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Ant Colony Optimization towards Image Processing

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Abstract

Objectives: This paper deals with the various tasks of image processing which could be achieved with the help of Ant Colony Optimization (ACO) an important field of soft computing. **Methods/Statistical Analysis:** Soft Computing refers to the techniques of problem solving which are inspired from the human behavior, natural genetics and the behavior of insects. All these techniques are parallel computational techniques which aim to handle imprecise, incomplete, non-linear and complex data. ACO, a field of SC, is a computational intelligence based approach which is used to solve combinatorial optimization problem. **Findings:** The simplicity and optimal approach of ACO has led its applicability to routing, scheduling, sub-set, assignment and classification problems. Focus of the current paper is onto the use of Ant Colony Optimization in the field of Image Processing. **Application/Improvements:** Edge detection, edge linking, feature extraction, segmentation and image compression are the various image processing tasks in which ACO has been applied successfully. The details pertaining to each of the approach have been discussed. Benefits of using ACO over the conventional techniques have also been presented.

Keywords: Ant Colony Optimization (ACO), Soft Computing Image Processing

1. Introduction

Images play a vital role in the life of human beings. They form a part of our day today life and affect almost every aspect of our being. With the immense advancements in technology image processing techniques can be applied to commercial, medical, scientific, military and industrial applications. The field of image processing is vast and thus caters to an ongoing research in this area in a quest to address various challenges in the field. Soft computing techniques have proven to be a boon in the analysis and processing of images. The techniques of soft computing include Artificial Neural Networks, Genetic Algorithms Fuzzy Logic, and Ant Colony Optimization (ACO). All these techniques work in a direction to handle uncertainties and decision-making. Uncertainties in image processing include noise, fragmentation, incomplete and imprecise information.

ACO is a meta-heuristic approach initially given in[1,2] in order to solve Travelling Sales Man Problem (TSP). The algorithm is based on the behavior of the real ants while moving to their food source. Ants deposit pheromones on the path on which they move. So the decision pattern of the ants is controlled by the pheromones that they leave on the path which they follow. This helps them to communicate with each other via environment. Initially ants can choose any random path from their initial position to the food source but eventually the shortest path would have more pheromone level. This in-turn leads the complete ant colony to follow the shortest path from source to destination.

The main features of ACO[3,4] are as follows:

- Colony based multi agent approach: The optimization process in ACO based approaches is carried out by a collective system of ants. Each ant contributes to the solution but convergence to the solution is possible by the collective behavior of ants.
- Distributed and Concurrent System: The ants work in parallel towards obtaining the solution of any problem. This approach leads a way for solving NP hard problems. Also the ants can exchange information between them to obtain a better solution.

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- Iterative system: Each iteration in ACO is designed to improve the solution and thus with each passing iteration solution gets better. The reinforcement used after each iteration of ACO helps to achieve this objective.
- Search Capabilities: ACO can explore the entire search space to achieve global search capabilities. Also the pheromones are updated by each ant on each arc while constructing a partial solution. So a local search could be applied in ACO which helps to improve the solution. This step of local search is an optional step but as suggested in[3], it improves the overall performance of the algorithm

Three variations of ACO were proposed in the beginning for solving TSP problem – ant density, ant quantity and ant cycle algorithm. The major difference in ant quantity, ant density and ant cycle algorithms lies there approach to update pheromone levels. In case of ant quantity and ant density algorithms pheromones are updated after every move whereas in ant cycle algorithm this updation takes place after all the ants have constructed tour[4]. The general process of an ACO algorithm is depicted in the flowchart

Any optimization problem could be solved using ACO if the problem could be represented using a graph in the discrete search space with all the transitions represented in a valid way. Among other necessary factors are[5]:

- The mechanism to update pheromones in order to accommodate the positive feedback,
- Mechanism to represent and construct the solutions,
- Constraints defined over the problem so that the method constructs only feasible solutions,
- An evaluation function which serves as a measure for the generated solutions, and
- Termination condition.

