A Swarm Approach for Emission Sources Localization (PDF)

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A Swarm Approach for Emission Sources Localization

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Abstract

*In this paper, we provide a biasing expansion swarm approach (BESA) for using multiple simple mobile agents, with limited sensing and communication capabilities, to collaboratively search and locate an indeterminate number of emission sources in an unknown large-scale area. The key concept in this approach is swarm behavior. By applying the three properties of the swarm behavior: separation, cohesion and alignment, our approach can ensure the agent group attains dynamically stable ad-hoc connectivity and fast target convergence. Using a grid map to represent the unknown environment, an ad-hoc network for wireless communication and our biasing expansion algorithm for path planning, each agent simultaneously considers all concentration values collected by other swarm members and determines the positive gradient direction of the whole coverage area of the swarm. This will make the swarm immune to the random sensor errors, local aerosol accumulations and other local interference effects during their search. We present a simulated environment that has multiple emission sources and complex aerosol accumulation and distribution. Based on the simulation, **our** approach can achieve better performance than the gradient descent approach, which currently appears to be the most popular algorithm for emission source localization.*

1. Introduction

When emission sources such as hazardous gas containers are accidentally or intentionally released in an open area, the material inside the container will mix with air to become an aerosol and be diffused into the surrounding area with the flow of air. The traditional source localization approach uses continued sampling and careful search of the entire suspected area by a specially trained human to locate the aerosol emission sources. But such approach is not efficient in terms of time requirements, not to mention the risk to the human operators. In recent years, many research groups have investigated sending robots to the suspected area to locate emission sources. Most research seems to focus on techniques for locating the sources by using a single robot [4,14,18]. However, because of the spatial limitation of a single robot, few robotic systems have been developed that demonstrate the capability to carry out the source localization task in a large-scale area with multiple emission sources and complex environment status [3,4,9].

In this paper, we provide a biasing expansion swarm approach (BESA) to allow multiple simple mobile agents with limited-range communication to collaboratively search a large-scale environment and efficiently identify the emission source(s). The agent control algorithm in this approach is based on swarm behavior [11,151, a computational metaphor inspired by social insects. This paradigm, which has been demonstrated by flocks of birds, is an ideal model for solving problems in distributed manner.

2. Related work

2.1. Hazardous aerosol detection

Research into hazardous aerosol detection is focused in two primary areas. One research concept focuses on establishing the accurate boundary or perimeter of a dynamically changing hazardous material contaminated area for preventing human exposure or enabling evacuation from the dangerous area. Hardin et al. [8] proposed a modified particle swarm algorithm for robotic mapping of an area contaminated by hazardous materials. Flanigan [6] proposed using passive infrared to remotely detect hazardous vapors and map the contaminated area.

Another research area is odor source localization. The research focuses on the use of mobile agents to

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detect, track and seek the odor source. Previous approaches include spiral surge [7], gradient-seek [9], and mobile sensor array [17]. These sets of techniques are all based upon gradient-seeking approaches. They use the natural phenomena of gas/aerosol diffusion. Gases and aerosols tend to disperse into the environment inducing a concentration gradient that can be used as a clue for tracing emission sources. A mobile agent's movement is dependent upon the spatial changes in aerosol concentration as sensed by the agent. An increase in the concentration along the agent's path is called a positive gradient while a decrease is called a negative gradient. The agent will always try to move in a direction that will generate a positive gradient. The goal is for the agent to track the gradient back to the source.

With today's advanced technology, different kinds of mobile systems equipped with electrical gadaerosol-sensors have been investigated to locate hazardous material emission sources in a suspected area [6,9,11,12,13}. However, the electronic gas/aerosol sensors in those mobile systems can only provide gas/aerosol concentration information about a very small area [7] and each agent can only collect local environment information around it. Further, the sensors usually cannot provide an instantaneous and precise measurement of the gas/aerosol concentration. An individual agent using the concentration gradient seeking approach is easily trapped in a local aerosol concentration if the concentration area is larger than the individual agent's sensor range.

2.2. Swarm Robotics

A swarm is a distributed system with a large number of agents [10}. Traditionally, there is a belief that group behavior in a multiple-robot system needs to be centralized, with global planning and decision.

