Mobile Robot based Odor Path Estimation via Dynamic Window Approach

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***Abstract*—This paper addresses the problem of estimating the odor path which is most likely taken by the odor patch detected by the concentration sensor on a mobile robot moving in an indoor dynamic airflow environment. The odor path estimation is useful for plume tracing and odor source declaration. A novel algorithm for odor path likelihood mapping in the dynamic airflow environment is proposed. The algorithm has a low computation cost by importing the idea of dynamic window approach. Experiments are carried out on the mobile robot in which odor concentration sensor, airflow sensor, encoder and compass are equipped. To extract useable concentration information from the odor sensor, a practicable data pre-processing method is put forward. The experiment results in the indoor dynamic airflow environment show that the odor path can be well estimated online.**

***Keywords*—Mobile robot, odor path, plume tracing, online mapping, dynamic window.**

I. Introduction

Odor information is widely used by many animals for searching for food, finding mates, exchanging information, and evading predators. Some animals can be trained to help humans seek appointed odor or gas sources. Inspired by the olfaction abilities of many animals, in the early 1990s, people started to try building mobile robots with similar olfaction abilities to replace trained animals [1–4]. Compared to animals, robots can be deployed quickly and maintained with low cost. In addition, robots can work for long periods without fatigue, and most importantly, they can enter dangerous areas. With motion capability, robots with onboard sensors actually form a mobile sensor network, so mobile robot olfaction is more flexible and can cover more area than a stationary wireless sensor network. It is expected that mobile robots developed with such olfaction capability will play more and more roles in such areas as judging toxic or harmful gas leakage location, checking for contraband (e.g., heroin), searching for survivors in collapsed buildings, humanitarian de-mining, and antiterrorist attacks. Some biological inspired approaches have been designed for plume tracing on an autonomous vehicle, such as gradient-following-based algorithm in low Reynolds number [5, 6] and up-wind algorithm in a wind tunnel [6, 7], which intended to mimic the behaviors of chemotaxis and anemotaxis of a few biological entities, respectively. Practical environments are not always being low Reynolds number, however. In addition, an odor source is not necessarily in up-wind direction, either. Therefore, neither gradient-following-based algorithm nor up-wind algorithm can be used simply in most real airflow environments [6]. Recently the so-called fluxotaxis [8] and infotaxis [9] plume tracing algorithms have also been proposed, where the knowledge of computational fluid dynamics and information entropy are applied, respectively.

This paper considers the development of an algorithm for estimating the most likely path taken by the odor patch detected by the concentration sensor on a mobile robot in an indoor dynamic airflow environment. The estimation of odor path will be useful for plume tracing and source localization problem. Similar simulation work can be found in [6], where the hidden Markov method was applied. As we know, the assumption that the flow velocity vector is spatially invariant is not true if there exist significant terrain features that locally affect the flow or the temporal variations of the airflow are rapid enough in the search area [6]. Therefore, spatial variation must be considered in an unknown environment. And for this reason, a novel method for odor path estimation is proposed by choosing a dynamic window which covers the possible area only in which the spatial variation of the flow velocity might be neglected and the probability of there being an odor path is updated. The dynamic window approach used for odor path estimation is described in detail in Section IV. The mobile robot used in our experiments is capable of self-localization, sensing chemical concentration, airflow velocity and direction. The concentration sensor is perfect except the relatively long response time delay. The odor path estimation problem is analyzed in two dimensions, but the algorithms presented herein can be extended to three-dimensional environments.

II. Pre-Processing of Sensors' Data

A. Wind velocity and direction

A wind meter sends airflow data (wind velocity and direction) to the computer embedded in the mobile robot at a higher rate than the calculation period of the odor path estimation algorithm. Suppose there are M_f airflow readings per calculation period, the following mean value of the M_f readings at the time t_i is used.

$$u_x(t_i)=\frac{1}{M_f}\sum_{k=1}^{M_f}u_x(t_{ik}),\qquad u_y(t_i)=\frac{1}{M_f}\sum_{k=1}^{M_f}u_y(t_{ik}),\qquad (1)$$

where $u_x(t_{ik})=u_{ik}\cos\theta_{ik}, u_y(t_{ik})=u_{ik}\sin\theta_{ik}$; u_{ik} and θ_{ik} stand for the wind velocity and direction of the k th reading at time $t_{ik}\in(t_{i-1},t_i]$, respectively. Note that all the measurements occur at the location of the sensor equipped on the robot, including odor concentration measurements introduced subsequently.

