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The DustBot System: Using Mobile Robots to Monitor Pollution in Pedestrian Area

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The EU project DustBot addresses urban hygiene. Two types of robots were designed, the DustClean robot to autonomously clean pedestrian areas, and the DustCart robot for door-to-door garbage collection. Three prototype robots were built and equipped with electronic noses so as to enable them to collect environmental data while performing their urban hygiene tasks. Essentially, the robots act as a mobile, wireless node in a sensor network. In this paper we give an overview of the DustBot platform focusing on the Air Monitoring Module (AMM). We describe the data flow between the robots through the ubiquitous network to a gas distribution modelling server, where a gas distribution model is computed. We describe the Kernel DM+V algorithm, an approach to create statistical gas distribution models in the form of predictive mean and variance discretized onto a grid map. Finally we present and discuss results obtained with the DustBot AMM during experimental trials performed in outdoor public places: a courtyard in Pontedera, Italy and a pedestrian square in Örebro, Sweden.

1. Introduction

Environmental monitoring is important to protect the public and the environment from toxic contaminants and pathogens in the air. The EU (framework directive 1996/62/EC) has imposed strict regulations on the concentration of many airborne environmental contaminants, including sulfur dioxide, carbon monoxide, nitrogen dioxide, and volatile organic compounds, which originate from vehicle emissions, power plants, refineries, and industrial and laboratory processes, to name but a few. Nowadays, pollution monitoring in the city is performed by a network of sparse fixed stations that send the pollution values to a central station for data processing (Fenger, 1999). Their total number and consequently the number of sampling locations are limited due to economical and practical constraints. Thus, the selection of monitoring/sampling locations becomes very critical, especially considering the time-varying, complicated local structure of the gas distribution. A further disadvantage of stationary air monitoring stations is that they are typically placed at expected "hot spots", close to busy roads, for example, and accordingly pedestrian areas and parks, away from road

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traffic are not always monitored. To improve pollution monitoring a refinement of the monitoring scale is needed. In existing sensors networks this can be achieved by integration of mobile platforms equipped with an “electronic nose”. Marques (2002) suggested integrating “e-noses” into city buses and, Carvalho et.al (2009) proposed a solar powered device, to be integrated on buses and taxis, sending data through the GSM/GPRS network to a central server that publishes the gathered pollution levels on top of a map. In both cases the monitoring is limited to roads but not pedestrian areas. This limitation can be overcome by using autonomous mobile robots equipped with gas sensors. The robots can act as autonomous wireless nodes in a monitoring sensor network, and due to their mobility, self-localisation capability and the ability to adaptively select sampling locations, they offer a number of important advantages: higher and adaptive monitoring resolution, source tracking, first aid and cleanup of hazardous or radioactive waste sites, compensation for inactive sensors, and adaption to the dynamic changes of the environment. Using mobile robots for air quality monitoring has been addressed in the EU project DustBot (Mazzolai et.al, 2008), in which robot prototypes are developed to clean pedestrian areas and concurrently monitor the pollution levels. The collected data are sent to a server, where the computation of a gas distribution model (GDM) is performed. Gas distribution modelling is the task of deriving a truthful representation of the observed gas distribution from a set of spatially and temporally distributed measurements of gas concentration. Building gas distribution model is a very challenging task because in many realistic scenarios gas is dispersed by turbulent advection where packets of gas follow chaotic trajectories (Shraiman and Siggia, 2000). In principle, CFD (Computational Fluid Dynamics) models could be applied, which try to solve the governing set of equations numerically. However, CFD models are computationally very expensive and depend sensitively on accurate knowledge of the state of the environment (boundary conditions), which is not available in practical situations. Moreover, many gas distribution models were developed to atmospheric dispersion (Olesen et.al, 2005). Such models cannot capture all the relevant aspects of gas propagation with a sufficient level of detail. High resolution models are required particularly at small scales and in typical complex indoor and outdoor settings where critical gas concentrations often have a local character. The system described in this paper fits the requirement of high resolution. It uses the Kernel DM+V (Lilienthal et. al 2009), a statistical model that treats the sensors measurements as random variables. This model makes no assumptions about a particular functional form of the model, other than that it can be described as a time-constant random process. Thus it avoids the need to have compulsive knowledge of the boundary condition, as in the case of a CFD model.

