Levy Distributed Search Behaviors for Mobile Target Locating and Tracking

William Lenagh, Prithviraj Dasgupta
Computer Science Department
University of Nebraska, Omaha, NE 68182.
402-554-2380
{wlenagh,pdasgupta}@mail.unomaha.edu
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ABSTRACT: *We consider the problem of tracking visually identifiable mobile targets using a distributed system of mobile robots. We propose a behavior-based approach where mobile robots with limited sensory range use a search pattern observed in nature - the* Levy distributed search*, to locate a mobile target. The Levy search pattern is inspired by the foraging pattern exhibited by social insects such as honeybees, albatrosses, etc. We consider two Levy-distributed search patterns - a Levy linear search and a Levy looped search, and determine their performance in locating and tracking mobile as well as stationary targets. Our results show that for locating stationary targets, the Levy length for a search leg is strongly correlated with the distance of the target from the location where the search starts. For locating and tracking mobile targets, we find that the search performance improves as the p.d.f. of the Levy distribution is made flatter. The Levy looped search also performs better than the Levy linear search in tracking mobile targets because its looping property helps in relocating targets that have been observed previously.*

1 Introduction

Over the past few years, autonomous robots have been used extensively for unmanned search and reconnaissance related operations in different domains such as unmanned search and rescue, exploration and mapping of unmanueverable regions, surveillance and patrolling of high-security regions to restrict access, etc. Visually tracking the movement of mobile targets within an area of interest (AOI) is an essential operation during search and reconnaissance. Recently, there have been several efforts to perform search and reconnaissance using multiple mini-robots or mini-UAVs(unmanned aerial vehicles) that operate as a cohesive unit such as a swarm or a fleet. The evident advantage of using a swarm of mini-robots is the considerable reduction in the costs of fielding a large system of mini-robots as compared to operating larger robots. Swarms of robots are also robust because they do not have a single point of failure where the system can be compromised. However, mini-robots typically have limited capabilities such as limited sensor range and accuracy, limited on-board memory and limited computation capabilities. Because of these limited capabilities, it becomes very challenging to perform complex operations such as visually tracking mobile targets using mini-robots. To address this challenge, several systems have been proposed that use emergent, swarm-based techniques with simplistic behavior patterns on each robotic swarm unit and allow more complex behaviors to *emerge* from the local interactions of the swarm units [3, 7, 8, 12]. Such behavior-based systems are particularly attractive because the inherent operation of each swarm unit or robot is simple and it is easy to implement and modify such behaviors.

In this paper, we consider a behavior-based system where robots use a nature-inspired search pattern called the Levy-distributed search that is observed in many social insects and animals, to visually (re)acquire and track mobile targets. We compare two types of Levy search patterns - the linear Levy search and the looped Levy search and determine their relative performance in locating and tracking stationary and mobile targets. Our experimental results with simulated mini-robots within the Webots simulator show that the two types of Levy search patterns perform comparably in locating targets, both stationary and mobile. However, the Levy looped search performs better in tracking mobile targets because its looping property helps in relocating targets that have been observed previously.

2 Related Work

One of the earliest techniques to track mobile targets using a distributed multi-robot system was described in [9] using the CMOMMT (Cooperative Multi-robot Observation of Multiple Moving Targets) approach. In CMOMMT, robots are able to perceive and track mobile targets using laser sensors. Robots experience attractive forces towards targets and repulsive forces between each other. Robot motion strategies using both unweighted and weighted force vectors are reported to perform significantly better than random robot movement in simulation as well as on real robots. Jung and Sukhatme [5] describe and implement a technique for mobile target tracking that disperses robots based on robots' density within a region and robots' visibility of targets. Each robot is provided with *a priori* knowledge of the environment in the form of a topological map and uses laser range sensors and visual identfication to track targets. Both the above mentioned approaches rely primarily on the ability of robots' sensors such as sonar or camera, to identify and track mobile targets efficiently. In contrast, we consider robots that have limited sensory range and noisy sensors, and rely on the emergent behavior of the system to locate targets. In [2], the authors describe a graph theoretical approach for a team of three mobile robots to track a mobile mobile target optimally. A pursuit-evasion game(PEG) is another approach that has been used to solve a problem similar to mobile target tracking. In a PEG, the mobile targets are called evaders while the robots tracking the mobile targets are called pursuers. The objective of a PEG is to maximize the probability of locating the pursuers by the evaders. Several techniques for solving pursuit evasion games have been proposed which range from control theory[15], to probabilistic analysis [17], computational geometry[6], and algorithmic analysis[14]. PEGs involve considerable computation either on-board robots or at a centralized location where the information obtained by the robots from the environment is uploaded. In contrast, we consider lightweight robots with limited computation capabilities that might not be amenable to implement complex calculation.

