Fire Detection Robot Navigation Using Modified Voting Logic

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Abstract: Autonomous robots can be equipped to detect potential threats of fire and find out the source while avoiding the obstacles during navigation. The proposed system uses Voting Logic Fusion to approach and declare a potential fire source autonomously. The robot follows the increasing gradient of light and heat to identify the threat and approach source.

1 INTRODUCTION

Industrial fires are a leading cause of injuries at industrial workplaces. According to NFPA (National Fire Protection Agency, USA) 2012 statistics:

- 1,375,000 fires were reported in the U.S during 2012.
- $12.4billion in property damage
- 480,500 of these fires were structure fires.

The current safety systems mainly consist of smoke detectors at various locations in a factory, sensing the smoke in the air and activating a sprinkler system but there are certain scenarios when a fire does not emit smoke.

The proposed system in this paper consists of an autonomous mobile robot using modified voting logic fusion to monitor and approach the fire source in an industrial environment, minimizing the losses and not disrupting the production processes at other locations. It navigates on a sinusoidal path to increase the area of vision of the sensors such that to detect targets that are not necessarily on the way.

2 LITERATURE REVIEW

E. Zervas et al, 2011, discuss the forest fire detection by using the fusion of temperature, humidity and vision sensors. A belief of fire probability is established for each resultant node and then this data is fused with the data from vision sensors that monitor the same geographical area.

Khoon et al., 2012, proposed a new design of an autonomous robot dedicated to fire fighting. This robot, called Autonomous Fire Fighting Mobile Platform or AFFPM, has a flame sensor and obstacle avoidance systems. The AFFPM follows a preset path through the building. At some points, it will leave its track and go toward the identified fire source reaching within 30 cm of the flame. It then engages a fire extinguisher that is mounted on the platform. After it has extinguished the fire completely, it returns to its guiding track to carry on with its further investigation of any other fire source.

Viswanathan et al, 1997, discuss series and parallel architectures and the governing decision rules to be implemented. An optimization based on Neyman-Pearson criterion and Bayes formulation for conditionally independent sensor observations is proposed. The review of sensor fusion methods were done in a paper by (Sasiadek, 2002).

Lilenthal et al., 2006, discuss the detection strategy of a silkworm to reach the elevated levels of heat. Sinusoidal movement, adopted also in this paper, is used to increase the possibility of detecting other potentially stronger sources.

3 DIFFERENTIALLY DRIVEN MOBILE ROBOT

In this paper a differentially driven mobile robot, shown in Fig. 1, was used for experimentation and testing. The two driving wheels are at the front. A line bisecting them crosses the centre of gravity of the robot.

The angular velocities of these wheels are

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denoted by ω_l and ω_r.

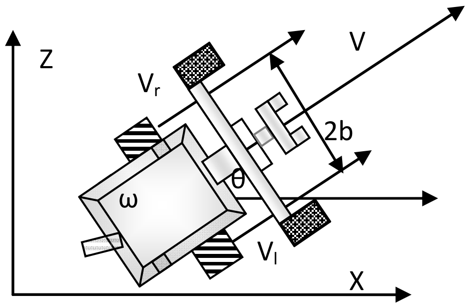

Figure 1: Differentially driven mobile robot.

The nomenclature is:

V_l = Velocity of the left wheel,
V_r= Velocity of the right wheel,
V = velocity of the assembly,
ω = Angular velocity of the center point of the vehicle,
2b = Distance between front wheels,
R = Wheel radius,
$\varphi_r(t)$ = Rotation angle of the right wheel
$\varphi_l(t)$ = Rotation angle of the left wheel

The following equations show the relations between velocities

$$V_x = \frac{V_r + V_l}{2} \cos\theta \quad (1)$$

$$V_y = \frac{V_r + V_l}{2} \sin\theta \quad (2)$$

$$\omega = \frac{V_r - V_l}{2b} \quad (3)$$

The configuration of the robot can be described by:

$$q = [x, y, \theta, \varphi_r, \varphi_l]^T \quad (4)$$

Where, x and y are the two coordinates of the center of mass and θ is the orientation angle of the robot.