B. Odor concentration

The odor concentration sensor equipped on the robot has accurate readings in comparison with the binary values mentioned in [6] and [10]. Due to the concentration sensor has an un-negligible time delay τ, the sensor reading at time t_i should be recorded as

$$c(t_i-\tau)\cong c(t_i-k\Delta t_c)=c(t_{i-k}),\quad k=\mathrm{int}(\tau/\Delta t_c),\qquad (2)$$

where Δt_c is the sampling period of the concentration sensor; $\mathrm{int}(\tau/\Delta t_c)$ is the greatest integer less than or equal to $(\tau/\Delta t_c)$.

It is reasonable to assume that an odor source has leaked for some time when the robot starts to search for the source. In such a case, there might be a common foundational odor concentration in local or even the whole area where the robot locates. In other words, it is possible that the odor concentration of the local or even the whole area is bigger or smaller than a concentration threshold. It is therefore not helpful to search for the odor path only by a binary concentration. This might be the reason that the valid detection events sometimes were rare in [6]. The moving average value expressed as follows is recorded as the common foundational concentration,

$$\bar{c}(t_i)=\begin{cases}\dfrac{\bar{c}(t_{i-1})+c(t_i)}{2} & i>1\\ c(t_i) & i=0\end{cases}.\qquad (3)$$

Thus, the detection signal can be represented by the following relative concentration

$$c'(t_i)=\begin{cases}c(t_i)-\bar{c}(t_{i-1}) & c(t_i)\geq\bar{c}(t_{i-1})\\ 0 & c(t_i)<\bar{c}(t_{i-1})\end{cases}.\qquad (4)$$

Furthermore, the signal intensity of the detection event is defined as follows

$$s(t_i)=K_c\frac{c'(t_i)}{\bar{c}(t_{i-1})}=\begin{cases}K_c\left(\dfrac{c(t_i)}{\bar{c}(t_{i-1})}-1\right) & c(t_i)\geq\bar{c}(t_{i-1})\\ 0 & c(t_i)<\bar{c}(t_{i-1})\end{cases},\qquad (5)$$

where K_c is a positive constant; $s(t_i)$ represents the information quantity of the detection event at time t_i.

III. Map Representation

W is defined as a 2D workspace in which the robot searches. Its boundary is marked with ∂W . W can be uniformly divided as

$$W_{m\times n}=\{C(i,j)\mid 1\leq i\leq m, 1\leq j\leq n\}.\qquad (6)$$

Where $C(i,j)$ is the square cell which lies in the i th row and the j th column; m and n , which are calculated as follows, are the number of rows and columns of the discrete workspace, respectively.

$$m=\mathrm{int}\left(\frac{\Delta_y(\partial W)}{a}\right), n=\mathrm{int}\left(\frac{\Delta_x(\partial W)}{a}\right),\qquad (7)$$

where $\Delta_x(\partial W)$ and $\Delta_y(\partial W)$ are the maximal length of the workspace W in x (horizontal) and y (vertical) axes, respectively; a is the side length of each cell.

Given a point (x,y), the direct calculation of the index (i,j) of the cell containing this point is as follows

$$i=\mathrm{int}(y/a), j=\mathrm{int}(x/a).\qquad (8\text{-a})$$

Inversely, given the index (i,j) of the cell, the coordinates of the points in the cell can be expressed as follows

$$y\cong(i+0.5)a, x\cong(j+0.5)a.\qquad (8\text{-b})$$

For notational convenience, we introduce a constant $M=mn$, and shorten $C(i,j)$ as C_k. The index k is calculated as follows

$$k=(i-1)n+j, k\in[1,M].\qquad (9\text{-a})$$

Inversely, given the index k, the index (i,j) can be calculated as follows

$$i=\mathrm{int}((k-1)/n)+1, j=k-(i-1)n.\qquad (9\text{-b})$$

Let $\pi_{kl}=\Pr(C_k)$ represents the probability that the cell C_k is on the path taken by the odor patch detected by the concentration sensor located in the cell C_l . The set $\{\pi_{kl}\mid 1\leq k,l\leq M\}$ can be interpreted as the probability map of the odor path that will be estimated subsequently.

