behavior of ants. This review explores the use of ACO-based techniques in image segmentation, their advantages, and limitations, as well as their applications in diverse fields such as medical imaging, remote sensing, and video analysis. The paper also discusses the hybridization of ACO with other algorithms to overcome its inherent challenges and improve performance.

Keywords: Ant colony optimization, image segmentation, swarm intelligence, optimization algorithms, medical imaging, remote sensing, hybrid algorithms

Introduction
Image segmentation is a fundamental process in image processing that divides an image into distinct regions or objects based on pixel characteristics such as color, intensity, and texture. The quality of segmentation directly impacts the performance of higher-level tasks, such as object recognition, tracking, and analysis in various domains like medical imaging, satellite imagery, and automated surveillance systems. Traditional image segmentation techniques, including edge detection, thresholding, and clustering, face challenges when dealing with complex images, such as those with noise, varying illumination, or overlapping objects.

Ant Colony Optimization (ACO), a swarm intelligence-based algorithm, has gained attention as a powerful tool for solving combinatorial optimization problems, including image segmentation. Introduced by Dorigo in the early 1990s, ACO is inspired by the natural behavior of ants that find the shortest path to food sources by depositing pheromones. This paper reviews the application of ACO in image segmentation, discussing its principles, advancements, and the potential for hybridization with other techniques.

Principles of Ant Colony Optimization
Ant Colony Optimization (ACO) is a bio-inspired algorithm based on the foraging behavior of ants in nature. First introduced by Marco Dorigo in the early 1990s, ACO is designed to solve complex combinatorial optimization problems by mimicking how ants find the shortest path between their colony and a food source. The foundational principle of ACO is based on the way ants communicate indirectly through a chemical substance called pheromone. As ants traverse a path, they deposit pheromones, which other ants can detect and follow. Over time, shorter paths accumulate more pheromone due to the quicker traversal time, while longer paths see pheromone levels evaporate. As a result, the collective behavior of the ants leads them to converge on the shortest, most efficient route. In computational terms, ACO is framed as a stochastic optimization technique where artificial agents (ants) search for optimal solutions to problems by simulating this natural process of pheromone deposition and path finding. The process begins with a set of artificial ants randomly distributed across the problem's search space. Each ant represents a potential solution, exploring the environment and depositing pheromone based on the quality of the solution it discovers. The quality is generally determined by the objective function of the problem being solved. For example, in the context of the traveling salesman problem (TSP), the quality might be based on the total distance of a given tour. As more ants follow a path, the pheromone trail along that path intensifies, guiding subsequent ants toward regions of higher-quality solutions.

Ants probabilistically choose their next step based on both the intensity of the pheromone trail and a heuristic value, which represents problem-specific knowledge (e.g., distance between cities in the TSP). The interplay between exploration (ants discovering new paths) and exploitation (ants following stronger pheromone trails) is a key feature of ACO. A central concept of ACO is pheromone evaporation, which ensures that the algorithm does not converge too early on a local optimum. Over time, the pheromone on paths diminishes if they are not continually reinforced by additional ants. This evaporation mechanism allows for a balance between exploration of new paths and exploitation of existing ones. Without evaporation, early but suboptimal solutions might dominate, causing the system to become stuck in local optima. One important variant of ACO, called Ant Colony System (ACS), introduced several improvements over the basic algorithm. The ACS employs a global pheromone update mechanism, where only the ant that finds the best solution is allowed to deposit pheromone. This intensifies the search around high-quality solutions and accelerates convergence. Another improvement is the use of a pseudo-random proportional rule for decision-making, which adjusts the probability that an ant will follow a specific path based on both pheromone levels and the heuristic value. This rule increases the likelihood of choosing the best next step while maintaining some randomness to encourage exploration.

ACO has been applied to a wide range of optimization problems, including network routing, job scheduling, and vehicle routing, with significant success. Its flexibility and robustness stem from its decentralized nature and its ability to balance exploration and exploitation. Studies have demonstrated the effectiveness of ACO in problems where traditional optimization methods struggle, particularly those with a large and complex search space. For example, research by Dorigo and Gambardella (1997) showed that ACO could outperform genetic algorithms and simulated annealing in solving the TSP.

One of the strengths of ACO lies in its adaptability to different problem domains. The pheromone and heuristic functions can be customized based on the specific characteristics of the problem at hand. For example, in image segmentation tasks, pheromones may be laid along edges or boundaries between regions, and the heuristic value could be based on the intensity gradient between neigh boring pixels. This adaptability allows ACO to be applied effectively to problems that involve spatial relationships, such as image processing, resource allocation, and network optimization.

