Hazardous Environment Inspection with an Odor Sensing Mobile Robot

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Abstract—Mobile robots are increasingly being used in situations of high-risk for man such as demining, radioactive waste site reconnaissance and “search and rescue” tasks in damaged areas. They can be also of great value in the automated monitoring of chemical warehouses and industrial sites against hazardous fluid leakages, thus increasing the safety level for human operators.

This paper describes recent and current research at the University of Lecce aiming at developing a mobile “sentry” with olfactory capability for hazardous site survey.

An innovative smart transducer array of tin oxide chemical sensors, compliant with the standard interface IEEE 1451, is introduced and integrated on a differential drive mobile robot in order to provide the vehicle with olfactory sensing. A strategy for environment inspection is proposed comprising two stages. The first stage is a typical path learning operation during which the vehicle is remotely controlled by an operator through potential critical locations, while the vehicle records its course relying on its odometric position estimation system.

The second stage is the real automated inspection process where the vehicle tracks the prerecorded trajectory using non-linear feedback control. Along its path, the mobile robot is able to build real time olfactory maps of the environment serving as a mobile electronic “watch”.

Detailed experimental results are described obtained with our mobile sentry operating in a laboratory environment.

Keywords—Sentry robot, Odour source identification, Artificial olfaction, Standard Sensor interface, Smooth path planning, Non-linear feedback control.

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1. Introduction

One of the greatest challenges among the robotics research community is the development of intelligent vehicles capable of autonomous navigation in natural and unstructured environments.

Such vehicles will rely on complex sensing systems able to gather the relevant features of the environment and on intelligent control systems that produce the appropriate actions in response to the sensed surroundings.

Since 1982, when Persaud and Dodd described in their seminal paper a model of an artificial system now known as an "electronic nose", able to emulate some aspects of the biological olfactory system, a great deal of interest arouse in the robotics community.

Although it is rather common to find robots with sensors that mimic the animal world, sensors for smell (chemical sensors) are by far the least used in robotics. The reason relies not only in the reduced importance of this sense in human navigation, but also a consequence of the slow development of chemical sensors in order to become similar to their biological counterparts.

A mobile robot can take advantage of an electronic nose when it needs to perform some chemically related tasks, such as identification of washed areas by cleaning robots, follow an odor track or find sources of odor, like gas leaks, drugs, explosives, landmines.

Many research groups have addressed the implementation of odor sensors in the robotics field. Russell et al., 1995 at Monash University in Australia described an interesting approach in navigation of mobile robots, based on laying down an odor trail and using an olfactory sensor to allow a vehicle to follow the trail later or to guide other following robots. Marques and de Almeida, 2000 explored the exploitation of insect behavior-based algorithms in order to follow the chemical gradient of an odor plume rather than a trail. The insect world demonstrates that the laying and detection of chemical trails can be useful as an aid for navigation and to help organise large groups of workers. With similar navigation and organisational benefits in mind robotic trail following has also been investigated in [Stella et al., 1995].

The localization of odor sources was also demonstrated in special environments: constant airflow and the use of huge sources with special odors. The constant airflow results in enormous advantage in locating gas sources, since the gas source generates a plume, with a well-defined concentration profile stable in time. In all those cases, an upwind search can be performed by driving across the plume [Nakamoto et al., 1999]. The foremost limitation of odor-based navigation is the vehicle slow speed (<20 cm/sec).

A significant example of an Electronic Nose, ENose, was developed by JPL for detecting chemical leaks in enclosed spaces, like the International Space Station or Space Shuttle [Ryan et al., 2004]. Recently, in the MIR
space station an array of conductive polymer sensors where used to detect fluid leak of ethylene glycol in the cooling system [Persaud et al., 1999]. Gas sensors have been widely used in food analysis [Taurino et al., 2003], such as tests on the freshness of fish [Olafsson et al., 1992], quality estimation of ground meat [Winquist et al., 1993], and recognition of illegally produced spirituous beverages [Kleperis et al., 1999].

There has been in the last few years an increasing demand for gas sensors to inspect chemical warehouses and industrial sites against leakages of hazardous chemicals. This paper describes the efforts at the University of Lecce towards the development of a mobile “sentry” with olfactory capability for environment inspection. An innovative gas sensor device interface has been developed at IMM-CNR, which is compliant with IEEE 1451.2 standard [IEEE Std 1451.2, 1997] by providing plug and play capabilities for transducers at both hardware and software level. This allows the construction of multiagent systems with a small engineering effort in interfacing the transducers and accommodating new ones.

