

# Odor Recognition and Localization Using Sensor Networks

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## 1. Introduction

Odor usually quantified by five parameters which are 1) intensity, 2) degree of offensiveness, 3) character, 4) frequency, and 5) duration. It has different forms including Gas, Chemical, Radiation, Organic Compounds, and Water odors including different water contaminations. For such odors, there are many of the traditional methods that have been used for a number of years. However, these methods suffer from different problems including the detection cost, the long time taken for analysis and detection, and exposing human to danger. On the other hand, the advances in sensing technology lead to the usage of sensor networks in many applications. For instance, sensors have been used to monitor animals in habitat areas and monitor patients' health. In addition, sensor networks have been used to monitor critical infrastructures such as gas, transportation, energy, and water pipelines as well as important buildings. Sensors are tiny devices that can be included in small areas. At the same time, they are capable of capturing different phenomena from the environment, analyze the collected data, and take decisions. In addition, sensors are able to form unattended wireless ad hoc network that can survive for long time. Such features enable wireless sensor networks (WSN) to play an essential role in odor detection. In fact, odor detection became one of the important applications due to the terrorist attack that started by the one occurred at Tokyo Subway in 1995. Since this time, odor detection and localization is considered as one of the important applications. Researchers believe that sensors and sensor networks will play an important role in odor detection and localization. In this chapter, we generalize the term odor to include the radiation detection and localization since the radiation in most of the recent work is considered as an odor.

Odor detection in human depends on the smell sense; therefore, it is considered as other senses such as vision and hearing that have a theory behind it. The theory behind the smell is explained in (Al-Bastaki, 2009) where olfactory systems simulate the neurobiological information processing systems (biological neural networks) as shown in Figure 1. The collected olfactory information is processed in both the olfactory bulb and in the olfactory cortex. The function of the cortex, then, is to perform the pattern classification and recognition of the odors. Once the odor is identified, its information is transmitted to

hippocampus, limbic system and the cerebral cortex. At this moment, the conscious perception of the odor and how to act on it takes place.

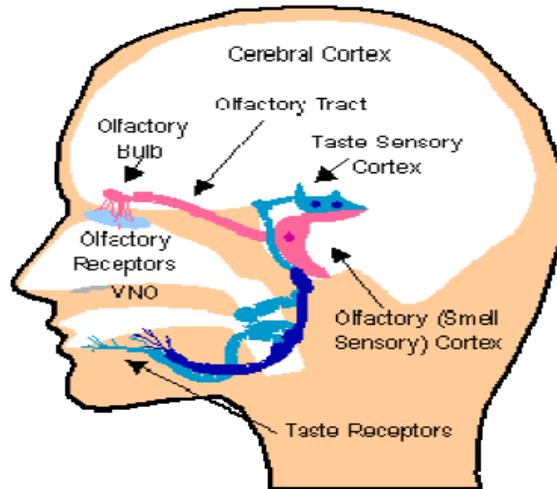


Fig. 1. The major processes of the olfactory system (Al-Bastaki, 2009)

To simulate such process, electronic noses have been developed. As can be understood, the main components of such noses are the sensing and the pattern recognition components. The first part consists of many of the sensors including gas, chemical, and many other sensors. The term chemical sensors refer to a set of sensors that respond to a particular analyte in a selective way through a chemical reaction. The second part, pattern recognition, is the science of discovering regular and irregular patterns out of a given materials. Many Artificial Intelligence (AI) algorithms and techniques are utilized in this part. Some of these techniques will be explained later in this chapter. To simplify the idea of the electronic noses, Figure 2 shows the basic components of an electronic nose. The figure shows that an electronic nose must contain a processor and a memory for analyzing the received digital data. At the same time, it has to have the appropriate set of sensors that identifies the smell print of an odor.

Once the odor is detected, its source has to be localized and contaminated if it is dangerous such as chemicals or radiations. There are different localization methods including the one that use mobile robots as well as different AI algorithms. Therefore, for odor manipulation, we have three phases as shown in figure 3 which are odor sensing, recognition, and localization. In each phase different techniques and algorithms are used. In the following sections we explore some of the detection and localization methods. Then, we propose a hybrid odor localization method that is based on Genetic Algorithms (GA), Fuzzy Logic Controller (FLC), and Swarm Intelligence. The initial results showed some significant results in localizing the odor sources.

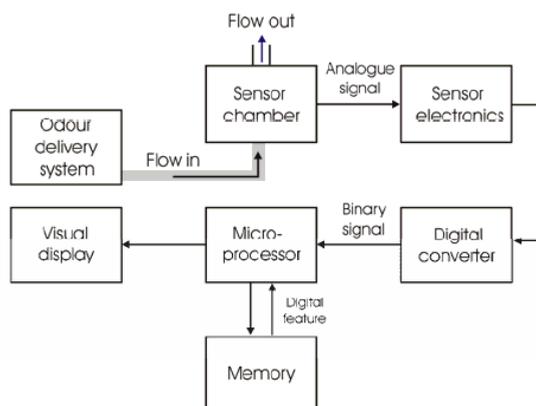


Fig. 2. Basic components of an electronic nose (Gardner et al., 1999)



Fig. 3. Odor manipulation phases

## 2. Odor Sensing

As mentioned, there are many types of odors including the odor in environment pollution. In fact, the need for detecting odors that causes pollution and the need for clean environment are leading the research in this field. Reliable real time detection techniques are urgently required especially with the increasing of new diseases that are caused by these odors. Sampling and analytical procedures are no longer on call due to the availability of other techniques that can produce the results on demand.