The kinematic model of the robot is given by

$$\begin{bmatrix} v \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} R/2 & R/2 \\ R/2b & -R/2b \end{bmatrix} \begin{bmatrix} \omega_r \\ \omega_l \end{bmatrix} \quad (5)$$

The differentially driven robot is able to change its direction by controlling the speed of its driving motors. The robot used for illustration in this paper, NXT 2.0™, has four available sensor inputs and three available outputs for motors. The four sensors are connected to the inputs, namely to the two light sensors, one TIR (Thermal Infrared Sensor) and one ultrasonic sensor for obstacle avoidance.

The input ports are named 1, 2, 3 and 4. The sensors connected to the input ports are as follows:

- Sensor A, Thermal Infrared Sensor, connected to the input port 1,
- Sensors B and C, light sensors connected to the input ports 2 and 3, respectively,
- Sensor S, a Sonar Sensor (Ultrasonic Sensor), connected to the input port 4

Motion control is based on an open loop approach providing commands to the two output ports that are in use for this robot and are connected to motors "B" and "C", such that:

- If Motor B and C run at the same speed, the robot will move forward or backwards,
- If Motor B is running forward and Motor C is stopped the robot would turn LEFT (or rotate in anticlockwise direction) with the center of radius as the left wheel,
- If Motor C is running forward and Motor B is stopped the robot would turn RIGHT (or clockwise direction) with the center of radius as the right wheel,
- If Motor C is running forward and Motor B is running backwards, the robot will rotate clockwise at that particular spot, and vice versa.

The speed of these two motors can be modified to have different values of the motor singular speeds. The controller for the motors is programmed in LabVIEW® for Mindstorms robots.

4 NAVIGATION STRATEGY

Since the sensors are fixed on the robot and the movement of robot determines the direction of these sensors, the vision of these sensors is limited to 45˚. The sinusoidal movement, used for the navigation strategy, turns the robot either 45˚ to the right or 45˚ to the left while searching for increasing levels of light or heat. Control of this sinusoidal movement, shown in Fig. 2, requires sensors with peripheral vision of 180˚ in the direction of motion of the robot.

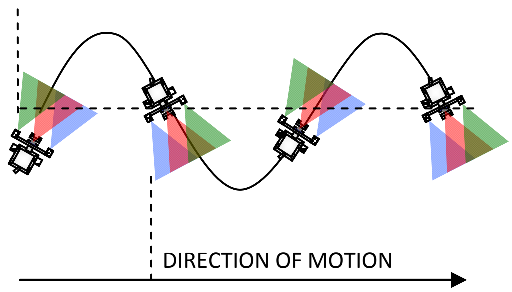

Figure 2: The visible range of sensors in a sinusoidal movement.

In order to cover 180˚ in the direction of motion it was chosen to use a scanning approach such that, as the robot travels in a straight line, the sensors cover the area surrounding it.

The speed of the robot is 0.3 m/s at 100% voltage input. The voltage can be modified in the range from 0% to 200% to change speeds. The sampling rate for the sensors is 10 times a second. A sine wave, of given amplitude, had to be selected to optimize the distance traveled, area scanned and time elapsed to complete one cycle (Fig. 3).

The distance covered by the robot is directly proportional to the amplitude of the sine curve path chosen by the programmer. In a sine curve with amplitude of 1, the length of a sine curve is 2.63π. Depending on the requirements, the amplitude and frequency can be chosen by the programmer. If there is a need to scan a wider area, the amplitude can be changed to a different value.

