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Comparative analysis of Ant Colony Optimization problem with Tabu Search

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ABSTRACT

This paper focuses on the comparative analysis of most successful methods of optimization techniques inspired by Swarm Intelligence (SI), Ant Colony Optimization (ACO) and Tabu Search (TS). An elaborate comparative analysis is carried out to endow these algorithms with fitness sharing, aiming to explore whether this improves performance which can be implemented in the evolutionary algorithms.

Keywords: Swarm intelligence, Ant Colony Optimization, tabu Search.

INTRODUCTION

Tabu Search is essentially a sophisticated and improved type of local search, an algorithm that in its simplest form, also known as Hill Climbing, works as follows. Consider a starting current solution, evaluate its neighboring solutions (according to a given neighborhood structure), and set the best or the first found neighbor which is better than the current solution as new current solution. Iterate this process until an improving solution is found in the neighborhood of a current solution. The local search stops when the current solution is better than all its neighbors, that is, when the current solution is a local optimum. Swarm intelligence (SI), which is an artificial intelligence (AI) discipline, is concerned with the design of intelligent multi-agent systems by taking inspiration from the collective behavior of social insects such as ants, termites, bees, and wasps, as well as from other animal societies such as flocks of birds or schools of fish.

Colonies of social insects have fascinated researchers for many years, and the mechanisms that govern their behavior remained unknown for a long time. Even though the single members of these colonies are non-sophisticated individuals, they are able to achieve complex tasks in cooperation. Coordinated colony behavior emerges from relatively simple actions or interactions between the colonies and the individual members. Many aspects of the collective activities of social insects are self organized and work without a central control. Clustering means the act of partitioning an unlabeled dataset into groups of similar objects. Each group, called a cluster, consists of objects that are similar among themselves and dissimilar to objects of groups. In the past few decades, cluster analysis has played a central role in a variety of fields ranging from engineering (machine learning, artificial intelligence, pattern recognition, mechanical engineering, electrical engineering), computer sciences (web mining, spatial database analysis, textual document collection, image segmentation), life and medical sciences (genetics, biology, microbiology, paleontology, psychiatry, pathology), to earth sciences (geography, geology, remote sensing), social sciences (sociology, psychology, archeology, education), and economics (marketing, business).

Swarm intelligence can also be implemented in the field of clustering for obtaining approximately solutions to optimization problems in a reasonable amount of computation time. These are two important and recent methods of optimization such as ACO and PSO, which is implemented for this purpose. The main properties of the collective behavior can be pointed out as follows and is summarized. Homogeneity: Every bird in a flock has the same behavioral model. The flock moves without a leader, even though temporary leaders seem to appear. Locality: its nearest flock mates only influence the motion of each bird. Vision is considered to be the most important senses for flock organization. Collision Avoidance: avoid colliding with nearby flock mates. Velocity Matching: attempt to match velocity with nearby flock mates. Flock Centering: attempt to stay close to nearby flock mates The ability of Particle Swarm Optimization (PSO), heuristic technique for search of optimal solutions based on the concept of swarm, to efficiently face classification of multiclass database instances. PSO reveals itself very effective in facing multivariable problems in which any variable takes on real values. It has roots in two methodologies. Its links to Artificial Life in general, and with bird flocks, fish schools and swarm theory in particular are very evident. Nonetheless, TS is also tied to Evolutionary Computation, namely to Genetic Algorithms (GA) and to Evolutionary Programming. The ACO and TS can be analyzed for future enhancements such that new research could be focused to produce better solution by implementing the effectiveness and reducing the limitations of PSO. Plans to endow PSO with fitness sharing, aim to investigate whether this helps in improving performance can be implemented in the evolutionary algorithms.

ANT COLONY OPTIMIZATION

The Ant Colony Systems or the basic idea of a real ant system is illustrated in Figure 1. In the left picture, the ants move in a straight line to the food. The middle picture illustrates the situation soon after an obstacle is inserted between the nest and the food. To avoid the obstacle, initially each ant chooses to turn left or right at random. Let us assume that ants move at the same speed depositing pheromone in the trail uniformly. However, the ants that, by chance, choose to turn left will reach the food sooner, whereas the ants that go around the obstacle turning right will follow a longer path, and so will take longer time to circumvent the obstacle. As a result, pheromone accumulates faster in the shorter path around the obstacle. Since ants prefer to follow trails with larger amounts of pheromone, eventually all the ants converge to the shorter path around the obstacle, as shown in Figure 1.

