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A Novel Evolving Mutation Analysis approach of Hybrid Parallel Ant Colony Optimization algorithm for DICOM images

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Abstract

The information contained in a DICOM image is very crucial for telemedicine, tele-radiology and other medical diagnosis and prognostic applications. In the field of medical transcription there have been various techniques in detecting the edge of an image. In most of the computer vision systems, DICOM image is considered as a standard digital imaging process of storing, capturing and transmitting the required medical information of an individual. The meta-heuristic process used in detecting the edge of an image, topologically, while the evolving non-deterministic behavior, stochastically, is to be addressed through a natural selection process. In this paper we propose a hybrid genetic algorithm coupled with effective parallelism topology based Ant Colony Optimization (ACO) and Hamilton's rule for evolutionary scenarios. The initial analysis of the algorithm showed an appreciated performance in handling the dynamic attributes of the DICOM images. This is successively enhanced with the parallelism topology, as multi-processor environment is considered which has shown an improved speed and efficiency.

Keywords: Edge detection, ACO, Hybrid PACO, Mutation Analysis, As Built Critical Path (ABCP), Genetic Algorithm, Evolution

INTRODUCTION

The medical standard digital imaging paradigm, DICOM befits a best fitting solution for the paradox in image edge detection. Many algorithms and techniques were proposed for computer vision systems, for this essential analysis application. The process of detecting an edge of an image yields ample amount of data at a reduced rate. The quantification of the evolving image data, specifically among the DICOM standard medical images, the need for an enhanced performance in rendering the solution is necessary. This was duly addressed by the proposal of an enhanced, hybrid effective parallelism topology for ACO algorithm with critical Path methodology by Chetan S et al. [2]. This technique takes into consideration the very essential factors of heterogeneous computation techniques and algorithms in solving the NP-hard scenarios as addressed by Chetan S et al. [1]. Increasing complexities in the paramount metrics within DICOM medical images, their data, intensity variations around the local region and its integrity & restructuring relating to the edge of an image are integrated parts of edge detection. In all these handling and processing of medical images and its derivatives & standards are real hard tasks. These kind of images are dynamically low contrast, complex to analyze and discontinuous with intensity variations. The advanced qualifying value of evolution, to be evaluated, was prominently provided by Hamilton rule [3]. The social behavior exhibited, is synthesized with the purview of this behavior as a genetically cohered issue.

The genetic evolution being considered as a fundamental and enduring problem for which various quantitative tests have been quantified manipulations justified by the equation, as given in [4],

$$rb - c > 0$$

r – genetic relatedness

c – fitness cost of PACO-CPM edge detection algorithm

b – fitness benefit for the heuristic behavior of the ants and the evolving feature of the DICOM image

This befitting solution shows that the behavior of the ants in the ACO algorithm, even though resolves the metaheuristic related issues, exhibits certain critical trails of weaknesses. These criticalities are weak selection of the points for edge detection, best fitting solution and time involved for the analysis. The numerical value of the relatedness proves to provide with a crucial correlations between the similarity among the individual ant, differentiated as virtual and real ants [1]. The technique proposed in this paper involves the hybrid combination of the genetic algorithm as proposed by M K Lee et al. [5], with the extraction of certain quantifying metrics. A kind of this work was proposed by Zhang et al. [6]. Also this technique involves the effective PACO-CPM algorithm in improvising the points of selection being made by the natural selection process by the ants [1]. Further with the introduction of the evolution evaluation, governed by the Hamilton's rule [7(8)], this hybrid technique proves to more rugged and highly reliable in extracting the required essential data from the edge of an image. The quantitative metrics such as relatedness, fitness cost and the fitness benefit are being evaluated [8] to justify this technique.

APPROACH

For a non-deterministic behavior of ants (both real and virtual ants) during the edge detection in a medical standard DICOM image is considered to be basically a search and optimize process, with the evolution and natural behavior characteristics [9]. This entire process of search and optimize happens within a search space of the image, provided. The objectives crossover and mutation along with the fitness cost and benefit calculations are inherited from the very basic principles of genetic algorithm. While the best possible fitting path (Critical Path – with the shortest path), processed parallel are considered from ACO methodology. The random path is generated as per the hybrid As Built Critical Path (ABCP) Ant Colony Optimization from a literature study, proposed by Chetan S et al. [10], the selection is made based on the numerical values obtained from the fitness calculations, as suggested by the Hamilton's rule. The characteristics inherited individuals, off-springs, are generated with through the process of Crossover, to be mutated with their probabilities being governed as suggested in the genetic algorithm. The process of mutation is considered to occur dynamically with the image element values changing randomly.

The nature inspired meta-heuristic [11] process of finding solutions to hard combinatorial problems are addressed by hybrid ABCP-ACO algorithm. The only relative concerning factor in this is the computation time. This de-facto metric is taken care effectively by PACOCPM technique.

The process of mutation also helps in verifying and validating the syntactical correctness of the off-springs generated from the parents, as with the generation of a counter-example, if necessary.