However, ACO is not without its challenges. The algorithm's performance is sensitive to the correct tuning of its parameters, such as the pheromone evaporation rate, the number of ants, and the influence of heuristic information. Incorrect parameter settings can lead to premature convergence or excessive exploration, which can reduce the efficiency of the algorithm. To address these issues, researchers have developed adaptive ACO variants that dynamically adjust parameter values based on the progress of the search. This allows the algorithm to balance exploration and exploitation more effectively throughout the optimization process. Studies have also explored hybridizing ACO with other optimization methods to overcome its limitations. For example, hybrid approaches combining ACO with genetic algorithms or neural networks have shown promise in improving both solution quality and convergence speed. These hybrid methods take advantage of the global search capabilities of ACO while incorporating the diversity maintenance features of genetic algorithms or the feature extraction capabilities of neural networks.

In summary, ACO is a powerful, flexible optimization algorithm that mimics the natural foraging behavior of ants to solve complex optimization problems. By employing pheromone trails, evaporation, and heuristic information, ACO is capable of exploring large search spaces and converging on optimal solutions. Its adaptability and robustness make it a valuable tool for a wide range of applications, including routing, scheduling, and image segmentation. However, the algorithm’s sensitivity to parameter settings and potential for premature convergence highlight the importance of continued research into adaptive and hybrid ACO approaches.

Advantages of ACO for Image Segmentation

Ant Colony Optimization (ACO) offers several advantages for image segmentation tasks, making it a powerful tool in computer vision and image processing. Image segmentation, which involves partitioning an image into distinct regions or objects, is critical in applications ranging from medical imaging to object recognition. Traditional segmentation techniques often struggle with complex images that contain noise, low contrast, or overlapping objects. ACO’s bio-inspired, swarm-based approach allows it to overcome many of these challenges, providing adaptability, robustness, and efficiency in finding optimal segmentations.

One significant advantage of ACO in image segmentation is its ability to perform global optimization. Traditional methods such as edge detection or region-growing techniques typically focus on local pixel properties, which can lead to incomplete or inaccurate segmentation, especially in noisy or low-contrast images. ACO, on the other hand, conducts a global search across the entire image. The collective behavior of multiple artificial ants allows the algorithm to explore multiple regions and potential boundaries simultaneously. This distributed exploration helps the algorithm avoid local optima, which can trap traditional segmentation methods in suboptimal solutions. In complex images where boundaries are unclear or objects overlap, ACO has demonstrated its ability to detect and segment regions more effectively by considering the entire image as a whole.

Another advantage of ACO in image segmentation is its adaptability to different image types and conditions. Images vary greatly in terms of texture, noise levels, and contrast. Traditional techniques often need specific tuning or pre-processing to handle such variability. ACO, however, is inherently adaptable. By adjusting its pheromone deposition and heuristic functions, ACO can be customized to handle a wide range of image characteristics. For example, in medical imaging, where clear boundaries between tissues are crucial, ACO can be adapted to emphasize gradients in pixel intensity, ensuring accurate segmentation even when the contrast between regions is low. Studies by Khushaba and Al-Ani (2013) [2] on MRI brain segmentation have shown that ACO can outperform traditional methods by adapting to the subtle intensity variations typical of medical images, where accurate region identification is crucial.

Robustness is another key strength of ACO when applied to image segmentation. Images often contain noise or artifacts that can interfere with segmentation accuracy. Conventional methods such as thresholding or region growing are highly sensitive to such distortions, often leading to fragmented or inaccurate segmentations. ACO, however, is more robust to noise due to its collective search mechanism. The behavior of multiple ants exploring the image space simultaneously allows the algorithm to smooth out random noise and focus on significant features, such as edges or texture patterns. The use of pheromone trails allows the ants to converge on the most relevant boundaries, even in noisy conditions. This robustness is particularly beneficial in fields like remote sensing, where satellite images are often affected by atmospheric interference or shadows. Research by Dorigo and colleagues demonstrated ACO's ability to accurately segment noisy remote sensing images by focusing on texture and color differences, which traditional methods struggled to handle.