In the current paper we have given the application of ACO to different areas of image processing and discussed how the imprecise information and decision making is handled in images using ACO. The tasks that have been reviewed and discussed include edge detection, edge linking, feature selection, segmentation and compression. The subsequent sections cover the details of each of the areas of image processing using ACO.

2. Edge Detection

Edges in an image are attributed to the sharp transition from high intensity to low intensity regions and provide significant information about an object. A number of methods for detecting the edges of objects have been given in the literature such as the statistical methods[6-8], difference methods[9,10] and curve fitting based methods[11,12].

Classical methods are based on calculating the first directional derivative in order to determine the location of the edges. The zero-crossing edge detectors and the second derivatives incorporated with the Laplacian operator give better accuracy than first derivative operators[13]. Canny edge detector[14], which is based on the concepts of Gaussian detectors, is one of the most frequently used edge detectors. It gives better performance but is computationally expensive than classical methods. All these methods extract edges by adopting specific formulas and are used with smoothing functions. The major drawback with all the conventional approaches of edge detection comes with the drawback that all these approaches are computationally expensive. The reason lies in the fact that any operation has to be executed for every pixel in the image and thus the computational time gets proportional to the image.

The approaches based on ACO have the potential to overcome these limitations by parallel implementations which makes them evitable for distributed systems as well. The edge detection techniques based on ACO use a number of ants to move on the image. This movement leads to the construction of a pheromone matrix. Edge information at each pixel is represented by an entry in the pheromone matrix. Variation of the intensity values in the image is the key to the movement of ants.

In[15] a simple ACO based approach has been applied successfully to extract the edges of the image. Initially certain number of ants is distributed randomly on the image. These ants update their pheromone intensity in each of the iteration. This approach uses simple set of rules to update the pheromone intensities. An image vision model has been designed in[16] for effective extraction of edges in an image. A variation of ACO has been used in[17] in order to derive a relationship between the size of the image and the parameters of the algorithm. A number of extensions of ACO have been emerged since its development. A new technique for edge detection has been given in[18] based upon the distinguishing features of ant colony systems. In this, a pheromone matrix is established by movement of ants and pseudorandom proportional rules are used for updating the matrix. However adjustment of various parameters in this algorithm depends upon the nature of image. Adjustment of ACO parameters gives a typical problem and further hybrid approaches have been emerged to set these parameters. A combined approach ACO with statistical estimation of pixel intensities in its circular neighborhood to update the pheromone intensities to detect the edges in an image has been given in[19]. Fuzzy derivatives along with ACO for detecting edges have been used in[20]. These fuzzy derivatives calculate the fuzzy probability which in turn decides the number of ants in the algorithm.

A model has been proposed in[21] that utilizes three linear spatial filters- low-pass high-pass and edge enhancement filters. The strength of the edges at each pixel is generated through spatial convolution. These edge strength values are provided as input to fuzzy system. The decision whether a pixel is a n edge or not is based on the fuzzy rules. Mamdani defuzzifier method has been used to detect the edges. An improved hybrid ACO-fuzzy approach has been proposed in[22] in which ant movement is decided by simple fuzzy rules and heuristic information is updated dynamically.

Selection of parameters for ACO has proven to be a challenge in all the previously suggested approach. This complex problem in ACO based edge detection has been solved in[23] by using particle swarm optimization algorithm to optimize these parameters.

3. Edge Linking

Edge detection techniques suffer from certain drawbacks including false edge detection, missing true edges, producing thin or thick lines and the problems that arise due to noise[24].

Connecting broken edges accurately is a difficult task. The local information of the original image is generally used to bridge these broken edges. A simple technique has been suggested in[25] to link these broken edges so as to improve the edge detection. It works on the idea that end points of edges are very important components which contain the necessary information and thus direct lines could be drawn between these points to connect the broken edges.

A mask is acquired to determine the direction of endpoints in order to estimate the cost of the linking line which determines whether the line is selected or not. The advantage of these method lies in there simplicity and ease of implementation. But on the other hand they can generate incomplete edges. In another classical approach[26] Hough transform is applied on edge image and specific shape is extracted to connect broken edges. Variable shapes of the edges make this approach unfavorable.