METHODOLOGY

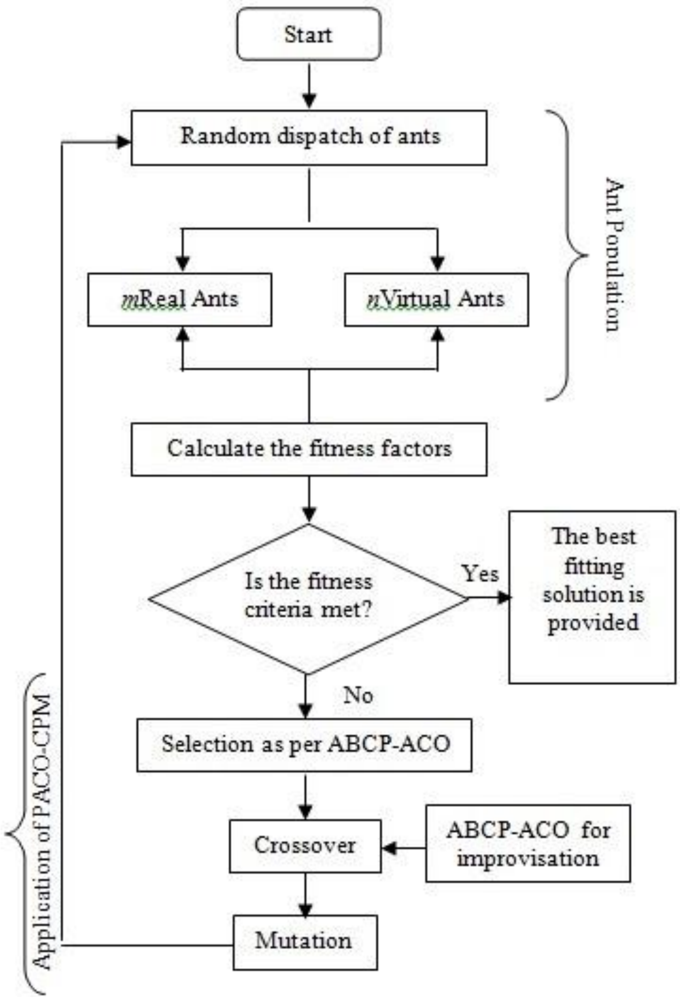

Figure 1: Evolutionary Workflow of Genetic Algorithm for Hybrid ABCP-ACO Algorithm

The process starts with the random dispatch of accumulative set of m Real Ants and n Virtual Ants, over the square DICOM standard, grayscale medical image. The dispatch of the ants is such that, it is well within the specified resolution of the square sized image. The ants which make over major portion on the edge of an image are considered. Here we assume that the performances of the individual sect of ants are proportional pheromone deposition and the intensity of the pheromone deposited at the points of intensity variations in an image. Under these circumstances it was also given that the ants are provided with the instance of allocating the fitness values based on the pheromone deposition success. This is done among themselves or between each other among the group of real and virtual ants. This is can also be laid to happen between a real and a virtual ant as well.

The basis of pre-fixing or choosing an appropriate fitness numerical value in the shared scenario proved to be one of the best fitted solutions. Hence precise values are assigned to calculate the fitness benefit and the fitness cost metrics. The criterion for the fitness is evaluated on a continuous basis, all along, with its neighboring cell intensity variation values. The greater differences between their respective intensity values ascertain that the point is fit.

As per the performance metrics generated by the As Built Critical Path – Ant Colony Optimization technique, the best possible path with the better deposition of pheromone which is considered to be the Critical Path is selected. This enhances the performance of the algorithm thus making its survival extensive for the next generation, after Crossover and Mutation. With the start of this process the entire algorithm transits into parallel mode of operation as governed by PACO-CPM.

The process of Crossover is taken over and here each individual is handled exclusively. The number of ants (both real and virtual) cumulatively records to the pointing location, which is the source point for the ants in ABCPACO. Here the transition probability matrix variables, á and â are considered to be equivalent to 0.8 and 0.2, respectively. These factors are essential in determining the pheromone deposition and heuristic information from ABCP-ACO. The pheromone matrix is constructed based on the concentration of the pheromone deposition made by both the real and the virtual ants.

There appears a similarity in the fitness function, as specified by Hamilton’s rule and the heuristic function. The former is required in order to manipulate the probability of an ant traversing to the neighboring cell, with variations in intensity values with respect to its neighboring cells.

The traversing of the ants in the image provides the genetic algorithm with the new updated points as the parent individuals. These points and the magnitude of them being traced, along with their quality improvises upon crossover. The Crossover points within an image are randomly generated and this governed by the genetic algorithm. The parent individuals are exchanged with these crossover points as a result of which new off-springs are being produced.

The produced off-springs are mutated further to obtain their characteristic behavior and its deviations from that of their parent individuals. Mutation is also a random process in which the individuals are evaluated based on the min-max condition of occurrence.

