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Simulation of coordinating sniffer robots for building odor maps

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ABSTRACT
In this paper we present a method to generate an odor map of a remote environment. The paper consists of three major modules: [1] odor processing- consisting of sensing the odor, recognizing through neural networks and representing it in an appropriate format, [2] algorithms for odor detection in a 3D space and locating odor source in variable wind direction, [3] map building- consisting of autonomous navigation and coordination among multiple robots towards building the map of the environment. The coordination among the robots ensures the best possible odor map building. Thus we propose an approach to build maps using sniffer robots that coordinates in a decentralized manner.

Categories and Subject Descriptors
J.2 [**Physical Sciences and Engineering**]: Earth and atmospheric sciences

General Terms
Algorithms, Design, Experimentation

Keywords
remote environment, map building, odor format, multiple robots, decentralized.

1. INTRODUCTION
1.1 Odor detection
Detection of odor is an active research field. E noses are employed for the sensing and recognizing odor. There has been a comprehensive review of E noses in [4].

1.2 Odor Recognition
Odor is discriminated by sensors based on their composition. Any slight change in Odor, which may not be discriminated by humans, is still discriminated by E noses. E Noses employ recognition techniques based upon Artificial Neural Network. [2]

1.3 Coordination of the robots
Coordination of the robots effectively decides the next move towards building the odor map. The technique used is similar to the frontier approach used in autonomous exploration [2] and coordination among multiple robots for exploration and mapping of the physical environment [4].

1.4 Map building
The concept of building odor map already exists. In these maps, the odor emanating from a source is recorded. *To the best of our knowledge these maps are generated manually and not using robots.*

We propose a method to plot the odor map of a remote area using multiple coordinating autonomous Robots. Each robot has its own system for odor detection, recognition and construction of the odor map.

The paper has been divided into 4 sections: Section 1 gives the brief overview. Section 2 deals with the design of the proposed system. Section 2.1 expounds upon the Odor detection and the recognition system using Back-Propagation Artificial Neural Network. Section 2.2 expounds upon the coordinated movements of the robots towards detecting the odor source. Section 2.3 deals with the building of odor maps. The odor map stores the location of the smell, digitized format of the smell and the nearest matched smell

Section 3 deals with our proposed algorithms. Section 3.1 deals with the algorithm for the detection of odor source in a 3D space. Section 3.2 deals with locating the odor source under varying wind direction.

Section 4 deals with the ongoing implementation of the proposed system. Simulation of the system is in its inception and is being done using Java. Section 5 deals

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with the limitations and scope for improvements to our system.

2. SMELL DETECTION AND SMELL RECOGNITION

The sensing system consists of several different sensing elements (Chemical sensors) where each element measures a different property**.** Each chemical vapor presented to the sensor array produces a signature or pattern characteristic of the vapor. By presenting many different chemicals to the sensor array, a database of signatures is built up. This database of labeled signatures is used to train the pattern recognition system

[7] Recognition is defined as the process of identifying structure in a data by comparing to a known structure. Patterns are typically described in terms of multidimensional data vectors, where each component is called a *feature*. The aim of a pattern recognition system is to associate each pattern with one of the possible *pattern classes* (or simply *classes*). Obviously, different patterns should be associated with the same class or with different classes depending on whether they are characterised by similar or dissimilar features, respectively. In the case of the electronic nose, the patterns and the classes are, respectively, the responses of the sensor array to odorants, and the odorants being considered. In order to develop a pattern recognition system, the sample data are split into two sets, namely, the *training set* and the *test set*. The training set is used to establish the design parameters of the pattern recognition system, whereas the test set contributes to evaluate the system performance. Typically, the performance of the pattern recognition system is measured by computing the percentage of correctly recognised patterns on all the patterns presented to the system

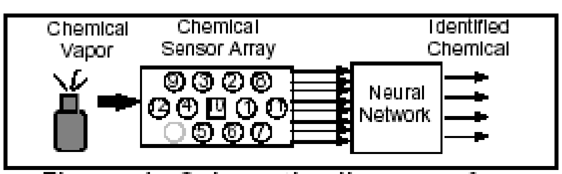


Figure 1: Schematic diagram of an electronic nose

The quantity and complexity of the data collected by sensors array can complicate the conventional chemical analysis of data in an automated fashion. One approach to chemical vapor identification is to build an array of sensors, where each sensor in the array is designed to respond to a specific chemical. With this approach, the number of unique sensors must be at least as great as the number of chemicals being monitored. But this is an expensive technique as the number of chemicals can be large.