IV. Odor Path Estimation via Dynamic Window

This section introduces the proposed solution to the problem of odor path estimation in dynamic airflow environments. As discussed in section I, the dynamic window (DW) covers the possible area which can be decided by a rule and some parameters in real time. Only in the DW, the spatial variation of flow velocity might be neglected and odor path estimation can be carried out.

Suppose the odor patch detected at the robot's location $X_v(t_c)$ at time t_c was at position $X_s(t_r,t_c)$ at time $t_r (t_r < t_c)$. The relation between $X_s(t_r,t_c)$ and $X_v(t_c)$ can be expressed as follows

$$X_s(t_r,t_c) = X_v(t_c) - \int_{t_r}^{t_c} U(X(t))dt - \int_{t_r}^{t_c} N(t)dt, \qquad (10)$$

where $U(X(t))$ is the airflow velocity recorded at position $X(t)$; $\int_{t_r}^{t_c} N(t)dt$ is a Gaussian noise process with zero mean and variance $[(t_c-t_r)\sigma_x^2,(t_c-t_r)\sigma_y^2]$, where $[\sigma_x^2,\sigma_y^2]$ is the variance of the airflow velocity and can be estimated online by the records $\{U(t_i)\}_{i=0}^{c}$. t_0 is the time of the first record. Since we only have the measurements at discrete times $\{t_i\}_{i=0}^{c}$ at the location of the robot, and $\int_{t_r}^{t_c} U(X(t))dt$ is approximate to $\sum_{i=r}^{c} U(X_v(t_i))\Delta t = (v_x(t_r,t_c), v_y(t_r,t_c))$.

Let $S_{ij}(t_r,t_c)$ stands for the probability that an odor patch was in the cell C_i at time t_r and moves to the cell C_j at time t_c $(t_c > t_r)$. $S_{ij}(t_r,t_c)$ can be expressed as follows [10]

$$\begin{aligned} S_{ij}(t_r,t_c) &= \frac{1}{2\pi(t_c-t_r)\sigma_x\sigma_y}\int_{-\frac{a}{2}}^{\frac{a}{2}}\int_{-\frac{a}{2}}^{\frac{a}{2}} e^{-\frac{(\Delta x(t_r,t_c)-x)^2}{2(t_c-t_r)\sigma_x^2}} e^{-\frac{(\Delta y(t_r,t_c)-y)^2}{2(t_c-t_r)\sigma_y^2}} dxdy \\ &\approx \frac{a^2}{2\pi(t_c-t_r)\sigma_x\sigma_y} e^{-\frac{\Delta x^2(t_r,t_c)}{2(t_c-t_r)\sigma_x^2}} e^{-\frac{\Delta y^2(t_r,t_c)}{2(t_c-t_r)\sigma_y^2}} \end{aligned}, \qquad (11)$$

where $\Delta x(t_r,t_c) = x_j - x_i - v_x(t_r,t_c)$, $\Delta y(t_r,t_c) = y_j - y_i - v_y(t_r,t_c)$, (x_i, y_i) and (x_j, y_j) are the geometrical center coordinates of the cells C_i and C_j, respectively.