In[27] an ACO based approach has been used to link these broken edges. The approach works on the fact that each pixel in an image is connected to its 8-neighborhood pixels. The distance between adjacent pixels is estimated from the original image. Conventional edge detection approaches are used for edge detection and the ants are placed on the extracted endpoint. An image is composed of hundreds of endpoints and this incurs lot of complexity to the search process. Also it may lead to redundancy as different ants may search the same region. To tackle this problem the ants are split into several groups with different labels. These groups of ants attempt to repair the breaks in edges. In the due course of search they extend their range in order to determine compensable edges.

In[28] an ACO based approach has been proposed to accurately find edges in noisy image. The images were contaminated with Gaussian and salt and pepper noise. Proposed technique is able to detect edges using ACO assuming the edge frequencies to be closer to the noise frequency. Further an integrated ACO and edge detection approach has been proposed in[29] to provide continuous and clear object boundaries. The approach is also able to suppress the noisy surroundings. So with ACO, the major issues in edge linking have been resolved

4. Feature Selection (FS)

Selection of appropriate feature from a given set of features is a problem which is encountered in many fields of engineering including image processing. Pattern recognition, image recognition and text recognition are the subfields of image processing which use feature selection as a part of their processing. Any standard feature extraction method is used to extract the features for the images. The features can be local or global i.e. features can be of any specific object in the image or of the complete image. Features may include the shape of objects, color variations, texture variations, contrast, cluster prominence, spatial correlations in an image etc. Representation of the entire image using a feature vector, which is sufficient enough to capture its properties, is a task which forms the key to further classification of images. This process reduces the dimensionality of feature space thus reducing the overall complexity of processing and analyzing the data. In other words the main goal of feature selection in image processing is to remove the useless, redundant and spurious features to reduce the computational complexity.

Exhaustive search provides an optimal solution to the problem. But it involves the evaluation of all possible subsets of complete feature set and thus incurs exponential complexity making it unsuitable for practical applications. For certain datasets exhaustive search uses tens of billions of subsets to find the optimal feature set thus making it impossible to solve[5].

So feature selection is a NP hard problem. ACO has shown its capability in solving the problems which are NP hard.ACO follows the global search and finds the optimal solution subsets from the entire feature space on the basis of ant's behavior. The FS problem can be represented using a graph where all the features are represented by the nodes of the graph and the ants can recognize the best features from the entire graph.

Feature sections methods can be broadly divided into two types are Filter Methods and Wrapper Methods. The major difference between these methods lies in their evaluation criteria. Filter Methods select the best feature subset by using the statistical properties of data whereas wrapper methods use a learning algorithm to guide the feature subset selection.

In filter methods the feature subset selection is performed as a pre-processing step using PCA, mutual information computation, independent component analysis, class separability measures, variable ranking etc. So with these approaches features are selected based on their statistical properties. It does not take into account the effect of these selected features whereas in Wrapper approaches a learning algorithm with classifier is used to evaluate the effect of selected feature subset. These classifiers could be artificial neural networks, support vector machine, k- nearest neighbor or maximum likelihood classifiers.

A diagrammatic view of both the approaches is shown in Figure 2 adopted from the concepts given in[30].

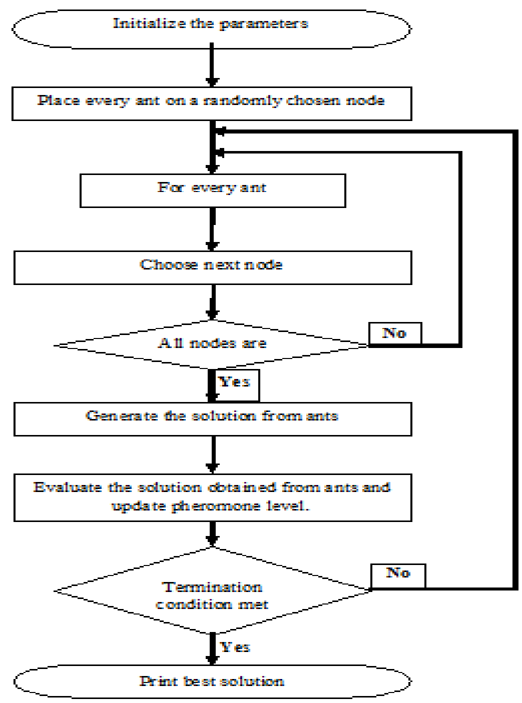

Figure 1. Flow chart of ant colony optimization.