3 Levy-Distributed Search

A Levy search is essentially a random walk pattern comprising of several short segments interspersed with turns at random angles. The lengths of the straight line segments are sampled from a stable probability distribution called the Levy distribution given by:

$$L(x, c, \mu) = \sqrt{\frac{c}{2\pi}} \times \frac{exp^{\frac{-c}{2(x-\mu)}}}{(x-\mu)^{\frac{3}{2}}} \qquad (1)$$

where c is the scale parameter that controls the height of the curve and μ is the shift parameter that shifts the mean value of the curve. A sample Levy distribution is shown in Figure 1.

The Levy distribution is particularly attractive from a behavioral perspective because certain species of animals have been shown to exhibit the Levy search as an optimal search strategy for locating a mobile resource such as a food source, or a specific location of interest such as their nest [10, 11, 16]. Levy distribution-based techniques have also been successfully applied to other disciplines where stochastic processes are of great interest, such as financial market analysis [4], statistical mechanics, fluid and gas dynamics, cryptography and signal analysis [13]. The specific scenario used in this paper is inspired by the search behavior observed in honeybees [11]. In this scenario, honeybees start out from their nest with *a priori* knowledge of the location of an object of interest such as a flower bed, and move towards its location. However, upon arriving at the location they are unable to locate the object of interest and infer that it has either moved or been depleted. The bees then execute a search pattern, that has been empirically shown to follow a Levy distribution, to reacquire the resource or discover a similar resource nearby.

We hypothesize that the search patterns used by animals and insects to locate stationary or moving objects of interest can be programmed in artificial socities comprising swarming robots to locate stationary or mobile targets. Levy search patterns consist of a relatively simple set of manuevers and can be encoded on each swarm unit or robot using a simple set of rules while maintaining the inherent distributed nature of the swarmed robotic system. Most biological systems [16, 11] using Levy-distributed search models have observed the movement patterns of animals while varying the location of an object of interest and have shown that the movement paths of the animals conform to the Levy distribution. Our objective in this paper is to observe what effect different values of the shift and scale parameters of the Levy distribution have on the search performance of mobile swarming robots for different locations of stationary as well as mobile targets. To verify the performance of the swarmed system we use two types of Levy-distributed searches that are observed in nature:

- **Levy linear search**: A Levy linear search comprises of a sequence of straight line patterns, called *search legs*. The length of each search leg is sampled from the Levy distribution. At the end

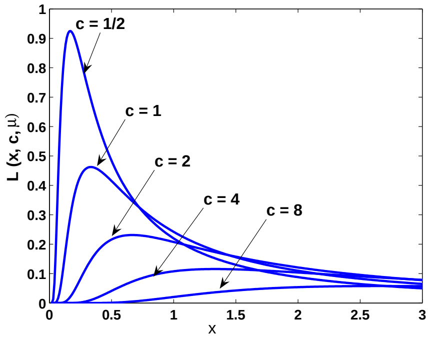

Figure 1: Levy distributions for different values of the scale parameter c with shift parameter $\mu = 0$

