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Meta-heuristic Approaches for Active Contour Model based Medical Image Segmentation

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Abstract

In last few decades, the application of biological methods and systems to the study and design of engineering systems and modern technologies have fascinated many researchers. Numerous mathematical and meta-heuristic algorithms for solving optimization problems have been developed and widely used in both theoretical study and practical applications. To realize the application of such meta-heuristics for problem solving, the problem exercised here is the medical image segmentation. Image segmentation has an imperative role in medical image analysis for computer aided diagnosis and classification. In this paper, a number of population based meta-heuristic algorithms are reviewed and analyzed. The paper focuses on the principles behind each algorithm, the issues in designing a hybrid framework in view of the application in medical image segmentation. It extends a platform to develop novel meta-heuristics, and utilize the hybrid framework for improved image segmentation.

Keywords: *Medical Image Segmentation, Active Contour Model, Genetic Algorithm, Differential Evolution, Honey Bee Mating Optimization, Particle Swarm Optimization, Ant Colony Optimization, Firefly Algorithm.*

1 Introduction

Image segmentation plays a vital role in medical image analysis and classification for radiological evaluation or computer aided diagnosis. Since, many artifacts do arise in medical images; it may lead to incorrect segmentation of regions of interest. Furthermore, different organs and tissues have very similar gray levels that consign threshold to limited utility. With the instance of operation, the absolute gray levels observed also differ extensively. Due to lack of organ tissue homogeneity within and among different image slices both in shape and texture, further increase the difficulties. As a consequence of these difficulties the earlier segmentation methods i.e. either edge based or region based do fail in segmenting the regions of interest effectively. However, the Active Contour Model (ACM) [1] that include the key concepts of both edge and region based approaches is more effective. The model is highly analytical and involves extensive computations in order to incorporate powerful and useful concepts of energy, force, velocity, and curve constraints. Originally known as Snakes, the active contour model was introduced by Kass et al. in which the contour deforms to minimize the contour energy that includes the internal energy from the contour and the external energy from the image. These energies are converted to forces by using variation methods that deform the contour. The deformation stops when the forces balance i.e. the contours reach an energy minimum. Many approaches [2-4] have been proposed to solve this model. However, sensitivity to the initial position of contour and the entrapment within local minima are among the problems inflicted on the active contour models. Former methods to solve optimization problems require enormous computational efforts, which tend to fail as the problem size increases. These are few of the motivations for employing nature inspired stochastic optimization algorithms as computationally efficient alternatives to deterministic approaches.

The objective of this study is to identify and understand ACM based segmentation as a multi-decision based optimization problem with the intention that different meta-heuristics can be successfully employed. Nature inspired algorithms are meta-heuristics that mimic the nature for solving optimization problems, opening a new era in computation. Formulating a design for such algorithms involves deciding a proper representation of the problem, assessing the quality of solution using a fitness function and defining operators so as to generate a new set of solutions. Different meta-heuristic approaches represent and solve the same optimization problem differently. Number of control parameters, the heuristic information used and the way the solutions evolve in the search space are also different. The effectiveness of results to the given optimization problem immensely depend on these attributes. Therefore, various meta-heuristic approaches such as Genetic Algorithm (GA) [5], Differential Evolution [6], Honey Bee Mating Optimization (HBMO) [7, 8], Particle Swarm Optimization (PSO) [9, 10], Ant Colony Optimization (ACO) [11] and Firefly Algorithm [12] have been assessed. Recently, many researchers [14-26] utilized such meta-heuristics to efficiently guide the active contours in ACM based image segmentation and demonstrated its ability and suitability in medical image segmentation. To further improve the exploration and exploitation ability of the meta-heuristics researchers have divided the search space into different sections and employed multiple swarms to guide [17, 19, 21, 22] the evolution of active contours. This not only improves the searching ability, but endorses parallel implementation. In this paper, generalized frameworks to hybridize the active contour model using such meta-heuristics have been discussed. Section-2 illustrates ACM based image segmentation as a multi-decision based optimization problem. Section-3 discusses different meta-heuristic approaches. Section-4 demonstrates the hybrid frameworks for meta-heuristic based ACM for image segmentation. Sections 5 and 6 endow with discussions and conclusion about the study.

