Environmental Monitoring with Mobile Robots

Lino Marques, André Martins and Aníbal T. de Almeida
Institute of Systems and Robotics
University of Coimbra
Polo II, 3030-290 Coimbra, Portugal
{*lino,amartins,adealmeida*}*@isr.uc.pt*

***Abstract*— This paper describes an architecture for estimating environmental odor maps and presents experimental results obtained using that architecture with five mobile robots inside a large laboratory with two odor sources and forced ventilation. The mobile sensing agents employed in the experiments have self localization capabilities and carry an electronic nose and a thermal anemometer. The proposed architecture allows integrating sparse olfaction data gathered by the mobile agents along their trajectories and dynamically estimate the spatial concentration of different odor fields. The data assimilation process is made centrally by a PC that polls periodically each robot through a RF network in order to get the data gathered during the previous acquisition period. The estimation of odor fields is made in two steps: first each agent estimates the odor mixture and concentration by means of a neural network-based regression algorithm that converts values from gas sensor space to the corresponding odor space. Then the sensed data is assimilated into an advection-diffusion model by means of a reduced order Kalman filter. In the current implementation the central controller, responsible for the maps estimation, specifies to each agent their target area to explore. The proposed architecture was validated with a set of experiments that demonstrated its ability to estimate and capture the dynamics of overlapping odor fields. This work can easily be adapted to city buses or other local transportation systems in order to monitor the pollution or quickly detect hazardous chemicals inside cities.**

I. INTRODUCTION

When a potentially dangerous airborne chemical is detected, whether its origin results from an industrial accident or malicious attack, it is obviously necessary to take containment measures to avoid harm to the surrounding environment. However, containing the chemical agent can be very difficult, especially if the chemical is released from an active source. In this case, detecting the source for its neutralization becomes a priority. In such hazardous environment, the use of animal teams is not a solution. Human teams with hazard suits and detection devices could locate the gas source efficiently, given enough time, but the risk of flammable or explosive chemicals or any damage to the personal protective suit can bring considerable risk to the team. The use of autonomous robotic teams acting as mobile sensor networks is an efficient alternative. Simple, inexpensive, replaceable robots can be deployed in the area and trace the chemical's odor plume, finding its source while avoiding any additional risk to human or animal lives.

In the last ten years or so, the integration of olfaction in mobile robots and the exploration of navigation algorithms using olfaction has been a research area of increased interest, as can be demonstrated by the increased number of published works. Most works research the search, track and detection of odor sources with a single [5], [19] or multiple robots [9], [16], sometimes with the capability to discriminate different odor sources [17]. Other works research the use of chemical marks, like following of odor tracks [4] and covering areas [13]. The research of olfaction systems developed specifically to be integrated in mobile robots is an important and usually disregarded area [1], [15].

Recently, the topic of environmental sampling and estimation has gained interest as a possible application for sensor networks [21], [23]. In this context, the focus has been in the estimation of stationary environmental fields or in the deployment of nodes for achieving some kind of optimal criterium [11]. A SpreadNose architecture for estimating odor fields with heterogeneous mobile chemical sensing agents has been proposed in [18]. This architecture was formulated based in the electronic nose concept, that uses an array of several non-selective gas sensors and estimates odors or odor mixtures processing the sensor matrix output through pattern recognition algorithms [18]. The SpreadNose architecture proposed to estimate spatial maps in the sensor space and use those maps as input to pattern recognition algorithms in order to estimate the corresponding odor maps. In practice, this approach was very difficult to implement because even sensors with the same reference present slightly different responses to the same odor. This paper proposes that each agent already provides odor concentrations, so odor maps are directly estimated from the assimilation of odor information (see figure 1). Additionally, this paper uses a reduced rank Kalman filter based in the advection-diffusion model of odor transport instead of the kriging Kalman filter used in [18]. This approach demonstrated better capability to track the dynamics of odor fields.