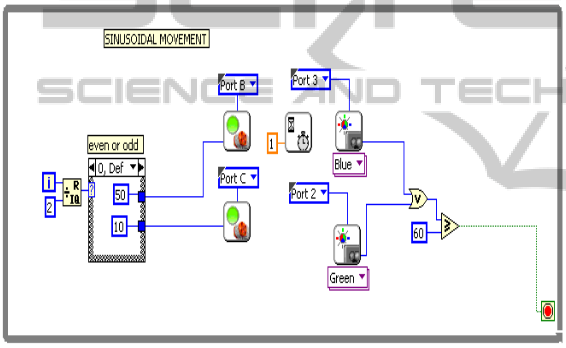

Figure 3: LabVIEW Virtual Instrument (VI) for sinusoidal movement of the robot ending as a given high level of light intensity is reached.

5 VOTING LOGIC APPROACH

5.1 Confidence Level

Confidence level is defined as the degree of matching of the input signal to the features of an ideal target, signal to interference ratio or number of predefined features that are matched to the sensor reading with the input signal. Here A_1 is denoted as low confidence, A_2 and A_3 are denoted as medium and high confidence levels for the sensor A, respectively.

The number of confidence levels required for a sensor is function of the number of sensors in the system and the ease with which it is possible to correlate target recognition features, extracted from the sensor data, with distinct confidence levels. If more confidence levels are available, the easier it is to develop combinations of detection modes that meet system detection and false-alarm probability requirements under wide-ranging operating conditions.

5.2 Voting Logic Sensor Fusion

As evident from the name, voting logic fusion fuses the data of multiple sensors and based on the information and confidence levels of these inputs from the sensors, decision making is carried out (Fig. 4). Voting logic fusion has many advantages over single sensor based readings, used in series or parallel. It provides a great deterrence against false alarms, not compromising on the ability to detect suppressed targets in a noisy environment. It may be preferable technique to detect, classify and track objects when multiple sensors are used.

Since one sensor, the ultrasonic sensor, is mainly used for detection and avoidance of obstacles, it does not need to be part of voting logic to declare the presence of a fire (Fig. 5).Rather it would work independently of the other sensors (Fig. 4). The priority level for the sensor output is very high. As the obstacle avoidance is very important to keep the robot moving, the increasing gradient direction is used for this purpose.

5.3 Modified Voting Logic

A fire declaration is only possible in the current circumstances when the light readings above threshold and the temperature above a certain level are available. The probability of fire diminishes if the light sensors are providing a reading that is higher but the robot does not detect elevated temperatures (Fig. 6). The robot may reach close to the target where, due to robot geometry, the light sensors may not give a reading that falls in any confidence level given that the robot reached the source. At that instance, the sensor A will give the highest confidence level due to the temperature present but, since the other sensors are not able to sense it, voting logic will not declare a target based on the output of just one sensor. At this point the reading from the other sensors becomes irrelevant.

Normal voting logic does not keep this scenario into account. In order to reach the point of interest the robot has to follow any lead of increased light only and will not declare the fire source until it reaches a point where elevated temperatures are also detected. To maximize the possibility of identifying the target, an average of the previous four readings is taken into account to linearize the readings hence making the detection more reliable (Fig. 6). This is achieved by introducing a while loop with shift register in LabVIEW.