2 Active Contour Model based Image Segmentation

The original ACM described by Kass et al. refers to a set of points, $P(s, t) = (x(s, t), y(s, t))$ on an image parameterized with respect to $s \in [0,1]$ and t the time step. Each possible configuration of the contour has an energy associated with it, which is a combination of internal and external energies. The energy function can be written as:

$$E_{Snake} = \int_0^1 [E_{in}(P(s) + E_{ext}(P(s)]ds \quad , \tag{1}$$

where E_{in} and E_{ext} represents the internal and external energy of the active contour. These energies are converted to forces by using variational methods that deform the contour. During the contour deformation, the gradient based external force attracts the contour towards the desired boundary, while the curvature based internal force maintains the curve smoothness. The deformation stops when the forces balance i.e. the contours reach an energy minimum. For practical implementation, a snake is characterized by a set of control points P_i, $i = \{1, 2 \dots M\}$. Let P_i^k be the k^{th} point in the searching window of the i^{th} control point P_i. The local energy function is defined as,

$$E_{i,k} = \frac{1}{2}\alpha\left|P_{i+1} - P_i^k\right|^2 + \frac{1}{2}\beta\left|P_{i+1} - 2P_i^k + P_{i-1}\right|^2 - \gamma\left|\nabla I(P_i^k)\right|^2 \quad , \tag{2}$$

where α and β are the weights to the energy terms and γ is the weight factor of the external energy term computed for the given image $I(x, y)$. The total snake energy is approximated as,

$$E_{Snake} = \sum_{i=1}^{M} E_{i,k_i} \tag{3}$$

Usually, the process terminates when the energy E_{Snake} becomes stable.

3 Meta-heuristic Algorithms

Nature inspired algorithms are meta-heuristics that mimic the nature for solving optimization problems, opening a new era in computation. Meta-heuristics are based on the iterative enhancement of either a single or a population of solutions. It mostly employ randomization and local search to solve a given optimization problem. Different meta-heuristic approaches represent and solve the same optimization problem differently. Designing such algorithms involves deciding a proper representation of the problem, assessing the quality of solution using a fitness function and defining operators so as to generate a new set of solutions. Different meta-heuristic approaches and their characteristics have been recapitulated in Table 1 and Table 2.

Genetic algorithm is a nature inspired algorithm that mimics the process of natural evolution. Being a global search procedure, GA has shown its robustness in many tasks. It is not limited by restrictive assumptions such as derivatives of the objective function. However, GAs do not scale well with complexity; if large number of elements is exposed to mutation then there is often an exponential increase in search space size. In several problems, GA may have a tendency to converge towards local optima. This propensity depends on the form of the fitness landscape. Few of these limitations may be alleviated by using a suitable fitness function, increasing the rate of mutation, or by using selection operators that maintain a diverse population of solutions. Based on the existing literature, the selection criteria of different control parameters are listed in Table 3.

Differential Evolution (DE) is a population based stochastic optimization algorithm that is very similar to evolutionary algorithms. It has a faster convergence in solving global optimization problems with non-differentiable and non-linear functions. Mutation step creates a mutant vector at each generation based on the distribution of current population by performing a classical mutation strategy controlled by differentiation factor. After mutation the crossover operator is applied to create the trial vector. The selection procedure selects according to fitness function, the better one between the trial and mutation vector. This procedure is repeated until the stopping criterion is met. Since, it is easy to implement and not computationally expensive, it has been used in many real world applications [6] for solving optimization problems. The efficiency of DE depends on the settings of the control parameters such as population size, selection method, crossover parameters and the differentiation factor. Based on the literature tuned control parameter values are listed in Table 4.

Honey bee mating optimization is a meta-heuristic approach that is inspired by the natural mating process and biological statements of honeybees. HBMO combines GA, Simulated Annealing (SA) [13] and local search to enhance the ability of finding an optimum solution for given complex problems. It is one way superior to the classic evolutionary algorithms; since, the queen stores a number of different drone's sperm in her spermatheca parts of the genotype of different drones can be used to create a new solution, which gives the possibility to have fittest broods. It further combines the goodness of SA with that of GA to improve the exploration ability to reach to the global minima. Based on the existing literature, the values of control parameters that give the optimum efficiency to HBMO have been listed in Table 5.

Table 1: Assessment of GA, DE and HBMO for optimization problems

	GA	DE	HBMO
Idea	To improve the population using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.	To improve the population by applying variation operators such as mutation, crossover and selection on the floating point encoding.	To combine GA, SA and local search to enhance the ability of finding an optimum solution.
Represen-tation	Chromosome encoding as arrays of bits or character strings.	Agent encoding as a vector of floating point numbers.	Chromosome encoding to keep genotype, speed, energy, and a spermatheca with defined capacity.
Memory	No memory.	No memory	No memory.
Information sharing	Chromosomes share information with each other, thus the whole population moves like one group towards an optimum.	Agents share information with each other within the population.	Queens communicate with broods and workers share information with broods.
Selection	Only the fittest chromosomes survive for the next generation.	Only the fit agents survive for the next iteration; weaker agents are replaced by the newly generated solutions.	Only the best broods survive by replacing weaker queens.
Control Parameters	Population size, GA operators and operator probabilities, representation of decision variables	Population size of agents, Selection method, crossover rate, differential weight	No. of queens, population of drones, spermatheca size, no. of broods generated by each queen, GA operators and operator probabilities, SA parameters (decay rate and rate of energy reduction)

