A Novel Object Recognition Method for Mobile Robot Localizing a Single Odor/Gas Source in Complex Environments

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***Abstract*—An improved single odor/gas source searching approach using a mobile robot by combining image recognition in complex environments is presented. First, color image segmentation of prospective visual candidates is achieved using Support Vector Machines (SVM). Second, the features of those candidates, such as color, shape and orientation (the posture of the object) are extracted. Third, the robot finds a salient object according to the characteristics of analysis areas. Last, the robot moves towards the object which is the most likely to be an odor/gas source. The robot moves upwind if gas concentration is detected. Otherwise, the robot moves along the new direction obtained from the further analysis. Experimental results show the efficiency and practicality of the approach for localizing a leaking ethanol bottle in complex indoor environments.**

***Keywords*—mobile robot, odor/gas source localization, object recognition, support vector machines (SVM), complex environment**

I. INTRODUCTION

Many animals, such as moths, rats, lobsters and blue crabs [1-5], use olfaction for finding same species, communication, behavior modification, avoiding predators and searching for food. Such successful olfaction based search examples have encouraged the development of mobile robots to search for chemical leaks, mines, unexploded bombs, and pollutant sources.

Research on robotic odor/gas source localization started with pure chemotactic search [6, 7], where the robot was only equipped with a pair of gas sensors. Chemotactic search strategies require the odor/gas concentration to be high enough to ensure that its average difference measured at two nearby locations is larger than typical fluctuations. However, the concentration is extremely small as the elongating of the plume in the direction of the airflow. Moreover, the robot will wander randomly at the beginning when there is no concentration information and also it may lead to locations that are far away from the true source. Therefore, the searching efficiency is very low. Inspired by the specific flight behavior of male moths following sexual pheromones over distances to find their mates, where the upwind plume tracking method is used [1, 2], airflow sensors have also been equipped on the robot in addition to the gas sensors in order to increase the efficiency of odor/gas source location [8]. Despite the successful experiments on upwind tracking have been implemented under unidirectional wind fields, where the flow has no large-scale turbulence and remains mostly laminar for the duration of the plume tracing activity, the anemotaxis search methods often fail due to the turbulence of airflows in general indoor environments. Recently the so-called fluxotaxis [9] and infotaxis [10] odor/gas searching algorithms have also been proposed, where the knowledge of computational fluid dynamics and information entropy are applied, respectively.

It is well known that human being normally first look around to search for the most plausible region or object and then identify if the region or object is an odor/gas source by olfaction. Vision contains abundant information, so visual sensor could be a good assistant of odor/gas sensors for mobile robot localizing an odor/gas source. Ishida [11] proposed a behavior-based architecture to search for an odor/gas source by combing vision and olfaction information. Similar idea was also adopted by Martinez [12]. However, the experimental conditions in [11, 12] are too ideal compared with the complex environments in real-life applications. Meanwhile, only using color information is too simple to distinguish different objects in practical environments, which would cause higher misjudgment rate in finding plausible targets and therefore can not accomplish practical search tasks. In this paper, we propose an improved object recognition method by making use of multi-features, such as color, shape, area and orientation etc.

The aim of the study presented in this paper is to achieve robust detection of a visual candidate in complex environments by using the priori knowledge of the plausible odor/gas source. The emphasis of our work is to make the robot accomplish the gas-source-localization task with visual aid rapidly, accurately and robustly.

II. TASK DESCRIPTION

Usually, the robot wanders randomly at the beginning when no information about concentration or wind direction is detected [6-8]. However, the random research methods are inefficient. To cope with this problem, visual sensing system is implemented as assistance of olfaction to navigate the robot moving towards a possible odor/gas source. Experiences from a large amount of accidents tell us that some devices are more likely to leak, such as bottles, pipelines, valves, etc. Once a plausible object is detected in the field of view, the direction and distance to the object can be obtained.

The odor/gas source search strategy is comprised of following three steps.

1) Plausible objects recognition: The images captured by a video camera are analyzed and the direction and distance of the plausible object with high priority is obtained according to the visual cues, such as color, shape, area of objects.

2) Vision and olfactory search: The robot moves along the obtained direction, and makes new moving decision when gas concentration is detected in the processing.

3) Source declaration: When the robot reaches in front of the object, it measures the odor/gas concentration for a little while and determines whether or not the object is the gas source.

