A Fluid Dynamics Approach to Multi-Robot Chemical Plume Tracing

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Abstract

This paper presents a novel chemical plume tracing algorithm executed by a distributed network of mobile sensing agents that measure the ambient fluid velocity and chemical concentration. The algorithm drives the robotic network to the source of the toxic plume, where measures can be taken to remove or extinguish the source emitter.

1. Introduction

The objective of this research is the development of an effective, efficient, and robust distributed search algorithm for a team of robots to use for locating an emitter that is releasing a toxic chemical gas. The basis for the search algorithm is a physics-based framework for distributed multi-agent control, which scales well to a large number of robots, ranging from ten agents to a thousand and beyond [8].

This framework, called *physicomimetics* or *artificial physics (AP)*, assumes several to hundreds of simple, inexpensive mobile robotic agents with limited processing power and a small set of on-board sensors. Using AP, the agents will configure into geometric lattice formations that are preserved as the robots navigate around obstacles to a source location [9]. In this paper, we present a summary of a novel algorithm for chemical plume tracing that is built upon the AP framework. The technique is founded upon solid theoretical principles of fluid dynamics, which will make further analysis and improvement possible. Our algorithm assumes an AP-maintained lattice which acts as a distributed computational fluid dynamics (CFD) grid for calculating derivatives of *flow-field variables*, such as wind velocity and chemical concentration. Due to the space constraint, we present our results here without proof, but the expanded analysis and additional discussion can be found in [10].

2. Related Work

Current research in the field has been inspired by biological olfactory systems of lobsters, ants, and moths [6, 5]. The best understood and most widely applied approach is that of *chemotaxis*, which consists of following a local gradient of the chemical concentration within a plume [7, 2, 6]. While chemotaxis is very simple to perform, it frequently leads to locations of high concentration in the plume that are not the source, such as a corner of a room.

To overcome this problem, another common approach, called *anemotaxis*, is sometimes employed. An anemotaxis-driven agent measures the direction of the fluid's velocity and navigates "upstream" within the plume [4, 2]. This strategy is successful in problems where the flow has no large-scale turbulence. However, large turbulent, circulatory eddies create a region where simple upwind travel will result in a cycle, causing the anemotaxis technique to fail.

3. Computational Fluid Dynamics

Our approach makes use of the methods and concepts developed in the context of computational fluid dynamics (CFD). Flow of fluids is described by the three Governing Equations that express the conservation of mass, Newton's Second Law, and conservation of energy [1]. For realistic flows, an analytical solution of these equations is impossible, due to the inherent non-linearity. Thus, our CFD approach replaces the continuous partial derivatives with corresponding discretized finite-difference approximations, and computes the unknown flow-field variables using a computational grid which spans the region of interest. Our algorithm takes advantage of the lattice formations formed by our robotic agents to simulate the computational grid, thereby allowing the agents to perform a sophisticated (but efficient) analysis of the flow and make navigational decisions based on this analysis.

4. Fluxotaxis Algorithm

In [10] we formally defined a chemical emitter in a way that facilitates our localization technique called *fluxotaxis*. The algorithm combines information about both velocity and chemical density, and the extensive theoretical analysis provides assurance that we will find the emitter as opposed to a local density maximum. The following presentation of several basic lemmas supports this statement. The proof of the lemmas can be found in [10]. Each of the lemmas represents an incremental step toward our main theorem, which says that the fluxotaxis algorithm will drive the robotic network toward the chemical emitter.

We assume a local coordinate system shared by all of the robots in the robotic lattice. Such a shared coordinate system is achievable via local communication accompanied by coordinate transformations [9, 3]. Furthermore, the chemical source emits the trace element continuously, rather than intermittently. The first three lemmas in this section assume a single coordinate axis (1D) for simplicity; generalization to 2D is straightforward.