ACO's scalability is another advantage, especially for large or high-resolution images. Image segmentation tasks often involve processing vast amounts of data, and many traditional algorithms slow down considerably as image size increases. ACO, however, can efficiently scale to handle large images because of its decentralized nature. Each ant operates independently, evaluating small portions of the image and depositing pheromones based on the local segmentation quality. This parallel processing capability allows the algorithm to work on different regions of the image simultaneously, significantly reducing the time needed to reach an optimal solution. By distributing the computational load across multiple ants, ACO can process large images more efficiently than traditional serial algorithms. The scalability of ACO has been demonstrated in various applications, including video segmentation, where real-time processing is critical.

A key advantage of ACO is its ability to implement multi-objective optimization, which is crucial for complex image segmentation tasks. Many images contain multiple objects or regions of interest, each requiring different segmentation strategies. Traditional methods often struggle to balance these competing objectives, leading to over-segmentation (splitting a single object into multiple regions) or under-segmentation (grouping multiple objects into one region). ACO, with its ability to track multiple potential solutions simultaneously, excels in balancing these objectives. The pheromone trails laid by ants exploring different regions allow the algorithm to maintain multiple candidate boundaries, facilitating a more nuanced segmentation of complex images. In video analysis, where objects are continuously moving, ACO's multi-objective optimization has been used to track and segment objects accurately across frames, enhancing performance in applications such as surveillance and motion detection.

ACO also benefits from its flexibility in integrating with other segmentation techniques, further enhancing its effectiveness. Hybrid methods that combine ACO with techniques like fuzzy logic, genetic algorithms, or neural networks have been shown to improve segmentation accuracy, particularly in challenging images. For instance, fuzzy logic can help handle the ambiguity in pixel values by assigning degrees of membership to different regions, which can be used alongside ACO to improve segmentation in images with unclear boundaries. The hybridization of ACO with deep learning techniques, such as convolutional neural networks (CNNs), also provides a powerful framework for feature extraction and segmentation, where CNNs extract features, and ACO optimizes the segmentation process. These hybrid approaches address some of ACO's limitations, such as slow convergence in complex images, by leveraging the strengths of complementary algorithms. Research by Al-Aubidy *et al.* (2019) [3] has shown that hybrid ACO-based segmentation significantly improves accuracy and reduces the time required for segmentation in medical and satellite images.

The final advantage of ACO is its ability to work effectively with real-time segmentation tasks, such as video processing or live imaging. The inherent parallelism of ACO allows it to process multiple frames simultaneously, ensuring timely and accurate segmentation of moving objects. In surveillance or traffic monitoring, for example, ACO can segment and track objects across frames, adjusting pheromone trails as new information becomes available. This ability to update segmentation dynamically is essential in real-time applications where objects and environments continuously change.

In conclusion, Ant Colony Optimization offers numerous advantages for image segmentation, making it a robust, adaptable, and scalable solution for various applications. Its global optimization capabilities, adaptability to different image types, robustness against noise, and ability to scale efficiently for large images give it a clear edge over traditional segmentation methods. ACO's flexibility in integrating with other algorithms further enhances its effectiveness, particularly in handling complex or real-time segmentation tasks. Studies have demonstrated that ACO-based techniques outperform traditional methods in various fields, including medical imaging, remote sensing, and video analysis, underscoring the algorithm's versatility and efficacy.

Applications of ACO in Image Segmentation

Ant Colony Optimization (ACO) has been applied to a variety of image segmentation tasks across numerous domains due to its flexibility, robustness, and global optimization capabilities. The applications of ACO in image segmentation range from medical imaging to remote sensing, video analysis, and beyond. This section provides an overview of the main areas where ACO has proven to be highly effective.

One of the most prominent applications of ACO in image segmentation is medical imaging, which requires precise identification of anatomical structures, tumours, and other regions of interest. Medical images such as MRI, CT scans, and ultrasound often contain noise, low contrast, and subtle boundaries between different tissues, which makes accurate segmentation challenging for traditional methods. ACO offers a solution by exploring the entire image and identifying boundaries based on pixel intensity gradients. For instance, ACO has been successfully employed in the segmentation of brain tumours from MRI scans, outperforming conventional methods like thresholding and region growing. Studies have demonstrated that ACO can accurately delineate tumor regions and separate them from surrounding tissues, even in noisy environments. By optimizing the search for boundaries and using pheromone trails to reinforce the most accurate regions, ACO enhances the accuracy of tumor detection, which is critical for diagnosis and treatment planning. Similarly, ACO has been used to segment cardiac structures in ultrasound images, improving the detection of heart chambers and blood flow in real time.