In the mid 1940s, Grey Walter, Wiener and Shannon did some research on turtle-like robot group. Each robot in the group was equipped with light and touch sensors. The robots followed very simple rules to generate their actions. When placed together, these robots represented complex social behaviors in response to each other's movements [4]. Early swarm researchers [1,2,4,10] suggest some complex social or intelligent behaviors of the whole robot group can be achieved through the interaction within the very simple group members. From this idea comes the concept of swarm intelligence. Swarm intelligence can be defined as the collective intelligence that emerges from a group of simple agents [2]. Swarm robotics is currently one of the most important application areas for swarm intelligence. Many different swarm control models have been proposed. Beni [1] introduced the cellular robotics system, which consists of a collection of autonomous robots cooperating under distributed control. Each robot can have limited communication with its neighbor robots to accomplish predefined global tasks. However, each robot in the system must have pre-programmed cooperative and reasoning ability to reach the goal. Currently, more researchers are focusing on problem solving approaches that use a collection of idealized agents. Each agent even does not have intention of "cooperation" and "problem solving". In other words, the individual agents do not know they are solving a problem, but the collective behavior of the group can solve the problem. One example is Reynold's boid project [15].

Reynold built a computer simulation to model the motion of a flock of birds. Reynold believes the motion of the bird flock, as a whole, is the result of the actions of each individual member that follow some simple rules. In the simulation, he referred to a bird as "boid". Each boid is implemented as an independent agent that flies in the simulated environment. There is no central control in the bird flock. Each boid navigates only according to its own perception of the environment. Three rule sets control agent behavior: separation, alignment and cohesion. Separation helps boids avoid collisions with each other. The alignment rule attempts to match velocity with nearby flock mates. The cohesion rule attempts to stay close to nearby flock mates. By following these three simple rules, the boids in the simulation can quickly form a stable swarm formation (whether flying, floating, rolling, etc.) where every boid is at least some minimum distance from every other boid and not any further than some maximum distance.

In our approach, we combined Beni's limited communication concept and simple rules control concept of Reynold's boid. The three basic control rules: separation, cohesion and alignment are used to govern the swarm member's movement to ensure individuals remain in a specific orientation and distance as well as maintaining connectivity between members of the agent swarm. All agents in the swarm can only directly communicate with its nearby agents and must maintain an ad-hoc network to exchange information with other agents in the swarm. By gathering the data from other agents, an agent can detect the remote environment's aerosol concentration that it cannot directly detect. That gives each agent a virtual sensor range wider than its real sensor range and allows them to easily escape from the local aerosol concentration location.

3. The Algorithm Description

3.1. Assumptions

In our swarm approach, we envision that an unknown number of hazardous gas containers are simultaneously vented to the atmosphere in a large-scale area. Wind disperses the hazardous aerosol over the area and forms aerosol plumes. In a global context, the concentration value of plumes surrounding the emission sources has gradient characteristics such that concentrations are reduced as distance from the source(s) increases. However, the turbulent nature of airflow typically breaks the plumes into isolated pockets and mixes them into a local chaos status.

A swarm of identical agents is deployed into this suspected area to search for the source(s). Each mobile agent is equipped with appropriate electronic gas/aerosol sensors. A sensor's response and recovery time at each measurement iteration is counted as the mobile agent's stop time for each cell. We assume the sensor cannot always read the correct environment aerosol concentration value and sensor errors are considered as a kind of random noise. Each agent is only equipped with a local wireless communicator such as WLAN [16,191. Compared to the scale of the potential search area, the local communication range is very small. No agent has global communication capability. However, each agent has the ability to forward data packets for each other over possible multi-hop paths to allow communication between agents otherwise out of direct wireless communication range. This facilitates creation of an ad-hoc wireless network for global communication capability in the swarm. Due to agent mobility, the ad-hoc network topology may change rapidly over time. A table-driven routing protocol [16] is used in the network for routing all messages.

3.2. Representation of the environment by occupancy grid map

Each agent in the system maintains an occupancy grid map [3,13,20} (Fig. 1) to represent the environment. Each cell in the grid map is a square block with a unique identity number. We assume each agent's communication range can only cover cells adjacent to an agent's current location. The time cost for an agent to move from one cell to its nearby cell is fixed. However, the time to measure the concentration value of each cell is variable. It varies in different cells and is unknown to the agent before agent moving into the cell. Upon initialization, the agents have no prior knowledge of the environment, each cell is labeled as un-explored and the concentration value is unknown.