II. SPREADNOSE ARCHITECTURE

A. Chemical sensing

The concentration of chemical species in the atmosphere can be measured by means of artificial olfaction systems. These olfaction systems can be specific, allowing the detection of individual chemical species - like some insect antennae's, or they can be general, allowing the detection of a broad range of chemical species, like a mammalian olfaction system. Selective olfaction systems have the advantage of giving a direct measure of a target species concentration whilst general systems, like electronic noses,

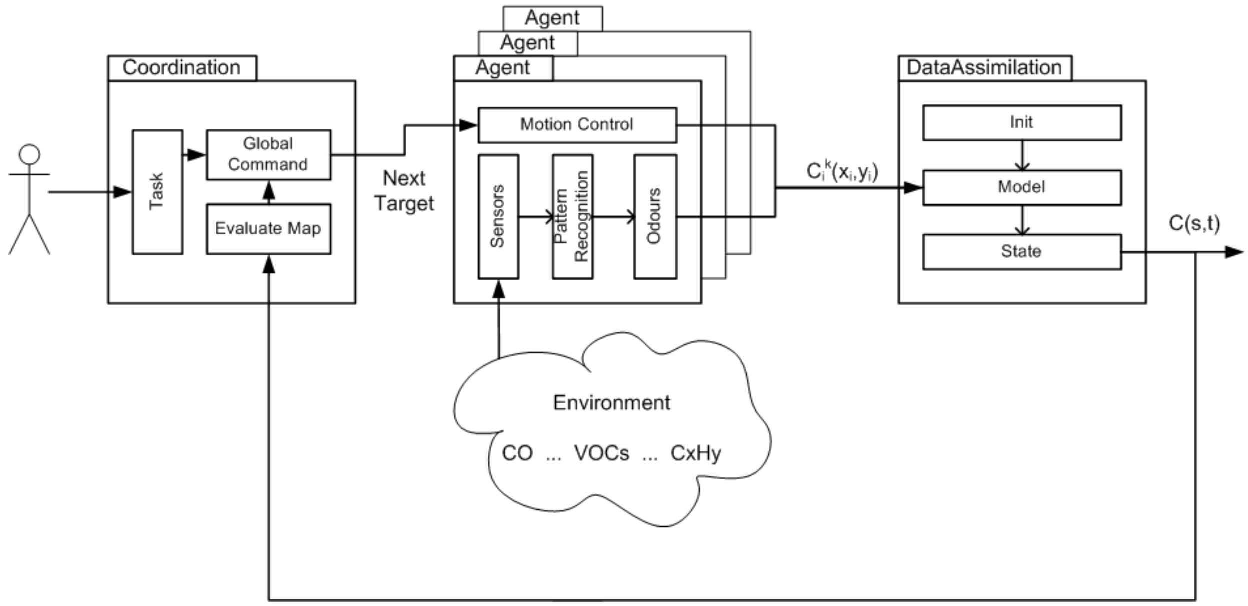


Fig. 1. Representation of the modified SpreadNose architecture.

are based in arrays of non-selective chemical gas sensors, so the output of such arrays needs to be processed in order to obtain an estimation of each species concentration. Selective artificial olfaction systems are usually based on optical methods, being bulky and expensive. The main advantages of electronic nose-based systems are their wide commercial availability, low price and the possibility of detecting multiple substances. The drawbacks of these systems are the complexity of the pattern recognition algorithms needed to obtain the chemical concentrations from the chemical sensor array non-linear output, the lack of sensitivity and their long term drift.

Tin oxide gas sensors are nowadays the most common type of chemical gas sensors. These sensors change an electrical resistance as a function of the concentration of chemical reducing species present in the atmosphere. The following equation is a good approximation for the sensitive resistance (R_s):

$$R_s = R_0 \cdot (1 + C)^{\alpha} \tag{1}$$

where R_0 is the resistance in clean air, C is the odor concentration and α represents the sensibility of the sensor.