Table 2: Assessment of PSO, ACO and FFA for optimization problems

	PSO	ACO	FFA
Idea	To have all the particles locate the optima in a multi-dimensional hyper-volume guided by inertial, cognitive and social information.	To exploit historic and heuristic information to construct candidate solutions and fold the information learned from constructing solutions into the history.	To gain higher mobility and efficient exploration ability by having adjustable visibility and being more versatile in attractiveness variations.
Represen-tation	D-dimensional vector for position, speed, best state.	Undirected graph (state graph, construction graph, etc.).	D-dimensional vector for firefly position.
Memory	Particles have memory to retain best solution found in previous generation.	ACO retains memory of entire colony instead of previous generation only.	No memory.
Information sharing	Only the 'best' particle gives out the information to others. The evolution only looks for the best solution.	The communication among the exploring agents (the ants) is indirect.	Fireflies directly communicate with neighboring fireflies.
Selection	No selection. All the particles survive for the length of the run.	No selection. All the ants survive for the length of run.	No Selection. All the fireflies survive for the length of run.
Control Parameters	No. of particles, particle dimension, particle range, max. change a particle can take during one iteration, learning factors, inertia weight	No. of ants, pheromone evaporation rate, amount of reinforcement, pheromone weight, heuristic in the transition rule	No. of fireflies, initial brightness, randomization term and absorption coefficient

Particle swarm optimization, a population based stochastic optimization technique is inspired by social behavior of bird flocking or fish schooling. While applying PSO to optimization problems, one of the advantages is that it takes real numbers to as particles. More specifically, PSO does not require that the optimization problem be differentiable as is required by classical optimization. During the development of several generations, only the most optimist particle can transmit information onto the other particles, and the speed of the researching is very fast. Being a meta-heuristic it makes few or no assumptions about the problem being optimized and searches very large spaces of candidate solutions. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc. PSO has simple computations as compared to evolutionary algorithms and it can produce high-quality solutions within shorter calculation time. It has more stable convergence characteristics than other stochastic methods. However, the performance of the traditional PSO radically depends on its parameters, and it often suffers from the problem of being trapped in local optima. Based on the existing literature, the controlling parameters of PSO and their selection criteria to avail maximum efficiency are listed in Table 6.

Table 3: Controlling parameters for Genetic Algorithm

Parameter	Selection Criteria
Population size	If too small, then there is not enough evolutions, and the whole population may converge prematurely. If too high, then more evaluations of the objective function are needed, which will require extensive computing time. Problem dependent; usually 20 – 1000.
Maximum no. of generations	For expensive problems where computational time is limited, it is inversely related to population size
Crossover operator and its probability	Single-point crossover is very common, and multi-point crossover is alternative for long strings. Crossover probability is usually very high, typically in the interval [0.7, 1.0]. When single point crossover is used, a reasonable default value for probability of crossover is 0.9-1.0 and as the number of crossover points increase, the probability of crossover should decrease.
Mutation Probability	If too small, then mutation rate may lead to genetic drift and if too high, it may lead to loss of good solutions unless there is elitist selection. Common value for probability of mutation is 1/[population size]. Typically it is in the interval [0.001,0.05].

Table 4: Controlling parameters for Differential Evolution

Parameter	Selection Criteria
No. of agents	Problem dependent; usually >= 4.
Differential weight	Also known as mutation factor parameter. Usually between 0 and 2.
Crossover rate	Crossover rate is usually between 0 and 1.