Considering the issues in the previous technique, we decided to go with Artificial Neural Networks (ANNs), which have been used to analyze complex data and to recognize patterns. It has been shown in [4] that ANNs are showing promising results in chemical vapor recognition. [5][4] Corroborates the fact that it is useful to use ANNs for chemical vapor recognition and that when an ANN is combined with a sensor array, the number of detectable chemicals can be greater than the number of sensors.

2.1 Training phase:

We present the ANN [2] with the training data and each vector form that is given as input is propagated through the network to adjust the weight of different nodes. The types of training algorithm that can be used are back propagation-trained, feed-forward networks, Kohonen's self-organizing maps etc. We chose back propagation-trained, feed-forward networks because it is effective and simple to construct [6].

Figure 2 illustrates the structure of the ANN. The nine tin-oxide sensors are commercially available Taguchi-type gas sensors. (Sensor 1, TGS 109; Sensors 2 and 3, TGS 822; Sensor 4, TGS 813; Sensor 5, TGS 821; Sensor 6, TGS 824; Sensor 7, TGS 825; Sensor 8, TGS 842; and Sensor 9, TGS 880). Exposure of a tin-oxide sensor to a vapor produces a large change in its electrical resistance [4]. An example of an ANN [4] with back propagation feed forward algorithm is shown below.

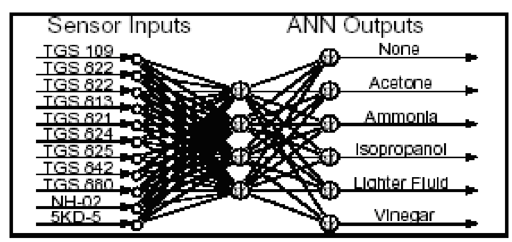


Figure 2: Structure of the backpropagation ANN used in the prototype to identify house hold chemicals

Another excellent discussion on use of ANNs for detection of honey is in [3].

2.1.1 Smell format storage

The response from the sensor determines the output format. There are varieties of sensors which may respond to a unique type of smell. If we take a finitely large array of sensors, then it is possible to have the smell value based on the combination of the response from each sensor. This type of output may be stored as a file which we are referring as a 'smell file'. To the best of our knowledge such a file doesn't exist. The potential of a smell file can be realized if we apply it in the concepts of [1].

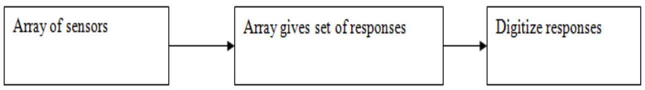


Figure 2.a Process to obtain and store odors

2.2 Robot movement:

The usage of multiple robots for detecting various odors from a region for creating an odor map has never been implemented, to the best of our knowledge

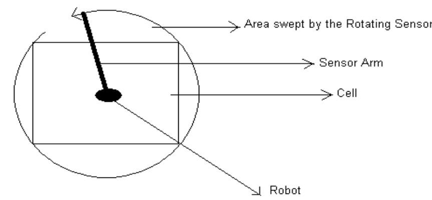
There are many independent-robot-exploration schemes such as a frontier-based approach for autonomous exploration [9] and autonomous exploration with continuous localization [10]. The environment to be mapped is taken in the form of a grid with three modes for each cell. A cell is either mapped, unmapped or an obstacle. The robot then decides which cell to visit by selecting one of the unmapped cells and proceeds towards that cell. On reaching the destination cell the same process is repeated until the entire region is mapped.

Usage of cheap expendable robots would be a better option to quickly search a large environment robustly. Coordination among multiple robots to efficiently cover an area was presented earlier in Coordinating multiple robots for exploration and mapping [11] is an extension of [9] wherein the only information exchanged will be the position of each robot and the modification to the map as the robots continue exploring.

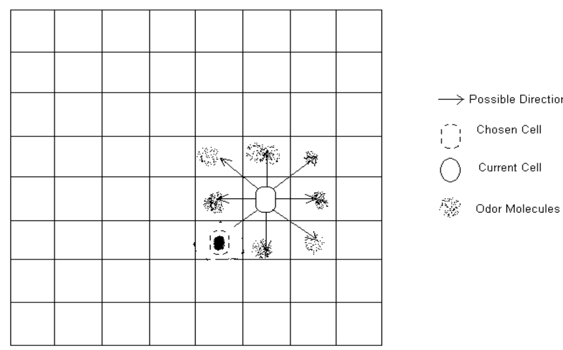
We employ a similar approach but assume that the environment is open without obstacles. There are many obstacle avoidance algorithms that efficiently perform the function and can be applied to the robots. We confine ourselves to the robots movement towards building the odor map. When an odor is detected at a point, the sensor mounted on a rotating arm makes a 360° horizontal sweep around the robot collecting information about the odor in the region. The size of a cell is equal to the largest square that can fit into circle swept by the rotating sensor as shown by the figure 5a**.**

Once the sensor has swept the area, the robot can find the direction of the greatest concentration of odor particles. Based on the inferred direction the robot decides upon the possible eight neighbor cells, thereby moving towards higher concentration, as shown in figure 5b. Repeating this procedure leads the robot towards the source.