If $\mathbf{C}$ is a vector representing the mixture of multiple species, the above equation can not be used because the constant α is gas and gas mixture dependant. So it is not possible to use an analytical or an algebraic inversion method to solve the problem of finding the mixture concentrations $\mathbf{C}$, given a set of output resistances $\mathbf{R}$. To solve this problem, a wide variety of multivariate regression and pattern recognition algorithms are available [8], [6]. The electronic nostrils used in this work (see subsection III-D) use a $4:5:2$ feed-forward neural network, trained for several concentrations of ethanol and butane in order to map a $\mathbf{R}$ sensor space into a target $\mathbf{C}$ $odorspace$ [15].

$$\mathbf{C} = \mathbf{PatRec}(\mathbf{R}) \tag{2}$$

B. Odor transport in the atmosphere

The transport of contaminants C in the atmosphere can be described by the advection-diffusion equation [2].

$$\frac{\partial C}{\partial t} = D\nabla^2 C - \nabla(\vec{\nu} C) + S \tag{3}$$

where D represents the diffusion constant, $\vec{\nu}$ represents the airflow and S represents odor sources.

In order to estimate a complete odor concentration field, the workspace can be divided into a grid of regular points and the partial differential equation 3 can be discretized with finite differences using the Crank-Nicholson method [3], [12].[1]

The resulting equations were used in a state space formulation as the model of odor transportation, were the concentration in each cell represents a state variable. Given initial conditions, the time evolution of the system can be estimated using the system model and integrating the measurements gathered inside the workspace by the mobile agents. The Kalman filter is a common approach to estimate linear dynamic systems, but the large number of state variables obtained with this type of problem and the availability of a reduced number of measurements per time step turns impracticable the employment of the classical Kalman filter. These types of problems have recently been address by numerous mathematicians and researchers from oceanography, meteorology, and atmospheric air quality fields that have proposed several alternative solutions that keep the advantages of a model based optimal estimation at

[1]finite differences were used, instead of finite elements or finite volumes, for the sake of implementation simplicity.

acceptable computational costs, like the Ensemble Kalman filter (EnKF) [7] or the Reduced Rank Square Root filter (RRSQRT) [10], to name just a few.

Let the evolution of the odor concentration in the workspace and observation of measurements be described with the following stochastic system:

$$\mathbf{x}^t[k+1] = \mathbf{A}[k]\mathbf{x}^t[k] + \eta[k] \quad (4)$$
$$\mathbf{y}^o[k] = \mathbf{H}'[k]\mathbf{x}^t[k] + \mathbf{v}[k] \quad (5)$$

with $\mathbf{x}^t[k] \in R^n$ the true state vector at time $t[k]$, $\mathbf{A}[k]$ a deterministic model, $\eta[k] \in R^n$ a Gaussian distributed model error (zero mean, covariance $\mathbf{Q}$), and $\mathbf{y}^o[k] \in R^r$ a vector of observations with $\mathbf{v}[k]$ the representation error (Gaussian with zero mean and covariance $\mathbf{R}$). Indices 't', 'o', and later on 'f' and 'a' refer to true, observed, forecasted and analyzed entities respectively. The notation with a linear operator $\mathbf{A}$ is chosen in order not to complicate the formula, although the stochastic transport model $M(\mathbf{x})$ is in fact nonlinear in $\mathbf{x}$. The goal of the filter operations is to obtain the mean $\mathbf{x}^a$ and covariance $\mathbf{P}^a$ for the probability density of the true state. The filter equations for this system are summarized by:

forecast:

$$\hat{\mathbf{x}}^f[k+1] = \mathbf{A}\hat{\mathbf{x}}^a[k] \quad (6)$$
$$\hat{\mathbf{P}}^f[k+1] = \mathbf{A}\hat{\mathbf{P}}^a[k]\mathbf{A} + \mathbf{Q}[k] \quad (7)$$

analysis:

$$\hat{\mathbf{x}}^a = \hat{\mathbf{x}}^f + \mathbf{K}(\hat{\mathbf{y}}^o - \mathbf{H}'\hat{\mathbf{x}}^f) \quad (8)$$
$$\mathbf{P}^a = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}^f, \quad (9)$$
$$\mathbf{K} = \hat{\mathbf{P}}^f\mathbf{H}'(\mathbf{H}\hat{\mathbf{P}}^f\mathbf{H}' + \mathbf{R})^{-1} \quad (10)$$