Table 5: Controlling parameters for Honey Bee Mating Optimization

Parameter	Selection Criteria
No. of queens	Problem dependent. Usually 1.
Population of drones	Same as GA.
Spermatheca size	There is always a tradeoff between the diversity and the computational complexity. Usually kept small around 20-50.
GA operators and operator probabilities	Same as GA.
SA parameter (decay rate)	Larger cooling rate leads to faster convergence, but sub-optimal solutions and vice-versa. Usually kept close to, but smaller than, 1. Typically [0.8-0.95]

Table 6: Controlling parameters for Particle Swarm Optimization

Parameter	Selection Criteria
No. of particles	Commonly set to the number of components in the problem. Usually kept low around 20-40.
Velocity clamping factor	It is required to limit the maximum velocity of each particle. Usually kept between 0.1 and 1.0.
Learning factors	The cognitive coefficient affects the step size the particle takes towards its individual best solution and the social coefficient represents the step size the particle takes towards the global best solution. Should be between 0 and 4, typically 2.
Inertia weight	Lower values of the inertial coefficient speed up the convergence of the swarm to optima, and higher values of the inertial coefficient encourage exploration of the entire search space. Usually kept between 0.8 and 1.2

Ant colony optimization is a meta-heuristic approach inspired by the foraging behavior of real ants. The basic idea of the ACO approach is to use the equivalent of the pheromone trail (used by real ants as a medium for communication) as an indirect form of memory of formerly found solutions. The ants construct solutions directed by heuristic information and the pheromone trails left by ants in preceding iterations. When one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to all the ants' following a single path. The pheromone trail evaporates over time and in addition, the quantity left also depends on the number of ants using this trail. Integrating the pheromone evaporation in ACO has an advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the former ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve. ACO uses both historic and heuristic information to optimize the solution and the positive feedback here accounts for rapid discovery of good solutions. ACO can be effectively applied on dynamic applications as it adapts. ACO has found its applications where source and destination are precise and predefined. At the same time, PSO is used in the areas of multi-objective, dynamic optimization and constraint handling. Based on the existing literature, the criteria to tune the controlling parameters of ACO are listed in Table 7.

Table 7: Controlling parameters for Ant colony Optimization

Parameter	Selection Criteria
No. of ants	Commonly set to the number of components in the problem
Decay factor	It controls the influence of the history on the current pheromone trail. It takes value greater than 0 and less than equal to 1; commonly set around 0.5.
History coefficient	For positive values, the larger the value, the stronger the exploitation of the search experience. For a value 0, the pheromone trails are not taken into account at all, and for negative values, the most probable choices taken by the ants are those that are less desirable from the point of view of pheromone trails. Commonly set to 1.0
Heuristic coefficient	It has an analogous influence on the exploitation of the problem-specific heuristic information. Commonly set between 2 and 5, such as 2.5

Firefly algorithm (FFA) is a meta-heuristic algorithm that is inspired by the flashing behavior of fireflies. For simulating the behavior, Yang et al. [ ] used the following idealized rules: 1) one firefly is attracted to all other fireflies, 2) attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly, and 3) the brightness of a firefly is affected or determined by the landscape of the objective function. FFA can indeed provide a good balance of exploitation and exploration and it also requires far fewer function evaluations. It has been successfully applied to solve many linear and on-linear optimization tasks. Though FFA has very few controlling parameters, but they need to be tuned to achieve maximum efficiency. The criteria based on existing literature for fine-tuning of such parameters are given in Table 8.

The meta-heuristics have their own advantages and limitations, but the theoretical analysis of their behaviors when applied on a specific optimization problem is difficult. Implementation, efficiency and robustness of these algorithms require the tuning of various controlling parameters for a given optimization problem.

Table 8: Controlling parameters for Firefly Algorithm

Parameter	Selection Criteria
No. of fireflies	Commonly set to the number of components in the problem. Usually kept low around 50-100.
Initial Brightness	Initial brightness decides the fitness of initial population. Usually taken as 1.
Randomization term	It provides randomness in movement of fireflies. Usually a random number generated between 0 and 1, but can be easily extended to a normal distribution or any other distribution.
Absorption coefficient	It characterizes the variation of attractiveness and its value is critical in determining the speed of convergence and how FFA behaves. In practice, it typically varies from 0.01 to 100.

4 Meta-heuristic based Active Contour Models

As mentioned the classical ACMs suffer from limitations such as contour initialization and local minima. Recently researchers [14-26] have created hybrid methods utilizing different population based meta-heuristic algorithms in order to overcome few such limitations thereby improving the efficacy of ACM based segmentation. For designing such hybrid methods require a proper representation of the problem, assessing the quality of solution using a fitness function and defining operators so as to generate a new set of solutions.