Different sensors have been used to detect odors including Conductivity, Piezoelectric, Metal-oxide-silicon field-effect-transistor (MOSFET), Optical Fiber, and Spectrometry-Based Sensors. The idea behind the operation of these sensors are explained in (Korotkaya, 2010) and summarized as follows:

The conductivity sensors exhibit a change in resistance when exposed to volatile organic compounds. Such sensors respond to water vapor, humidity difference, but not too sensitive for specific odorants. The Piezoelectric sensors are used to measure temperature, mass changes, pressure, force, and acceleration. The main idea behind these sensors is that the gas sample is adsorbed at the surface of the polymer, increasing the mass of the disk-polymer device and thereby reducing the resonance frequency. The reduction is inversely proportional to odorant mass adsorbed by the polymer. The MOSFET odor-sensing devices are based on the principle that volatile odor components in contact with a catalytic metal can produce a reaction in the metal. The reaction's products can diffuse through the gate of a MOSFET to change the electrical properties of the device. Optical-fiber sensors utilize glass fibers with a thin chemically active material coating on their slides or ends. A light source at

a single frequency (or at a narrow band of frequencies) is used to interrogate the active material, which in turn responds with a change in color to the presence of the odorant to be detected and measured. Finally, Spectrometry-Based sensors use the principle that each molecular has a distinct infrared spectrum

The state-of-the-art method for detecting odor emissions is the classical olfactometry. In this method, the odor detection is based on a group of people (panelists) with 95% probability of average odor sensitive. The results depend on the smelling capabilities of the panel members. This method is expensive and it is not feasible where continuous and online monitoring is required. Devices like electronic noses that utilize different odor sensors, stated previously, are more effective and much cheaper. The following are some examples on the usage of electronic noses in odors' detection.

In (Staples & Viswanathan, 2005), the authors used an electronic nose named zNose that simulates an almost unlimited number of specific virtual chemical sensors, and produces olfactory images based upon aroma chemistry. Figure 3 shows the zNose device and its components. Using zNose odor detection is done in seconds. The nose uses a handheld air sampler that consists of a battery operated sample pump and a tenax® filled probe. This enables organic compounds associated with odors to be remotely collected.



Fig. 4. zNose device (zNose, 2010)

Another example of electronic noses is in detecting the human body odor. One may think that it is not that important to use an electronic device for human body odor detection. However, the argument is if we succeeded in detecting the human body odor, the same device and experience will be applicable for other important applications such as healthcare monitoring, biometrics and cosmetics. Further to these applications, human odor could be used to uniquely identify a person which might be important in other fields such as in security. In addition, the electronic noses could be used to diagnose the urine odor of the patients with kidney disorders (Natale et al., 1999). Moreover, the human odor detection, armpit odor, is studied in (Chatchawal et al., 2009) using an electronic nose. The authors reported two problems they face when trying to detect the human body odors; the first problem is that the human may have different sweat at different time and environment; therefore, the humidity might affect the odor detection procedure in which it affects the gas sensors quality. The second problem people may use deodorants to reduce unpleasant body odor. The authors controlled the humidity using two methods including hardware-based and software-based methods through adding some of the sweat thresholds.

Electronic noses also used to detect explosives to help fighting international terrorism. The main idea behind a nose that detects explosives is to emulate the dog nose capabilities avoiding some of the dogs' drawbacks such as rigorous training, testing, and validation exercises in various operational scenarios with different types of explosives. Various types of noses have been developed; some of them are based on sensor arrays to detect different combinations of explosions. An example on this type of nose is the one developed by Walt and his group where they developed an expensive sensor array of fiber optics cable. Some others are based on vapour sensors to detect different vapors such as DNT and TNT emanating from landmines. A good source on reviewing about the electronic noses that are used for explosive detection could be found in (Jehuda, 2003).

A network of the previous electronic noses might be efficient in detecting the odors or explosives in a specific area. However, the difficulties of building a network of different noses involve the wireless media problems, the data analysis coming from all of these nodes, and the deployment of these nodes. One prototype of wireless sensor (e-noses) networks is mentioned in (Jianfeng et al., 2009) where the authors developed a network to monitor odorant gases and accurately estimating odor strength in and around livestock farms. Each nose consists of four metal-oxide semiconductor (MOS) gas sensors. Figure 5 shows the e-nose with gas chamber, pump and sensor array. For communication and networking purposes, this node (e-nose) is mounted on a MICAZ board (MICAZ, 2010). The sink node uses a modified Kalman filter for the data filtering.