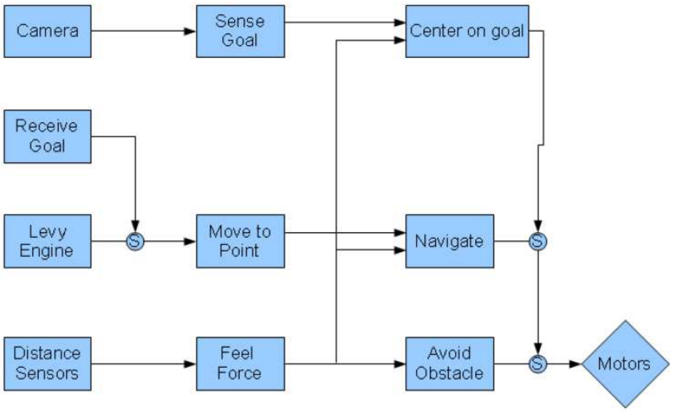

Figure 2: The subsumption architecture based controller of a robot performing a Levy loop search

of each search leg, a swarm unit selects a new direction to start the next search leg. A study of the Levy flight patterns of honeybees[11] showed that when honeybees change their direction of flight, the new heading lies between 0 to 360 degrees of the original heading, following a uniform distribution. Based on this observation, each swarm unit in our system selects a new heading at the end of each search leg from a uniform distribution given by $U[0, 2\pi]$. The next leg then starts from the location where the previous leg ended. The swarm units performing a Levy linear search in effect exhibit a random walk pattern consisting of a series of straight line segments with Levy distributed lengths.

- **Levy looped search**: Experiments with insect colonies foraging for objects of interest have shown that insects revert to the origin of their search after a certain period of time if they are unsuccessful in locating their object of interest [1, 11]. In the Levy looped search, each swarm unit models this reverting behavior by moving back to the location from where it started the search after a certain time period of unsuccessful search has elapsed. A Levy-looped search is behaviorally similar to the Levy linear search with the exception that after a certain time period of unsuccessful search, a swarm unit moves back to the location from which the series of legs started. This results in successive loop-like patterns centered at the origin of the first search leg. As in the Levy linear search the length of each leg within a loop is sampled from the Levy distribution and the angle at which each new loop starts is sampled from the uniform distribution $U[0, 2\pi]$.

4 Levy Flight Controllers

The controller program of a robot using the Levy search is implemented using a subsumption reactive architecture, as shown in Figure 2. The most primitive behavior, and lowest on the subsumption diagram, is an

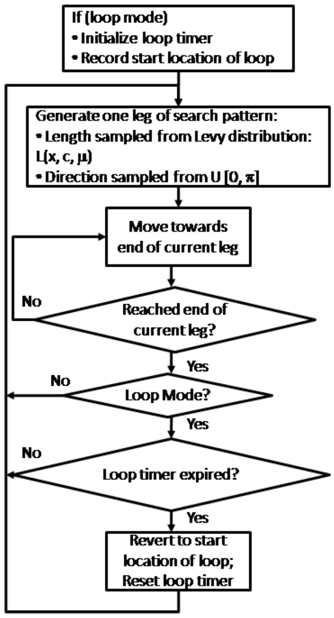

Figure 3: Flowchart showing the operation of the Levy engine.

obstacle avoidance system. Reading the values reported by the distance sensors, this system computes the force of any nearby object using a Braitenberg controller and outputs a resulting speed value based on these computations. Above this level is a more sophisticated *Navigate* behavior which subsumes the output from the *Avoid obstacle* behavior, if present. This behavior takes the input from a Braitenberg controller that calculates the virtual forces on the robot from obstacles based on the distance sensors' readings. The output from the Braitenberg controller is then combined with another input, *Move to point*, that is driven by either the Levy engine or a goal coordinate received by a transmission from another robot. The *Navigate* behavior directs the motion of the robot while taking into account any obstacles that may be present. The highest level behavior is the *Center on goal* and incorporates both obstacle avoidance and a goal sensing algorithm driven by the image rendered by the robot's camera. The output from this behavior subsumes the output from *Navigate*, which in effect overrides all other behaviors. When active the robot will ignore any goal point and attempt to follow and identify the stimulus which activated the behavior. If it loses contact it will resume navigating, as this output will no longer be subsumed.