In the optimization process, each solution (active contour *C*) is represented as a set of *M* control points (P_1, P_2 … P_M). With an initial contour C_0 placed in the image, a set of neighboring points is selected about each control point on the contour. Then a point is randomly selected from the neighboring set of each control point, and interpolated to create a contour (candidate solution). This is repeated to create *N* number of contours to form the initial population. The fitness function to evaluate the quality of a solution is realized from the Snake energy. If the algorithm handles the problem as a minimization problem, then the fitness function is directly proportional to the Snake energy associated with the solution; otherwise it is indirectly proportional to the Snake energy. For example, GA is based on the principle of “survival of the fittest”; the generalized GA framework treats the problem as a maximization problem. Therefore, when GA is applied to solve ACM problem, the fitness function considered is indirectly proportional to Snake energy. Once solutions have been represented and the fitness function decided, in the optimization process, operators are required to generate new set of solutions. These operators are based on the kind of meta-heuristic algorithm being applied. Following sections, briefly discuss the frameworks for utilizing different meta-heuristics for ACM based image segmentation based on the existing literature.

4.1 Genetic Algorithm for Active Contour Model

To apply GA based energy minimization procedure for solving ACM based medical image segmentation, each solution (chromosome) is represented by a set of control points (the positions of the snake in the given image space). To evaluate their fitness, a function is created from the total snake energy. With the local energy function $E_{i,k}$ (computed as in Eq. (2)) of each control point, the overall fitness of the contour is defined as:

$$Fittness = \frac{1}{1 + E_{i,k}} \tag{4}$$

The contour which is situated on the object boundary possesses the least amount of energy, thereby having maximum fitness. Once the initial contour is placed, few points in the local neighborhood of each control point are randomly selected. These points are interpolated to form a number of contours (candidate solutions) in the initial population. After computing the overall fitness values, contemplating the rate of selection, few best individuals are selected and put into the reproduction pool. Then, the members of the pool are paired up and reproduce using a crossover operator. Subsequently, mutation operation is performed on the chromosome populations to prevent quick convergence and to have a better generation. Reiterate the process until a set of best contours is at last acquired. Once the algorithm terminates, the best points of each contour are selected from the generation that remains. The final contour is obtained by joining these points.

4.2 Differential Evolution for Active Contour Model

To use differential evolution for optimization of active contour model based segmentation is to find the final contour that better delineates a region of interest. Thus, the candidate solutions are the agents that represent an active contour with a number of control points. The fitness of an agent is evaluated according to the external energy derived from last term of Eq. (2) as,

$$Fitness = -\gamma \left|\nabla I(P_i^k)\right|^2 \tag{5}$$

The ACM and DE parameters are manually set. Initial population with a number of agents is randomly generated. For each individual, a mutant vector is generated by applying the mutant strategy as per the differentiation factor. According to the crossover operator a trial vector is computed from the mutant vector. This vector randomly picks the original value or the mutant value for an individual based on the crossover rate. Now the selection operator selects the best individual from the original population and the trial vector depending on their fitness value. This forms the next generation. This procedure is repeated until the stopping criterion is met. The stopping criterion might be stability or number of generations.

4.3 Honey-Bee Mating Optimization for Active Contour Model

As in GA, the HBMO algorithm uses chromosome to represent an active contour, where each gene of this chromosome represents the position and parameters of local energy function of a control point. The parameters $\alpha_i, \beta_i, \gamma_i \in (0,1)$ are randomly generated for each point. The fitness function is defined as,

$$Fitness(t_1, t_2 ... t_n) = \frac{1}{E_{Snake}} \tag{6}$$

Once the initial contour is placed, few randomly selected points in the local neighborhood of each control point are linked to form a number of contours (candidate solutions). Furthermore, the corresponding parameters α_i, β_i and γ_i for each selected point on the contours are randomly generated within the range [0, 1]. All the initial solutions are assigned to the drone set. The initial solutions are ranked according to their fitness and the best one (with minimum Snake energy and maximum fitness) is selected as the queen *Q*. The probability of successful mating between a drone *D* and queen is computed as,

$$p(Q,D) = e^{\frac{-diff}{speed}} \quad , \tag{7}$$

where, *diff* is the absolute difference between the fitness of D and Q, and *speed* is the speed of the queen Q during the flight. During the flight mating of queen, the best drone D_k with the largest annealing function (Eq. (7)) among the drone set is first selected as the object of mating for the queen. Queen starts with a very large speed and after each mating, the queen's speed is decayed by,

$$speed(t+1) = \alpha * speed(t) . \tag{8}$$

The flight mating continues until the number of sperms in the queen's spermatheca is more than a predefined threshold which is always less than the number of drones. In breeding process, the j^{th} individual of the queen's spermatheca is selected to breed if its corresponding random number R_j is less than a user-defined breeding ratio P_c. Then the population of broods is improved by applying the mutation operator. Finally, the best brood with maximum fitness is selected as the candidate queen and if the fitness of the best brood is superior to the queen, then it replaces the queen. This procedure is repeated until the convergence.

