Collective Lévy walk for Efficient Exploration in Unknown Environments

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Abstract. One of the key tasks of autonomous mobile robots is to explore the unknown environment under limited energy and deadline conditions. In this paper, we focus on one of the most efficient random walks found in the natural and biological system, i.e., Lévy walk. We show how Lévy properties disappear in larger robot swarm sizes because of spatial interferences and propose a novel behavioral algorithm to preserve Lévy properties at the collective level. Our initial findings hold potential to accelerate target search processes in large unknown environments by parallelizing Lévy exploration using a group of robots.

Keywords: Multi-robot systems · Swarm Robotics · Random Walks · Lévy Walk.

1 Introduction

Exploring unknown environments to spot targets is one of the most fundamental problems in the context of mobile robots used for search and rescue, environment mapping or agricultural applications [3]. An efficient exploring strategy that provides a maximized area coverage in a minimized time interval is the main design goal. Since there are no clues for the robot on where to explore, it must execute a random walk. Amongst the random walks that were revealed in natural collective systems, the Lévy walk (LW) is one of the most efficient patterns [4]. For sparse targets, the LW maximizes the search efficiency, i.e. the number of targets found in a specific time interval. With a LW, the step orientation is sampled from a uniform distribution, while the step lengths are sampled from a heavy-tailed (power-law) distribution:

$$p(l) \sim l^{-(\alpha+1)} \tag{1}$$

where l is the step length and the distribution exponent $0 < \alpha < 2$.

LWs allow the agent to execute several short steps before executing a long one. In case of sparse targets, the LW provides an optimal search behavior because the long steps sampled from the power-law distribution maximize the number of visited sites. Taking only short steps, the robot will frequently pass sites that it has already visited [6]. In the absence of any knowledge about the target distribution, the optimal value of the exponent is given by $\alpha = 1$ [5].

In existing works on efficient exploration by robot swarms, the trajectory followed by each robot is sampled from a Lévy distribution [1]. Despite the promising results in terms of exploration and area coverage [2], the main drawback is that the Lévy distribution and its properties are lost when the swarm size increases. As the swarm size increase, the probability that independently generated Lévy walks is intersecting also increases and already with moderate swarm sizes the collective trajectory no longer follows a Lévy distribution. Consequently, the current strategies to implement Lévy walks in robot swarms are not scalable. To the best of our knowledge, no previous works addressed the question of how to generate a *collective* Lévy walk that emerges from the different robots' trajectories and which preserves Lévy properties.

In this paper, we address this key challenge in an unbounded space by introducing an efficient algorithm which controls robot swarms to generate a Collective Lévy Walk (CLW) for large swarm sizes. We introduce our CLW algorithm in Sec. 2 and compare its performance for different swarm sizes with the baseline of independently generated Lévy walks.

2 Collective Lévy Walk (CLW) Algorithm

As a first step, we have launched a set of exploration experiments using swarms of different sizes to investigate the presence of Lévi properties in the trajectory obtained by summing up the individual LWs generated by the robots independently. Our results (see Sec. 3) reveal that the obtained trajectory follows a Lévy distribution for small swarm sizes only. The main reason is that long steps are interrupted (aborted) by intersecting robots. Intuitively, increasing the number of robots in the swarm leads to more spatial interferences and consequently to a decrease in the probability of obtaining the heavy tail (Eq. 1) for the step length in the combined trajectory.

Our CLW algorithm prioritizes longer steps in robot trajectories by exploiting information exchanged between robots. The CLW algorithm is described by the deterministic finite automaton that is shown in Fig. 1. Each robot starts in the "Walk state" to explore the unknown environment. Robots move with a fixed linear speed and sample the duration of their next step T_L from a Lévy distribution. When the interval T_L is over, the robot switches to the "Rotate state" and rotates at a constant angular velocity during T_U, with T_U sampled from a uniform distribution. Whenever the walking robot detects an obstacle using its proximity sensors, it leaves the "Walk state" immediately and starts executing a collision avoidance behavior. In this state, the robot rotates with an angle that is determined based on the distance of the obstacle. When all obstacles have been avoided, the robot transitions to the "Walk state" again, and samples a new time interval T_L to proceed its next step in the Lévy walk.

The key part of the CLW algorithm resides in exploiting the communication between the walking robots to generate a collective Lévy walk. Robot i broadcasts its sampled time interval $T_L(c)$ to its local neighbors—i.e., these are the robots within its communication range and within line-of-sight. The step is categorized as ”short” or ”long” based on a predefined threshold $T_{Threshold}$. In case of a short step of robot i and a long step of its neighbor j, robot i starts moving away from robot j, using the principles of potential field [7]. The repulsive force $F(j)$ driving robot i away from neighbor j, which is executing a long step, is computed from the position of robot j. This position is obtained using the range-and-bearing sensors. Finally, the force F is computed for all neighbors of robot i, which are executing long steps, and these forces are averaged to generate the final repulsive force applied to robot i. In cases where all neighbors are executing short steps, robot resume their walking behavior as planned.