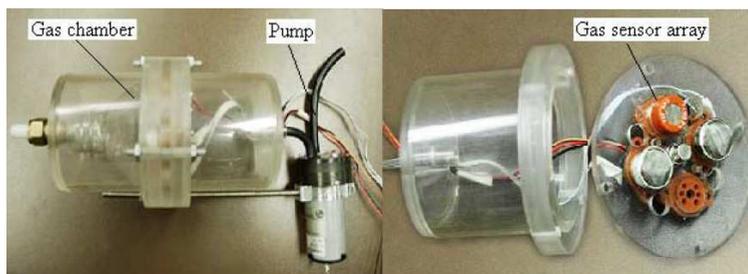


Fig. 5. E-nose with gas chamber, pump and sensor array exerted from (Jianfeng et al., 2009)

### 3. Odor Recognition

Once the odors are sensed, they have to be analyzed for decision making. However, such decision is not easy since there are many factors that affect for instance (Roppel and Wilson, 2000) (i) sensors have some overlapping specificities, (ii) not all the sensors will have the same performance in sensing the odors, and (iii) no general agreement has been reached on what constitutes the fundamental components of odor space. Therefore, recognizing the odor and taking the appropriate decision still a problem to many of the applications. In the following paragraph, we will go through some of the artificial intelligence techniques that try to solve such problem including neural networks and fuzzy logic.

In (Linder et al., 2005), the authors use a standard feedforward network for odor intensity recognition for multiclass classification problem. As shown in Figure 6, the network consists of the following inputs: (1) peaks D1 (acetone), (2) D2 (ethanol), (3) C1+D3 (first peak of

matrix, i. e. lemon oil, and isopropanol) , (4) C2+D4 (second peak of matrix and isoamyl acetate), and (5) C3 (third matrix peak). The output of the network is three classes which are weak, distinct, strong odour. The network has been trained based on some of the medical data prepared by the authors. The authors claimed that such network was very successful in detecting different odors' intensity.

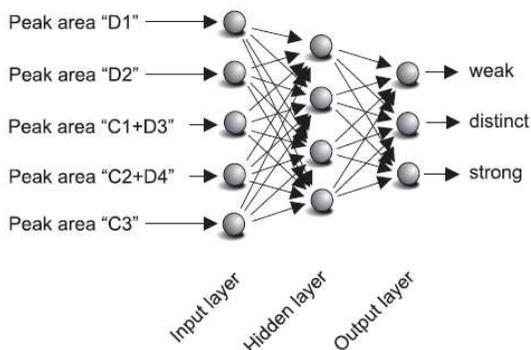


Fig. 6. Structure of a standard feedforward network that could serve for the assignment of different classes of odour intensity (Linder et al., 2005).

In (Bekiret et al., 2007) , the authors combined the fuzzy logic and neural networks for better odor recognition. The sensing is done by a handheld odor meter, OMX-GR sensor which is a commercial product. Figure 7 shows the used system diagram where a gas sensor array is used to differentiate between 11 types of gases. Once the sensors collect the odors data, the data is transferred to the unsupervised feature extraction block where a fuzzy c-mean algorithm is applied for data clustering. As it is known, fuzzy c-mean divides the data into fuzzy partitions, which overlap with each other. Therefore, the containment of each data to each cluster is defined by a membership grade in (0, 1). This clustering reduces the number of inputs given to the neural networks given in the following block. The function of the neural network is to classify the sensor array output into odor categories. The authors trained the network using 16 types of perfumes with 20 samples of each. The accuracy of the developed algorithm claimed by the authors was 93.75%.

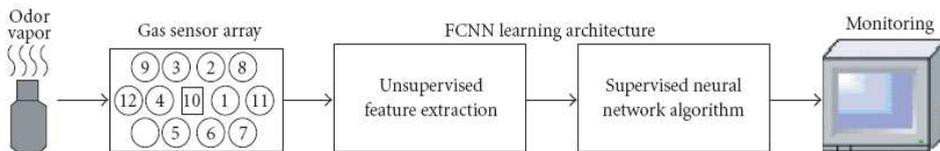


Fig. 7. Fuzzy Neural system for odor recognition (Bekiret et al., 2007)

Another AI technique is used for odor recognition is proposed in (İhsan et al. , 2009). The authors use Cerebellar Model Articulation Controller (CMAC) based neural networks. The CMAC concept is not new; The CMAC was firstly proposed during the 1970s by James Albus, whose idea was based on a model of the cerebellum which is a part of the brain responsible for learning process (Cui et al., 2004). The CMAC can generally be described as a

transformation device that transforms given input vectors into associated output vectors (Wisnu et al., 2008). It plays an important role in nonlinear function approximation and system modeling. CMAC is extremely fast learning technique compared to multiple layer perceptron (MLP) neural networks. As shown in Figure 8, the CMAC basically consists of three layers which are the normalized input space, basis functions, and weight vector. The output of the network could be considered as associative memory that holds the odor detection decision.