4.4 Particle Swarm Optimization for Active Contour Model

Hybrid PSO based ACM can be adopted to guide the control points quickly into the boundary concavities, which utilizes the PSO algorithm to find the best movement of control points with a swarm of particles corresponding to each control point P_i. At each stage, only a local neighborhood of a point on the active contour is considered. Let P_i^k be the k^{th} position in the searching window of the i^{th} control point P_i. In iteration, based on global best (*gBests)* of the neighboring swarms, the local energy is computed for particles in each swarm according to Eq. (2). The point is the choice point or not depends on whether it makes the energy function decrease. The best neighbor k_i with N number of local neighbors is obtained by,

$$k_i = \arg\min_k E_{i,k} \qquad \forall k, 1 \le k \le N . \tag{9}$$

Since k_i is the local best position (*pBest*) in the searching window of the control point P_i, updating the position of the i^{th} control point to the position of k_i will decrease the local energy of the snake. Once every control point has been processed, a new snake is formed with total snake energy approximated by Eq. (3). As the movements of the particles in each swarm have been performed, the *gBest* of the swarm is the new control point for P_i. The PSO algorithm continues for each swarm until the *gBest* of that swarm becomes stable. Meanwhile, other swarms corresponding to other control points may still evolve. We get the final contour when all the swarms get stable.

4.5 Ant Colony Optimization for Active Contour Model

ACO when applied to ACM based image segmentation; it is used to search for the best path in a constrained region. The segmentation problem is transferred to the ant colony searching process by means of constructing cost function, solution space, pheromone model, and heuristic information. The ACM solving process is interpreted as a searching graph in ACO framework. An initial contour is placed in the given image with *M* control points (*M* ants). The pheromone value τ_{ij} is assigned to each possible edge (*i, j*). Based on the length (d_{ij}) of an edge (*i, j*), the heuristic information is computed as,

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{10}$$

An ant P_i at location *k*, selects the next point *l* from the local neighborhood of P_i, under the influence of pheromone. The transition probability of the k^{th} ant moving from node *i* to node *j* is given by,

$$p_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum\limits_{l \in allowed_k} \tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}} & if \quad j \in allowed_k \\ 0 & otherwise \end{cases} \tag{11}$$

The next position of an ant is selected according to the probability decision. After doing this for each dimension and for each ant, compute the energy for each sub-cell $l \in (1,2...N)$ as:

$$E_{i+1,k,l} = E_{i,j,k} + \frac{1}{2}\alpha\left|P_i^k - P_{i-1}^j\right|^2 + \frac{1}{2}\beta\left|P_{i+1}^l - 2P_i^k + P_{i-1}^j\right| - \gamma\left|\nabla I(P_i^k)\right|^2 \tag{12}$$

Aggregating this local energy for each ant, find the minimized energy path. In each iteration, update the pheromone values for all ants.

$$\tau_{ij} \leftarrow (1-\rho) \cdot \tau_{ij} + \sum_{k=1}^{M} \Delta\tau_{ij}^{k} \quad , \tag{13}$$

where, ρ is the evaporation rate, and τ_{ij}^{k} is the quantity of pheromone per unit length laid on edge (*i, j*) by the k^{th} ant. This process is repeated for a predefined number of iterations. With the cooperation of the ant colony, the path of final minimal energy is acquired.

4.6 Firefly Algorithm for Active Contour Model

Firefly algorithm (FFA) being very efficient in solving global optimization problems has been utilized to guide the evolution of active contours in ACM based image segmentation. Each active contour with a discrete representation is a firefly. The ACM and FFA parameters are manually set. Attractiveness of each firefly is directly proportional to the value computed in Eq. (3).

Initial population of fireflies is generated by randomly placing a number of contours in the image space. Now each firefly is evaluated and its attractiveness is computed. The less attractive ones move randomly towards the more attractive ones in the space. The new solutions are evaluated and their light intensities are updated. This procedure is repeated for a maximum number of generations. Then the fireflies are ranked according to their light intensities and the best represents the final contour to segment the image.

5 Discussion

GA based active contour model (GA-ACM) have been successfully applied [14 - 16] to segment medical images generated by different equipments. Mishra et al. [14] implemented GA based ACM and successfully applied it for segmentation of left ventricle with echocardiographic image sequences. The algorithm is found to be computationally expensive, but the results are promising. T. Mohammad et al. [16] used GA to guide the ACM based segmentation of ill-defined ultrasound images. The choice of control parameters for GA-ACM and the type of medical images used for experiments are listed in Table 9.