4.1 ACO as a Wrapper Approach

ACO is used in FS as a wrapper approach by including the idea of evaluating the constructed subsets using some learning algorithm. The rules for pheromone updation have been designed in different ways in different

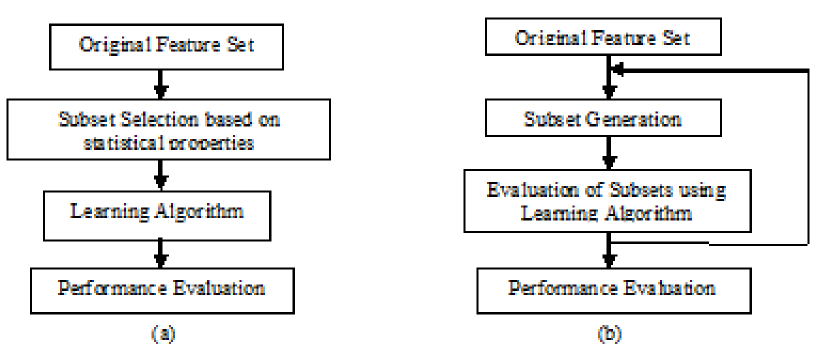

Figure 2. (a) Filter approach; (b) Wrapper approach.

algorithms. But the underlying similarity of all these approaches lies in the process of updating pheromones on the basis of the outcomes of the classifier.

Author in[31] have used ACO along with ANN as a classifier function to find the optimal feature subset from a given set of features. Global update rule ensures the selection of the best feature subset whereas local updating rule prevents the ants to converge to a common tour. The method has been applied to the medical data set. Author in[32] have also used ACO with BPNN as classifier for feature selection for Quantitative EEG data. Authors have considered the best and the worst paths after each ant cycle, and the pheromones are updated for both these paths. So as a part of global pheromone updation the pheromones of the paths giving the highest and the lowest cost are updated.

Most of the ACO based approaches use static parameter settings but this may lead the search to converge to a local optimum solution. Author in[33] have used fuzzy controllers to adaptively generate the ACO parameters. Selected feature set has been evaluated by using a SVM classifier.

The graph of features in ACO based FS algorithms contains $O(n^2)$ edges with n features represented as n nodes. A directed graph with only $O(n)$ edges have been used in[34] to solve the FS problem. Each directed edge represents the choice of the next feature. The algorithm uses performance of the classifier and the number of the selected features as heuristic for finding an optimal feature set. The algorithm is able to able to obtain high processing speed, lower memory requirement with reduced feature set.

ACO along with nearest neighbor classifier have been used in[35] to evaluate the subsets generated by ACO. The algorithm has been implemented on face recognition and ORL databases. The method has been compared to genetic algorithm based method and it has been shown that this method outperforms GA based method by generating lesser features and reduced execution time.

Author in[5] have also applied ACO for finding a minimal feature set in text categorization. The classifier used is the nearest neighbor classifier. A similar algorithm with ant-miner classifier has been givenin[36].

4.2 ACO as a Filter Approach

Fuzzy c means algorithm along with ACO have been used in[37] to solve FS problem without any learning algorithm. The heuristics used in the algorithm are the size of the feature subset and the error rate obtained from fuzzy c means clustering.

Author in[38] have used Rough set theory along with ACO to find a reduced feature subset. Rough set theory holds its importance for dealing with incomplete information and thus Rough set based ACO can find a feature subset with faster convergence speed.