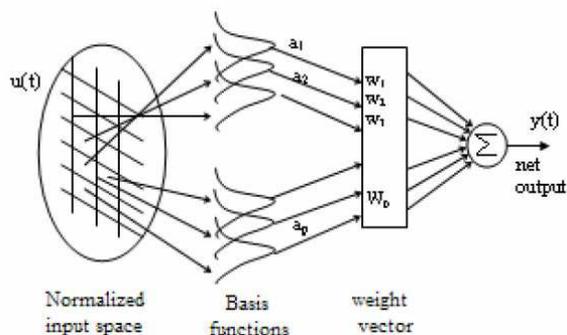


Fig. 8. CMAC layers

#### 4. Odor Localization

Odor localization has gained a lot of attention after some of the terrorist attacks such as the one occurred at Tokyo Subway in 1995. Odor localization problem falls into one of two main approaches which are Forward problems and Inverse problems. In the forward problems, the state of the odor is estimated in advance while in the inverse problems the prior state of the odor is estimated based on its current state. Odor localization usually done through using robots which is an emulation to the usage of dogs to find bombs, mines, and drugs. However, the dog has the capability to sense, recognize, and analyze the data; then naturally takes the decision. For robots, there is a need for localization algorithms. In the following paragraphs, we review the main ideas behind the work done in this area. Then, in the next section, we introduce our approach for odor localization.

Odor localization using robots has attracted many of the researchers and most of the work done in this area is trying to imitate the animals, birds, and swarms behaviors. For instance, insects fly in a zigzag pattern towards their mating partners. Ants use the same strategy to follow the pheromones trails. Therefore, robots could also do the same to locate the odor sources (Wei et al., 2001). On the other hand, animals may follow spiral surge algorithm to locate the odor sources (Hayes et al., 2002) where animals move in spiral path until it perceives a certain concentration and then moves straight upwind. As soon as it loses the scent, it starts spiraling again. A simple example on the zigzag and spiral procedures is shown in Figure 9. A comparison between the spiral and the zigzag algorithms are presented in (Lochmatter et al., 2008). The results show that the spiral is more efficient than the zigzag algorithm.

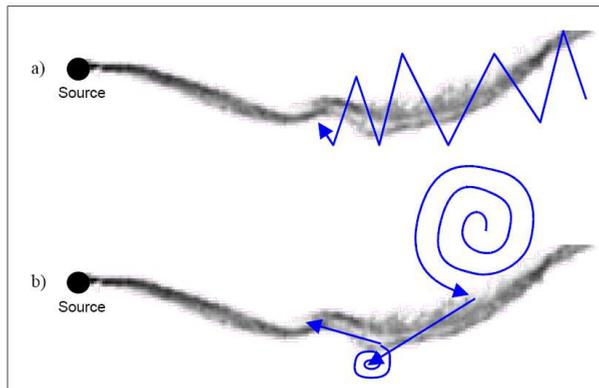


Fig. 9. Zigzagging (a) and spiral surge (b) are two bio-inspired odor source localization algorithms for single-robot systems (Lochmatter et al. , 2007).

Another method is reported in (Duckett et al., 2001) where the mobile robot turns around for  $360^\circ$  to point to the direction of the odor. Then it moves in the odor source direction. A similar technique has been used in (Loutfi and Coradeschi, 2002) where two gas sensors are mounted on the front and back of a Koala mobile robot given in Figure 10. The robot has programmed to use a wall following algorithm to avoid obstacles. The odor tracking algorithm used in (Loutfi and Coradeschi, 2002) is very simple. The default move direction for the robot is to move forward. If the front sensor has a strong reaction to the odor, the robot turns  $180^\circ$  and move forward. This turn is used to avoid sensors saturation. If the rear sensor has stronger reaction to the odor than the front sensor, that means the robot has passed the odor source and it has to turn around. If both sensors have the same reaction, the robot is adjusted to move forward.

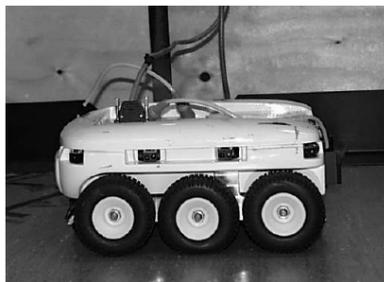


Fig. 10. Koala mobile robot

In (Wisnu et al. , 2008) , the authors try to localize the odor sources using swarm intelligence by a group of robots. The main challenge in the swarm intelligence in the authors' design is the interaction. The interaction process is divided into three phases which are encoding, synchronization, and comparison. The output of the overall interaction process is one of two outputs according to the robot that has the interaction box and the one is communicating with it. The encoding phase deals with formatting the received signals in a suitable format to the robot processing component. The synchronization phase defines which robot the

holder of the interaction box can communicate with. In the third phase, comparison, the robot compares its sensed data to the received ones. Figure 11 shows the interaction state diagram for a robot. As stated in (Wisnu et al. , 2008), a robot is wandering in the arena is in the state of wandering. If it perceives some robots who are in beaconing state, it selects one of them randomly to make a contact. The robot compares the odor concentrations received by the two robots. If the concentration received by its mate is higher, the robot approaches its mate; otherwise it keeps wandering. To get out of the wandering state, either the robot loses its mate signal or its concentration indicates inverse result. If no way the robot changes its state to attraction state, after certain period of time, the robot changes its beaconing state. After another period of time, the robot goes back to wandering state. If two robots move close to each other, they should avoid collision which is the obstacle avoidance state. The overall designed swarm behavior follows spatio-temporal model based on Eulerian framework.