3.3 Maintaining the ad hoc communication network during exploring

At the initial time, all agents are deployed near each other and an ad-hoc wireless network is established connecting all agents. Via the ad hoc network, each agent can collect the aerosol concentration value and other information from the other agents. After an agent completes the measurement of the aerosol concentration of its current cell, a swarm behavior controller implemented on each agent will be used for planning the next target cell.

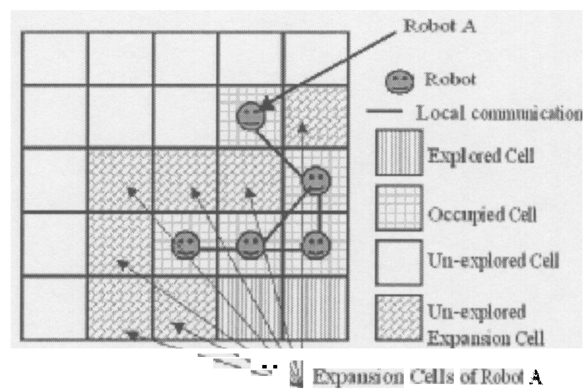


Figure 1 Environment grid map and expansion cells

To ensure wide coverage without overlapping or interference between agents, the separation property of the swarm behavior specifies that each agent should avoid exploration of a cell occupied by another agent. Although all unexplored and unoccupied cells in the grid map can be chosen as the agent's next target cell, moving to a cell without another agent in an adjacent cell could result in lost network communications. To maintain connectivity of the ad hoc network, the cohesion property of the swarm behavior uses the gradual expansion algorithm [5] to control each agent's movement. Each agent can only navigate to the "expansion cells" in the grid map. According to [5], an agent's "expansion cell" is defined as the cell in the grid map that is unexplored and unoccupied. In the grid map, each expansion cell has at least one agent located in one of its eight adjacent cells. This keeps the agent in contact with the ad hoc network. To steer an agent towards the emission source, a unique agent movement direction must be generated.

3.4 Environment grid map and expansion cells

As indicated in the previous section, the aerosol diffusion in the contaminated area will induce a gradient phenomenon. A high concentration indicates a location near the source. However, the combined impact of multiple sources will weaken the gradient phenomena. At the same time, unstable wind flow may disturb this distribution and generate some local maxima in aerosol concentration. To eliminate those local mutations and keep the whole agent swarm following the right gradient direction toward the source, we developed a bias expansion algorithm. This algorithm will assist agents to select the most suitable target cell from the swarm's expansion cell list. In the algorithm, a new notion: the biasing parameter is introduced. Each expansion cell's biasing parameter, B, can be given by following equation:

$$B_{(x,y)} = \frac{K}{n} * \sum_{i=0}^{n} \left(\frac{C_i}{r_i^2} \right) \quad (1)$$

In equation (1), n is the total number of agents that share their sensor reading with the swarm. C_i is the aerosol concentration of the cell where agent i is located. K is constant and r_i is the distance between the expansion cell (x,y) and the cell that agent_i locates.

At each iteration, when an agent finishes its current cell measurement, it will plan its next target cell. Through the ad-hoc network of the swarm, the agent can discern all available expansion cells around the swarm. By moving to any of those expansion cells, the agent can avoid a cell occupied by another agent as well as maintain network connectivity with other agents in the swarm. To ensure quick convergence on the emission sources, the agent uses equation (1) to evaluate the suitability of all candidate expansion cells. All agents' sensor values and their distance to the expansion cell influence the expansion cell's biasing parameter value. The expansion cell that has highest biasing parameter value will be selected as the agent's next target cell. Since each agent in the swarm should occupy a different cell in the environment grid map, the swarm's sensors coverage area is the summation of all individual agent sensor coverage. That enables agents in the swarm to avoid being trapped by a local maximum concentration.

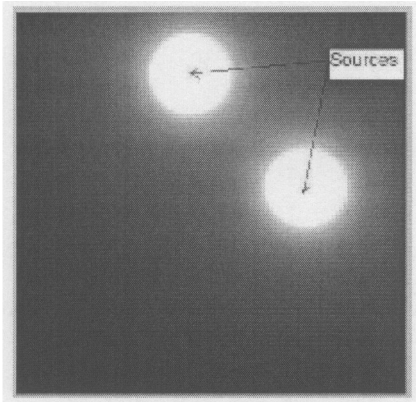
4. Simulation Experiments

A simulation was developed to evaluate our approach. The simulation describes the suspect area as a two-dimensional grid of size 100x100. We initialized two sources S_1 and S_2 of aerosol at randomly selected positions in the grid. The concentration of the aerosol at each grid cell depends on the distance from the aerosol source point. The farther away from the sources, the lower the concentration of the aerosol. This is the required working environment for most schemes utilizing the gradient-seek approach. To simplify our simulation, we used following mathematical model generate the concentration of each cell in the grid.