The data assimilation and filtering algorithm was implemented with Martin Verlaan's Sub-Optimal Schemes (SOS) toolbox for Matlab [22]. This toolbox provides a framework to use several reduced rank methods, like the ensemble Kalman filter (EnKF) and the RRSQRT. The EnKF does not require adjoints of either the forecast model or observation operators, it integrates data assimilation and ensemble forecasting and thus produces estimates of forecast uncertainty at no extra cost. It is highly parallel, and largely independent of the forecast model. This method uses an *ensemble* $\mathbf{X}$ of $n_e << N$ state variables to calculate the Kalman gain $\mathbf{K}$, according to the following equation, providing a highly effective way to use a Kalman based approach in environmental monitoring.

$$\mathbf{K} = \mathbf{X}^f(\mathbf{H}\mathbf{X}^f)'((\mathbf{H}\mathbf{X}^f)(\mathbf{H}\mathbf{X}^f)' + \mathbf{R})^{-1} \quad (11)$$

The model and measurement noise were previously estimated and were kept constant during the data assimilation process.

C. Trajectory generation

In a practical situation, the SpreadNose architecture can be supported by a group of mobile agents to monitor the environment with one of two objectives:

- Maximize the global knowledge about chemical species in the environment.
- Maximize the knowledge of a chemical cloud boundary.

The agents' trajectories can either be predetermined (e.g., a group of buses or other public transportation systems equipped with chemical sensors), or they can be generated by a high-level controller in order to optimize some criteria allowing a better achievement of the cooperative task (e.g., if the objective is to have a better knowledge of the environment, the agents should explore preferably the least known areas).

A common approach to deal with the complexity of controlling multiple agents and achieving common goals consists in the control of each agent using global and local rules. The local rules are governed by the knowledge that each agent gathers from the environment and from other nearby agents (e.g., keep some distance from nearby agents; move to the better neighbor). The global rules are specified by the global controller, or central station (e.g., explore a specific area).

In our case, the central controller assigns a target position inside the workspace to each agent. Each agent then tries to achieve its target by a potential fields based control strategy. To compensate the lack of obstacle detection sensors, the localization system sends to each robot information about its localization and obstacles in its neighborhood.

III. Experiments

In the present paper, the robots were moved using a random walk strategy at a maximum velocity of 0.3 m/s. Whenever a robot was trapped in a local minima or reached a goal boundary, it received a new target position chosen randomly from the workspace. Considering the useful space (approximately 50 m^2) and the number of robots employed (5) this strategy seemed adequate for the envisaged goal of obtaining dynamic maps of an environmental pollutant.

A. Experimental setup

The validation of the proposed environmental monitoring architecture was conducted at the ISR LSE.[2] The laboratory presents a 15×6 m^2 space with several obstacles (tables, chairs, and other furniture) and two opposing windows left open to create a draft (see figure 3). A forced advection was created across the lab by means of an aspiration system coupled to one of the laboratory windows (see figure 2). This system is composed by a $1 \times 1 \times 1$ m^3 box with a laminar filter on the room side and a 90 V DC, 0.3 kW ventilator in its interior. The average airflow map inside the laboratory was previously measured.

[2]LSE - Embedded Systems Laboratory

Fig. 2. Ventilator used to produce an advected airflow inside the laboratory.