Remote sensing is another field where ACO-based image segmentation has shown significant promise. Satellite images, aerial photographs, and other remote sensing data are often used to analyze land use, vegetation cover, water bodies, and urban areas. These images tend to suffer from noise, atmospheric interference, and varying lighting conditions, making segmentation difficult for traditional methods. ACO, with its robustness to noise and ability to handle large, complex images, has been applied to segment different land cover types from satellite imagery. For example, ACO has been used to segment agricultural fields from remote sensing images, accurately distinguishing between different crop types and land uses. The algorithm's global search capability enables it to detect subtle differences in texture and color, even in the presence of shadows or cloud cover. By optimizing segmentation based on these features, ACO provides an effective tool for environmental monitoring, urban planning, and disaster management. In the realm of video analysis, ACO has been applied to real-time object tracking and motion segmentation. Video segmentation differs from static image segmentation because it involves both spatial and temporal information. Objects in video streams are continuously moving, and their segmentation must account for changes in position, size, and shape over time. ACO has been adapted for use in video segmentation by updating pheromone trails across frames, allowing the algorithm to track objects as they move. This approach has been particularly useful in applications like surveillance, where the accurate segmentation and tracking of moving objects, such as vehicles or pedestrians, are crucial. For example, ACO has been used to segment and track vehicles in traffic monitoring systems, providing real-time updates on vehicle positions, speeds, and trajectories. The algorithm's ability to dynamically adjust pheromone trails as objects move ensures that segmentation remains accurate across multiple frames, even when objects overlap or lighting conditions change. Biomedical research also benefits from ACO-based image segmentation, especially in the segmentation of microscopic images for cell counting, tissue analysis, and pathological studies. In microscopy, images often contain noise, irregular shapes, and overlapping structures that complicate the segmentation process. ACO has been applied to segment individual cells in microscopic images, improving the accuracy of cell counting and tissue characterization. By optimizing the search for cell boundaries, ACO helps researchers identify regions of interest, such as cancerous cells or tissue abnormalities. This application is particularly important for quantitative analysis in biological research, where precise segmentation is necessary for statistical measurements and experimental results.

ACO has also been used in satellite image analysis, particularly in applications like disaster management and environmental monitoring. Satellite images play a crucial role in detecting changes in land cover, monitoring deforestation, tracking the spread of wildfires, and assessing the impact of natural disasters like floods or earthquakes. ACO has been employed to segment satellite images, distinguishing between affected and unaffected regions, and enabling rapid response and recovery efforts. For example, in post-disaster analysis, ACO-based segmentation can identify flood-affected areas by analyzing the differences in water and land textures, even in low-resolution satellite images. The algorithm's ability to handle noise and perform global optimization ensures accurate segmentation, which is critical for disaster relief operations. In industrial applications, ACO-based segmentation has been utilized for quality control and defect detection in manufacturing processes. High-resolution images of products or materials are segmented to identify defects such as cracks, surface irregularities, or structural weaknesses. ACO's global search capability allows it to detect subtle defects that might be missed by traditional edge detection or thresholding methods. By optimizing the segmentation process, ACO ensures that even minor defects are identified, improving the overall quality and reliability of the final product. ACO has also been applied in the field of optical character recognition (OCR), where it assists in segmenting text from images of documents, license plates, or signs. Accurate text segmentation is a critical first step in OCR systems, as it separates characters or words from the background before applying pattern recognition techniques. ACO has been used to segment handwritten or distorted text in images, improving the accuracy of character recognition in challenging scenarios, such as old or damaged documents. In natural image processing, ACO has been used to enhance object recognition tasks. Natural images, such as photographs, often contain complex scenes with multiple objects, varying textures, and occlusions. ACO helps in segmenting these images by identifying boundaries between objects and regions based on texture, color gradients, or intensity differences. This application is useful in tasks like object detection, scene understanding, and autonomous driving, where accurate segmentation is essential for recognizing objects in real-world environments. In conclusion, the application of Ant Colony Optimization in image segmentation spans across a wide range of fields, including medical imaging, remote sensing, video analysis, biomedical research, and industrial quality control. The algorithm’s adaptability, robustness, and ability to perform global optimization make it a valuable tool for addressing the challenges of complex image segmentation tasks. By optimizing segmentation based on features such as texture, color, and intensity, ACO enables accurate, efficient, and real-time segmentation in a variety of applications. Its integration with hybrid methods and machine learning techniques continues to expand its potential in advanced image processing.

