A New Local Search Algorithm for Continuous Spaces Based on Army Ant Swarm Raids

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***Abstract*— It is well known that evolutionary algorithms often perform much better when augmented with a local search mechanism. While many local search methods exist for combinatorial optimization problems, there are relatively few methods designed to work over continuous fitness landscapes. This paper describes a novel continuous space local search algorithm for evolutionary algorithms that emulates army ant swarm raids. Our preliminary results show the method is remarkably effective.**

I. Introduction

Arguably the most challenging optimization problem is to find the global minimum (or maximum) of a continuous function $f(\vec{x})$ over a compact set $\mathcal{S} \subseteq R^N$ with $N > 3$. These type of problems are ubiquitous throughout the scientific world. For example, the global minimum on a potential energy surface provides valuable clues about the reactivity of an atomic cluster [3] or the biological function of a protein [4].

The two problems mentioned above—and virtually all other scientific optimization problems of any real interest—are provably NP-hard. Consequently, reliable methods for finding minima or maxima on these continuous surfaces don't really exist. One problem that complicates the search is these surfaces often have local minima that increase exponentially with N. Nonlinear programming approaches are simply inadequate under such circumstances [2]. Meta-heuristic methods such as simulated annealing [5] and evolutionary algorithms [1] have been used in the past, but with varying degrees of success. Moreover, these algorithms require special precautions to prevent them from getting trapped in local optima.

Nature has already solved many optimization problems of interest using methods and procedures man has only begun to comprehend. New methods are sometimes developed by just mimicking exactly what nature does even if the underlying principles aren't fully understood. In particular, insects have existed for over 150 million years; they are experts at exploring continuous, nonlinear 3-D surfaces for food and suitable habitat.

In this research effort we will develop a new global optimization algorithm that mimics raiding patterns of army ants (*Eciton burchelli*) to explore N-dimensional, non-convex continuous surfaces for global optima. We already have preliminary results (over 3-D surfaces) which indicates the algorithm is remarkably thorough and effective. We anticipate this research effort will produce a search algorithm capable of exploring continuous, non-convex N-spaces with $N > 100$.

II. Problem Formulation

Let $\mathcal{S}$ be a compact subset of R^N. The global optimization problem to solve is

$$\max_{\vec{x} \in \mathcal{S}} f(\vec{x})$$

where $f : \mathcal{S} \rightarrow R$ is a continuous function defined on $\mathcal{S}$. f is expected to have a global maximum f^* over $\mathcal{S}$.

$\mathcal{S}$ and the mapping generated by f form a continuous surface where the mapping determines the surface elevations. The above optimization problem can be solved by locating the highest peak elevation on this surface. The surface is not necessarily convex, which means there may be multiple peaks with different elevations.

III. How Ants Explore

Our new search algorithm is based on the raiding patterns of army ants, specifically the species *Eciton burchelli*. We begin with a brief summary of exactly how army ants conduct swarming raids.

Army ant colonies are terrestrial and live in warm, humid climates. Although they do conduct raids over open terrain, they prefer forested areas. Communication between ants is restricted to local chemicals and some physical touching. *E. burchelli* colonies are harvesting animals; they consume all available prey along their entire life-time's track [6]. (It is this latter characteristic which convinced us to use army ant behavior as a new search strategy.)

Figure 1 shows the raiding patterns of *E. burchelli*. Typically hundreds of thousands of ants participate. At the start of the raid only a few ants are involved, but soon a distinct swarm takes form. The swarm begins an advance away from the colony site generally in one direction. Within three hours the swarm begins to form a complex fan-shaped networks tapering down to a single trunk trail back to the colony location [8]. Outbound ants are thought to deposit small amounts of chemical called *pheromone*. Once prey is found, usually some unfortunate arthropod[1], the ants return to the colony laying even greater amounts of pheromone. This pheromone attracts

[1] invertebrate animals such as insects, arachnids and crustaceans

Fig. 1. Foraging patterns of *E. burchelli* (from Burton and Franks [7])