Construct a sub-dynamic window for time t_r

$$DW(t_r,t_c) = \left\{ C_i \mid \left(\frac{\Delta x(t_r,t_c)}{\sigma_x}\right)^2 + \left(\frac{\Delta y(t_r,t_c)}{\sigma_y}\right)^2 \le 2k(t_c - t_r) \right\}_{i=1}^{M} \qquad (12)$$

where

$$k = \ln\left(\frac{a^2}{2\pi\eta(t_c-t_r)\sigma_x\sigma_y}\right). \qquad (13)$$

So that the set $\{S_{ij}(t_r,t_c) \mid C_i \in DW(t_r,t_c)\}$ satisfies the following constraint

$$S_{ij}(t_r,t_c) \ge \eta, \qquad (14)$$

where η is the probability threshold. Normally we choose $\eta = 1/M$, thus $S_{ij}(t_r,t_c)$ is greater than the average probability. Therefore, (13) becomes

$$k = \ln\left(\frac{Ma^2}{2\pi(t_c-t_r)\sigma_x\sigma_y}\right), \qquad (15)$$

The main idea of (14) is that only the cells in which the odor patch could arrive at C_j after a time period $(t_c - t_r)$ according to the flow velocity records $\{u_x(t_i), u_y(t_i)\}_{i=r}^{c}$ should be considered in the current step. The cells satisfying (14) form a region which is called Sub-Dynamic Window. On the contrary, the cells which are not in $DW(t_r,t_c)$ shouldn't be considered. As a result, the current range for odor path estimation is restricted within the $DW(t_r,t_c)$.

The sub-dynamic window $DW(t_r,t_c)$ is only a small part of the map, i.e., $\sum_{C_i \in DW(t_r,t_c)} S_{ij}(t_r,t_c) < 1$. So $\{S_{ij}(t_r,t_c) \mid C_i \in DW(t_r,t_c)\}$ is normalized with the factor $1 \Big/ \sum_{C_i \in DW(t_r,t_c)} S_{ij}(t_r,t_c)$.

Since $t_r \in [t_0, t_c)$, the complete dynamic window at the time t_c in cell C_j should be

$$DW(t_c) = \bigcup_{r=0}^{c-1} DW(t_r,t_c). \qquad (16)$$

Due to the spatial variation of the airflow velocity in complex environments, the size of $DW(t_c)$ should be further restricted on time axis. A simple method is let $(t_c - t_0) \le t_{thr}$, where t_{thr} is a positive constant, i.e., we only maintain the latest velocity records. Thus, the area of $DW(t_c)$ is a quite small quantity compared with the whole work space. It's therefore appropriate to assume that the airflow velocity vector is spatially invariant within the $DW(t_c)$, at least, better than in the whole work space. Note that the profile of $DW(t_c)$ is a function of the parameters t_c, σ_x and σ_y, in case of M, a are constants. Actually, σ_x and σ_y are also functions of the time t_c. So $DW(t_c)$ depends on the variances of airflow velocities and time difference.

Let $\{\pi_{ij}(t_0,t_c)\}_{i=1}^{M}$ stands for the odor path probability map at the time t_c. Then, according to the signal intensity $s(t_c)$ of detection event at time t_c, the odor path probability map can be described as follows

$$\pi_{ij}(t_0,t_c) = \begin{cases} \max\{S_{ij}(t_r,t_c)\}_{r=0}^{c-1} & \text{for} \quad s(t_c) > 0 \ \text{ and } \ C_i \in DW(t_r,t_c). \\ 0 & \text{else} \end{cases} \qquad (17)$$

The computational complexity of the odor path estimation algorithm described by (17) is $O\left(\sum_{r=0}^{c-1} N\left(DW\left(t_r, t_c\right)\right)\right)$, where $N\left(DW\left(t_r, t_c\right)\right)$ means the number of the cells contained in the $DW\left(t_r, t_c\right)$, while the algorithms in [6] is $O\left(M^2\right)$ at least. Due to $\sum_{r=0}^{c-1} N\left(DW\left(t_r, t_c\right)\right) << M^2$, the algorithm (17) has a better real-time performance than that in [6].

