Diffuse algorithm for robotic multi-source localization

Kathleen McGill*, *Student Member, IEEE*, and Stephen Taylor*, *Member, IEEE*
Thayer School of Engineering, Dartmouth College, 8000 Cummings Hall, Hanover, NH 03755
Kathleen.N.McGill@dartmouth.edu, Stephen.Taylor@dartmouth.edu
Ph: (603) 646-9945
Fax: (603) 646 -9795

I. INTRODUCTION

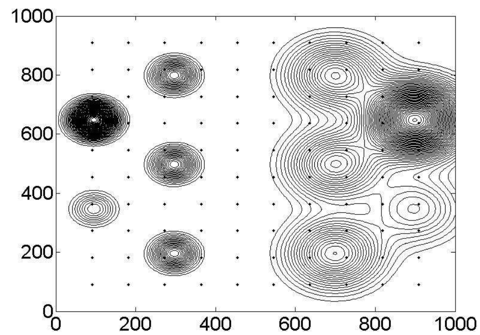
There is an increasing drive to develop robotic systems that can replace humans in a broad range of sensory applications. This push is often motivated by applications that involve significant risk to humans, such as search and rescue operations [1]-[2] and the location of chemical, biological, radiological, and explosive materials [3].

A common theme in many of these applications is the need to sample the *gradient* of some physical, chemical, or electromagnetic property in order to locate potential sources. The use of robotic systems for the *simultaneous* localization of *multiple* gradient sources has received little attention. In this problem, a large number of robots, or agents, equipped with sensors and inter-robot communication, collectively search for all sources in minimal time. Although some partial solutions to the general multi-source problem have evolved, they have not been integrated in a cohesive manner [4]-[16]. We have introduced a set of benchmark cases and a reference algorithm to provide *ground-truth* for comparative analysis of multi-source robot localization algorithms [17]-[18]. We demonstrate how the benchmarks are used, in combination with sensitivity analysis, to provide insights into the relative performance of algorithms.

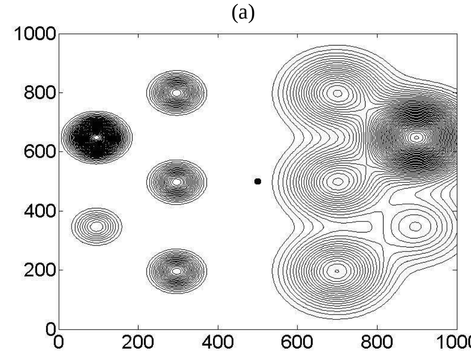
This paper describes a new robotic multi-source localization algorithm based on *diffusion* of robots. Our DIFFUSE algorithm accelerates source localization by combining robot diffusion from purely local communication with random local search. We compare our approach to the BRW, GSO, and HYBRID algorithms from the robotics literature using the benchmark cases. Our DIFFUSE algorithm is the only algorithm that locates all sources in all benchmarks.

II. BENCHMARK CASES

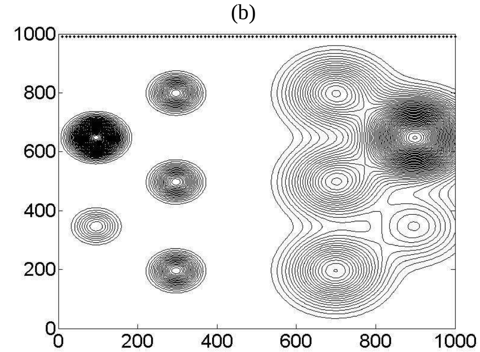
Fig. 1 shows the parameterized benchmark cases with the same basic source distribution and three alternative initial robot distributions. The characterization and distribution of the sources in the field provide sources that are occluded by other sources of lesser, greater, or equal intensity. Extensive dead space is included in half of the space to determine the impact of an imperceptible gradient on search performance. The initial robot distributions are devised to represent robotic swarm deployment strategies: the *uniform*, *drop*, and *line* distributions. These benchmarks serve as an initial test case for different types of sources. A general solution must be refined to be robust to environmental challenges specific to the end application.



(a)



(b)



(c)

Fig. 1 Three benchmark cases: (a) uniform, (b) drop, and (c) line initial distributions.

III. DIFFUSE ALGORITHM

The DIFFUSE algorithm includes two modes of swarm control: SEARCH mode and COVER mode. In SEARCH mode, robots conduct an independent local search using the

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BRW algorithm [5]. In COVER mode, the robots emulate diffusion and spread out to cover the space. Using techniques derived from coverage control and swarming literature [19]-[21], the COVER algorithm builds a virtual electrostatic potential field in the search space. The robots and the border of the space are modeled as positively charged particles that repel each other. Overall, the robots' local interactions and random motions emerge as a collective *diffusion* of the swarm across the search space.