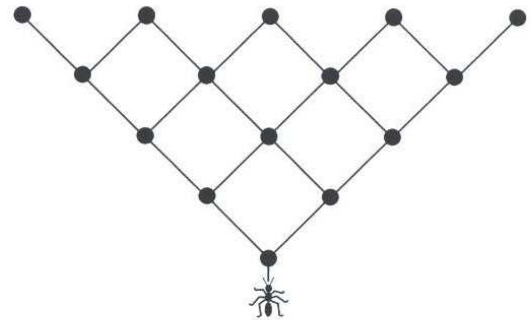

Fig. 2. Lattice used to control ant behavior (from Camazine et.al [9])

(recruits) other ants to the food source. The presence of prey and their capture has a major influence on the behavior of individual army ants and hence the structure of the swarm raid [9].

A number of researchers strongly believe the swarm dynamics are *self-organizing* (e.g., see [10]). Self-organization means there is no leader, no master program directing the activities of individuals. Camazine et al. [9] define self-organization this way:

> *"Self-organization is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of the system. Moreover, the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern"*

Army ants don't raid every day. Each raid is in one general direction radiating straight out from the nest. The next raid is always in a different direction from the last raid. Colonies rotate their successive raids about the central nest site [6]. This forced structure to the search pattern ensures adequate coverage of the surrounding area.

A. Modeling Ant Behavior

Deneubourg, et al. [11] developed a mathematical model that emulates the dynamics depicted in Figure 1. (For brevity, we refer to it as the DGFP model.) Since our new search algorithm is based on the DGFP model, it is worthwhile briefly describing it.

Ants move over a 2-D lattice superimposed on the continuous surface. (See Figure 2.) At each time step the ant chooses to move left or right and adds to the pheromone at the point it moves to. Initially the choice is random, but later the probability of choosing left or right depends on the pheromone at the left and right points. A maximum of 20 ants can occupy any point; an ant does not move if both the left and right points are overpopulated. Whenever food is found, an ant takes it and returns to the colony following the same movement rules; food is not renewed once it is removed. There is one difference in behavior on the return trip: ants deposit one unit of pheromone while advancing, but they deposit ten units while returning. During each time step a fraction of the pheromone is removed to simulate evaporation. Finally, ten ants leave the colony at each time step.

Figure 3 shows two Monte Carlo simulations of the DGFP model. In each run it was assumed a lattice point has a fixed amount of food with a fixed probability, which approximates the *E. burchelli* feeding environment—i.e., a diet of primarily scattered arthropods. The figure on the left has a 1% probability of each point having food. Notice the well defined swarm with a narrow trunk trail back to the colony. The figure on the right has a 50% probability of each point having food. Now notice the returning ants have well established return paths back to the colony that form a structures like a river delta. The DGFP model was subsequently verified via field experiments [12].

B. Details of the Army Ant Algorithm

Our search algorithm uses a modified version of the DGFP model to explore continuous surfaces for the global maximum. The original DGFP model was only developed to study self-organizing behavior in army ant swarms; it was never intended to be used as an optimization method. Hence, a number of modifications were necessary before it could be used for optimization. Our changes to the model are as follows:

- (*ant orientation*) Apparently ants have some internal mechanism, compass if you will, that orients them back towards the colony should they get separated from the pheromone-laden truck trail [13]. The DGFP model forces returning ants back towards the trunk trail if neither point in front of them has any pheromone. In our model the probability of choosing a point to move to is purposely biased toward the trunk trail. This modification

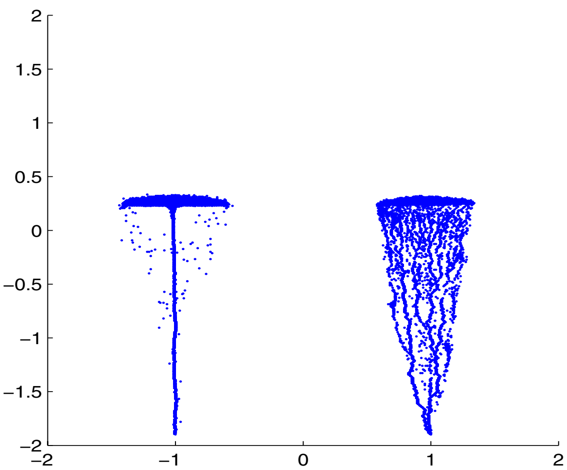

Fig. 3. Monte Carlo simulations of the DGFP model. See text for explanation.

was necessary to obtain the structure depicted in Figure 1.