V. EXPERIMENTS

The size of the map is 10m by 10m, and the side length of each cell is a=5cm. Thus, m=n=200, M=40000. The period of the odor path estimation algorithm is 0.5s, which equals to the measuring period of the concentration sensor. The mobile robot used in the experiments is shown in Fig. 1. The concentration sensor, airflow meter, sonar sensors, electronic compass, and CCD camera are mounted on the robot, but the camera is not used in this experiment. The electronic compass and the embedded odometer are used for mobile robot localization. The concentration sensor is a commercial PID (Photo Ionization Detector) from Industrial Scientific Corporation. Because the PID does not have digital output, another CCD camera is used to read the concentration data displayed on VX500 through a pattern recognition algorithm (c.f. Fig. 2). The airflow meter WindSonic is manufactured by Gill Instruments Ltd.

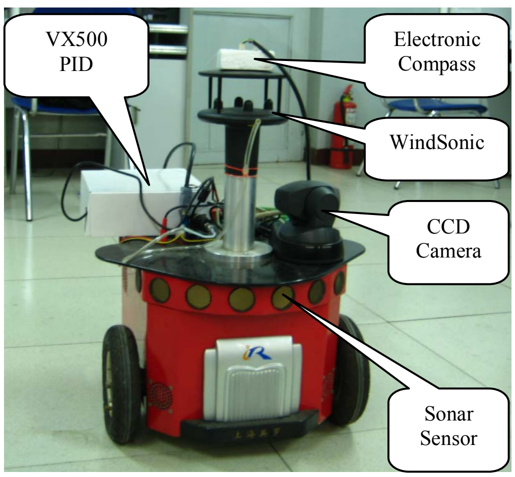


Figure 1. The mobile robot and the onboard sensors.

Figure 2. The PID sensor and the assistant CCD camera used to recognize the concentration reading.

As discussed in section II-B, the concentration sensor has the time delay τ, which is a key constant which we will attempt to estimate. A hair drier is used to blow warm airflow through an entry hole into a plastic vessel containing liquid ethanol. The odor patch is then blown out from the outlet of the vessel. Due to the intensive turbulence of the airflow in the vessel, the airflow from the outlet was mixed with the volatilized ethanol molecules. The concentration and wind sensors are placed together in front of the outlet. The experiment results are illustrated in Fig. 3, where the airflow velocity and the concentration are normalized for convenience. The delay time of the concentration sensor is about 5~6s through about 10 experiments in various conditions.

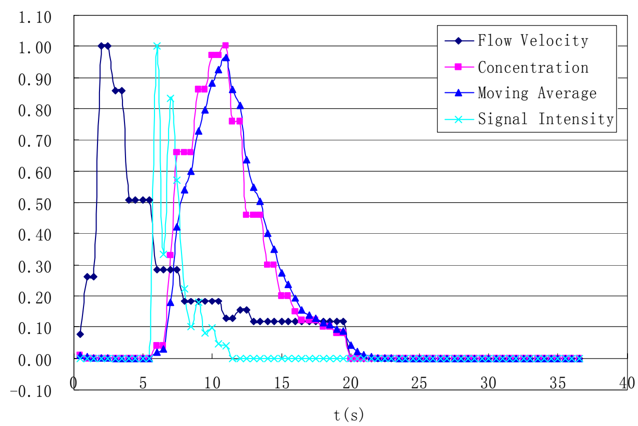
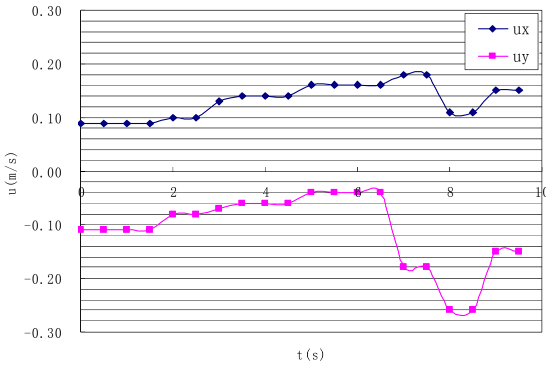