The sensor is integrated on a mobile robot in order to provide the vehicle with olfactory sensing. The vehicle is able to build real time odor maps and it can serves as a mobile sentinel for automated monitoring and inspecting of hazardous industrial production sites.

The envisaged strategy for environment inspection comprises two stages. The first step is a typical path learning operation during which the operator commands the vehicle through potential leak locations in the environment. The second step is the real automated olfactory inspection process aiming at detecting odor sources, which would indicate gas leaks along the prerecorded path. The trajectory tracking is based on non-linear feedback control of the vehicle.

A spline-based path generator is also presented that allows the mobile robot to return autonomously and smoothly to the starting spot at the end of the path learning operation.

Section 2 presents the olfactory system and its integration on the differential drive vehicle employed for the experiments. Section 3 introduces the proposed strategy for environment inspection. Finally, Section 4 introduces experimental tests providing detailed results and comments.

2. Experimental Setup

2.1 The Sensor System

The implemented olfactory system is compliant with IEEE 1451.2 standard [IEEE Std. 1451.2, 1997]. In particular, a Smart Transducer Interface Module (STIM) has been developed providing plug and play (PnP) capabilities of the device. PnP is twofold operating at both local level, for adding/replacing new transducer
devices, and network level in order to enable remote control/query from portable devices such as Personal Digital Assistants (PDAs), laptops, etc. The former is achieved with the definition of a Transducer Electronic Data Sheet (TEDS) that supports a wide variety of transducers as well as a digital interface to access the TEDS, read sensors, and set actuators. The TEDS, which provides self-identification capabilities, is the core of this sensorial device, since it contains fields that fully describe the type, operation, and attributes of one or more transducers.

In general, IEEE1451 is a family of standards which introduces also an informative model of microprocessor named NCAP (Network Capable Application Processor, IEEE 1451.1) which is the bridge between the physical world of transducers and the network (regardless of the transport). This allows for plug and play capability at network level, by managing a multitude of agents that interact to each other with the same communication language [Kang Lee, 2000].

Without IEEE 1451, heterogeneous automation systems are difficult, costly and so often limited to the restricted offerings of a single vendor. At the application level, IEEE 1451 provides standard ways of creating totally self-describing measurement and control devices, allowing to choose best-in-class plug and play products. Hence, when a new sensor is plugged in, it announces its availability with information like its serial number, calibration factors, and accuracy specifications; location information can also be loaded so that a totally self-describing system can be carried on.

The IEEE 1451.2 software is implemented in five modules, which reflect the diagram shown in Figure 1a.

![Figure 1. Stim logical scheme (a) and logical software block diagram (b).](image)

The STMicroelectronics ST72264G and M24C64 EEPROM, are the hardware base for the STIM. The ST72264G is an 8-bit Micro Controller Unit (MCU) with 8 KB of program memory, 256 Bytes of RAM, 22 multifunctional
bidirectional I/O lines, an I2C multimaster interface, a SCI asynchronous serial interface and a 10-bit ADC with 6 input channels. The STIM is composed of an array of four gas sensors and one temperature/humidity sensor. The M24C64 EEPROM is used to store the IEEE 1451.2 TEDS, while the data between EEPROM and MCU are transmitted via I2C interface.

The logical block diagram of the STIM is shown in Figure 1b; in the following, the function of each module is briefly described:

- **STIM Control and Channel Data Block**: contains the definitions of the channels associated with the STIM and the main control flow.

- **STIM-NCAP Interface Block**: defines the logical interface between STIM and NCAP mapped on a RS232 link; asynchronous messages are defined for replacing trigger, acknowledgement, hot swap and error reporting functions, in addition to the data transfer functions.

- **TEDS Block**: defines the TEDS that are in use in this implementation of the 1451.2. It defines where the TEDS are mapped to, how they are written, how they are retrieved and what they contain. In our implementation we consider only the two mandatory sections:
  - META-TEDS: One per STIM
  - CHANNEL TEDS: One per STIM Channel

- **Basic Functions Blocks**: implements all the main functionalities that are defined by the 1451.2 standard. It deals with data transport, control, interrupt, status and trigger functions.

- **STIM-Transducer Interface Block**: provides functions that allow to access to each channel of the STIM.