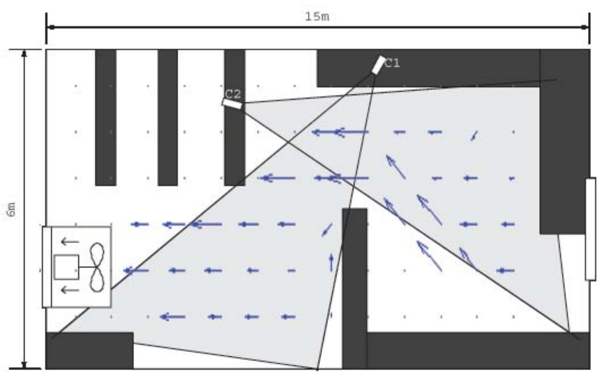


Fig. 3. Workspace map with a representation of obstacles and wind values measured at 25 cm height from the ground (about the height of each sensing nostril input in the mobile robots).

The experimental setup used a vision based tracking system which consisted of 2 Logitech QuickCam Pro 4000 webcams positioned for maximum coverage of the lab floor; and 5 mobile robot platforms with circular color markers placed on top. The cameras were connected to the computer's USB ports. Communication with the robots was achieved through the use of a master-slave configuration, where the master is connected to the computer via serial port (RS-232) and keeps a wireless communication with the robots.

B. Robots

The mobile robots used in the experiments were developed at LSE as modular mobile platforms for use in cooperation experiments (see figure 4). They are of circular shape (about 30 cm diameter) and have about 25 cm of height. At the top is a color marker used by the visual tracking system. The robots are driven with two differential drive wheels centered on the platform. Each motor is coupled to an optical encoder which is used for dead reckoning localization of the robot when no other localization method is present. The communication with a central computer is achieved by means of a RadioMetrix RPC2 RF module. A HC12 microcontroller is used to run control algorithms and interface with the hardware.

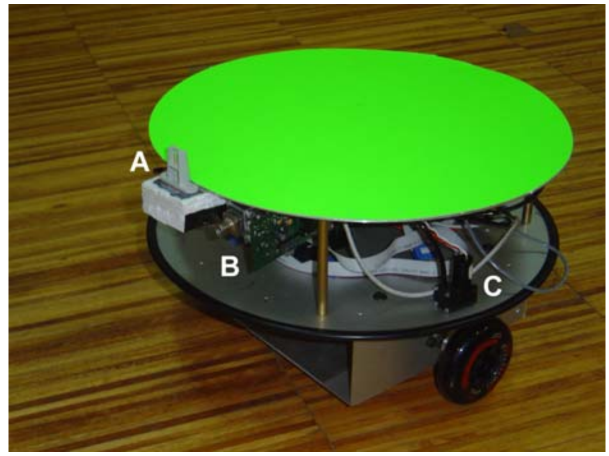


Fig. 4. Mobile robot used in the experiments. A-Thermal Anemometer; B-SmartNose; C-Vacuum Pump.

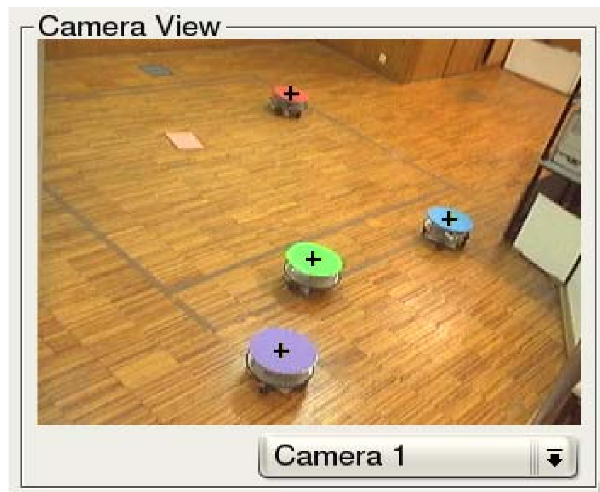


Fig. 5. Vision based localization system of the robot community. Crosses represent centroids for detected markers.