2. The DustBot System

In the framework of the EU project DustBot (Ferri et. al, 2010) we have developed a multi-robot system for urban hygiene management (Fig. 1 left). One of the two types of robots created during the project is DustCart. DustCart is a two-wheeled robot, based on the commercial Segway RMP200 platform. The robot is designed to provide an automatic door-to-door garbage collection service in the pedestrian areas of the historical centers of towns where other larger vehicles could face difficulties in movement. In a typical operational scenario, a user requests garbage removal by placing a call to the automated DustBot call center. A robot is then dispatched to the predefined user home address. The robot interacts with the user through a touchscreen and receives a garbage bag. Then, it moves to a discharging site where it deposits the bag in different locations based on the type of garbage the user chose on the touchscreen.

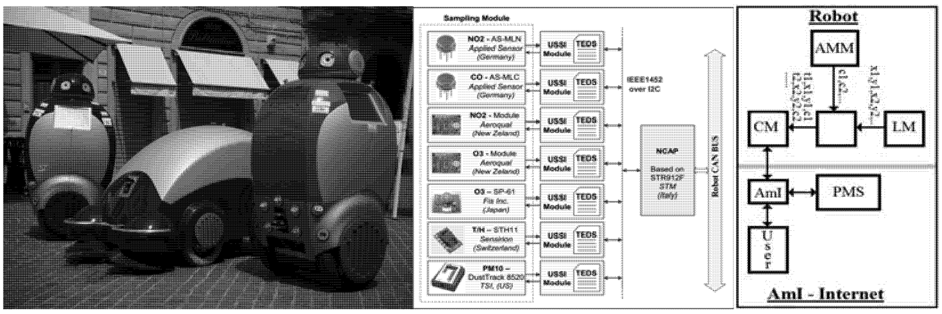

Figure 1. Left: Two DustCart Robots and one DustClean. Middle: Scheme of the AMM module architecture and the sensors used. Right: Data flow between the robots and the Pollution Modelling Server (PMS).

The second type of robot is a four-wheeled robot endowed with brushes and cleaning equipment, the DustClean robot. It is designed to autonomously sweep and clean the pedestrian area. The robot operations are managed by an Ambient Intelligence system (AmI) receiving the phone calls, selecting the robot to move and managing the robots' navigation. The capability of these robots to autonomously navigate in real urban environments avoiding static and dynamic obstacles suggested us to endow it with additional features: monitoring air quality using different environmental sensors. Different kinds of sensors were integrated and collectively operated in the Ambient Monitoring Module (AMM). The sensors include NO_2, O_3, CO, PM10, temperature and humidity (Ferri et.al). To create the gas distribution model, every two seconds the data coming from the AMM are transmitted together with the measurement time to the AmI infrastructure through the Communication Module (CM) which uses a WiFi, UMTS or GPRS channel, according to the currently available network. The data are collected by a central server and stored in a database. When a user makes a query for some data, the AmI platform performs a call to the Pollution Model Server (PMS) where the gas distribution model is computed and then sent back in the form of an image, or table format. This system enables AmI to build maps receiving at the same time data from different robots.

3. The Kernel DM+V Algorithm

In this section we briefly describe the basic ideas of the Kernel DM+V algorithm, a detailed description could be found in (Lilenthal et.al, 2009). The general gas distribution mapping problem addressed is to learn a predictive two dimensional model $p(r|\mathbf{x},\mathbf{x}_{1:n},r_{1:n})$ for the gas reading r at location $\mathbf{x}$, given the robot trajectory $\mathbf{x}_{1:n}$ and the corresponding measurements $r_{1:n}$. To study how gas is dispersed in the environment we consider measurements from metal oxide sensors. The central idea of kernel extrapolation methods is to understand gas distribution mapping as a density estimation problem addressed using convolution with a Gaussian kernel □. The first step in the algorithm is the computation of weights $\omega_i^{(k)}$, which intuitively represent the information content of a sensor measurement i at grid cell k (Eq. 1). The weights are computed by evaluating a Gaussian kernel □ at the distance between the location of the measurement x_i and the center $x^{(k)}$ of cell k. Using Eq. 1, weights $\omega_i^{(k)}$, weighted sensor readings $\omega_i^{(k)} \cdot r_i$, and weighted variance contributions $\omega_i^{(k)} \cdot \tau_i$ are integrated and stored in temporary grid maps (Eq. 2). From the integrated weight map $\Omega^{(k)}$ we compute a confidence map $\alpha^{(k)}$ which indicates high confidence for cells for which a large number of readings close to the center of the respective grid cell is available. The confidence map is computed in Eq. 3. Normalising Eq. 3 with the integrated weights $\Omega^{(k)}$ and linear blending with a best guess for the case of low confidence, we obtain the map estimate of the mean distribution $r^{(k)}$ (Eq. 4) and the corresponding variance map $v^{(k)}$ (Eq. 5).