- (*scout ants*) The DGFP model does not rely on scout ants to determine the raid direction. Our model uses scout to help select the best direction for a raid.
- (*distribution of food*) The DGFP model assumed each lattice point had a fixed quantity of non-renewable food. We assume high elevations in the surface are the only places where food exists. These means the ants in our model may travel a considerable distance without finding any food or, conversely, they may encounter regions where virtually every lattice point contains food.

This last point requires clarification. It is important to understand prey—i.e., food—in our model has a completely different interpretation from that used in the DGFP model. In the DGFP model prey is a physical entity at a lattice point; in our model prey is the elevation of a surface at a lattice point. The ants seek higher elevations on the surface because that's where the best prey is. In other words, the higher the elevation, the more delectable the prey.

Our model uses scout ants to determine the direction of the raid. We deploy 100 scout ants simultaneously from the colony. Each scout makes random moves over the continuous surface recording where prey (high elevations) are located. At the end of this reconnaissance phase the scout who found the highest elevation determines the raid direction. The raid begins immediately.

Let H be the highest elevation found by any scout ant and let (H_x, H_y) be its grid coordinates. (The distance D at an angle of θ from the colony to that point can be computed.) The raid moves at an angle θ, recording elevations as it moves, but no prey is found until an elevation of αH is encountered. Any lattice point with a surface elevation of αH or greater is assumed to have prey. The ant that first moves to such a lattice point takes the prey and sets the elevation to 0 so that any ant subsequently visiting the same lattice point won't find any prey. An ant with prey immediately starts the return journey to the nest. The raid terminates when the first ant has traveled distance βD from the nest. (In our work $\alpha = 0.9$ and $\beta = 1.1$. Both coefficients are user-selectable.)

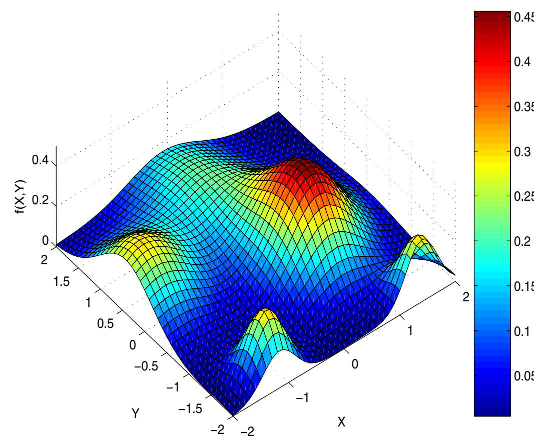

Fig. 4. The surface used to obtain preliminary results. This surface represents a local neighborhood of an arbitrary individual in the population of an evolutionary algorithm.

All ants initially move forward and only reverse direction if prey is found. Ants lay 1 unit of pheromone while moving forward and 10 units while returning. Ten ants leave the colony to begin foraging at each time step. The steps in our algorithm are listed as Algorithm 1 in the Appendix.

C. Preliminary Results

We have preliminary results to show how our ant search algorithm works. So far the algorithm only works for 3-D surfaces, but that was done on purpose so that a detailed performance analysis could be conducted. Figure 4 shows the surface used for these preliminary tests. The objective is to find the highest peak, which has an elevation of 0.4601 and is located at (x, y) = (0.5996, -0.3383).

Figure 5 shows the scout ants, which were dispatched from the colony located at (-0.5,-1.4). Figure 6 shows the resultant swarm. Notice the swarm crosses the global peak. The best prey (elevation) found had a value of 0.46 at location (0.5934,-0.3441).