Levy Engine. The Levy engine implements the Levy flight behavior. A flowchart showing the operation of the Levy engine is shown in Figure 3. The Levy engine can operate either in the loop search mode or in the linear search mode to implement the two types of Levy search patterns. In the loop search mode, the engine first initializes a loop timer and records the start location of the loop so that the robot can revert to this location after the loop timer expires. It then generates one leg of the Levy search which consists of the distance that the robot will travel (generated from the Levy distribution given in Equation 1), and the heading that the robot will take (drawn from $\frac{\pi}{2} + \phi$ where $\phi \in U(0, \pi)$). The new heading is offset by $\frac{\pi}{2}$ because a change in orientation is defined to occur only at angles greater than $\frac{\pi}{2}$ from the current heading[11].

5 Experimental Results

We have tested our Levy search based mobile target following algorithm within the Webots 6.1 robot simulator. The scale and shift parameters of the Levy distribution define different search patterns of the swarm units or robots. The main objective of our experiments is to determine how the different values of these parameters affect the locating time of stationary or mobile targets whose location is not known *a priori* by the robots. The two parameters that control the behavior of the Levy search are the scale parameter c and the shift parameter μ. For all our settings we use five robots to locate and track targets and one target that can be either stationary or mobile. The robots are situated with a 10×10 m^2 square environment. Each robot

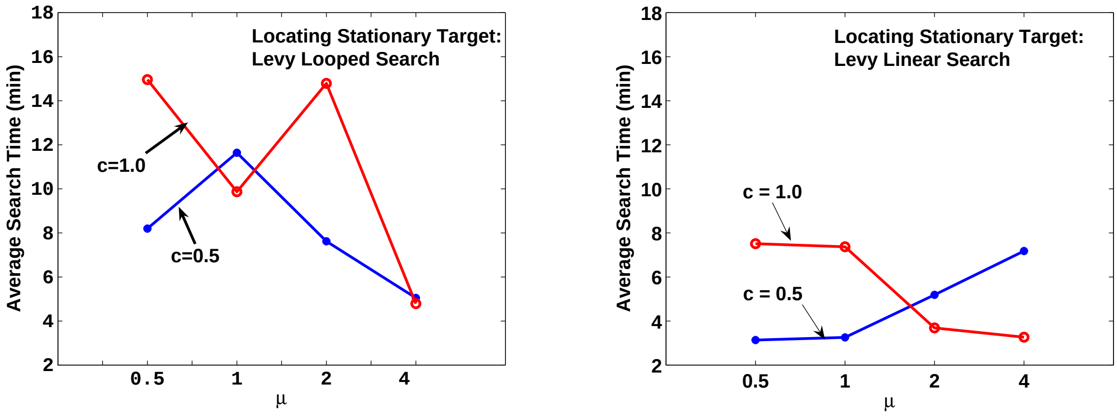

Figure 4: Average time required locate a target that moves from an initial location to a final location and remains stationary thereafter using Levy looped search (left) and Levy linear search (right).

is simulated as a mini-robot that has the following sensors: (1) Camera: a color VGA camera with a maximal resolution of 640×480 . (2) Eight infra-red distance sensors measuring ambient light and proximity of obstacles in a range of 4 cm. (3) Two wheels controlling speed and direction by the rotation of stepper motors, and, (4) A Bluetooth-enabled transmitter and receiver for sending and receiving messages between robots. To localize each robot, we have added a GPS node on each simulated robot. (In a system with real robots, localization can be realized using an overhead camera-based localization system.) Mobile targets are simulated as colored cylindrical robots, which can either remain stationary or move in the environment at a certain speed that is slower than the speed at which the tracking robots can move. The robots simulating the mobile targets have two forward looking IR distance sensors to avoid obstacles. When the tracking robot's camera encounters a colored object of interest, it informs other robots that converge on the last observed location of the target and perform a Levy search to locate it. All the results reported in our simulations were averaged over 10 simulation runs.