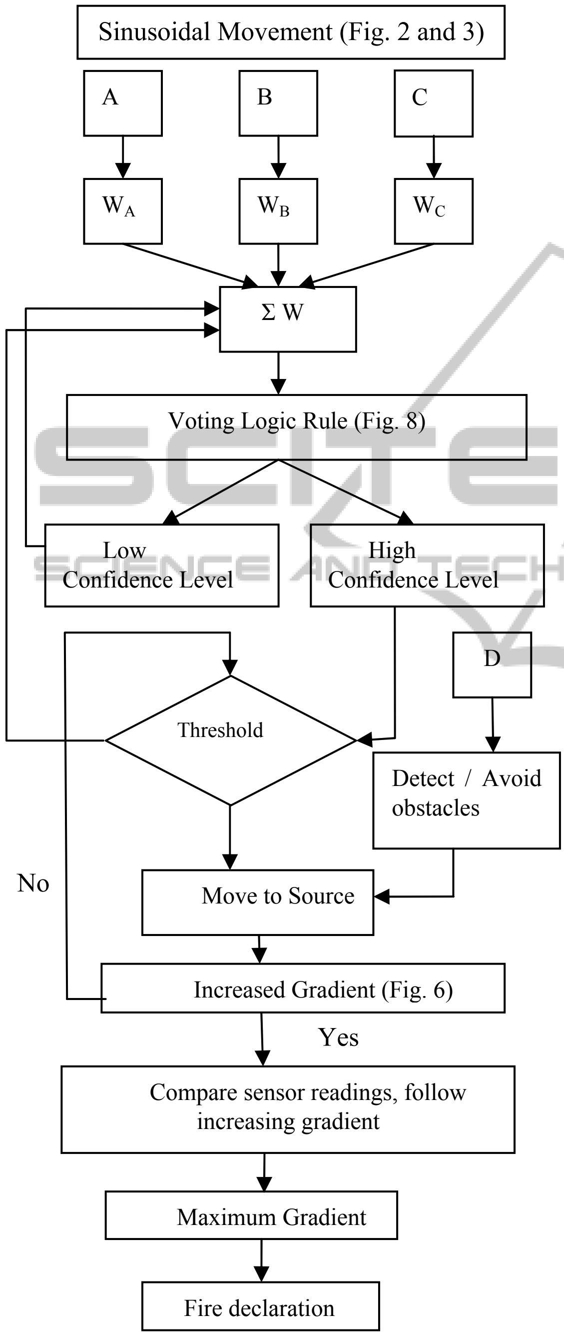

Figure 4: Fire declaration algorithm.

In the modified voting logic are incorporated some of the attributes of parallel sensor combination along with the conventional voting logic (Fig. 7). The combinations of interest in fire detection with two light sensors will only contain the ones that include readings from the thermal infrared sensor. Hence, the combination of the outputs containing the two light sensors only has been excluded.

In the instance where light sensors are giving a low confidence reading, or no reading, but the temperature sensor is giving a very high confidence reading, the fire incident is declared (Table 1). If the thermal infrared sensor was defined as A and the two light sensors were designated the letters B and C, the voting logic described by the Venn diagram shown in Fig. 7.

Fig. 8 shows LabVIEW implementation of modified voting logic algorithm.

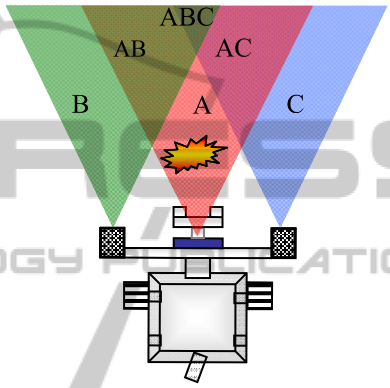

Figure 5: Possible combinations of sensor readings.

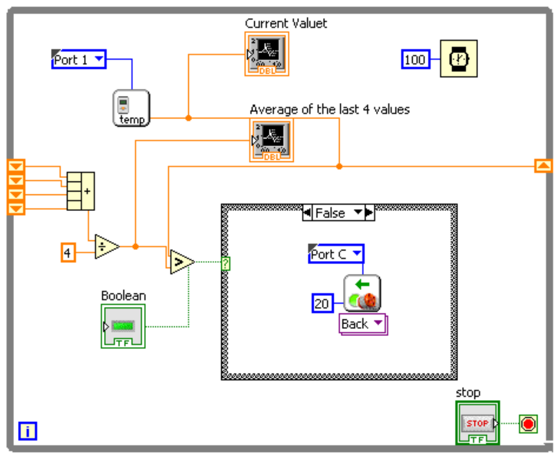

Figure 6: Single sensor based increasing gradient tracking in LabVIEW implementation.

Table 1: Sensors and confidence levels.