Author in[4] have also used ACO to select feature subsets without any learning algorithm. It is based on the idea of removing redundancies between the features over the successive interactions. Feature selection is carried out by finding similarity between the features. In each of the iteration every ant selects a feature which has least similarity to the previously selected feature. A pseudo-random-proportional rule has been defined to add features to the already created feature set which is initially assumed to be empty. It is claimed that the method selects the best feature subset where the size of the reduced feature set is known in advance. The computational complexity of this method is very low in comparison to the wrapper based approaches.

4.3 Analysis of Filter Approaches and Wrapper Approaches

As discussed earlier wrapper approaches use a learning algorithm to produce a feature subset. This makes them efficient in the task but at the same time the computational cost associated with the process gets increased. The filter based approaches give results in a single iteration and as a result the solution may converge to locally optimum solution. Thus a filter based approach may not provide a quality solution to the problem. To some extent a tradeoff has been achieved between the computational complexity and quality of solution in the algorithm given in[4] but it uses an iterative procedure which thus increases the complexity of the algorithm than the other filter based approaches

The major issue with both the wrapper and the filter based approaches is that a stopping criterion has to be decided in the beginning which could be either the number of iterations or the feature subset size. If we decide the number of iterations then it is possible that a number of irrelevant features may get included in the set. Also deciding the number of elements in the feature subset is a difficult task as this number may become either too large or too small and thus it can reduce the effectiveness of the solution[39].

A solution to this problem has been provided in[30] in which the authors have proposed a subset size determination scheme which guides the ants through subset construction and do not provide the size of the subsets any iteration.

5. Segmentation

Image segmentation can be defined as the process of partitioning a digital image into small segments. These smaller segments are more meaningful and could be analyzed easily which thus simplifies the processing of complete image. In this process every pixel is labeled and the pixels which possess similar visual characteristics are assigned the same label. The task of segmentation seems to be simple but certain factors such as illumination variation, image contrast, image noise, diversity and complex nature of images makes it challenging. Numerous approaches like thresholding[40], clustering[41], compression-based[42], histogram-based[43], edge detection[44], region-growing[45], watershed transformation[46] and model based segmentation[47] have been proposed in literature for segmenting an image. All these approaches have shown success in different problems.

Clustering is the most favorable method for segmentation and could be applied to variety of situations. But it poses a complex optimization problem and the reasons could be the large search space of the optimization and the non-convex nature of clustering objective function. This may lead to a large number of local minima. In this approach an image is viewed as a set of multi-dimensional data which can be classified into different parts on the basis of certain predefined criterion. Improvements in clustering techniques could be obtained by integrating it with fuzzy theory, neural networks and evolutionary techniques like ACO. Enormous approaches have been proposed in the literature in order to increase the accuracy and reduce the time.

An ant colony based multi-agent approach has been proposed by authors in[48]; in which *Max-Min* ant system has been used to segment an image by forming clusters. Every pixel of the image is mapped to its closest cluster. Performance of this approach has been further improved in[49] by integrating Markov Random Field (MRF) and the AGO meta-heuristic characteristics to segment an image. Population of simple agents has been used in this algorithm to construct a candidate partition by a relaxation labeling with respect to the contextual constraints. Main problem associated with these ACO based algorithms is that the search process in segmentation problem is random and uses large number of computations for convergence because of the constant evaporating coefficients. Author in[50] have suggested an idea of setting primary cluster center to deal with this problem. The proposed algorithm uses a small window with an aim to reduce the number of computations. Constant evaporation of coefficient leads to early convergence or stagnation which can be prevented by allowing the coefficients to change with the number of ants. Another ACO based segmentation approach has been given by Xiao et al, which is inspired from a multistage decision algorithm[51]. Precise contours have been obtained in this algorithm by determining the best path in a constrained region. However these algorithms suffer from slow rate of convergence because of random selection of clustering centers. To solve this issue author in[52] have proposed a k-means clustering based ACO algorithm in which k-means clustering has been applied to determine accurate clustering centers. Although k-means clustering has proven to be useful but the drawback is that it depends upon the initial state[53]. This issue has been resolved in [53]resolved and the authors have presented a hybrid evolutionary algorithm that could solve nonlinear partitional clustering problems. A hybrid of fuzzy adaptive particle swarm optimization, ant colony optimization and k-means algorithm has been proposed which is able to identify better cluster partitions than the existing approaches.