For our first set of experiments we considered a target that moves from an initial location to a final location and remains stationary after that. The distance between the initial and final locations of the target has an average value of 4.5m. The robots are only aware of the initial location of the target and have to discover the final location of the target using a Levy search starting from the target's initial location. Figure 4 shows the effect of different values of the shift and scale parameters on the time required to locate the target at its final location. The scale parameterc was set at either 0.5 or 1, while the shift parameter, μ, was varied from 0.5 to 1, 2, and 4. With the Levy looped search, we observe that as the length of a leg of the Levy search, determined by the shift parameter μ, approaches the mean distance of the target's initial and final locations, the search times successively improve. The best search time occurs when μ is set to 4 which is closest to the average distance between the initial and final locations of the target (which is 4.5 m). A similar behavior of the search performance is observed for the Levy linear search when the scale parameter $c = 1.0$. However, the performance of the Levy linear search deteriorates for increasing values of μ when $c = 0.5$. This can be attributed to the fact that when $c = 0.5$, the search legs that are closer the value of μ are selected with higher probability. As μ increases, the search legs are longer and unsuccessful searches tend to persist longer resulting in lower search performance. This behavior is not observed with the Levy looped search as the robots "loop back" to their start location after a certain time and are able to explore different directions around the start location more effectively.

For our next set of experiments, we analyzed the performance of the Levy search on locating and tracking a mobile target. All other parameters for the experiment are retained from the previous experiment. The target moves at half the speed of the tracking robots. We used the same combination of Levy parameters as was used for the previous experiment. Figure 5 shows the effect of different values of the shift and scale parameters of the Levy distribution on the time required to locate the target. As before we observe that searches with $c = 0.5$ result in lower performance because higher persistence for longer search legs (with higher values of μ) can misguide the search in directions where the target is not present.

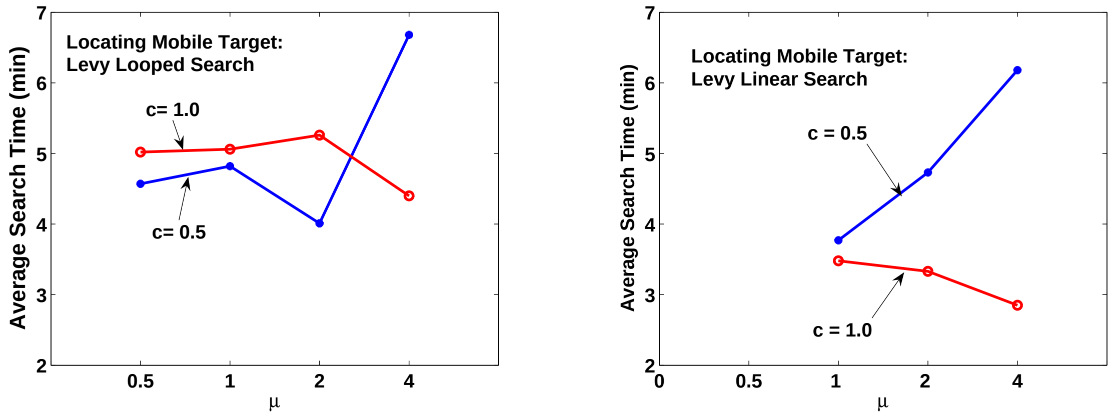

Figure 5: Average time required to locate a mobile target that moves at half the speed of the tracking robots, using Levy looped search (left) and Levy linear search (right).