Mode	Sensors and Confidence Levels		
	A	**B**	**C**
ABC	A_2	B_2	C_2
ABC	A_3	B_1	C_1
AB	A_2	B_3	-
AC	A_2	-	C_3
A	A_4	-	-

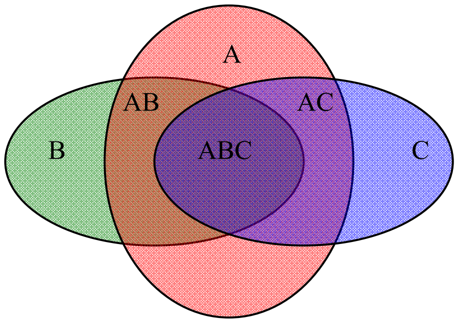

Figure 7: Combinations of interest in sensor outputs with two light sensors and one thermal infrared sensor.

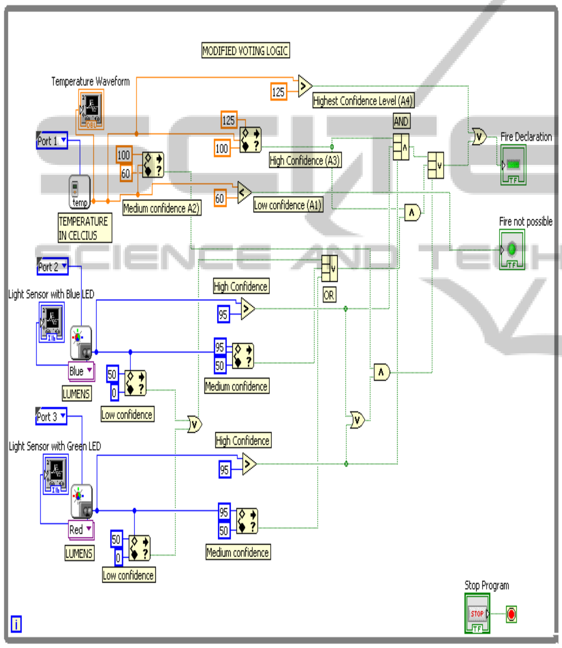

Figure 8: LabVIEW implementation of Modified Voting Logic.

5.4 Detection Modes

In this section are presented the combinations of sensor outputs that are able to declare a fire incident. As more sensors detect different confidence levels, the need to have higher confidence levels decreases. Modes that contain two sensors are not required to have the highest confidence levels as an intermediate confidence level from all the sensors may be sufficient to declare a fire incident. For the low confidence level, however, all three sensors have to be a part of the decision making process.

As mentioned in the last section, the voting logic has to be modified in certain scenarios, so some scenarios need to be excluded and some need to be added. In the above mentioned case exclusions will include any confidence levels of the sensors B and C since they do not signify the presence of fire alone. Also, if the highest confidence level from sensor A is obtained, a fire incident is declared.

It can be noticed from Table 1 that there was no mentioning of confidence level A_1, as temperature being a mandatory variable in fire detection, the possibility of declaring fire is not considered when confidence level A_1 is reported.

As the detection modes have been defined, now it is possible to proceed with the derivation of system detection and false-alarm probability using the distributions presented in Table 2-4,with assumed chosen for the illustration of the approach.

Table 2: Distribution of detections conditional probabilities among sensor confidence levels for Sensor A.

Sensor Confidence Level	Sensor A			
	A_1	A_2	A_3	A_4
Distribution of Detections	1000	700	500	400
Conditional Probability	1.0	0.7	0.5	0.4

Table 3: Distribution of detections conditional probabilities among sensor confidence levels for Sensor B.

Sensor Confidence Levels	Sensor B		
	B_1	B_2	B_3
Distribution of Detections	100	500	300
Conditional Probability	1.0	0.5	0.3

Table 4: Distribution of detections conditional probabilities among sensor confidence levels for Sensor C.