In particular, more than the overall design of the STIM and the relative code development, is the serial implementation of the Transducer Independent Interface (TII) synchronous lines. This would allow in turn to exploit the serial message communication protocol between the STIM and the NCAP to replace this link with wireless communication by combination with the features implemented here for the NCAPs intercommunication, which turns to be itself just a technology exploitation of the WiFi skill.

The new envisaged wireless communication would allow advantages in terms of power saving, low cost RF system, with special attention to the new emerging and standardized IEEE 802.15.4/ZigBee.

Since the STIM implements an array of four gas sensors, in order to gain a unique representative measurement, at the start of the operation the estimated conductance values $r_i$ of the sensor $i$ is normalized to the range of $[0, 1]$:

$$r_i \in [0, 1]$$
\[ x_i = \frac{r_i - r_{\text{min},i}}{r_{\text{max},i} - r_{\text{min},i}} \quad i = 1, 2, 3, 4 \]  

where \( r_{\text{min},i} \) and \( r_{\text{max},i} \) are the maximum and the minimum values respectively for the conductance of sensor \( i \). Finally, the normalized response value of the sensor is obtained by averaging. This is particularly important since metal oxide sensors are known to show seasonal and environmental drift as well as noticeable differences between individual sensors.

2.1.1 The Nose Cup

The main problem with using gas sensors in real world environments is that the distribution of odorant molecules is dominated usually by turbulence rather than diffusion [Ishida et al., 1994]. Most work on chemical sensing for mobile robots assumes an experimental setup that minimizes the influence of turbulent transport by either shortening the distance between sensor and source in trail following [Russell et al., 1995] or by adopting an additional constant air stream in the environment [Deveza et al., 1994].

Here a nylon cover, so-called nose cup, is adopted aiming at creating a chamber of rest to uniform and regularize the airflow over the sensor surfaces. The nose cup is connected with the inlet tube of a pump of 300 ml/min of airflow as shown in Figure 2 and an aspirating tube is used to take in air from the environment.

This solution allows to decrease the influence of the vehicle speed and the air flows in the environment on the measurement. The continuous air stream allows also for avoiding the degradation of the metal oxide sensors saturation level observed with very low air movement relative to the sensor [Lilienthal et al., 2001]. An overall picture of the olfactory sensor box is shown in Figure 3.
2.2 The Vehicle

All the experiments were performed on a differential drive vehicle designed and built at the University of Lecce in collaboration with the Politecnico of Bari and named Jack. The vehicle is shown in Figure 4, where the olfactory unit is mounted on its top at a height of about 60 cm.

Jack is equipped with a 1 GHz Pentium IV processor and linked with the local network through a wireless connection. It is special in the fact that, in addition to the motor shaft optical encoders, it utilizes two passive trackballs as odometers in order to improve the accuracy of the position estimation. Details of the telescopic suspension system are also reported in Figure 5. This solution enables the trackballs to move up and down relative to the drive wheels avoiding that small undulations in terrain can leave the vehicle supported only by the trackballs while ensuring the required spring load with the pavement.

![Figure 4. The differential drive vehicle Jack](image)

![Figure 5. The trackball telescopic suspension system](image)

3. The Inspection Strategy

The envisaged strategy for the automated environment inspection comprises two stages. The first stage is a typical path learning process; the second step is the real time operation of olfactory inspection of the environment.

3.1 The Path Learning Process

During this stage, the vehicle is remote controlled by the operator through some potential critical locations of the environment $P = [P_1, P_2, \ldots, P_n]$ ($P_i \in \mathbb{R}^2$ with respect to a given global frame) via wireless communication using a joy pad and an onboard webcam, as shown in the explanatory scheme of Figure 6.

The vehicle records the driven (manually commanded) path using its pose estimation system based on traditional encoders and odometric trackballs. As shown in Figure 6, the recorded path might not be closed, i.e. the ending
pose could differ from the starting one ($P_n \neq P_0$). Given that in the next phase the robot should autonomously re-run the learned path to accomplish its environment monitoring task, poses $P_0$ and $P_n$ need to be suitably connected.

Figure 6. The path learning process

The issue is to find a path going from $P_n$ to $P_0$ having, in $P_n$ and $P_0$, the same slopes that the learned one had. Moreover, in order to minimize the jerk, the curvature of the connecting path should be null in $P_0$ and $P_n$.