Every movement of the robot and its detected odor of the current cell are broadcasted so that every robot can update their respective map. Each robot ensures that it does not revisit a cell and moves in a direction that is away from other robots. In this way the robots coordinate with each other without any central coordinator.



3a determination of size of the cell



3b direction of movement chosen by the robot

Figure3.a Determination of the size of the cell,

Figure3.b Direction of the movement chosen by the robot.

2.3 CHARTING ODOR MAPS

The updated odor map is shared amongst the robots. Thus a message is broadcasted from a robot as soon as it detects odor in a particular cell. The procedure followed can be classified as shown below.

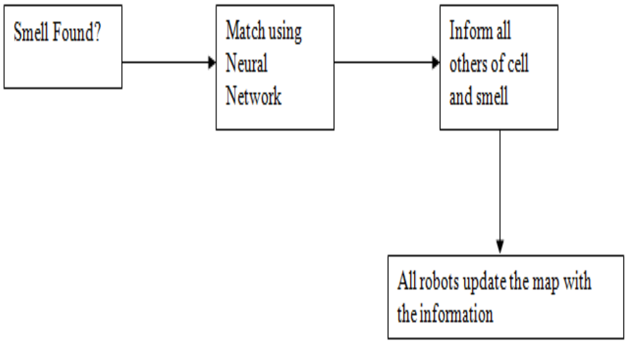


Figure 3.c Process flow for map building

The smell found should be above a threshold limit. This threshold is calculated based upon the probable density of odor molecules near the center of the odor source. At this stage, the pattern recognition module comes into picture. The algorithm will match the identified odor with the nearest known pattern. Then a message is broadcasted. The contents of the message are:

(i) The location (x, y, z) of the robot.

(ii) The identified smell in the digitized format

(iii) The best matched pattern of the smell. This is obtained as the output from the smell recognition algorithm module.

Some other protocol related information will also be transmitted like the sender robot's name. Now each of the robots will update their own maps. Constantly updating the map with other ensures synchronization. Thus a map will be constructed with the location of the smell, digitized format of the smell and the nearest matched smell.

3. Algorithms Proposed:

It is important to consider the external factors while sensing odor source. There are several algorithms proposed for this purpose. [7] There are two main factors for sensing the odor source.

(i) The speed of the wind: Wind plays a significant role in the process of locating the odor source. The wind will naturally carry more number of odor molecules in the direction in which it flows. Concentration of odor molecules is affected to wind speed. Hence it influences detection of odor.

If the speed of the wind is low, then there are chances of problems in detection of odor. To overcome such problems, the active sampling sensor has been developed [1]. In the active sampling sensor, the speed problem is overcome by artificial introduction of wind using an electric fan.

(ii)Wind direction: The direction of the wind plays an important role in deciding the path of the robot. The robot always moves in the direction of the wind.

3.1 Algorithm – Detection of odor source in a 3D space

We propose an algorithm for the detection of odor source in a 3D space. There are existing algorithms that support 2D sensing. But in our system we are considering 3D detection of odor. Since the odor source is assumed to be a plant, density of odor molecules is high near the leaves of the tree. The scenario has been shown in figure 4, where 'a' denotes height of the robot and 'h' marks the height of the sensing arm.

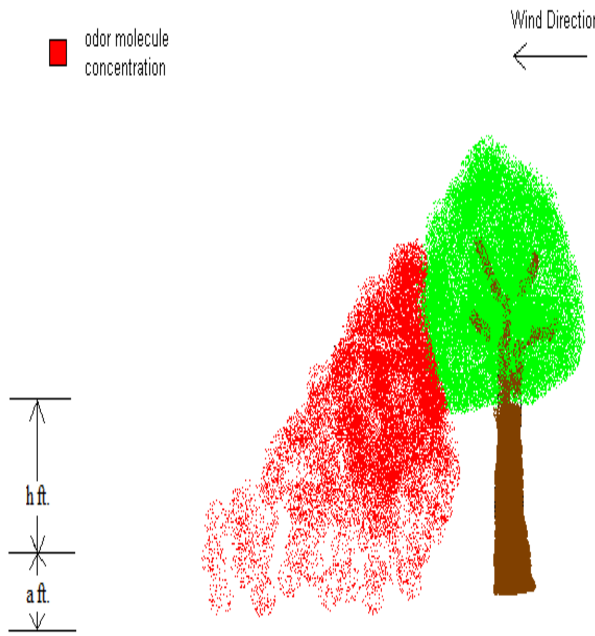


Figure 4. Concentration map of the distributed odor molecules

The proposed system will take care of the scenario above. The basic components of the sensing system would be:

1) A sensing arm that has the sensors mounted on it. The arm is movable and extendable.