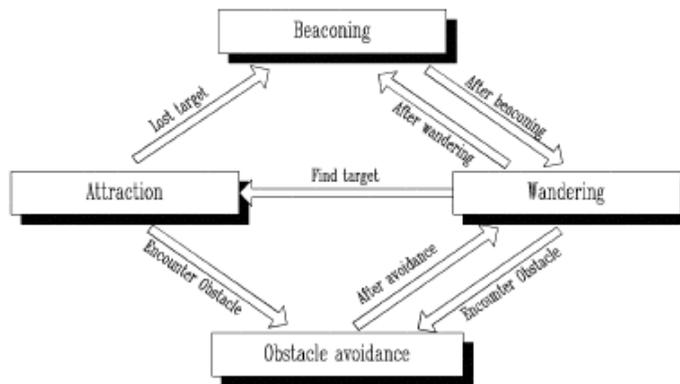


Fig. 11. Interaction state diagram for a robot (Wisnu et al. , 2008).

A swarm based fuzzy logic controller approach is also proposed (Cui et al. , 2004) for odor localization. The swarms are assumed to be the mobile robots deployed in the odor field. Robots form a wireless network to exchange their findings using table-driven routing protocol (Royer and Toh, 1999). The monitored odor field is divided into a grid of cells that are marked differently by the robots as given in Figure 12. To avoid collision and wasting of time and energy, each robot avoids exploration of a cell occupied by other robot. To keep the robots connected, the swarm cohesion property is utilized for this purpose. The expansion cell in the Figure is the cell in the grid map that is unexplored and unoccupied. The fuzzy logic controller is used to avoid the uncertainties in the collected information. The rule-based fuzzy logic controller is used as shown in Figure 13 where the robot movement direction is decided by the controller based on the collected information from other robots. The directions are identified by 8 linguistic variables shown in Figure 14. As shown in the Figure, the direction limited to only  $45^\circ$  only.

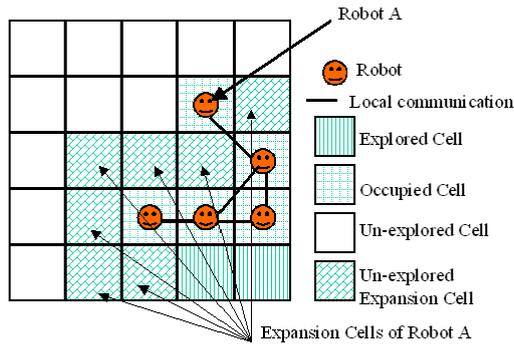


Fig. 12. Monitored field cells and their marking (Cui et al. , 2004)

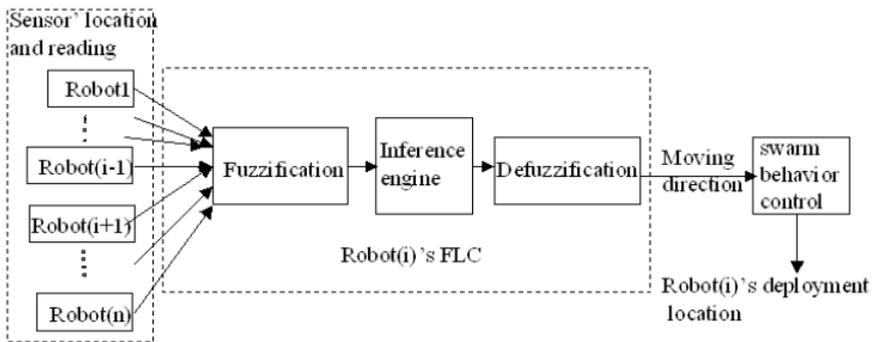


Fig. 13. Robot's Fuzzy Logic Controller (Cui et al. , 2004).

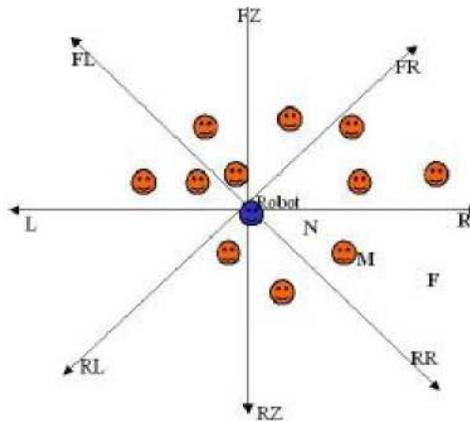


Fig. 14. Fuzzy Logic used linguistics (Cui et al. , 2004).