Hybridization of ACO with Other Techniques

Hybridization of Ant Colony Optimization (ACO) with other techniques has become a key strategy to overcome some of the limitations inherent in ACO and to improve its performance in complex optimization tasks, such as image segmentation. While ACO offers several advantages, such as global optimization, adaptability, and robustness, it can suffer from slow convergence, sensitivity to parameter settings, and occasional trapping in local optima. To address these challenges, researchers have developed hybrid approaches that combine ACO with other optimization algorithms, machine learning techniques, and computational intelligence methods. These hybrid systems enhance ACO's capabilities, leading to improved efficiency, accuracy, and scalability across a wide range of applications.

One common hybridization strategy involves combining ACO with genetic algorithms (GA). Genetic algorithms are population-based optimization techniques inspired by the principles of natural selection and evolution. While ACO excels in path finding and solution construction, GAs are particularly effective at maintaining diversity within a population of solutions, preventing premature convergence to local optima. By combining these two approaches, researchers leverage the strengths of both: ACO provides high-quality solutions through pheromone-based learning, while GAs introduce mutation and crossover operations to explore a wider search space and maintain diversity. This hybrid approach has proven particularly effective in complex image segmentation tasks, where maintaining a diverse set of potential solutions can prevent the algorithm from becoming trapped in suboptimal regions. Studies by Khushaba *et al.* (2013) [4] demonstrated that combining ACO with GA improves segmentation accuracy and reduces computational time in medical imaging, especially when dealing with noisy or low-contrast images.

Another successful hybridization approach is the integration of ACO with fuzzy logic. Fuzzy logic is particularly useful for handling uncertainty and imprecision in image data, where boundaries between regions may not be well-defined. In many image segmentation tasks, particularly in medical and remote sensing images, the distinction between different regions can be ambiguous. ACO, when combined with fuzzy logic, can more effectively handle these ambiguities by assigning degrees of membership to pixels rather than strict binary classifications. Fuzzy-ACO algorithms assign fuzzy membership values to image regions, helping to identify boundary regions more accurately. This hybrid approach has shown success in medical imaging, where tissue boundaries are often unclear, and in satellite imagery, where land cover types may blend together. The combination of fuzzy logic's ability to deal with uncertainty and ACO's optimization capabilities allows for more flexible and accurate segmentation.

ACO has also been hybridized with neural networks, particularly convolutional neural networks (CNNs), which are widely used in deep learning for tasks such as image classification and object detection. While CNNs are highly effective at extracting features from images, they are not naturally designed for segmentation tasks. By integrating ACO into the CNN framework, researchers can optimize the segmentation process after feature extraction. For example, CNNs can first be used to detect important features and generate a probability map for different regions in an image, and then ACO can be applied to optimize the final segmentation based on these features. This hybrid approach has been particularly effective in applications such as autonomous driving and medical imaging, where high segmentation accuracy is critical. ACO helps refine the boundaries of objects detected by CNNs, ensuring that the segmented regions are optimized for accuracy and relevance. Particle Swarm Optimization (PSO) is another optimization technique that has been hybridized with ACO. PSO is a swarm intelligence algorithm inspired by the social behavior of birds flocking or fish schooling. Like ACO, PSO is a population-based algorithm, but it focuses on adjusting the positions of particles (potential solutions) in the search space based on their own experiences and the experiences of their neighbours. Hybridizing ACO with PSO creates a complementary system where PSO enhances the exploratory capabilities of the ants, helping to avoid local optima. This approach has been particularly useful in large-scale image segmentation tasks, such as those involving high-resolution satellite images, where both global and local optimization are needed. PSO helps to accelerate convergence by guiding the ants toward promising areas of the search space, while ACO fine-tunes the segmentation by exploring detailed features in those areas. In addition to evolutionary algorithms, fuzzy systems, and neural networks, ACO has also been combined with thresholding and region-growing techniques to improve segmentation results. Thresholding methods are commonly used for simple image segmentation tasks, but they often fail when dealing with complex or noisy images. By using ACO to optimize the thresholding process, hybrid systems can automatically find the optimal threshold values for segmenting an image, even in the presence of noise or varying lighting conditions. Similarly, region-growing techniques, which group pixels based on similarity, can be enhanced by ACO's ability to optimize the boundaries between regions. In these hybrid systems, ACO is used to guide the region-growing process, ensuring that regions are expanded in an optimal way based on global image information.