2) The rotating system. The arm would rotate by sweeping the 360 degrees in the xy plane. It has been demonstrated in figure 5.

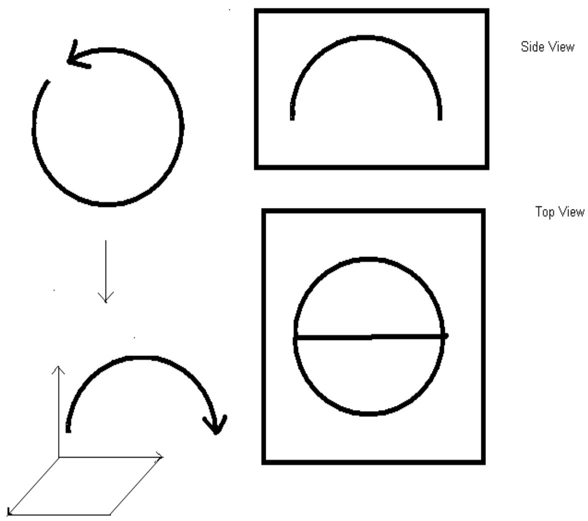


Figure 5: The xy and yz rotation system

The algorithm proposed is as follows:

Step 1: Move in the direction of wind as per the anemometric sensor reading

Step 2: For every t sec [1 sec for 90 deg]

2.1. Rotate in XY plane.

2.2. Repeat step 1.

Step 3: For next t sec

3.1. Move in Z direction

3.2. Repeat step 1

Step 4: If sensor reading is more in upper direction (Z) then raise the stick

Step 5: For every consequent move repeat steps 1 to 3

Step 6: Note the position [x, y, z] for that place

Step 7: Now to continue for navigation repeat steps 1 to 6

Step 8: End

Based on the above algorithm, the arm would extend towards the direction where the odor concentration is found to be the maximum. The movement in z direction is continuously calculated from the movement of the arm. When any decrease in the concentration is encountered then we retrace to the earlier coordinate, and its corresponding x, y, z coordinates are calculated which in turn is stored in the odor map. In this way the system overcomes the limitations of a 2D odor detection system.

3.2 Algorithm – Robot movement in variable wind direction

We now propose an algorithm describing a robots movement under varying wind direction. Figure 6 shows this scenario.

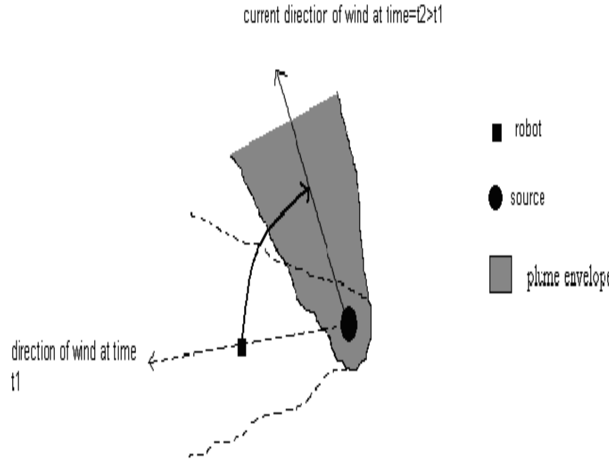


figure 6: movement of the robot to stay in the center of the plume envelope when the direction of the wind changes.

Two algorithms that take into account the change in direction of wind are discussed in the book 'odor detection by mobile robots' [1]. These are step-by-step method and zigzag method. In the former when the odor concentration falls bellow a threshold, the robot stops and waits until the sensor registers a higher concentration. In the zigzag method the robot sweeps diagonally across the odor plume. On reaching the far edge of the plume it changes its direction to cut across the plume in the opposite direction. On each sweep the diagonal path is angled upwind so that the robot makes progress towards the odor source.

Our algorithm ensures that the robot remains in the center of the odor plume even when the wind direction changes. It neither waits till the wind direction to become suitable as in step-by-step method nor does it move in a zigzag manner towards the source as in the zigzag method.