$$\omega_i^{(k)}(\sigma_0)=\square(|x_i-x^{(k)}|,\sigma_0), \tag{1}$$
$$\Omega^{(k)}(\sigma_0)=\textstyle\sum_{i=1:n} \omega_i^{(k)}(\sigma_0), \quad R^{(k)}(\sigma_0)=\sum_{i=1:n} \omega_i^{(k)}(\sigma_0)\cdot r_i, \quad V^{(k)}(\sigma_0)=\sum_{i=1:n} \omega_i^{(k)}(\sigma_0)\cdot \tau_i, \tag{2}$$
$$\alpha^{(k)}(\sigma_0)=1-\exp(-\Omega^{(k)}(\sigma_0)^2/\sigma^2_\Omega), \tag{3}$$
$$r^{(k)}(\sigma_0)=\alpha^{(k)}R^{(k)}/\Omega^{(k)}+\{1-\alpha^{(k)}\}\cdot r^*, \tag{4}$$
$$v^{(k)}(\sigma_0)=\alpha^{(k)}R^{(k)}/\Omega^{(k)}+\{1-\alpha^{(k)}\}\cdot v_{tot.}. \tag{5}$$

where, $\tau_i=(r_i- r_i^{k(i)})^2$ is the variance contribution of reading i and $r^{k(i)}$ is the mean prediction of the cell $k(i)$ closest to the measurement point x_i. The second terms in equations 4 and contain the best estimate, which is used for cells with a low confidence, i.e. for cells for which we do not have sufficient information from nearby readings, indicated by a low value of $\alpha^{(k)}$. As the best guess of the mean concentration r^* we use the average over all sensor readings. The estimate v_{tot} of the distribution variance in regions far from measurement points is computed as the average over all variance contributions. The Kernel DM+V algorithm depends on three parameters: the kernel width σ_0, which governs the amount of extrapolation on individual readings; the cell size c that determines the resolution at which different predictions can be made; and the scaling parameter σ_Ω, which defines a soft threshold between values of $\Omega^{(k)}$ that are considered “high” (where $\alpha^{(k)}$ is close to 1) and “low” ($\alpha^{(k)}$ is close to 0). Smaller values of σ_Ω entail a lower threshold on $\Omega^{(k)}$, i.e. an increasing tendency to trust the distribution estimate obtained from extrapolation on local measurements. The parameters of the model were determined by cross validation optimization.

4. Results

We carried out gas distribution mapping experiments in an outdoor courtyard in Pontedera (Italy) and in a pedestrian square in Örebro (Sweden). Measurements were recorded at frequency of 0.5 Hz. In the monitoring trials in Pontedera the robot followed a predefined sweeping trajectory (Fig. 2 left). The sweeping motion was performed twice in opposite directions and the robot was driven at a maximum speed of 20 cm/s. The gas source was a fumigator located in the middle of the inspected area. Figure 2 (center) shows the PM10 response in the inspected area measured by the DustTrak 8520 sensor and the law limit (gray line). The peak that exceeds the law limit was obtained for a robot position close to the gas source. The learned model is represented as a pair of 2-d grid maps, one representing the distribution mean (Fig. 2 right top) and the other one the corresponding predictive variance per grid cell (Fig. 2 right bottom). In contrast to the covariance of the mean, that is estimated by a Kalman filter approach, which only decreases as new observations are processed, our estimate of the variance adapts to the