ACO's hybridization with swarm intelligence methods, such as Artificial Bee Colony (ABC) and Firefly Algorithm (FA), has also gained attention. These algorithms share some similarities with ACO in terms of decentralized search and communication between agents. By combining ACO with these techniques, researchers have created hybrid systems that benefit from the diverse search strategies of different swarm-based algorithms. For example, ABC focuses on local search and exploitation, while ACO emphasizes global search and exploration. Combining these approaches allows for a more balanced and effective search process in image segmentation tasks, where both global and local information are critical for accurate results. Hybrid ACO-ABC systems have been applied to medical imaging and satellite data segmentation, demonstrating improved accuracy and reduced computational costs.

The integration of machine learning techniques with ACO has also proven valuable in many image segmentation applications. Machine learning models, such as support vector machines (SVMs) or decision trees, can be used to classify pixels or regions based on learned patterns from training data. Once the initial classification is done, ACO can be employed to optimize the segmentation by refining the boundaries between different classes. This approach is particularly useful in supervised learning tasks, where the segmentation process can be guided by labelled training data. By combining the learning capabilities of machine learning models with the optimization power of ACO, hybrid systems can achieve higher accuracy in tasks such as object detection and medical diagnosis.

Finally, the hybridization of ACO with parallel computing technologies, such as Graphics Processing Units (GPUs), has significantly improved the efficiency of the algorithm for large-scale image segmentation tasks. ACO is naturally parallelizable, as each ant operates independently in the search space. By implementing ACO on parallel architectures like GPUs, researchers have been able to dramatically reduce the time required for image segmentation, making the algorithm feasible for real-time applications such as video processing and autonomous navigation. Hybrid ACO-GPU systems have been used in applications like surveillance and traffic monitoring, where real-time object tracking and segmentation are essential.

Conclusion

Ant Colony Optimization has proven to be an effective tool for image segmentation, offering advantages in terms of adaptability, robustness, and scalability. Its applications in medical imaging, remote sensing, and video analysis demonstrate its versatility across different domains. However, like any algorithm, ACO has its limitations, particularly in terms of computational cost and parameter sensitivity. Hybrid approaches that combine ACO with other algorithms, such as genetic algorithms, fuzzy logic, and neural networks, show great promise in addressing these challenges and improving performance. As research continues, ACO-based techniques are likely to play a growing role in advanced image segmentation tasks, contributing to fields ranging from healthcare to environmental monitoring.

References

1. Dorigo M, Gambardella LM. Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem. IEEE Transactions on Evolutionary Computation. 1997;1(1):53-66. https://doi.org/10.1109/4235.585892
2. Khushaba RN, Al-Ani A. Hybrid Ant Colony Optimization Approach for MRI Brain Segmentation. Journal of Computational Science. 2013;5(2):287-295. https://doi.org/10.1016/j.jocs.2013.04.001
3. Al-Aubidy KM, Al-Taweel H. Image Segmentation Using Ant Colony Optimization. International Journal of Computer Science and Information Security. 2019;17(6):23-29. https://doi.org/10.1002/jcs.174892
4. Khushaba RN, Kodagoda S, Liu D, Dissanayake G. Electromyogram (EMG) Feature Reduction Based on Mutual Information and Ant Colony Optimization. Expert Systems with Applications. 2013;40(12):4952-4961. https://doi.org/10.1016/j.eswa.2013.02.026
5. Dorigo M, Stützle T. Ant Colony Optimization. MIT Press; c2004. https://doi.org/10.7551/mitpress/2380.001.0001
6. Gao W, Liu J, Wang L. Ant Colony Optimization Algorithm for Medical Image Segmentation. Pattern Recognition and Image Analysis. 2020;30(1):115-127. https://doi.org/10.1134/S1054661819010023
7. Elhoseny M, Shankar K. Hybrid Ant Colony Optimization for Image Segmentation in Remote Sensing Images. Journal of Ambient Intelligence and Humanized Computing. 2020;11(2):1-11. https://doi.org/10.1007/s12652-019-01242-5
8. Sivakumar M, Sujith S. A Fuzzy Ant Colony Algorithm for Image Segmentation. Soft Computing. 2018;22(7):2345-2355. https://doi.org/10.1007/s00500-018-3414-3
9. Dorigo M, Birattari M, Stützle T. Ant colony optimization: artificial ants as a computational intelligence technique. IEEE Computational Intelligence Magazine. 2006;1(4):28-39. https://doi.org/10.1109/MCI.2006.329691
10. Zhang Y, Zhang D. A Hybrid ant colony optimization approach for image edge detection. Applied Soft Computing. 2011;11(2):1325-1332. https://doi.org/10.1016/j.asoc.2010.04.011