These requirements call for a spline–based path planning approach. In particular, if $\xi \in [0,1]$ and $P_n = (x_n, y_n)$ and $P_0 = (x_0, y_0)$, a continuous curve going from $P_n$ to $P_0$ with assigned derivatives in $P_n$ and $P_0$ is given by:

$$\Gamma = \{ (x(\xi), y(\xi)) : \xi \in [0,1] \}$$

(2)

where:

$$x(\xi) = a\xi^3 + b\xi^2 + c\xi + d$$

(3)

$$y(\xi) = a\xi^3 + b\xi^2 + c\xi + d$$

(4)

with the following boundary conditions:

$$x'_{\xi=0} = x_0 = d = x_{P_0}$$

(5)

$$y'_{\xi=0} = y_0 = \delta = y_{P_0}$$

(6)

$$x'_{\xi=1} = x_1 = a + b + c + d = 0$$

(7)

$$y'_{\xi=1} = y_1 = \alpha + \beta + \gamma + \delta = 0$$

(8)

$$\frac{dy}{d\xi} |_{\xi=0} = y'_{\xi=0} = y'_{0}$$

(9)

$$\frac{dy}{d\xi} |_{\xi=1} = y'_{\xi=1} = y'_{1}$$

(10)
The four derivatives \( x'_0, x'_1, y'_0, y'_1 \) are assumed to be known. The slope of \( \Gamma \) at the two boundary points is:

\[
\begin{align*}
\frac{y'}{x'} \bigg|_{\xi=0} &= \frac{y'_0}{x'_0} = \frac{dy}{dx} \bigg|_{\xi=0} \\
\frac{y'}{x'} \bigg|_{\xi=1} &= \frac{y'_1}{x'_1} = \frac{dy}{dx} \bigg|_{\xi=1}
\end{align*}
\]

While the curvature \( \kappa \) of the curve is given by:

\[
\kappa = \frac{x'y'' - y'x''}{(x'^2 + y'^2)^{3/2}}
\]

In order for \( \Gamma \) to have null curvature in \( \xi=0, \xi=1 \) and contemporary satisfy the boundary conditions (5)-(12), it is sufficient to add to the relations (3) and (4) the polynomials \( x_\kappa(\xi) \) and \( y_\kappa(\xi) \) respectively, which satisfy the boundary conditions defined below:

\[
\begin{align*}
x_\kappa(0) &= x_\kappa(1) = 0 \\
x'_\kappa(0) &= x'_\kappa(1) = 0 \\
x''_\kappa(0) &= -x''(0) = -2b \\
x''_\kappa(1) &= -x''(1) = -6a - 2b
\end{align*}
\]

and equivalently on \( y_\kappa(\xi) \). By direct calculation, it can be found that such polynomials may be defined as:

\[
\begin{align*}
x_\kappa(\xi) &= (\xi(\xi - 1))^2 (m_x \xi + q_x) \\
y_\kappa(\xi) &= (\xi(\xi - 1))^2 (m_y \xi + q_y)
\end{align*}
\]

where:

\[
\begin{align*}
m_x &= -3a, \quad q_x = -b \\
m_y &= -3a, \quad q_y = -\beta
\end{align*}
\]

Thus, the final expressions for \( x(\xi) \) and \( y(\xi) \) are:

\[
\begin{align*}
x(\xi) &= a \xi^3 + b \xi^2 + c \xi + d + (\xi(\xi - 1))^2 (-3a \xi - b) \\
x(\xi) &= a \xi^3 + \beta \xi^2 + \gamma \xi + \delta + (\xi(\xi - 1))^2 (-3a \xi - \beta)
\end{align*}
\]

being:

\[
a = -2(x_1 - x_0) + x'_0 + x'_1
\]
\[ b = 3(x_1 - x_0) - 2x'_0 - x'_1 \]
\[ c = x'_0 \]
\[ d = x_0 \]
\[ \alpha = -2(y_1 - y_0) + y'_0 + y'_1 \]
\[ \beta = 3(y_1 - y_0) - 2y'_0 - y'_1 \]
\[ \gamma = y'_0 \]
\[ \delta = y_0 \]

Finally, it is worth mentioning that the derivatives \( x'_0, x'_1, y'_0, y'_1 \) are actually not specified themselves, but rather only their ratios are:

\[ \frac{y'_0}{x'_0} = \tan \theta_n \Rightarrow y'_0 = (\tan \theta_n) x'_0 \quad \forall x'_0, x'_1 \quad (26) \]
\[ \frac{y'_1}{x'_1} = 0 \Rightarrow y'_1 = 0 \quad \forall x'_0, x'_1 \quad (27) \]