A. Plausible Object Recognition

It is not reliable for recognizing a plausible object only using color information in a complex environment. Shape, area and orientation also play important parts in object recognition. Given a digital image containing several objects, the plausible object recognition process consists of three major steps. Firstly, objects are segmented from the background of the scene. Secondly, some features for each object, including color, shape, area and orientation (the posture of the object) are extracted. Finally, the direction and distance for each object are calculated.

1) Image segmentation

A color image segmentation scheme using Support Vector Machines (SVM) [13, 14] is proposed here. SVM is a kind of machine learning method based on statistical theory, which integrates learning theories, kernel method, generalized theory and optimization methods, etc. Not only does it overcome the problem of small sample, over fitting, high dimension and local minimum in many learning methods, but also it has better generalization ability and keeps the integrity of the region-based segmentation.

Take a classification problem of two training samples as an example,

$$D=\{(x_1,y_1),\cdots,(x_l,y_l)\}, x\in R^n, y\in\{-1,1\} \tag{1}$$

Suppose we have a hyper-plane which separates the positive from the negative samples exactly and makes the distance of the two samples maximal. The points x which lie on the hyper-plane satisfy $(w,x)+b=0$. To normalize the hyper-plane function and let all the samples satisfy the following constraint condition,

$$y_i[\langle w,x_i\rangle+b]\geq 1, i=1,\dots,l \tag{2}$$

$2/\|w\|$ is the perpendicular distance from the hyper-plane to the origin, and the largest interval is equivalent to making $\|w\|^2$ minimum.

Therefore, to find the optimal separating hyper-plane can be translated to quadratic programming,

$$\begin{cases} \min \frac{1}{2}\|w\|^2 \\ s.t. \ \ y_i[\langle w,x_i\rangle+b]\geq 1, \quad i=1,\dots,l \end{cases} \tag{3}$$

We can compute (3) by solving the saddle point of the Lagrange function,

$$\Phi(w,b,\alpha)=\frac{1}{2}\|w\|^2-\sum_{i=1}^{l}\alpha_i(y_i[\langle w,x_i\rangle+b]-1) \tag{4}$$

α is Lagrange multiplier and the optimal solution can be obtained by computing the dual form of (4),

$$\begin{cases} \max\limits_{\alpha} \ -\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j\langle \mathbf{x}_i,\mathbf{x}_j\rangle+\sum_{k=1}^{l}\alpha_k \\ s.t. \ \sum_{i=1}^{l}\alpha_i y_i=0, \quad 0\leq\alpha_i, \quad i=1,\dots,l \end{cases} \tag{5}$$

Then, the optimal solution is obtained,

$$\alpha^*=(\alpha_1^*,\dots,\alpha_l^*)^T \tag{6}$$

And then,

$$w^*=\sum_{i=1}^{l}\alpha_i y_i x_i \quad b^*=-\frac{1}{2}\langle w^*,x_r+x_s\rangle \tag{7}$$

Where x_r and x_s are the arbitrary vectors of the two samples. From (5) we know that the hyper-plane is only determined by a very small subset of the sample. Then the final decision function is as follows,

$$f(x)=\mathrm{sgn}\left(\sum_{i=1}^{l}\alpha_i^* y_i(x\cdot x_i)+b^*\right) \tag{8}$$

The color components of the image are analyzed using the decision function, and the pixel category is decided according to its output. The positive is marked 1 and the negative 0, which form a segmented binary image.

2) Feature extraction

First, dilation and erosion are adopted to remove the noise of the segmented binary image in order to increase the marking efficiency. Second, the connected regions are marked because the area of each region is different and some regions can be removed if the area is out of the range according to the character of the objects. Third, the preserved regions are calculated to get the principal axis direction.

The traditional algorithm uses MER (Minimum Enclosing Rectangle) to calculate a direction of a random-geometry object. However, this algorithm is invalid to some objects, so a novel algorithm is proposed as shown in Fig.1.

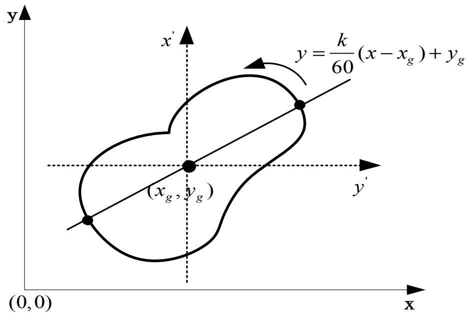


Figure.1 The direction of a random geometry

The proposed algorithm for determining the direction of geometry is explained as follows.

a) Calculating the centre of gravity of the object according to Eq. (9).