A combination of a static Wireless Sensor Network (WSN) and mobile robots are also used for multi-odor sources localization (Zhen et al. , 2010). The WSN is assumed to be deployed in the monitored area to collect information about the odor and the wind speed and

direction. The WSN works as backbone to the robots where nodes may sense the environment odor, transmit the data to other nodes, sense and transmit at the same time, and may be nodes could be in non-active state. for multi-hop routing , the authors uses GPSR-based protocol. Robots on the other side are assumed powerful machines where they are mounted with odor and vision sensors, Global Positioning System (GPS), and may be some of the tools to prevent odor from spreading. Robots could communicate to each other or to the WSN nodes using their wireless devices. However, robots are assumed to form an ad hoc network with one as a manager and others as workers. The manager collects the sensed information from the robots and the sensors; then it takes the decision to move the workers towards the correct direction. Again, the monitored field is divided into small zones and based on the historical data, the manager can assign different number of robots.

## 5. Localization and Hybrid Approach

In the following subsections, we introduce a new hybrid solution for odor localization. The solution uses Genetic algorithms for local search, fuzzy logic to select the suitable direction and the swarm intelligence to keep robots connected. This work is ongoing work and it is not finalized yet; however, the initial results seem promising and outperform the previous solutions.

### 5.1. The Problem

The problem that we tackle in this section is to find a single source of odor in a certain space  $R$ . The space is described as a 2D environment with known dimensions.  $R$  is assumed to contain a dangerous odor source(s) in unknown location  $x_s$  and  $y_s$ , where  $s$  refers to the hazardous source. Here, we investigate single odor source localization only; multiple odor sources localizations problem is considered as part of our future work. The space  $R$  could be divided into a grid of cells with known dimensions. In order to save the human rescue lives as well as to speed up the search in the contaminated space, a number of robots with appropriate sensors are used to locate the odor source.

Robots are assumed to have a wireless communication that enables them to form an ad hoc wireless network. The communication range does not have to be large enough to cover all of the search space. In addition, robots are assumed having the capability of running different algorithms such as Genetic Algorithms (GA) , Fuzzy Logic Controller (FLC), and Swarm Intelligence. Robots are also assumed to be capable of identifying their location from a priori given reference point. Moreover, we assume that the robots will have enough energy sources to complete their task. Robots are initially deployed close to each other to guarantee their connectivity. However, the deployment points could be anywhere in the search space.

Another fact that needs to be considered during the localization process is the wind speed which might cause sensors' readings uncertainties. The wind speed has its most effect at outdoor environments. However, indoor environments might have another source of readings noise. Therefore, an appropriate method is required to handle the readings uncertainties. We propose a fuzzy logic approach to solve this problem.

## 5.2 Hybrid Computational Intelligence Algorithm (H-CIA) for odor Source Localization

In this section, we explain the details of our algorithm for odor source localization. The algorithm consists of three phases; the first phase allows the robot to locally search its local area and come up with the best location to start from. This phase utilizes the GA for identifying the best location  $(x, y)$  to start from. A space search is proposed in the second phase where robots benefit from the neighbors' robots to identify the moving direction. Since the neighbors' readings might not be accurate and involve uncertain information, a fuzzy logic approach is proposed to identify the moving direction. In the third phase, to keep the sensors together and get the best of their readings, swarm intelligence is exploited. Through the next subsections, we explain the details of each phase.

### 5.2.1 Phase One: Local Search

As mentioned in the problem statement, the search space is divided into a grid of cells. These cells are assumed equal in terms of their area. Also, robots are initially loaded with the space map and its cells dimensions. Therefore, a robot  $i$  is assumed capable of localizing itself and identifying its location in the cell. A certain point  $Pr(x_r, y_1)$  is selected to be the robots' localization reference. Once robots are deployed in the search space, they start to localize themselves and determine their deployed cells. Our proposal in this phase is to allow the sensor to locally search their cell for the odor source. Our methodology in this search is the usage of GA. GA is a well-known optimization algorithm and proven to be efficient in many of the search problems. Therefore, we exploit the GA in the local search phase and we propose our own GA representation to the problem. This representation showed good results from among other representations.

First the robot's chromosome is its position in terms of  $x$  and  $y$  coordinates regarding the given reference point in the search space. A certain set of chromosomes  $C$  are initially generated to represent the GA initial population. This set of chromosomes is limited to the robot's current cell dimensions to limit the GA search space. The crossover is done between two chromosomes in two steps: 1) randomly select  $x$  or  $y$  from the chromosome to exchange and 2) exchange the selected coordinate. The mutation is done based on a probability  $P_m$  where  $0 < P_m < 1$ . If  $P_m$  is greater than 0.5, a random chromosome is selected from the initial population and its  $x$  coordinate replaces  $x$  coordinate in one of the current used chromosomes. On the next iterations, if the evaluation function enhanced, we keep replacing the  $x$ 's coordinates; otherwise we exchange  $y$ 's coordinates instead. The evaluation function is represented by the measured odor concentration value at each new location which in our case are two locations based on the current generated chromosomes. The odor distribution is assumed to follow the Gaussian distribution. The GA algorithm runs for a certain number of iterations and terminates. During these iterations, the best chromosome is stored and it will be the final robot's location in this phase.