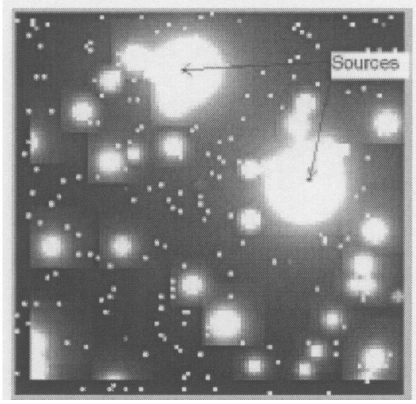
$$C_{(x,y)} = N_{(x,y)} + K * \left(\frac{P_1}{r_1^2} + \frac{P_2}{r_2^2}\right) \quad (2)$$

Equation (2) gives the concentration $C_{(x,y)}$ that can be sensed at a point (x,y) on the grid in the presence of *m* sources. P_1 and P_2 is the aerosol release speed of the source S_1 and S_2. K is a constant. r_i is the distance between the grid point (x,y) and the source S_i. $N_{(x,y)}$ is the environmental and sensor detection error impact on the point (x,y). To simulate the influence of the random aerosol sensor detection error, we randomly chose 1% cells from the grid map and changed their concentration values as random numbers. In addition, 40 randomly located apexes (local maximum concentration converge spots) are generated on the grid map to simulate the local aerosol accumulation. The possible aerosol distribution grid map is shown in Figure 3. The grey level of each cell represents the aerosol concentration value of the cell.

This simulation has n=20 mobile agents deployed in the simulated environment. Each agent can be randomly deployed in the grid or deployed based on the requirements of different approaches. The travel time for an agent to move from one cell to its neighbor cell equals 1 simulation time-step. The time that an agent requires for measuring the concentration value in its cell plus the sensor recovering time is the total stop time of an agent in a cell. This stop time is a random number that ranges from 1 to 4 time-steps, and this number is unknown to the agent before moving into a cell. The source is considered to be located only when an agent of the swarm moves into the cell where the source located. In our trials, we assume that the swarm's mission is completed when the source(s) are localized. Following the localization, we assume that a different type of agent would be deployed to mitigate the hazard.



(a)

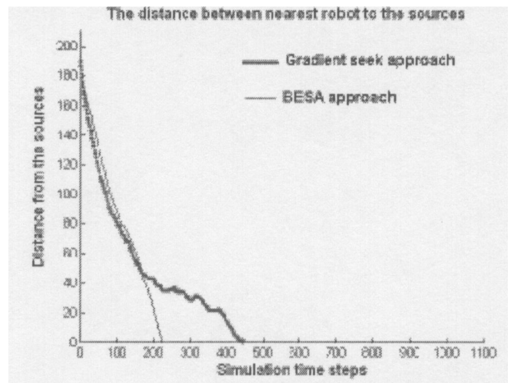


(b)

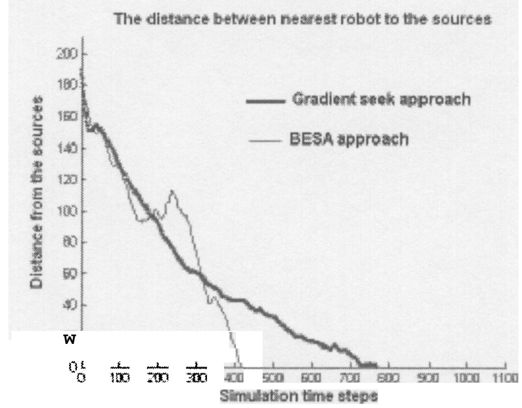
Figure 2 Aerosol concentration distributions. (a) Ideal case without any environment impact. (b) 1% random sensor detection errors and 40 random size localized aerosol accumulations

5. Results overview

Two performance indicators are used for evaluating the performance of the approach: 1. The length of simulation time-steps for the robots to locate the emission sources. 2. The distance between the source and the mobile agent nearest to the source at each time step. For performance evaluation, we implemented a gradient seeking based approach in the same simulation environments and compared its performance result with **BESA** approach. In each simulation, we calculated the number of time steps to find the source as compared to the gradient seeking algorithm. We also recorded the distance between the sources and the agents nearest to the sources at each time step to present how quickly the agents can approach the sources. Figure 3 presents these results. In different kinds of environment cases, the **BESA** approach requires only half of the time-steps that gradient seeking approach used for locating all emission sources. Figure 3(a) and (b) also demonstrate that the **BESA's** performance is stable while the gradient seeking approach's performance is greatly reduced in the environment cases influenced by random noise and local maximum concentration spots.