Constant Velocity Lemma 4.1. *Assume*

1. *Chemical plume has a general Gaussian distribution* $\rho(x) = \kappa \mathbf{e}^{-(x-c)^2}$*, centered at* $x = c$*.*
2. *Initial lattice position* x_0 *is such that* $x_L < x_0 < x_R$*, where* x_L, x_R *are solutions to* $\frac{\partial^2 \rho(x)}{\partial x^2} = 0$*; this implies that* $\frac{\partial^2 \rho(x)}{\partial x^2} < 0$ *in the region of interest.*
3. $\vec{V}$ *is of constant magnitude and is a vector in the direction away from the center point* $x = c$*.*

Without loss of generality, assume the existence of P_2 *and* P_3 *such that* P_2 *is closer to the emitter than* P_3*. Then, execution of one step of the fluxotaxis algorithm implies that the lattice moves closer to the emitter, or equivalently*

$$\left[u\frac{\partial \rho}{\partial x} + \rho \frac{\partial u}{\partial x} \right]_2 > \left[u\frac{\partial \rho}{\partial x} + \rho \frac{\partial u}{\partial x} \right]_3$$

The next two lemmas assume Gaussian density distribution and a non-zero first-order velocity derivative, $\partial u / \partial x$.

Divergence Lemma 4.1. *Fluxotaxis algorithm will move the agent lattice toward a chemical source.*

Divergence Lemma 4.2. *Fluxotaxis algorithm will move the agent lattice away from a chemical sink.*

Lemma 4.2 shows that a fluxotaxis agent will escape from a chemical sink (i.e. a location with a high chemical concentration, but without the emitter); however, a simple chemotaxis strategy is easily fooled by such sinks.

We already mentioned that the anemotaxis (“upwind”) strategy can fail when the flow has large turbulent eddies, such as those that form downstream of obstacles (e.g., buildings). Mathematically such vortices have a non-zero curl, and the following lemma addresses this scenario.

Curl Lemma 4.1. *The fluxotaxis-driven agent lattice will escape from a vortex.*

Lemma 4.1 says that a fluxotaxis agent will leave a large-scale eddy, but the anemotaxis strategy will fail in this case.

5. Summary and Future Work

In this paper, we presented a new chemical plume tracing algorithm called fluxotaxis that combines two of the most popular methods: chemotaxis and anemotaxis. The most important contribution of our work is the development of a control algorithm that can be analyzed with formal methods, and mathematical guarantees on the agent behavior can now be stipulated. The algorithm will also be implemented and tested on a massively distributed system of simple, inexpensive robotic agents currently under development for the task of chemical plume emitter localization.

References

[1] J. D. Anderson. *Computational Fluid Dynamics.* McGraw-Hill, Inc., 1995.

[2] Chemical plume tracing. In E. Cowen, editor, *Environmental Fluid Mechanics*, volume 2. Kluwer, 2002.

[3] J. J. Craig. *Introduction to robotics: mechanics and control.* Addison-Wesley Publishing Company, Inc., 1989.

[4] A. Hayes, A. Martinoli, and R. Goodman. Swarm robotic odor localization. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS’01)*, 2001.

[5] S. Koenig and Y. Liu. Terrain coverage with ant robots: A simulation study. In *Proceedings of the International Conference on Autonomous Agents (AGENTS’01)*, pages 600–607, 2001.

[6] H. V. D. Parunak and S. Brueckner. Entropy and self-organization in multi-agent systems. In *Proceedings of the International Conference on Autonomous Agents (AGENTS’01)*, pages 124–130, 2001.

[7] G. Sandini, G. Lucarini, and M. Varoli. Gradient driven self-organizing systems. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS’93)*, 1993.

[8] W. Spears and D. Gordon. Using artificial physics to control agents. In *Proceedings of the IEEE Conference on Information, Intelligence, and Systems (ICIIS’99)*, 1999.

[9] W. Spears, D. Gordon-Spears, and R. Heil. Distributed, physics-based control of swarms of vehicles. In *Autonomous Robotics, special issue on Swarm Robotics (in press)*, 2003.

[10] D. Zarzhitsky, D. Spears, D. Thayer, and W. Spears. Agent-based chemical plume tracing using fluid dynamics. In *Proceedings of the Formal Approaches to Agent-Based Systems (FAABS III)*, 2004.