$$x_g = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad y_g = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{9}$$

Where N is the total number of pixels covered by the object.

b) The centre of gravity is defined as the new origin of coordinate axes (see Fig.1.), and the straight line equation which is through the centre of the gravity is defined as follows.

$$y = \frac{k}{60}(x - x_g) + y_g \text{ , } k = 1,2,\cdots,60 \tag{10}$$

k (line slope) is changed from 1 to 60 (at 3º intervals).

c) Two new intersection points are generated between the line and the boundary of the region after every change of k and then the distance of the two points is calculated.

d) There are totally 60 distances after the line rotating from 0° to 180° with the interval of 3°, and then the maximum distance and the relative k are obtained. Thus the direction of principal axis θ is obtained, that is, $\theta = (3k)$ º. The relative distance is showed in Fig.2.

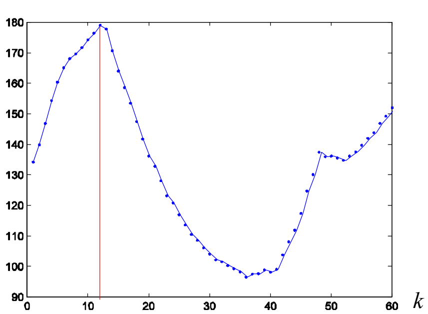


Figure.2 Intercepts of different k

From Fig.2 we can see that the distance is up to the maximum when $k = 12$, that is, $\theta = 36°$. If the graph has more than one peak, limitation conditions must be given to get the correct direction. If the energy of the second maximum distance is up to 80% of the maximum and the angle between them is in the range of 10° to 90°, the average k' is calculated. Given k_1, k_2 are relative to these two peaks, and then $k' = (k_1 + k_2)/2$. So the correct direction can be obtained.

B. Vision/Olfaction Search And Source Declaration

The robot is navigated towards the direction of the plausible object. It is well known that human being will turn to another direction when he or she does not get the concentration information after moving for a while. According to the same rule, the robot resumes visual search behavior if no gas concentration is detected after moving about half the distance to the plausible object. This strategy saves more time for the whole searching process and improves the searching efficiency. If concentration information is detected in the moving process, the robot compares the difference between the current moving direction and the wind direction. If the difference is in the allowable error range (± 15º), the robot moves forward along the predetermined route. Otherwise, the robot moves upwind.

Source declaration is to verify whether or not the plausible object is the odor/gas source. When the robot reaches in front of the object, it stops to measure the odor/gas concentration for four seconds. If the concentration has no big change, the object is declared to be the odor/gas source.

III. EXPERIMENTS

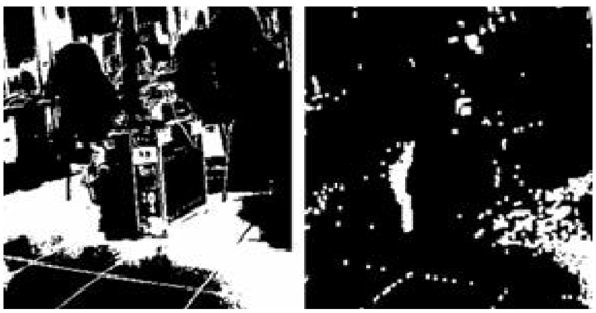
The mobile robot used in the experiments is shown in Fig.3, on which a gas sensor, a video camera and an airflow sensor are equipped. The range of the wind speed of the airflow sensor (WindSonic, Gill) is from 0m/s to 60m/s with accuracy of ±2% (at 12m/s) and the direction is 0º to 359º with accuracy of ±3° (at 20m/s). The gas sensor (VX500) is designed by Industrial Scientific Corporation and the accuracy is 1ppm. The video camera (SONY EVI-D100P) is mounted on the left side of the robot.

(a) Mobile robot (b) Gas sensor

Figure.3 Robot equipped with gas sensor, airflow sensor and video camera

A bottle containing liquid ethanol is used as the odor/gas source. The SVM based color image segmentation result is illustrated in Fig. 4. Fig.4 (a) is an original image, in which the bottle is placed on the carton. Fig.4 (b) and (c) present the segmentation results by using the threshold and the SVM method, respectively.

(a) The original image



(b) Threshold method (c) SVM method

Figure.4 Different results of segmentation

Comparing Fig. 4 (b) with (c), it can be found that the segmentation results of SVM are obviously better than results obtained by using thresholds. It is very difficult to distinguish the plausible object from the background (see Fig.4 (b)). But in Fig.4 (c) the bottle can be identified easily from the background.