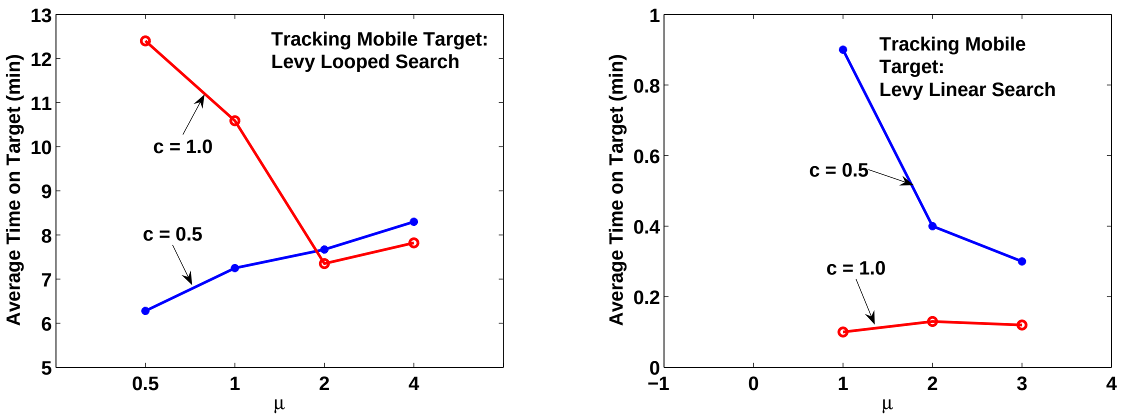

Figure 6: Average time for which a mobile target is tracked by at least one tracking robot using Levy looped search (left) and Levy linear search (right). The mobile target moves at half the speed of the tracking robot.

Figure 6 shows the effect of varying the parameters of the Levy distribution on the time for which the target is observed (tracked) by at least one robot. For the Levy looped search we observe that changing the scale parameter c from .5 to 1 has the effect of improving the ability to track the target for lower values of μ. Similarly, the tracking capability decreases as μ increases. On the other hand, when c is .5, the tracking time increase as μ increases. This seems to indicate that lower values of μ improve the target tracking times due to the flatter Levy distribution curve resulting when c is set to 1. The Levy linear search performs very poorly as compared to the Levy looped search for tracking a mobile target. This indicates that looping back to the location where the target was last observed helps in relocating the target and improves the performance of the Levy search. Based on the experimental results reported here, we can infer that a lower value of the scale parameter of the Levy distribution ($c = 0.5$) results in more persistent searches which can result in searches going down the wrong path for longer durations and adversely affect the performance of the search. Also, the closer the shift parameter μ of the Levy distribution is to the distance between the start location of the search and the location of the target, the better is the search performance. Finally, between the Levy looped search and the Levy linear search, we observe that their performance is comparable in locating targets (stationary or mobile), but the Levy looped search outperforms the Levy linear search in relocating and tracking mobile targets because of its looping property.

6 Conclusion and Future Directions

This work represents our first step in using Levy search for mobile target tracking. Our results show that the parameters of the Levy search can be adjusted appropriately to fine tune the performance of mobile target locating and tracking using mobile robots. In the future, we plan to investigate improved search strategies that dynamically adjust the parameters of the Levy distribution based on the search performance, and mechanisms for tighter coordination between robots after a target is located by one robot. We envisage that with appropriate techniques along the lines described in this paper, mobile target following with aerial mini-robots will emerge as an important direction for multi-robot systems.

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Author Biographies

WILLIAM LENAGH is a Master’s student in the Computer Science Department at the University of Nebraska at Omaha. His interests are in the field of artificial intelligence, multi-agent systems and swarming.

PRITHVIRAJ DASGUPTA is an associate professor with the Computer Science Department at the University of Nebraska at Omaha. His research interests are in the area of multiagent and multi-robot adaptive systems, swarm robots, and game theory and computational economics. His research is actively funded by federal agencies including the U.S. Department of Defense and NASA. He has published over 40 papers in leading conferences and journals in the area of multiagent and multi-robot systems.