*A. **Pseudo-Code***

Start the process

Random dispatch of ants: both *m* Real Ants & *n* Virtual Ants

Traverse on the image: population and points

While generation < (no. of generations)

Fitness Calculation: intensity variations among the neighboring cells are evaluated

Selection: Transition probability matrix is updated; Update the pheromone matrix. Evaluate the weight of deposition of pheromone deposition made based on its weight-age factor, Ei

Call: ABCP-ACO function and updated image matrix, no of points highlighted along with the information pertaining to the selected population of ants

While iteration < (no. of iterations) → refers to the cyclic iterations

For ant index n=1: number of ants

For steps index=1: number of cyclic iterations along with no. of steps for each ant

Move the m^{th} Real Ant and n^{th} Virtual Ant for 1 step according to the Transition Probability Matrix

Update: Pheromone Matrix

End While

End While

End While

Returns ABCP-ACO provides with the selected parent individuals with improved points before Crossover

Crossover: Crossover of two individuals, generation of off-springs

Mutation; End While

*B. **Mutation & Cross-Over***

Mutation is a gradual evolutionary process wherein the competition (selection) for the fit off-springs is selected out of a number of random variants of ants from the entire ant population. The length of chromosome defines the amount of information to be carried for mutation and cross-over. The process of mutation and cross-over is the basis upon which the evolutionary change is taking place and this is evaluated based on the Fitness. The number of off-springs carrying the necessary information as inherited from the parent ants will be defined by the fitness value. The probability of this value is assumed to be smaller than 1. The factors that are required for the process of mutation and cross-over are as listed below in Table 1.

Table 1. Factors of Mutation and Cross-Over

Sl No.	Factors	Values (ABCP-ACO)	Values (ACO)
1	Probability of Mutation (*pm*)	0.1	0.05
2	Probability of Cross-Over (*pc*)	1.0	0.1
3	Population Size (*popsize*)	1500	128
4	Chromosome Length (*chromlength*)	20	10

C. *Relatedness, Costs and Benefits*

The natural behavior of ants being exhibited as a swarm maybe, considered to be evolving within the same population or among a different population. The relatedness metric was calculated by creating duplicate copies for each swarm of population of ants and each group bearing different magnitudes of duplicate copies of them. The frequency of creation of such duplicate copies with different varieties of combination is given by,

$$x_i, i = 1 \ldots k, \sum_{i}^{\infty} = 1$$

This metric assists in evaluating the similarity between the ants or group of ants (individuals) which might be similar to each other. Here we also assume that the swarm of ants considered is comprised of a groups and b individuals with each,

$$\bar{p} = \sum_{i}^{\infty} x_i \frac{n x_i - 1}{mn - 1}$$

$$\bar{q} = \sum_{i}^{\infty} x_i \frac{n x_i - 1}{n - 1}$$

Where,

$\bar{p}$ → average probability of an individual being identical to another individual genetically

$\bar{q}$ → average probability of an individual being identical duplicate to another individual genetically

With all these assumptions and the equations preferred, the evolving populations and the individuals for case study is assumed to be as,

m = 250 groups

n = 10 individuals

Generally the social behavior impacts the numerical values pertaining to the fitness costs and benefits. The evolving change in the behavior of the ants which relatively sets for the absolute values of fitness costs and fitness benefits are as;

$$b = \frac{1}{c + 1}$$

While,

$$c + b = 1$$

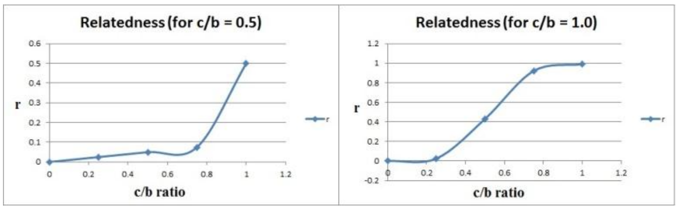

Figure 2. Relatedness Evaluation for c/b ratios

The performance is evaluated based on,

Performance = (Treatment Factors (rb - c) + Noise Factor (0.12)) *100

Treatment Factor (r)	Treatment Factor (c/b)	*Performance*
0.5	*0.5*	*2**
1	*0*	*1.12**

**Performance metric to be multiplied by 100*

CONCLUSION AND FUTURE SCOPE

In this paper we have proposed an effective, efficient and hybrid algorithm to perform edge detection with the evolving factors in a medical image to be analyzed. The performance metrics generated from the implementation of this algorithm shows a better deviation on par with the proposed and in effect algorithms and techniques on similar lines. It is also observed that the algorithm was capable of handling dynamic variations in the parameters of the image and sometimes the image itself may change. This is because in the field of medical diagnosis, different images with various time stamps are recorded for diagnosis and treatment purposes. The usage of a multi-processor parallel topological environment improved the overall performance of the system. As well the application of the proposed hybrid ABCP-ACO algorithm also yielded much better results in comparison with the other techniques.

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