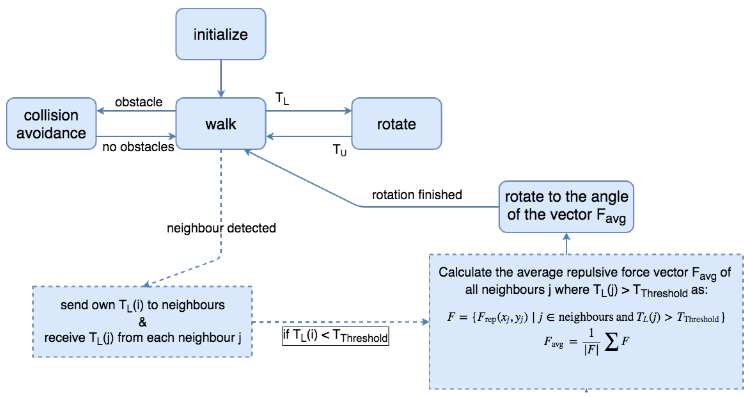

Fig. 1. Finite state diagram of the CLW algorithm.

3 Results and Conclusion

We have performed a set of physics-based simulations using the ARGoS simulator[1]. An arena of $20 \times 20\ m^2$ is implemented as an unbounded space: the robot that reaches a side of the arena will re-enter from the opposite side without interrupting its currently executed step. Simulation results are averaged over 30 runs, with each run lasting 5000 time steps. The exponent α is set to 1 (see Eq.(1)), the communication range of the robot is set to 1.35 m and the linear speed to 5 m/s. The step threshold is set to $T_{Threshold} = 9 \times 0.17 = 1.53$ m (0.17 the diameter of the simulated robot). We use the log-likelihood test to determine the best fitting of the obtained distribution of the collective trajectory. We rely on two outputs of the test to judge the fitting: the p-value of the test, and the log-likelihood ratio. If the log-likelihood ratio is > 0, the best fitting is a

[1] The ARGoS simulator allows to simulate large swarms of robots while taking the desired level of physical details into consideration.

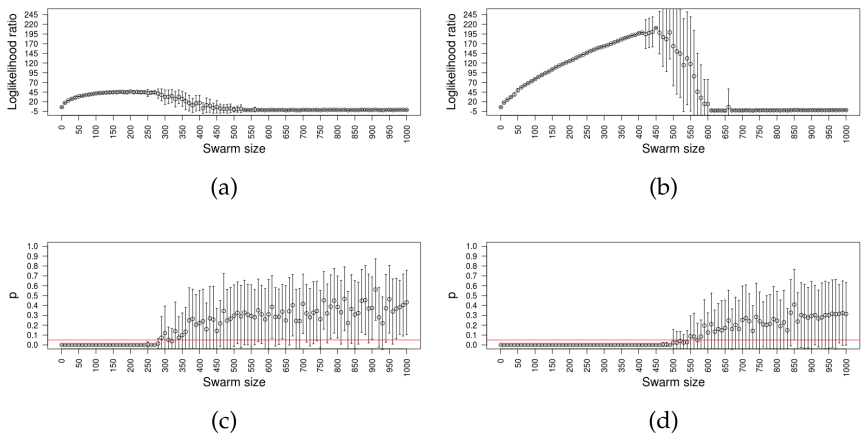

Fig. 2. The log-likelihood ratio of the independent Lévy walk implementation and of the CLW algorithm in (a) and (b), respectively. The p-value of the independent Lévy walk implementation and of the CLW algorithm in (c) and (d),respectively.

heavy-tailed Lévy distribution when the p-value is < 0.05; when the p-value is > 0.05 the best fitting is an exponential distribution. If the log-likelihood ratio < 0, neither the Lévy distribution nor the exponential distribution are best fittings and a transition between the two distributions is observed. Fig. 2 depicts the results for both the combined trajectory of the independent implementation of the robots' Lévy walks and the trajectory generated when applying the CLW algorithm. We can notice a clear phase transition from power-law distribution to exponential distribution. Following the independent implementation, the swarm up to 300 preserves a Lévy walk, and between 300 and 500, a transition from Lévy distribution to the exponential distribution is observed. When applying the CLW algorithm, the Lévy walk is preserved collectively up to 500 robot, between 500 and 600 the transition from Lévy distribution to the exponential distribution is observed.

In this paper, we have proposed an efficient algorithm for robot swarms that exploited local communication among robots to generate collective Lévy walk. Our results show the ability of the CLW to generate such a collective trajectory also for larger swarm sizes.

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