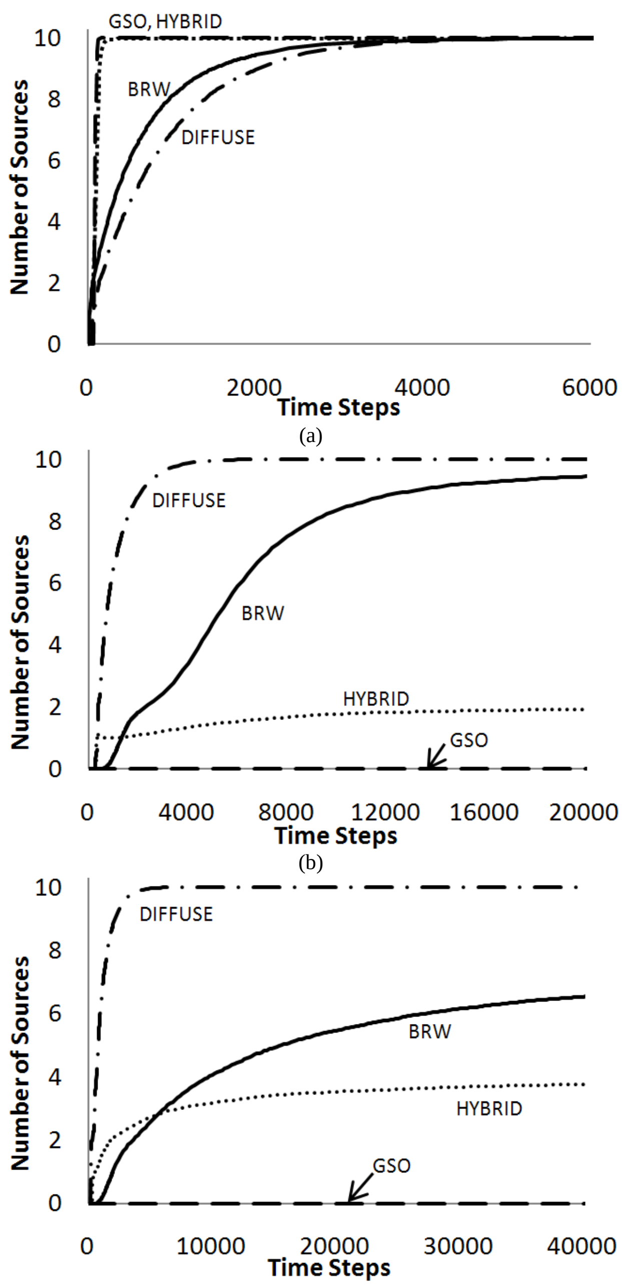

Fig. 2 Average sources found v. time step for BRW, DIFFUSE, GSO, and HYBRID on the (a) uniform, (b) drop, and (c) line initial distribution benchmark cases.

IV. Results

Each algorithm is tested on the benchmark cases by simulating 1000 searches. The average number of sources found at each time step for 1000 simulations of each benchmark case is plotted in Fig. 2.

All of the algorithms locate approximately 10 sources on the uniform benchmark. The uniform initial distribution provides coverage of the search area from the beginning. As a result, there is little advantage to the COVER mode of our algorithm. The efficiency of the DIFFUSE algorithm is comparable to the BRW algorithm, but the GSO and HYBRID algorithms converge on the sources faster than the DIFFUSE algorithm.

The DIFFUSE algorithm is the only algorithm that locates all ten sources on the drop and line benchmark cases. Because the initial robot distribution is non-uniform, the COVER mode accelerates source localization by enforcing coverage of the space from the start. Sources that are distant from robot deployment are located quickly. Thus, the key to source localization in the non-uniform distributions is to explore the search space.

V. Conclusions

We present a new robotic multi-source localization algorithm based on *diffusion* of robots. The DIFFUSE algorithm locates all sources on all three benchmark cases, unlike the BRW, GSO, and HYBRID algorithms from the robotics literature [17]-[18]. In particular, our DIFFUSE algorithm outperforms other algorithms when the initial robot deployment is non-uniform. We accomplish this success by diffusing robots across the space, providing complete coverage of the search area.

Our DIFFUSE algorithm shows great potential to solve the general multi-source localization problem. A key feature of the algorithm is that the coverage control is independent of the environment. This quality makes the algorithm robust to noisy gradient profiles, local maxima, and other environmental impacts in practice. The DIFFUSE algorithm also excels at large scale. We are conducting a comparative analysis of the same algorithms using the large scale benchmarks presented in [18]. The DIFFUSE algorithm locates all sources at large scale while the other algorithms suffer performance degradation. With these advantages, the DIFFUSE algorithm is an excellent candidate for real world, large scale applications.

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