### 5.2.2 Phase Two: Space Search

In this phase of the solution, we try to move the robot towards the odor source and avoid the GA local minima. At the same time, we make the most out of robots' readings so far. As stated previously, robots' readings are uncertain due to the wind speed in outdoor environments or other noise in indoor environments. In this case Fuzzy logic comes to to

handle the robots' readings uncertainties. The objective of fuzzy logic is to identify the correct direction of the robot to move to based on the current sensors hazardous concentration readings as well as neighbors robots' positions.

Therefore, for the fuzzy logic to work, there are two inputs with two membership functions. The first input is the robot's neighbor's readings and the second is their positions in terms of  $x$  and  $y$  coordinates. These coordinates are converted to a certain linguistics that relates the robots positions to the reference point. Here, we assume the reference point is located at the center of the space and each robot could identify its location to the reference points in terms of the following 8 directions: 1) Left (L), 2) Right (R), 3) Top (T), 4) Down (D), 5) Right Top (RT), 6) Left Top (LT), 7) Left Down (LD), and 8) Right Down (RD). The membership of the readings input is chosen to be dynamic based on the readings values. Five linguistics are chosen for this input which are Very-Low, Low, Medium, High, and Very-High. Each one falls in almost 20% of the input's range. For the defuzzification, it seems that the center of gravity (COG) of fuzzy sets is an essential feature that concurrently reflects the location and shape of the fuzzy sets concerned. Therefore, we use COG as our defuzzification process as shown in equation (1).

$$COG = \frac{\sum \mu_A(a) * a}{\sum \mu_A(a)} \quad (1)$$

Where,  $\mu_A(a)$  is the membership function of set A.

The output membership function produces the same eight directions as presented in the input. Once the robot decides on the direction, it moves according to the next phase restrictions. When it reaches a new zone, it starts again the GA.

### 5.2.3 Phase Three: Swarm Movement Control

Once the direction is identified, if the robots move freely, another problem might occur in which the robots might get disconnected from each other. A similar Swarm intelligence model presented in (Fei et al., 2008) is used to keep robots together. Probability Particle Swarm Optimization (P-PSO) algorithm uses probability to express the local and global fitness functions. More detailed description about the P-PSO algorithm can be found in (Fei et al., 2008). The coherence characteristic of the P-PSO moves only the robot that does not affect the robots connectivity.

It is worth mentioning that the initial results based on simulation setup shows that 85% of the time the robots reach the odor source. However, the cell size has to be small to prevent the robot in moving in a zigzag form and taken long time to converge. Currently we prepare a real robot experiments to check the performance of the hybrid approach in odor localization. Several parameters might not easy to handle in real environments such as the effect of obstacles, robots speed, robots batteries, etc.

## 6. Conclusion

In this chapter, we explored some of techniques and algorithms used for odor recognition and localization. We started by introducing different types of sensors that are currently used for odor sensing. We focused on one of the famous devices which is the electronic nose. Then, we reviewed some of the concepts used for odor recognition including neural networks and swarm intelligence. This phase is followed by odor localization using single and multi-robots. Finally, we proposed a new hybrid method based on Genetic Algorithms, Fuzzy Logic, and Swarm Intelligence. The Genetic Algorithm is used for local search and the fuzzy logic identifies the direction of the robot's movement. Then, the Swarm Intelligence is used for robots' cohesion and connectivity.

## 7. References

- Al-Bastaki, Y. (2009). An Artificial Neural Networks-Based on-Line Monitoring Odor
- Bekir, K. & Kemal , Y. (2007) Fuzzy Clustering Neural Networks for Real-Time Odor Recognition System. *Journal of Automated Methods and Management in Chemistry*, Vol. 2007.
- Chatchawal, W. ; Mario, L.; & Teerakiat, K. (2009). Detection and Classification of Human Body Odor Using an Electronic Nose. *Sensors 2009*, Vol. 9, pp.7234-7249.
- Cui , X.; Hardin , T. ; Ragade, R.; Elmaghraby, A. (2004). A Swarm-based Fuzzy Logic Control Mobile Sensor Network for Hazardous Contaminants Localization. In *Proceedings of the IEEE International Conference on Mobile Ad-hoc and Sensor Systems (MASS'04)*.
- Duckett, T.; Axelsson, M.; Saffiotti, A. (2001) Learning to locate an odour source with a mobile robot. In *Proc. ICRA-2001, IEEE International Conference on Robotics and Automation*, pp. 21-26.
- Fei, L.; Qing-Hao, M.; Shuang, B.; Ji-Gong, L.; Dorin, P. (2008). Probability-PSO Algorithm for Multi-robot Based Odor Source Localization in Ventilated Indoor. *Intelligent Robotics and Applications, Lecture Notes in Computer Science Springer*, Vol. 5314, pp. 1206-1215.
- Gardner, J. & Bartlett, P. (1999). *Electronic Noses Principles and Applications*. Oxford University Press. Oxford, UK.
- Hayes, A.; Martinoli, A.; Goodman, R. (2002) Distributed Odor Source Localization. *IEEE Sensors Journal*, Vol. 2, No. 3, pp. 260-271.  
<http://www.it.lut.fi/kurssit/03-04/010970000/seminars/Korotkaya.pdf> as visited on 06/09/2010
- İhsan, Ö. & Bekir, K. (2009) . Hazardous Odor Recognition by CMAC Based Neural Networks. *Sensor 2009*, Vol. 9, pp. 7308-7319;
- Jehuda, Y. (2003). Detection of Explosives by Electronic Noses. *Analytical Chemistry* , Vol. 75, No. 5, pp. 98 A-105 A.
- Jianfeng, Q.; Yi, C.; & Simon, X. (2009). A Real-Time De-Noiseing Algorithm for E-Noses in a Wireless Sensor Network. *Sensor 2009*. Vol. 9, pp.895-908;
- Korotkaya, Z. "Biometric Person Authentication: Odor", Pages: 1 - 6,
- Linder, R. ; Zamelczyk, M. ; Pöppel, R. ; Kośmider, J. (2005). *Polish Journal of Environmental Studies*. Vol. 14, No. 4, pp. 477-481