IV. Proposed Research Effort

Preliminary work has been completed on the army ant algorithm. Our next research effort is focused on achieving two goals. The primary goal is to incorporate two improvements to the army ant algorithm to help reduce the computational effort. The secondary goal is to incorporate the army ant algorithm

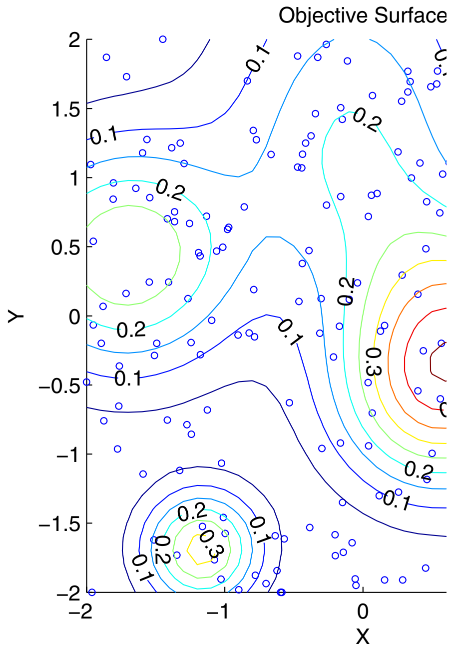

Fig. 5. Contour map of Figure 4 showing final placement of scout ants after a reconnaissance phase. Notice the uniform distribution across the surface. Several ants are in the vicinity of the global optimum (i.e., the highest elevation).

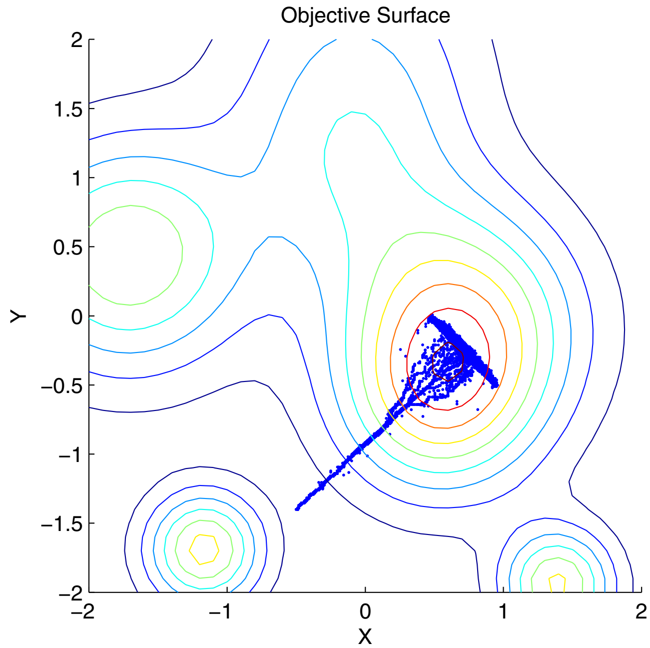

Fig. 6. Swarm raid conducted with the bearing angle automatically computed from the scout reconnaissance results. Notice the chosen bearing angle oriented the swarm correctly to traverse the area surrounding the global optimum. The colony, located at approximately (-0.5, -1.4), is an individual in the population of an evolutionary algorithm. The small (x, y) plane shown is a neighborhood of that individual.

into an evolutionary algorithm as a local search mechanism. This combination will produce a search algorithm capable of exploring continuous N-spaces with $N > 100$.

Primary Goal

Although the preliminary results are impressive, two key areas still need improvement. Specifically,

(1) The current version uses a fixed threshold elevation factor (αH) to indicate the presence of prey. Ant that find prey immediately turn around and start back to the colony—which lowers the density of the swarm front thereby diminishing the search effectiveness. This becomes especially problematic when the swarm crosses a high elevation plateau because every lattice point then contains prey.

It is well known that adapting algorithm parameters greatly improves the search performance of evolutionary algorithms. We need to develop methods for adapting the threshold elevation parameter α to keep the swarm front moving forward. One possible way to implement this adaption is to have returning ants report the elevation level (i.e., α) that caused them to return to the nest. This value can be stored at each node so that ants moving forward can readjust their elevation faction αH.

(2) The current version relies on scout ants to help choose the raid direction. This is not a problem, even with many local optima, so long as the surface has a prominent globally optimum peak. But at this point we do not know how the algorithm will perform over surfaces that either have few prominent topological features, like the Rosenbrock function, or when there are numerous local optima all with the same elevation. In these circumstances multiple raids may be needed. We need to develop rules for conducting multiple raids in the same 3-space.