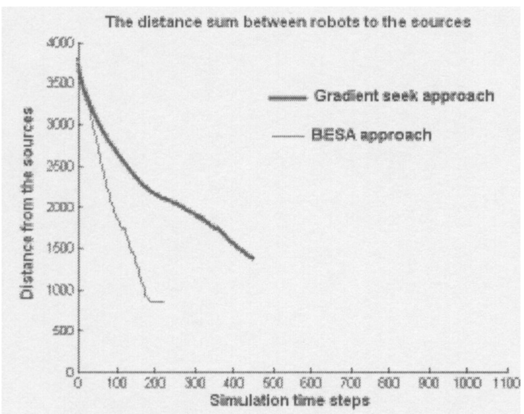
(a)



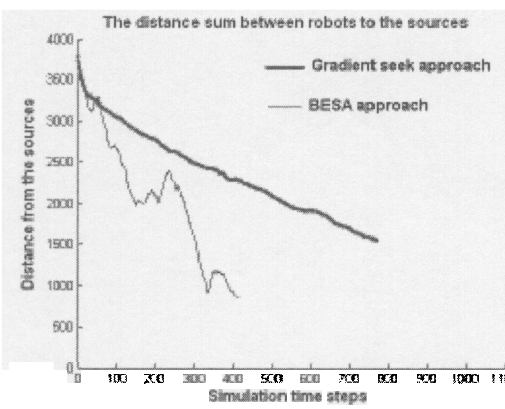
(b)

Figure 3 Distance sum between sources and nearest agent VS time-step (a) Ideal case without any environment impact. (b) 1% random sensor detection errors and 40 random size localized aerosol accumulations

In Figure 4, we present the total distance between all agents and the sources at each time step. This gives us an idea about the potential of the agent swarm moving toward the sources. As expected, Figure 4 (a) and (b) demonstrates that the **BESA** approach controls the whole agent swarm to quickly reduce their distance from the sources and also gathers the remaining agents into the area near the source when the source is located by one agent. This allows for additional collaboration, such as task allocation and heterogeneous agent cooperation in the area, if needed. On the contrary, the gradient seeking approach charts (Figure 4) indicate that the distance between the agent swarm and emission sources reduces slowly. That is because in the gradient seeking approach, a random movement had to be implemented to help individual agent escape the trap of the local aerosol accumulation spots. This random movement is also executed when the agent cannot find a positive gradient phenomenon. This behavior randomly deploys agent members in the environment and it hinders collaborative multi-agent work on the same task.



(a)



(b)

Figure 4 Aggregate Distance between two sources and all agents VS time-step. (a) Ideal case without any environment impact. (b) 1% random sensor detection errors and 40 random size localized aerosol accumulations

6. Conclusion

In this paper, we present a new approach, BESA, for coordinating multiple simple homogeneous mobile agents in the searching of gas or aerosol emission sources in a large-scale area. The swarm behavior used in the approach ensures all agent members maintain a dynamically stable ad-hoc communication network for collaboratively exploration and overlap avoidance. Compared to most gradient seek approaches, which can be trapped in local areas of high concentration, the BESA considers the sensor reading of all swarm members to determine a direction for the swarm as a whole. This will help immunize the agent swarm from random sensor errors, local aerosol accumulation and other local interference effect during their exploration.

The BESA performance was simulated with two aerosol-emission sources under different environmental scenarios. The simulation demonstrated that the BESA has better performance than the gradient seek approach. At the same time, the BESA approach guides the entire agent swarm to quick convergence to the cells surrounding the sources. This compares favorably with the gradient seek approach that randomly deploys agent members in the environment. Although in our search task scenario, when one agent moves into a cell with an emission source, the task is finished. Gathering all agent swarm members at the area near the sources is not required. This “side effect” feature of the BESA approach gives us a clue that it is also a potential task allocation algorithm for applications such as disaster rescue that require multiple heterogeneous agents.

7. Acknowledgments

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Biographies

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