Table 9: Parameter settings for GA guided ACM for medical image segmentation

Method	Medical Image	Parameter	Value
GA-ACM [14]	Left ventricle with echocardiographic image sequences	No. of Iterations	75
		Population size	40
		Crossover Probability	0.5
		Mutation Probability	0.08
		Search space dimension	11 for initial frames, 7 for subsequent frames
		ACM parameters	α=0.3, β=0.9, γ=0 for initial frame and α=0.5, β=0.6, γ=0.7 for subsequent frames
GA-ACM [16]	Ultrasound images of breast lesions	No. of Iterations	10,000
		Population size	40
		Control Points per each contour	40
		ACM Parameters	α=0.2, β=0.35, γ=013

DE a stochastic population based method that is quite similar to evolutionary strategies. It is very popular in solving non-differentiable and non-linear global optimization problems with a faster convergence. Therefore, Cruz-Aceves et al. [17] used DE to guide ACM based image segmentation (DE-ACM). To overcome the local minima problem and sensitivity to initial contour position, they partitioned the region of interest in polar sections. Multiple active contours are guided using DE in multiple polar sections to finally segment the whole region of interest. The experimental results revealed that the method is stable, efficient and highly suitable method for medical image application. It attained a higher accuracy in segmenting the CT scan image of human heart and MRI image of left ventricle images compared to the regions outlined by experts. The choice of control parameters for DE-ACM and the type of medical images used for experiments are listed in Table 10.

Table 10: Parameter settings for DE guided ACM for medical image segmentation

Method	Medical Image	Parameter	Value
DE-ACM [17]	CT image of Human Left ventricle, MRI image of Human Heart	ACM parameters	α=0.01, β=0.9, γ=0.05
		No. of Snakes	12
		Initial number of generations	10
		Differential weight	0.1
		Crossover rate	0.8
		Degrees of polar section	14 for CT images and 15 for MRI images

Ming-Huwi [25] used HBMO (HBMO-ACM) to search for the optimal position in a lager searching window around each control point in order to avoid the failure of precisely searching the boundary concavities. They experimented with different medical images and the method is able to locate the concavity of object boundary more precisely without requiring additional computational time. The choice of control parameters for HBMO-ACM and the type of medical images used for experiments are listed in Table 11.

The contour extraction from ill-defined medical images is convincingly insensitive to the initial approximation in the search space. Asl M. A. et al. [18] in their literature claimed that if time is an important factor, PSO would be the better choice and if it is not the case, both GA and PSO qualify for snake deformation. Chun-Chieh Tseng et al. [19] effectively applied multi-population PSO (PSO-ACM) to enhance the concavity searching capability of the active contour model.

They experimented with medical images and the results show that, PSO when combined with ACM finds the object concavities accurately and efficiently, without extra computation time compared with the traditional method. Thereafter, many researchers [20-22] have used PSO to guide ACM based segmentation to successfully segment regions of interest from different types of medical images. To further improve the efficacy, I. Cruz-Aceves et al. [21] employed multiple swarms (MPSO-ACM) by dividing the image space into different polar sections, whereas I. Cruz-Aceves et al. [22] used a shape prior to guide the active contours. The choice of control parameters for both PSO based active contour model (PSO-ACM) and Multiple active contours guided by PSO (MPSO-ACM) and the type of medical images used for experiments are listed in Table 12.

Table 11: Parameter settings for HBMO guided ACM for medical image segmentation

Method	Medical Image	Parameter	Value
HBMO-ACM [25]	CT knee, MRI knee, MRI shoulder, X-ray hand and X-ray vertebra	No. of queens	1
		Population of drones	60
		Decay rate	0.85
		Capacity of spermatheca	30
		Initial speed of mating flight	1
		Crossover probability	0.8
		Mutation probability	0.2
		Mutation variation	0.5
		No. of control points	30 for CT image, 15 for MRI and X-ray images
		ACM parameters	α=0.81, β=0.71, γ=0.87
		Searching window size	20X20
		No. of iterations	25 to 50

Xiao-Nian Wang [23] and Yuanjing Feng et al. [24] used ACO global optimization algorithm to solve image segmentation problem. Xiao-Nian Wang proposed an active contour model using ACO by constructing solution space and heuristic information. Yuanjing Feng applied Max-Min ant system (ACO-ACM) [24] by interpreting image segmentation to a problem of searching for the best path in a constrained region. Both proved that the results are more effective than the GA based approach proposed by Mishra et al. [14]. Yuanjing Feng applied

ACO for medical ultrasound transducers image segmentation.The object contours obtained after 48 iterations are quite precise. The choice of control parameters for ACO-ACM and the type of medical images used for experiments are listed in Table 13.