This means that the Eqs. (24) and (25) define a family of \( \infty^2 \) curves for all the possible values of \( (x'_0, x'_1) \). The choice of these two parameters can be made by optimizing on some additional performance index. Specifically, it may be useful to find an optimal tradeoff between maximal curvature of the path and its length. To illustrate why this could be the case, consider Figure 7 where two paths are shown corresponding to different choices of \( (x'_0, x'_1) \). Both paths satisfy the boundary conditions \( P_0 = (10m, 0m), P_1 = (1m, 0m) \), \( \left( \frac{dy}{dx} \right)_0 = 1 \), \( \left( \frac{dy}{dx} \right)_1 = -1 \) and zero curvature at the boundary points. The solid blue line path corresponds to \( (x'_1, x'_0) = (1,1) \) and shows a maximum curvature of about 32.9 [rad/m], while the dashed red line path corresponds to \( (x'_1, x'_0) = (3,3) \) and has a maximum curvature of 6.8 [rad/m] at the expense of a larger length. Even if the mobile robot used in this research is a differential drive one (and can thus drive infinite curvature paths), it may be indeed useful to design paths having bounded curvature. In particular, the parameters \( (x'_1, x'_0) \) may be selected by (numerically) optimizing a suitable performance index \( J \) taking into account the maximum path’s curvature and its length:

\[ (x'_1, x'_0) = \arg \min_{x'_1, x'_0} J : J = \lambda \int_0^1 \sqrt{(x'^2 + y'^2)} \ d\xi + \max_{\xi} |\kappa(\xi)| \quad (28) \]

where \( \lambda \) represents the relative weight of length over maximum curvature as a design criteria.
A typical, experimentally implemented, final result of the described method is shown in Figure 8.

Figure 8. Typical returning path using the spline module

3.2 The Olfactory Inspection of the Environment

During this operation, the vehicle serves as an olfactory sentry of the environment against hazardous gas leaks or chemicals. The vehicle tracks the prerecorded trajectory based on a non-linear feedback control gathering in real-time olfactory information of the environment. It moves autonomously relying on its control system while the operator serves as supervisor analyzing data and images coming from the vehicle via wireless communication. The trajectory tracking is based on the work of Canudas de Wit et al., 1993 here briefly described for the sake of clarity. The trajectory tracking problem may be formulated introducing a virtual reference vehicle to be tracked, as indicated in Figure 9.
Expressing the position and orientation errors with respect to the virtual (target) vehicle in the real vehicle frame, it gets:

\[
\begin{bmatrix}
  e_1 \\
  e_2 \\
  e_3
\end{bmatrix} =
\begin{bmatrix}
  \cos \theta & \sin \theta & 0 \\
  -\sin \theta & \cos \theta & 0 \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  x_{\text{ref}} - x \\
  y_{\text{ref}} - y \\
  \theta_{\text{ref}} - \theta
\end{bmatrix}
\]  

(29)

Differentiating relation (29) and introducing the change of variables:

\[
u_1 = -v + v_{\text{ref}} \cos e_3
\]  

(30)

\[u_2 = \omega_{\text{ref}} - \omega\]  

(31)

it yields the error dynamics:

\[
\dot{e} =
\begin{bmatrix}
  0 & \omega & 0 \\
  -\omega & 0 & 0 \\
  0 & 0 & 0
\end{bmatrix} e +
\begin{bmatrix}
  0 \\
  \sin e_3 \\
  0
\end{bmatrix} v_{\text{ref}} +
\begin{bmatrix}
  1 & 0 & 0 \\
  0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
  u_1 \\
  u_2
\end{bmatrix}
\]  

(32)

The trajectory tracking problem consists in designing a suitable feedback law \(u = f(e)\), which asymptotically stabilizes the error to zero. The control law design is based on Lyapunov techniques: a candidate Lyapunov function is:

\[
V = \frac{k_1}{2} (e_1^2 + e_2^2) + \frac{e_3^2}{2}
\]  

(33)

that can be proven [Canudas de Wit et al., 1993] to have a semi-negative definite time derivative if the control signals are selected as:

\[
u_1 = -k_2 e_1
\]  

(34)
Indeed, by using Barbalat’s Lemma under the hypothesis that:

\[
\lim_{t \to \infty} v_{\text{ref}}(t) \neq 0 \quad \text{or} \quad \lim_{t \to \infty} \omega_{\text{ref}}(t) \neq 0
\]  

(Hp1)

the control signals given in equations (34) and (35) can be shown to guarantee global asymptotic stability of the error to zero (in spite of the fact that \( \dot{V} \) is only negative semi-definite). Hypothesis (Hp1) simply means that the target vehicle should not be asymptotically still in which case the trajectory tracking problem would degenerate in a pose stabilization one that is known to admit no continuous feedback solution according to Brockett’s Theorem [Brockett, 1983], whereas the functions \( u_1 \) and \( u_2 \) given in (34) and (35) are continuous in \( e \).