C. Localization system

Each robot keeps track of it position in the workspace by fusion of its own odometry with a vision-based localization system [20]. The system tracks a color target placed on top of the robot, and different colors or color combinations can be used in order to track multiple robots (see figure 5). The use of more than one camera can provide a better coverage of the workspace, with a consequent reduction of

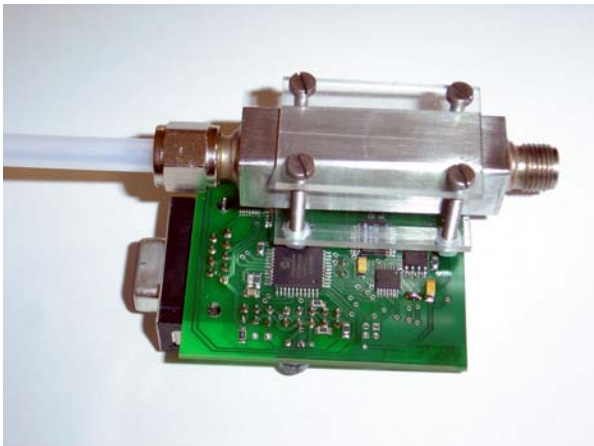


Fig. 6. Electronic nose used in the experiments.

the probability of occlusion. Sensor fusion with the robots' odometry is achieved using an Extended Kalman Filter, providing robust positional data over longer trajectories.

D. Chemical sensing system

The chemical sensing system used in the mobile robots was a SmartNose olfactory sensing nostril (see figure 4 B) [14], [15]. This electronic nose, developed at the LSE mainly for robot olfaction experiments, uses up to four tin oxide chemical gas sensors (26xx series from Figaro), and a 18F452 Microchip microcontroller allowing automatic adjustment of several functional parameters as heating temperature, measurement offsets and local processing of acquired sensor readings (see figure 6). The SmartNose has onboard processing capabilities allowing it to identify and quantify concentrations of previously trained odors. The air to the sensor chamber is drawn in by a small vacuum pump (see figure 4, C). In addition to the SmartNose, each robot carries a Shibaura thermal anemometer (see figure 4, A). This anemometer provides the airflow intensity, but not its direction. An estimation of the 2D wind vector is obtained combining the instantaneous intensity measured by the anemometer with the direction previously estimated from the average airflow map (see figure 3).

E. Experimental results

The proposed architecture was validated with experiments using two odor sources: a self-evaporating ethanol source and a controlled butane source. The choice of these chemicals was based on their availability, their density - close to that of the normal atmosphere - and on their easy detection by the SmartNose system. The ventilator was set with a flow of about 1.5 m^3/s. The butane source was activated with a gas flow of 50 ml/min 300 seconds after the beginning of the experiments and the release was terminated 240 seconds after activation. Figure 7 shows four butane maps estimated by the system for the obstacle free rectangular region of $4 \times 6\ m^2$ in front of the ventilator. Considering the map origin in the lower left corner, the butane was released from the ground level in position (1,2) m. In the first map, estimated 60 seconds after the butane activation, the release was detected and it is even possible to identify its approximate position. The second map, estimated when the release was terminated, shows what can be called a butane odor plume. The third and fourth map shows the vanishing of the butane plume.

IV. Conclusions

The paper described an architecture able to coordinate a group of environment monitoring agents and assimilate the odor information gathered in order to estimate complete odor maps of the environment. The integration of olfaction information is achieved by means of a data assimilation method based in a reduced rank Kalman filter. This filter allows an efficient updating of the system state using a reduced number of observations (the measures taken by each agent). The proposed architecture was tested in a very simplified setup with a community of five mobile robots equipped with a tin oxide sensor based electronic nose and a thermal anemometer performing random walks inside a laboratory with a small force advected airflow. The maps estimated during the experiments show the system's capability in tracking the dynamics of a specific odor field in the presence of an interfering gas and also some capability in estimating the approximated position of odor releases.

In the future the authors intend to characterize the quality of the odor maps estimated and deepen the concept, testing it in larger outdoors spaces - eventually coupling olfaction systems to city buses in order to estimate a city pollution map.