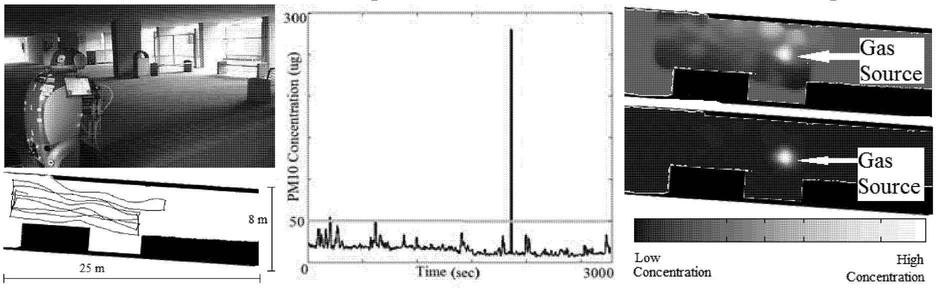

Figure 2. Left: The DustCart robot in the experimental scenario: a courtyard in Pontedera (Italy). Left Bottom: The map of the experimental environment and the robot's path (gray line). Center: DustTrak 8520 sensor response (PM10 Pollutant). Right: Gas distribution maps, mean (top) and variance (bottom, σ_0=80cm and c=10cm).

real variability of gas readings at each location. Both the two maps exhibit high values (bright spot in the map) close to the exact location of the gas source.

In the set of experiments ran in Örebro, the DustCart robot (Fig. 3) went from a docking station to a customer to collect garbage and then to the discharging area and finally back to the docking station. While performing the garbage collection task, the pollution level measurements were recorded. The robot was driven at a maximum speed of 1 m/s. A controlled fire was placed in the square as a pollution source. The second and the third maps in Figure 3 are the gas mean and variance maps obtained by the DustTrak 8520 sensor (PM10). The other two, the maps from the CO gas sensor (Applied Sensors). All the maps have a maximum region close to the source location. Here it is interesting to note that the variance distribution maps have high values in a closer and smaller region around the source location than the mean maps, where high values are spread in a larger area. This is in accordance with empirical knowledge that we have from previous work, where we observed that the variance distribution typically provides more accurate information about the source location. We have run a total of 22 successful trials without (3) and with an artificial gas source (19, fumigator, fire, car or truck exhaust), for the 4 pollutants mentioned in section 2.

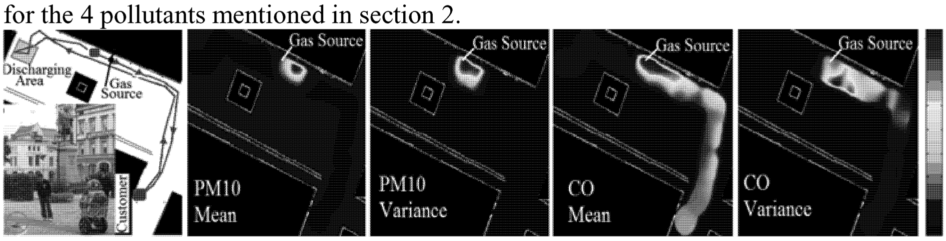

Figure 3 From left to right: DustCart in the experimental scenario (Stortorget, Örebro – Sweden). The robot's path (gray line), the user house, the discharge location and the pollution source position are shown on the map (•). The second and the third maps show the mean gas distribution and the variance distribution, respectively, for the

PM10 (DustTrak 8520) sensor and last two maps are the mean and variance gas distribution maps for the CO (Applied Sensors) sensors, for σ_0=100cm and c=10cm.

From all the experiments where the knowledge of the exact gas source location was available (19 trials) the variance map always shows high levels in a limited and small area around the source location (in the order of the kernel size). These results suggest us the utilization of the variance map as promising tool for gas source localization.

If the local wind information is available (no in the case of the DustBot) the method (Reggente and Lilienthal, 2009a) could be used. It takes into account the wind information (from an anemometer mounted on a mobile robot) by modeling the information content of the gas sensor measurements as a bivariate Gaussian kernel whose shape depends on the measured wind vector.

5. Conclusion

In this paper, first, we have briefly described the DustBot system, where an autonomous network of cooperating robots, while dealing with the task of urban hygiene, also perform pollution monitoring in their area of work (mostly pedestrian areas). Than we have shown results from pollution monitoring trials carried out in two public spaces in Italy and Sweden. The results show that the gas distribution model used (Kernel DM+V) is a useful tool for high resolution pollution monitoring and it is able to localize the gas source location using the information obtained by the variance map.

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