- Lochmatter, L.; Raemy, X.; Matthey, L.; Indra, S.; Martinoli, A. (2008). A Comparison of Casting and Spiraling Algorithms for Odor Source Localization in Laminar Flow. In Proceedings of the 2008 IEEE International Conference on Robotics and Automation (ICRA 2008), pp. 1138-1143.
- Lochmatter, T.; Raemy, X.; Martinoli, A. (2007). Odor Source Localization with Mobile Robots. Bulletin of the Swiss Society for Automatic Control, Vol. 46: pp.11-14.
- Loutfi, A. & Coradeschi, S. (2002). Relying on an electronic nose for odor localization," IEEE International Symposium on Virtual and Intelligent Measurement Systems. VIMS '02.
- MICAZ, [http://www.openautomation.net/uploads/productos/micaz\\_datasheet.pdf](http://www.openautomation.net/uploads/productos/micaz_datasheet.pdf) as visited on 06/09/2010
- Natale, C.D.; Mantini, A.; Macagnano, A.; Antuzzi, D.; Paolesse, R.; D'Amico, A. (1999). Electronic Nose Analysis of Urine Samples Containing Blood. Phys. Meas., pp. 377-384.
- Roppel, T. & Wilson, D. (2000). Biologically-inspired pattern recognition for odor detection. Pattern Recogn. Lett. 21, No.3, pp. 213-219.
- Royer, E. & TohToh, C. (1999). A review of current routing protocols for ad hoc mobile, IEEE Personal Communication, Vol. 6, No.2, pp. 46–55.
- Sensing System, *Journal of Computer Science*, Vol. 5, No. 11, pp. 878-882,
- Staples, E. & Viswanathan, S. (2005). Odor Detection and Analysis using GC/SAW zNose. Electronic Sensor Technology, School of Engineering and Technology, National University.
- Wei, L.; Jay, A.; Ring, T. (2001). Tracking of Fluid-Advection Odor Plumes: Strategies Inspired by Insect Orientation to Pheromone. *Journal of Adaptive Behavior*, Vol. 9, No. 3-4, pp. 143-170.
- Wisnu, J.; Petrus, M.; Benyamin, K.; Kosuke, S.; Toshio, F. (2008) Modified PSO Algorithm Based on Flow of Wind for Odor Source Localization Problems in Dynamic Environments. In Wseas transactions on Systems, Vol. 7.
- Zhen, F.; Zhan, Z.; Xunxue, C.; Daoqu, G.; Yundong, X.; LiDong, D.; ShaoHua, W. (2010). Multi-odor Sources Localization and Tracking with Wireless Sensor Network and Mobile Robots. 1st IET international Conference on Wireless Sensor Networks. IET-WSN-2010.
- zNose device available at <http://www.estcal.com/> as visited on 06/09/2010.





## **Wireless Sensor Networks: Application-Centric Design**

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Over the past decade, there has been a prolific increase in the research, development and commercialisation of Wireless Sensor Networks (WSNs) and their associated technologies. WSNs have found application in a vast range of different domains, scenarios and disciplines. These have included healthcare, defence and security, environmental monitoring and building/structural health monitoring. However, as a result of the broad array of pertinent applications, WSN researchers have also realised the application specificity of the domain; it is incredibly difficult, if not impossible, to find an application-independent solution to most WSN problems. Hence, research into WSNs dictates the adoption of an application-centric design process. This book is not intended to be a comprehensive review of all WSN applications and deployments to date. Instead, it is a collection of state-of-the-art research papers discussing current applications and deployment experiences, but also the communication and data processing technologies that are fundamental in further developing solutions to applications. Whilst a common foundation is retained through all chapters, this book contains a broad array of often differing interpretations, configurations and limitations of WSNs, and this highlights the diversity of this ever-changing research area. The chapters have been categorised into three distinct sections: applications and case studies, communication and networking, and information and data processing. The readership of this book is intended to be postgraduate/postdoctoral researchers and professional engineers, though some of the chapters may be of relevance to interested master's level students.

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