Acknowledgments

This work was partially supported by the Portuguese Science and Technology Foundation (FCT/MCT) by project **RoboNose**, contract POSI/SRI/48075/2002.

References

[1] N. Almeida, L. Marques, and A.T. de Almeida. Fast identification of gas mixtures through the processing of transient responses of an electronic nose. In *EuroSensors*, 2003.

[2] R. Byron Bird, Warren E. Stewart, and Edwin N. Lightfoot. *Transport Phenomena*. Wiley, 2nd edition, 2002.

[3] Steven C. Chapra and Raymond P. Canale. *Numerical Methods for Engineers: With Programming and Software Applications*. McGraw-Hill, 3rd edition, 1997.

[4] R. Deveza, D. Thiel, R.A. Russell, and A. Mackay-Sim. Odor sensing for robot guidance. *Int. Journal of Robotics Research*, 13(3):232–239, June 1994.

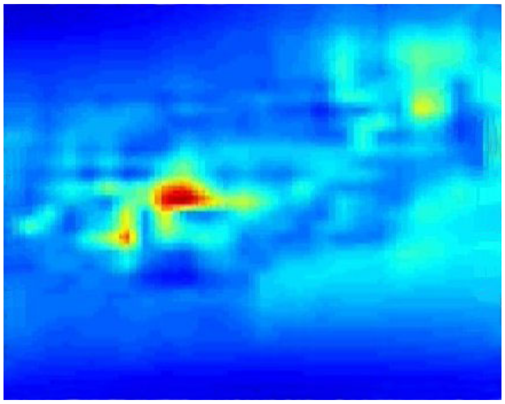
[5] T. Duckett, M. Axelsson, and A. Saffiotti. Learning to locate an odour source with a mobile robot. In *Proc. IEEE Int. Conf. on Robotics and Automation*, pages 4017–4021, 2001.

[6] R. O. Duda, P. E. Hart, and D. G. Stork. *Pattern Classification*. Wiley, 2nd edition, 2001.

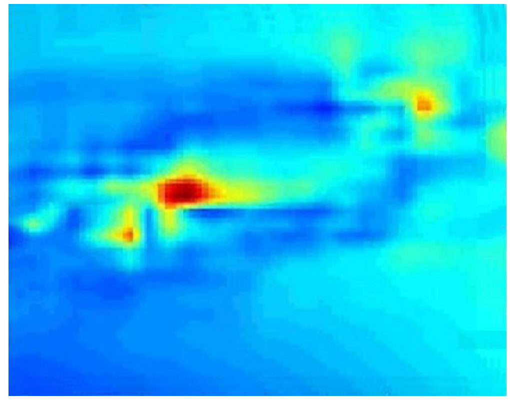
[7] Geir Evensen. The ensemble kalman filter: theoretical formulation and practical implementation. *Ocean Dynamics*, 53:343–367, 2003.

[8] K. Fukunaga. *Introduction to Statistical Pattern Recognition*. Academic Press, 2nd edition, 1991.

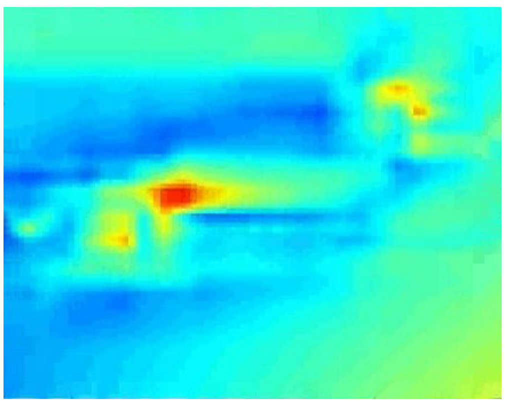
[9] A. T. Hayes, A. Martinoli, and R. M. Goodman. Distributed odor source localization. *IEEE Sensors*, 2(3):260–271, 2002. Special Issue on Artificial Olfaction.