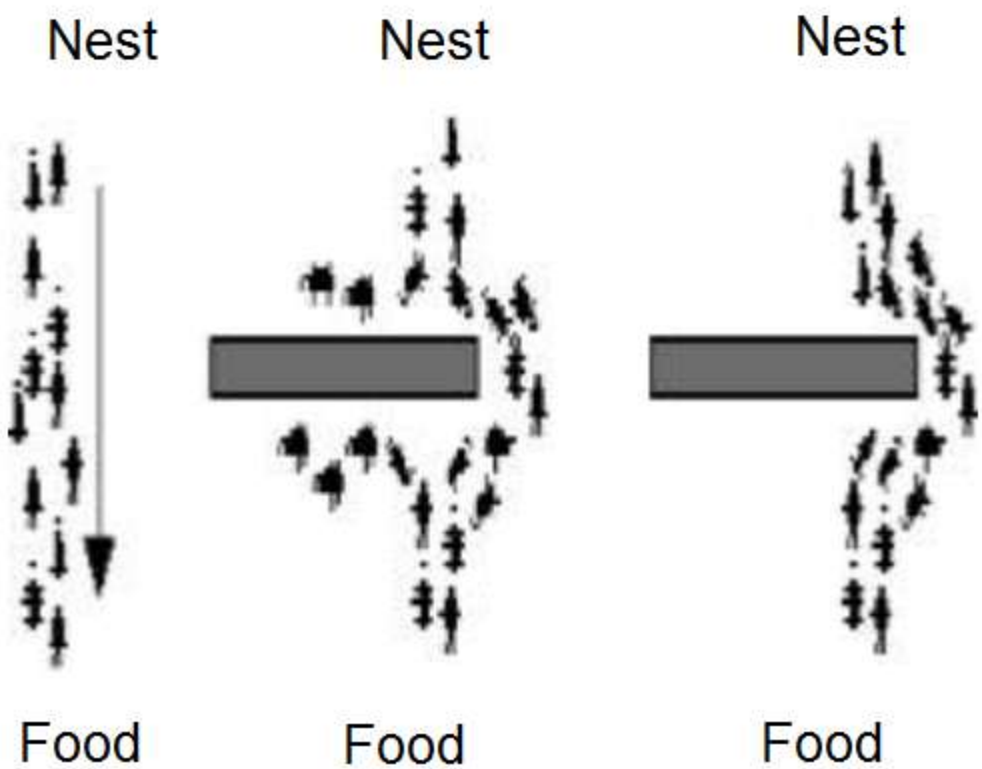

Fig. 1: Illustrating the behavior of real ant movements

An artificial Ant Colony System (ACS) is an agent-based system, which simulates the natural behavior of ants and develops mechanisms of cooperation and learning. This new heuristic, called Ant Colony Optimization (ACO) has been found to be both robust and versatile in handling a wide range of combinatorial optimization problems. The main idea of ACO is to model a problem as the search for a minimum cost path in a graph. Artificial ants as if walk on this graph, looking for cheaper paths. Each ant has a rather simple behavior capable of finding relatively costlier paths. Cheaper paths are found as the emergent result of the global cooperation among ants in the colony. The behavior of artificial ants is inspired from real ants: they lay pheromone trails (obviously in a mathematical form) on the graph edges and choose their path with respect to probabilities that depend on pheromone trails. These pheromone trails progressively decrease by evaporation. In addition, artificial ants have some extra features not seen in their counterpart in real ants. In particular, they live in a discrete world (a graph) and their moves consist of transitions from nodes to nodes. The ACO differs from the classical ant system in the sense that here the pheromone trails are updated in two ways. Firstly, when ants construct a tour they locally change the amount of pheromone on the visited edges by a local updating role.

Secondly, after all the ants have built their individual tours, a global updating rule is applied to modify the pheromone level on the edges that belong to the best ant tour found so far.

TABU SEARCH

Tabu Search is a kind of heuristic search and iterative method for solving optimisation problems. It uses memory structures to guide a hill-descending heuristic to continue exploration. The main ideas characterizing the TS metaheuristic were independently proposed in the eighties by Glover and Hansen and since then TS has been widely applied to combinatorial optimization problems. Tabu Search is a local search algorithm used to solve optimization problem. It uses local search to iteratively move from one solution to another solution which is a neighbour of the present solution until some stopping criteria has met. It may stuck to local optima during the local search and to avoid this it uses a memory structure which is called the TL. There are two components in the TS algorithm, the TL and the aspiration criteria. TL consist of Tabus which are those solution which causes sticking in local optima or cycling in the search space so as to avoid those solutions. Tabus are the short-term memory that help the search to move away from previously visited search space. Aspiration criteria: Tabus are sometimes so powerful that they prevent a solution even if there is no danger of being cycling with that solution. In that case algorithm must be given some devices tha cancel the tabus. These are called aspiration criteria. The most commonly used aspiration criteria is to allow a move if it result in a objective value better than the current solution even if it is in the TL.