Another improvement has been suggested in[54]. The approach is based on the idea of extracting certain features such as gray value, gradient and neighborhood of the pixels in order to improve the process of searching and clustering. Algorithm is based on initializing the clustering centers and enhancing the heuristic ACO approach to accelerate the search process.

Traditional ACO based approach suffers from probabilistic and hard path choosing problem. Author in[55] used a soft and fuzzy scheme along with ACO to deal with this problem. Each pixel in the image is assumed as an ant. Heuristic and pheromone information on each cluster center is used to calculate the membership function of fuzzy sets. The performance is further improved by using spatial information.

It has been analyzed in[56] that cluster centers are selected randomly therefore probability of trapping in local minima is high. In order to resolve this issue authors have given a hybrid scheme based on two optimizations Algorithms-artificial Bee Colony (ABC) and Differential Evolution (DE). In the first place best initial cluster centers are obtained by using seeds from cluster center algorithm. The evolutionary algorithm is then applied to find the global solution.

Author in[57] have also given a hybrid clustering algorithm which incorporates ACO based clustering into probabilistic C-means clustering for noisy image segmentation. This algorithm is able to solve the coincident clustering problem by utilizing pre-classified pixel information.

6. Image Compression

The main aim of image compression is to remove the redundancies in order to efficiently utilize the transmission bandwidth and the storage space. A raw image contains Mbs of data, which is reduced by image compression techniques. There are two types of image compression techniques - lossy compression and lossless compression. In lossless techniques no information is lost and hence the original image can be exactly reconstructed but the compression ratio is low. In case of lossy compression techniques there is a loss of information so that if the compressed image is decompressed then it would not be identical to original image but would be closer to it. In lossy technique Compression ratios are high but image quality gets degraded. Various lossy compression techniques are available like-transformation coding[58], vector quantization[59], fractal coding[60] and block truncation coding[61]. It has been found that higher compression ratios are produced by fractal coding techniques. Fractal coding technique works by dividing the starting image in to small, non-overlapping, square blocks, which are also called parent blocks. Each parent block is divided into 4 sub blocks or child blocks and each child block is compared against a subset of all possible overlapping blocks of parent block size. Larger block is determined by finding the lowest difference between it and the child block. A grayscale transform is calculated to match intensity levels between large block and child block precisely. This Fractal Image Compression (FIC) is based on the similarities of various blocks in an image. Linear regression technique is embedded into the encoding procedure to find the best solution for various blocks. This technique has emerged as one of the most popular coding methods in the recent years. However its high computational complexity greatly restricts its applications. Also this compression technique reveals poor image qualities when applied on corrupted images. This leads to a new concept of robust fractal image compression. Author in[62] have successfully applied ACO for fractal image compression and have achieved reduction in computation time in comparison to traditional approaches.

In order to reduce the encoding time an ant colony based fractal encoding algorithm has been proposed in[63]. The fractal encoding produced by the ACO algorithm is completely identical to that of the conventional full search. The major advantage achieved is the reduction in time. So this algorithm can realize the fractal image coding very well.

Author in[64] have compared the performance of evolutionary approaches like GA, PSO and ACO for fractal image compression and have shown the better performance of ACO over the other techniques.

7. Conclusion

ACO has immense potential in solving various image processing tasks including edge detection, edge linking, feature extraction, segmentation and image compression. Details of various ACO algorithms towards solving these problems have been discussed. Conventional techniques for solving these problems have also been presented while highlighting the advantages of using ACO over these techniques. The current paper gives in-depth analysis of ACO applied over image processing tasks thus giving future directions of research. Many other latest techniques like Cuckoo Search[65] have been used for optimization purposes. Future research may focus on comparing ACO to these latest approaches. Also search engine optimization given in[66] could be evaluated using ACO.

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