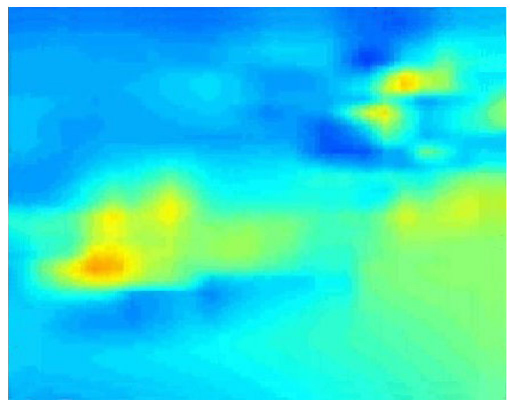
(a) $T = 360\ s$.



(b) $T = 540\ s$. Butane flow was closed.



(c) $T = 600\ s$.



(d) $T = 660\ s$.

Fig. 7. Butane concentration field estimated by the SpreadNose community pulsed controlled release of butane to the laboratory environment. The butane release started 300 seconds after the beginning of the experiment and was shut-off 240 seconds later. During the release, the gas flow was set to 50 ml/min by means of a mass flow controller.

[10] A. W. Heemink, M. Verlaan, and A. J. Segers. Variance reduced ensemble kalman filtering. *Mon. Weather Rev.*, 129:1718–1728, 2001.

[11] A. Howard, M. J. Mataric, and G. S. Sukhatme. An incremental self-deployment algorithm for mobile sensor networks. *Autonomous Robots*, 2:113–126, 2002. Special Issue on Intelligent Embedded Systems.

[12] H. P. Langtangen, K.-A. Mardal, and R. Winther. Numerical methods for incompressible viscous flow. *Advances in Water Resources*, 25:1125–1146, 2002.

[13] S. Larionova, N. Almeida, L. Marques, and A.T. de Almeida. Olfactory coordinated area coverage. In *Proc. International Conference on Advanced Robotics*, pages 501–506, 2003.

[14] L. Marques, N. Almeida, and A.T. de Almeida. Mobile robot olfactory sensory system. In *Proc. of 17th Eurosensors*, 2003.

[15] L. Marques, N. Almeida, and A.T. de Almeida. Olfactory sensory system for odour-plume tracking and localization. In *IEEE Int. Conf. on Sensors*, 2003.

[16] L. Marques and A.T. de Almeida. Finding odours across large search spaces: A particle swarm-based approach. In Manuel A. Armada and Pablo G. de Santos, editors, *Climbing and Walking Robots*, 2004.

[17] L. Marques, U. Nunes, and A. T. de Almeida. Olfaction-based mobile robot navigation. *Thin Solid Films*, 418(1):51–58, 2002.

[18] L. Marques, U. Nunes, and A. T. de Almeida. SpreadNose: Distributed agents for environmental monitoring. In P. Siciliano, editor, *Sensors for Environmental Control*, pages 234–238. World Scientific, 2003.

[19] L. Marques, U. Nunes, and A.T. de Almeida. Olfactory search by mobile robots: An evolutionary approach. *Autonomous Robots*, 2005. Special Issue on Mobile Robot Olfaction.

[20] A. Martins, L. Marques, and A.T. de Almeida. Robust localisation system for robot communities. In *Proc. 6th Port. Conf. on Automatic Control (CONTROLO 2004)*, 2004.

[21] M. H. Rahimi, R. Pon, W. Kaiser, G. S. Sukhatme, D. Estrin, and M. Srivastava. Adaptive sampling for environmental robotics. In *Proc. IEEE Int. Conf. on Robotics and Automation*, pages 3537–3544, 2004.

[22] M. Verlaan. *Sub-Optimal Schemes Toolbox for Matlab*. T.U. Delft, ver. 3.0 edition, 2003.

[23] B. Zhang, G. S. Sukhatme, and A. A. Requicha. Adaptive sampling for marine microorganism monitoring. In *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2004.