Algorithm: Maintaining the center position in the plume Envelope

Step 1: Measure the speed and direction of the wind, along with odor concentration levels in each direction while making the horizontal sweep with the robotic arm. A hot-wire anemometer can be mounted at the end of the robotic arm for measuring the wind speed.

Step 2: Move in a direction perpendicular to the wind until the reading is recorded to be the maximum. This indicates that the robot is in the center of the plume envelope where we believe that the concentration should be at the highest.

Step 3: Move in the upwind direction until the source is located. Repeat 'Step 2' if the direction of the wind changes.

In the Step 3 we ensure that the robot always stays in the center of the plume envelope, thus also ensuring that odor trace is not lost.

4. Implementation

The simulation of the proposed system has been started and is currently in its inception. We have developed the class diagrams for designing an Object Oriented Model of the system. There are 3 main modules:

1. Robot Movement through coordination.
2. Smell recognition using Back Propagation ANN
3. Creation of Odor Maps

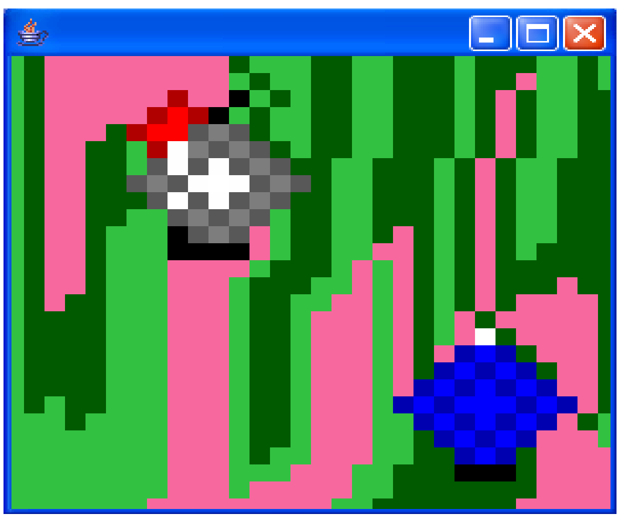


Figure 7 : Simulation of Robot movements in Java where the pink, light green and dark green areas represent the paths traversed by 3 different robots and red, grey and blue represent the areas where different smell were found.

5. Conclusion

The proposed system simulates the generation of odor maps for a remote region. The generation of odor maps doesn't require computation intensive algorithm, unlike a visual identification system for the same purpose. There are a few limitations in the proposed system as the movement of the robot is restricted to cells. We assume that the movement of the robot is precise and is not prone to errors. But in a practical scenario, localization algorithm to minimize the errors during movement is required. The system may be further improved by including obstacle avoidance algorithms which will be practically required. Thus we provide a new approach towards plotting odor maps for a remote region.

6. References

[1] Odor Detection by mobile robots… Andrew Russell's.. IEEE robotics 1995

[2] Gardner J.W., Hines E.L., Wilkinson M. The application of artificial neural networks in an e-nose (1990)

[3] Simona Benedetti, Saverio Mannino, Anna Gloria Sabatin, Gian Luigi Marcazzan. E Nose and neural networks use for the classification of honey. September 2004.

[4] Paul E. Keller, Lars J. Kangas,1 Lars H. Liden,2 Sherif Hashem,3 Richard T. Kouzes Electronic noses and their applications. IEEE, 1995.

[5] B.S. Hoffheins, Using Sensor Arrays and Pattern Recognition to Identify Organic Compounds. MS-Thesis, The University of Tennessee, Knoxville, TN, 1989.

[6] Book on Pattern recognition with MATLAB.

[7] Study of autonomous mobile sensing system for localization of odor source using gas sensors and anemometric sensors—Ishida , Suetsugu, nakamoto, and Moriizumi – Sensors and actuators-- 1994)

[8] J. Brezmes N. Canyellas E. Llobet X. Vilanova X. Correig

Application of ANN to the design, implementation of electronic olfactory system(1993)

[9] B.Yamauchi. Frontier-based approach for autonomous exploration. In Proceedings of the IEEE International Symposium on Computational Intelligence, Robotics and Automation, pages 146-151, 1997

[10] B.Yamauchi, A.Schultz and W.Adams. Mobile robot exploration and Map-building with continuous localization. In Proceedings of the 1998 IEEE/RSJ International Conference on Robotics and Automation, volume 4, pages 3175-3720, 1998

[11] Coordination for Multi-Robot Exploration and Mapping Reid Simmons, David Apfelbaum, Wolfram Burgard1, Dieter Fox, Mark Moors2, Sebastian Thrun, Håkan Younes American Association for Artificial Intelligence 2000