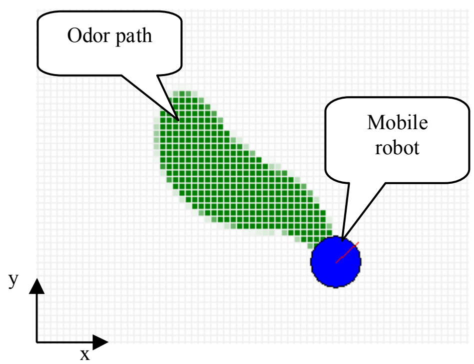
Figure 3. The response curve of airflow sensor and odor concentration sensor. (The velocity values of the airflow and the concentration are normalized for convenience)

Two estimated odor paths are shown in Fig. 4 (case 1) and Fig. 5 (case 2), respectively. The odor paths are calculated online by the computer embedded in the mobile robot in real time, where the probability threshold η is set to 1/40000. The instantaneous odor concentration detected in Fig. 4 is 58ppm, while the average value is 55.2ppm, and the signal intensity is 0.387. The variance of the airflow velocity corresponding to the case 1 is $[9, 36]\times10^{-4}$ m/s^2. For the case 2, the instantaneous odor concentration is 114ppm, while the average value is 113.4ppm, the signal intensity is 0.370, and the variance of the airflow velocity is $[1, 1]\times10^{-4}$ m/s^2.

In both cases, odor paths are estimated when the valid detect events occurred, and the airflow velocity adopted is the relative value between the detected one by the WindSonic and the speed of the mobile robot at that time. t_{thr} is set to 10s, i.e., only maintaining the latest 20 velocity records. The odor path is superimposed with a series of sub-dynamic windows with ellipse outlines. It can be found that the profile of the odor path in Fig. 4 is different to that in Fig. 5. This is because the outline of each sub-dynamic window is determined by the mean and variance of the airflow velocity (see (12)). The smaller is the variance of the airflow velocity, the thinner is the profile of the odor path. These results also meet common sense. So the odor path could be estimated by the algorithm expressed in (17), which would be very useful to the plume tracing and source localization.

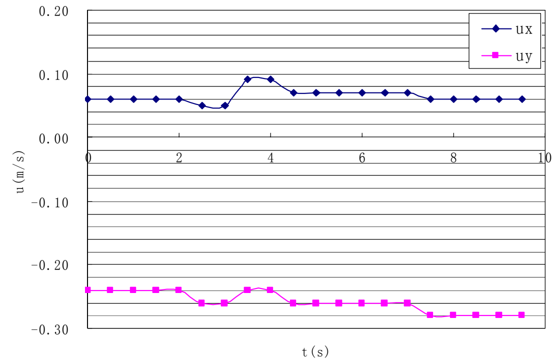


(a)

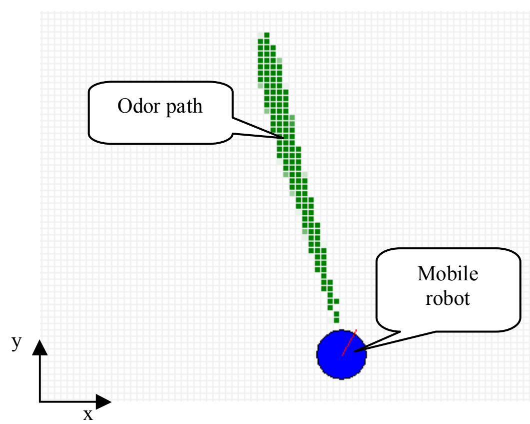


(b)

Figure 4. (a) Airflow velocities and (b) the estimated odor path (case 1)



(a)



(b)

Figure 5. (a) Airflow velocities and (b) the estimated odor path (case 2)

VI. Conclusions

A novel mobile robot based odor path estimation algorithm via the idea of dynamic window is proposed. The odor path is only estimated in the dynamic window where the spatial variant of airflow velocity is small enough. Consequently, the computation cost of the estimation algorithm is obviously reduced. Experiments on a wheeled mobile robot in an indoor airflow environment demonstrate the feasibility of the proposed algorithm. Experiments also show that, the smaller is the variance of the airflow velocity, the "thinner" is the profile of the odor path, and the faster is the estimation algorithm.

The proposed algorithm will be further improved and used for plume tracing and source localization in our future work.

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