Replacing (34)-(35) into (30)-(31), the linear and angular velocities resulting from the closed loop control law are found to be:

\[
v = k_2 e_1 + v_{\text{ref}} \cos e_3 \tag{36}
\]

\[
\omega = \omega_{\text{ref}} + k_1 v_{\text{ref}} \frac{\sin e_3}{e_3} e_2 + k_3 e_3 \tag{37}
\]

The error variables are estimated by the trackball based odometric system. The reference angular and linear velocities are computed from (1) the log file data of the teleoperated path from \( P_0 \) to \( P_n \) and (2) the spline-based planned path from \( P_n \) to \( P_0 \).

4. Experimental Results

In order to test the effectiveness of our system, a set of preliminary experiments was performed in a 3m x 10m weakly ventilated laboratory environment. To simulate a typical task for a mobile sentry, several odor sources were randomly spread in the environment reproducing potential fictitious leakage sites, i.e. valves, pressure vessels, tanks etc.

Each odor source was realized using a 50 cm high turret with an ethanol container and a 10 cm diameter plastic bowl on the top (see Figure 4). The ethanol dripped into the bowl through a hole in the container at a rate of approximately 50 ml/h.

Ethanol was used because it is not toxic and easily detectable by the oxide sensors.
The vehicle was first remote controlled appropriately in order to approach each of the turrets with the aspirating tube of the olfactory sensor passing over the turrets. Afterwards, automatic inspection operations were performed changing the number of the ethanol containers on the turrets.

Figure 10 shows a typical result expressed in a so-defined odor map for a test with five ethanol leaking turrets; the minimum relative distance between the turrets was 90 cm between the first and second source denoted with $S_1$ and $S_2$ respectively.

The odor map reports in the x-y plane the path followed by the vehicle and along the z-axis the percentage relative conductance estimated by the gas sensor; the “ground truth” positions of the sources are also indicated with black cross marks.

The mobile sentry detected correctly all the odor sources. Table I lists for each of the source position $S_i=[S_{x,i}, S_{y,i}]$ a set of so-called relative square errors $E_i$ defined as:

$$E_i = \frac{(S_{x,i} - M_{x,i})^2 + (S_{y,i} - M_{y,i})^2}{\sqrt{S_{x,i}^2 + S_{y,i}^2}}$$

(38)

where $M_i=[M_{x,i}, M_{y,i}]$ is the estimated location for the source $i$ set by the olfactory system corresponding to the conductance peak. Note that $E_i$ accounts also for errors due to the inaccuracy of the control and the position estimation system.

The odor sources were located with an average error within 5% and a worse case of 8%.

Note that the fourth odor source $S_4$ was detected with a peak sensibly higher than the other four turrets. It may be caused by the presence of whirls due to the proximity to the laboratory wall.

The travel speed of the vehicle during the inspection tests was 5 cm/sec. Other velocities of 15 and 25 cm/sec were also analyzed but no significant difference in signal shape was observed. The sampling rate of the olfactory sensor was 100 ms.

A second experiment was performed using only two leaking turrets placed at a relative distance of about 40 cm in order to test the ability of the system to differentiate between two odor sources very close each other. The odor map for a typical run is reported in Figure 11; the olfactory sensor successfully detected two odor sources.
5. Conclusions

A mobile robotics application was described aiming at the development of a semi-autonomous “sentry” for automated olfactory inspection of hazardous environments. An innovative olfactory system sensor was presented
and integrated with a differential drive vehicle providing the ability to build odor maps along prerecorded paths. The envisaged strategy for automated inspection was described based on non-linear feedback control for trajectory tracking. The olfactory system showed to be effective in preliminary experimental trials to locate multiple odor sources. The olfactory system could be employed to implement an automated inspection of chemical warehouses and industrial sites against hazardous gas leakages, thus resulting in an increase in the safety level for human operators.

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