Secondary Goal

The raid always moves in 3-space. This means each raid only explores some $\mathcal{S} \subseteq R^3 \subset R^N$ at a time. It is therefore essential that promising 3-D subspaces within N-space be quickly identified. We intend to accomplish this by combining our army ant algorithm with an *evolutionary algorithm* (EA).

EAs are stochastic search algorithms that manipulate a population of solutions. During each generation existing solutions in the current population are randomly varied to create new potential solutions. A survival procedure chooses the better quality solutions to survive to become parents in the next generation. Over time the population evolves high quality solutions.

Although genetic algorithms are the best known of the EAs, we intend to use an *evolution strategy* (ES) instead because the ES is far better suited for solving continuous optimization problems. Each individual in the ES population is a vector $\vec{x} \in R^N$. Every individual has to be evaluated for quality to determine which ones survive. (In our case "quality" refers to the surface elevation at the coordinates specified by $\vec{x}$.) We will use a (μ, λ) version where μ parents create λ offspring each generation where $\lambda > \mu$.

Studies have shown EAs—not just the ES but any type—are very good at exploration, but rather poor at exploitation. In other words, the EA can readily find regions containing good quality solutions, but they don't do as well finding good solutions within those regions. This has led to the development of *memetic algorithms* that augment the EA with a local search capability [1]. A variety of local search methods do exist for combinatorial search algorithms, but choices for continuous surfaces are limited and not universally applicable. For instance, gradient-based methods don't work all that well when the surface is replete with local optima.

For large search problems there are two possible ways of using our ant algorithm. The first way uses an ES to conduct a first search in N-space. The results of this first search will place the colony and a 2nd ES run will identify good 3-spaces for further exploration. A local search will be conducted in each of these 3-spaces using individual army ant raids. These raids form a pattern search in N-space similar to the rotational pattern search army ants do in 2-space. (See Algorithm 2 in the Appendix for more details.) A second way is to run a conventional evolutionary algorithm and conduct a local search for every individual in the current population. In this case each individual is treated as a colony location. In our future work we will explore both of these options.

APPENDIX

This appendix contains the pseudo-code of two algorithms. The first algorithm describes the step-by-step procedure for running our local search ant algorithm. The second algorithm shows how the local search algorithm can be combined with a conventional (μ, λ) algorithm.

Algorithm 1 Army Ant Search Algorithm

choose colony location (x_0, y_0)
dispatch scouts to find best region with prey
compute distance D and bearing angle θ to best region
Let $t \leftarrow 0$ and $M \leftarrow 0$
while swarm distance $\leq D$ **do** {swarm moves at angle θ}
    $t \leftarrow t+1$
    $M \leftarrow M+10$ {number of ants in swarm at time t}
    for all i such that $i \leq M$ and ant(i) is moving forward **do**
        move left with prob P_1 (right with prob 1-P_1)
        deposit one unit of pheromone
        if prey found **then**
            take prey
            change direction back to colony
        end if
    end for
    for all j such that $j \leq M$ and ant(j) is returning to colony **do**
        move left with prob P_2 (right with prob 1-P_2)
        deposit ten units of pheromone
        if arrived at colony **then**
            deliver prey {highest elevation visited}
            report location where prey was found
        end if
    end for
end while
return best prey and its location

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Algorithm 2 (μ, λ)-ES

Require: $\lambda > \mu$

create random initial population $P(0)$
$t \leftarrow 0$
while termination criteria not met **do**
    $t \leftarrow t + 1$
    $P(t) = \{\emptyset\}$
    for i = 1 to λ **do**
        randomly select parent $\vec{x}$ from $P(t-1)$
        $\vec{x}'$ = mutate($\vec{x}$)
        $P(t) = P(t) \cup \{\vec{x}'\}$
    end for
    evaluate $P(t)$ {check quality of new solutions}
    keep μ best solutions; discard the rest
end while
conduct local search {use army ant algorithm}
return best $\vec{x} \in P(t)$

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