A comprehensive introduction to TS can be found in the book by Glover and Laguna, or in Hertz, Taillard and de Werra. TS is essentially a sophisticated and improved type of local search, an algorithm that in its simplest form, also known as Hill Climbing, works as follows. Consider a starting current solution, evaluate its neighboring solutions (according to a given neighborhood structure), and set the best or the first found neighbor which is better than the current solution as new current solution. Iterate this process until an improving solution is found in the neighborhood of a current solution. The local search stops when the current solution is better than all its neighbors, that is, when the current solution is a local optimum. Such a simple and very general local search behaves quite poorly in practice, particularly because when a local optimum is found, the algorithm stops improving, and combinatorial problems often have local optima whose objective values are much worse than that of the global optimum. The strength of the TS metaheuristic with respect to simple local search is that, by employing three TS-specific concepts, it avoids toget pre- maturely stuck in a local optimum. These TS-specific concepts are: best improvement, tabu lists, and aspiration criteria. Best improvement means that each current solution is always replaced by its best neighbor, even if the best neighbor is worse than the current solution. This is clearly a way not to get stuck in local optima.

Using best improvement poses the problem of possible cycling among already visited solutions, because it is possible, for example, that the best neighbor of a solution is indeed the last visited current solution. In order to avoid cycling, choosing recently visited solutions is forbidden, by storing some attributes of these solutions in the so-called tabu lists. Whole solutions are not stored in a tabu list, because this would require too much memory for most combinatorial optimization problems. The choice of attributes is a delicate point. Typically, tabu lists store the ‘moves’ that should be performed in order to go from one solution to another, or the differences between solutions. In this way the memory requirement of tabu lists is feasible, but another problem arises: forbidding all solutions corresponding to a tabu attribute may forbid also solutions that have not yet been visited, and possibly also very good or optimal solutions. TS employs aspiration criteria for solving this problem. An aspiration criterion is a condition that, if satisfied, allows to set as new current solution a solution obtained by performing a tabu move. A typical example of aspiration criterion is requiring that a solution is better than the best solution found from the beginning of the algorithm.

The Tabu search metaheuristic is a procedure used to handle a heuristic local search algorithm to avoid the process stops at a local optimum. Therefore, Tabu search makes a scan through a configuration space appropriately defining the local optima. This type of algorithm does is keep a list of points in the problem space that have been evaluated wrong, away from it as much as you can, in order to make the search for its solution. So while searching for the solution by maintaining the list of bad results is that it prevents the process and return to local optima into repetitive cycle’s performed. The algorithms consider these movements as “Tabu movements” and therefore prohibit a configuration to be accessed again. The idea is to make moves on the solution space, when a movement has been classified as taboo and after being analyzed produces better chosen reference value (which can be a good solution uncertainty or another previously found) objective function, then a criterion called "rule of aspiration " consisting cancel the prohibition of a state and return to accept the motion for walking on the solution space applies.

The General framework of TS algorithm is given as follows:

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```
s ← s0
sBest ← s
tabuList ← []
while (not stoppingCondition())
candidateList ← []
bestCandidate ← null
for (sCandidate in sNeighborhood)
if ( (not tabuList.contains(sCandidate)) and(fitness(sCandidate) > fitness(bestCandidate)) )
bestCandidate ← sCandidate
end
end
s ← bestCandidate
if (fitness(bestCandidate) > fitness(sBest))
sBest ← bestCandidate
end
tabuList.push(bestCandidate);
if (tabuList.size > maxTabuSize)
tabuList.removeFirst()
end
end
return sBest
```

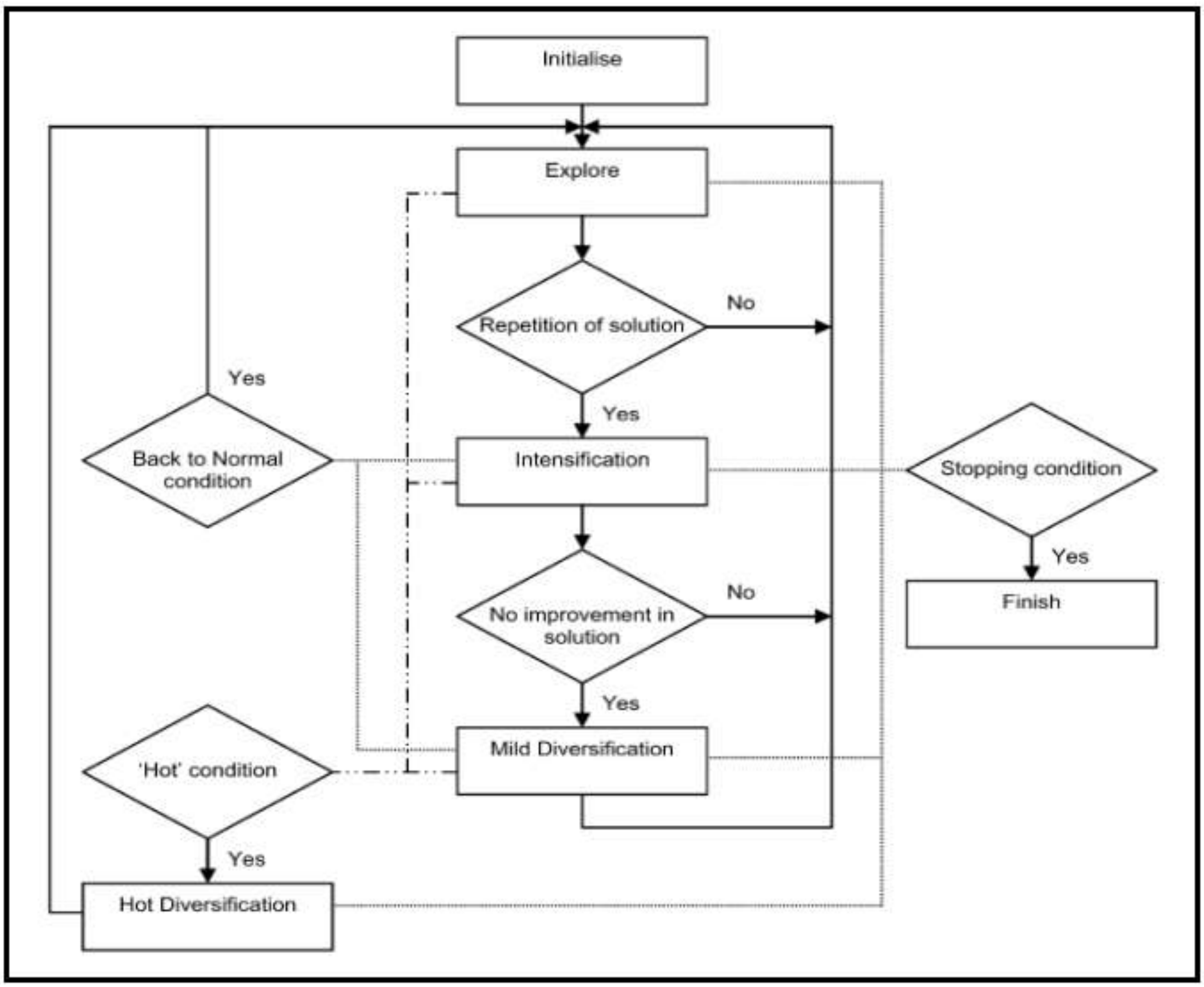

Fig. 2: Tabu Search Framework

The main benefit of TS over other methods is the ability of the memory to prevent searching the previously seen areas. It can easily leave the local optimum and attain the global optimum in a shorter time.

Tabu search (TS) was first proposed in its current form by Glover. It has been successfully applied to a wide range of theoretical and practical problems, including graph coloring, vehicle routing, job shop scheduling, course scheduling, and maximum independent set problem. One main ingredient of Tabu search (TS) is the use of adaptive memory to guide problem solving. One may argue that memory is a necessary component for _intelligence‘, and intelligent problem solving. Tabu search uses a set of strategies and learned information to _mimic‘ human insights for problem solving, creating essentially an _artificial intelligence‘ unto itself—though problem specific it may be. In its most basic sense, a Tabu search can be thought of as a local search procedure, whereby it _moves‘ from one solution to a _neighboring‘ solution. In choosing the next solution to move to, however, Tabu search uses memory and extra knowledge endowed about the problem. A basic Tabu search algorithm is shown below.

CONCLUSION

The Ant Colony Optimization and Tabu Search can be analyzed for future enhancement such that new research could be focused to produce better solution by improving the effectiveness and reducing the limitations. More possibilities for dynamically determining the best destination through Ant Colony Optimization can be evolved and a plan to endow Tabu search with fitness sharing aiming to investigate whether this helps in improving performance. In future the velocity of each individual must be updated by taking the best element found in all iterations rather than that of the current iteration only.

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