Figure.5 Six original images sampled by the video camera

Six images of the bottle captured by the video during the moving process of the robot are given in Fig.5. The corresponding searching results are presented in Fig.6, where the areas marked with red dots are the localized source.

Figure.6 The search results of the simulated odor/gas source

The direction and distance of the bottle can be obtained by analyzing the images and then the robot is navigated to the plausible object. The bottle can be localized by the robot in various conditions according to its priori knowledge. During the moving process the robot also makes further analysis of the wind and concentration information to determine the next motion direction. The experimental environment coincides with real-life applications. And also the object recognition algorithm is more practical and efficient compared with the method used in [11].

Initial experiments show that, without using visual information, the robot often wanders randomly when neither odor nor wind information is detected. Even the odor/wind information have been detected, the gradient-based chemotaxis method and the upwind search based anemotaxis method also often fail. For the chemotaxis method, the robot sometimes stops at local-optimum locations. Meanwhile, the robot might move in the wrong direction due to the air turbulence on the basis of anemotaxis method. Compared with the typical chemotaxis and anemotaxis methods, the proposed odor/gas localization method is better in both the search success rate and the search time. Moreover, the proposed methods can work in complex background experiments.

IV. CONCLUSIONS

A novel algorithm of object recognition in complex background environments, which is used to localize a single odor/gas source, is proposed. The algorithm includes support vector machine (SVM) based image segmentation, features extraction and salient object recognition by fusing multi-features (color, shape, area and orientation, etc.) of the candidates and robot motion planning on the basis of the identified object as well as the odor and airflow information. Experiments show the feasibility and advantage of the proposed odor/gas localization method.

The next work includes two parts. The first is to verify the feasibility of the proposed algorithm for several odor/gas sources. The second is to improve the robot tracing method.

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REFERENCES

[1] A. Mafra-Neto, R. T. Carde, "Fine-scale structure of pheromone plumes modulates upwind orientation of flying moths," Nature, 1994, pp. 142-144.

[2] J. H. Belanger, M. A. Willis, "Adaptive control of odor guided locomotion: Behavioral flexibility as an antidote to environmental unpredictability," Adaptive Behavior, 1996, pp. 217-253.

[3] U. Bhalla, J. M. Bower, "Multi-day recording from olfactory bulb neurons in awake freely moving rats: Spatial and temporally organized variability in odorant response properties," Journal of Computational Neuroscience, 1997, pp. 221-256.

[4] J. Atema, "Eddy chemotaxis and odor landscapes: Exploration of nature with animal sensors," Biological Bulletin, 1996, pp. 129-138.

[5] M. J. Weissburg, "From odor trails to vortex streets: Chemo and mechanosensory orientation in turbulent and laminar flows," in Orientation and Communication in Arthropods, M. Lehrer, Ed. Munich, Germany: Basel Birkhauser, 1997, pp. 215-246.

[6] G. Sandini, G. Lucarini, M. Varoli, "Gradient driven self-organizing system," IEEE International Conference on Intelligent Robots and Systems, 1993, pp. 429-432.

[7] Y. Kuwana, I. Shimoyama, H. Miura. "Steering control of a mobile robot using insect antennae," IEEE International Conference on Intelligent Robots and Systems, 1994, pp. 530-535.

[8] H. Ishida, K. Suetsugu, T. Nakamoto, "Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors," Sensors and Actuators A, vol. 45 no. 2, pp. 153-157.

[9] D. Zarzhitsky, D. F. Spears, W. M. Spears, "Distributed robotics approach to chemical plume tracing," 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2-6 Aug. 2005, pp. 4034-4039.

[10] Massimo Vergassola, Emmanuel Villermaux, Boris I. Shraiman. "'Infotaxis' as a strategy for searching without gradients," Nature 445, 25 January 2007, pp. 406-409.

[11] H. Ishida, H. Tanaka, H. Taniguchi, "Mobile robot navigation using vision and olfaction to search for a gas/odor source," Autonomous Robot, 2006, pp. 231-238.

[12] D. Martinez, L. Perrinet, "Cooperation between vision and olfaction in a koala robot," In Report on the 2002 Workshop on Neuromorphic Engineering, pp. 51-53.

[13] C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," Data Mining and Knowledge Discovery, 1998, pp. 121-167.

[14] C. Cortes, V. N. Vapnik, "Support vector networks," Machine Learning, 1995, pp.273-297.