Table 12: Parameter settings for PSO guided ACM for medical image segmentation

<table>
<tr><th>Method</th><th>Medical Image</th><th>Parameter</th><th>Value</th></tr>
<tr><td rowspan="4">PSO-ACM [19]</td><td rowspan="4">CT image for human shin, Supersonic image of the womb fibroma</td><td>No. of control points</td><td>30</td></tr>
<tr><td>ACM Parameters</td><td>α =0.02, β =0.86, γ =0.45 for CT image
α =0.01, β =0.85, γ =0.19 for Supersonic image</td></tr>
<tr><td>No. of particles in each swarm</td><td>9 for CT image, and 15 for Supersonic image</td></tr>
<tr><td>Searching window size for each swarm</td><td>30X30</td></tr>
<tr><td rowspan="7">MPSO-ACM [21]</td><td rowspan="7">CT image of Human Left ventricle,
MRI image of Human Heart</td><td>No. of iterations</td><td>20</td></tr>
<tr><td>No. of Control Points</td><td>42</td></tr>
<tr><td>ACM Parameters</td><td>α=0.02, β=0.86, γ=0.45</td></tr>
<tr><td>Snakes</td><td>15 for CT images and 9 for MRI images</td></tr>
<tr><td>Degrees of each polar section</td><td>15</td></tr>
<tr><td>Learning factor</td><td>0.5</td></tr>
<tr><td>Inertia weight</td><td>0.8</td></tr>
</table>

Firefly algorithms based meta-heuristics are even better than GA and PSO [12] because it can find the global optima as well as local optima simultaneously in a very effective manner. The fireflies aggregate more closely around each optimum leading to faster convergence. A. Sahoo et al. [26] exploited these capabilities to efficiently guide the active contours in ACM based segmentation (FFA-ACM). It has been demonstrated that FFA is very suitable in segmenting cervix lesions from Contrast Enhanced CT image of lower abdomen. The approach successfully delineates the region of interest by overcoming the problem of local minima. The choice of control parameters for FFA-ACM and the type of medical images used for experiments are listed in Table 14.

The choice of control parameters for different meta-heuristic based hybrid algorithms listed in Table 9 – 14 are fine tuned for the specific task. These parameter values are set to effectively segment the region of interest from a given image type. These values are different for different kinds of image. Though the control parameters are manually selected for a particular kind of image, meta-heuristics can be further applied to optimally select these values for a given task.

Table 13: Parameter settings for ACO guided ACM for medical image segmentation

Method	Medical Image	Parameter	Value
ACO-ACM [24]	Heart image; left ventricle	No. of control points	100
		Candidate points about a control point	2*N+1 with N=5
		No. of ants	10
		ACM parameters	α=0.06, β=0.03, γ=1.0
		No. of iterations	48

Table 14: Parameter settings for FFA guided ACM for medical image segmentation

Method	Medical Image	Parameter	Value
FFA-ACM [26]	CECT image of lower abdomen	No. of control points	30
		No. of Fireflies	8
		Initial brightness	1
		Absorption coefficient	1
		ACM parameters	α=0.04, β=0.86, γ=0.06

6 Conclusion

Medical image processing is vital for every medical image analysis task. Because of the powerful segmentation abilities, the ACM is widely used for segmenting noisy, ill-defined medical images. Though the technique is quite effective, it suffers from few limitations. Interpreting ACM based segmentation to be an optimization problem, recently the researchers have applied various meta-heuristics such as GA, DE, HBMO, PSO, ACO and FFA to solve and improve its efficacy. Since, the hybrid algorithms are not applied on a single dataset, the results cannot be reasonably compared. The frameworks of different hybrid approaches have been illustrated in this paper, which tempts researchers engrossed in medical image analysis. Hybrid methods can be implemented and experiments can be conducted on different types of real medical images in order to analyze the performances. The paper also exhibits a pathway to design different meta-heuristics so as to further improve the efficiency.

To provide a balance between the exploration and exploitation ability of such meta-heuristics, multiple swarms may be employed in different sections of the search space. These swarms simultaneously search different parts of an image space and collaboratively guide the evolution of active contours leading to an effective segmentation. This not only improves the searching ability, it also facilitates parallel implementation of ACM based segmentation.

It is also noted that the controlling parameters of both the ACM and meta-heuristics used in the hybrid approaches are different for different image types. Researchers experimentally set their values to obtain effective segmentation for a given type of image. Since, the objective here is to adaptively obtain optimal values for such controlling parameters in order to effectively segment the regions of interest from a given image, meta-heuristics being very suitable for solving optimization tasks may be employed to fine tune such parameters.

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