Sensor Confidence Levels	Sensor C		
	C_1	C_2	C_3
Distribution of Detections	100	500	300
Conditional Probability	1.0	0.5	0.3

5.5 Fire Declaration Algorithm

As the detection modes have been defined, now it is possible to proceed with derivation of system detection and false-alarm probability

$$\text{System } P_d = P_d\{A_2B_2C_2 \text{ or } A_2B_3 \text{ or } A_2C_3 \text{ or } A_3B_1C_1 \text{ or } A_4\} \quad (6)$$

Applying the repeated Boolean algebra expression for five detection modes a total of 4 combinations are obtained

$$\text{System } P_d = P_d\{A2\}P_d\,\{\text{B}2\}P_d\,\{\text{C}2\} + P_d\{A3\}P_d\,\{\text{B}1\}P_d\,\{\text{C}1\} + P_d\{A2\}P_d\,\{\text{B}3\} + P_d\{A2\}P_d\,\{\text{C}3\} + P_d\{A4\} \quad (7)$$

Similarly, the probability of false alarm calculation for the system would be:

$$\text{System } P_{fa} = P_{fa}\{A2\}P_{fa}\,\{\text{B}2\}P_{fa}\,\{\text{C}2\} + P_{fa}\{A3\}P_{fa}\,\{\text{B}1\}P_{fa}\,\{\text{C}1\} + P_{fa}\{A2\}P_{fa}\,\{\text{B}3\} + P_{fa}\{A2\}P_{fa}\,\{\text{C}3\} + P_{fa}\{A4\} \quad (8)$$

5.6 Confidence Levels Calculation

Mapping of the confidence-level space into the sensor detection space is accomplished by multiplying the inherent detection probability of the sensor by the conditional probability that a particular confidence level is satisfied given detection by the sensor. Since the signal-to-interference ratio can differ at each confidence level, the inherent detection probability of the sensor can also be different at each confidence level. Thus, the probability $P_d\{A_n\}$, that Sensor A will detect a target with confidence level A_n, is

$$P_d\{A_n\} = P_d'\{A_n\}\ P\{A_n/\text{detection}\} \quad (9)$$

Where $P_d'\{A_n\}$ is the inherent detection probability calculated for confidence level n of sensor A using the applicable signal-to-interference ratio, false alarm probability, target fluctuation characteristics, and number of samples integrated and $P\{A_n/\text{detection}\}$ is probability that detection with confidence level A_n occurs given a detection by sensor A.

Similar process can be repeated to obtain the false alarm probability of the system using P_{fa} values. Using the data from Table 2-4, the results for the detection probabilities for the sensor system are shown in Table 5.

Table 5: System detection probabilities.

Detection probabilities for the suggested sensor system				
Mode	**Sensor A**	**Sensor B**	**Sensor C**	**Mode P_d**
$A_2\,B_2\,C_2$	0.58	0.35	0.35	0.07
$A_3\,B_1\,C_1$	0.45	0.4	0.4	0.07
$A_2\,B_3$	0.58	0.26		0.15
$A_2\,C_3$	0.58		0.26	0.15
A_4	0.39			0.39
System P_d				0.83

6 EXPERIMENTAL RESULTS

Experiments were performed on the robot NXT 2.0 for the validation of the algorithm. The results showed a very high success rate of detecting the source. In fact, the robot was able to identify the light and heat source each time provided there was no light reflecting off the surface of other objects.

Figure 9 presents the different steps in searching, locating, obstacle avoidance, approaching the source and declaring a fire incident.

The robot was able to identify the light and heat source for different obstacle orientations and configurations.

Figure 9: Robot starting behind an obstacle andmovingon a sinusoidal path while detecting the heat source.

Figure 9: Robot starting behind an obstacle andmovingon a sinusoidal path while detecting the heat source (cont.).

By limiting the detection mode of sensor A to the 2nd level for declaration, false alarm possibilities have also decreased. There were few false alarms during any experiment. The experiment were performed a total of 30 times with 27 true declarations. The success ratio was 90% in declaration of the source.

7 CONCLUSIONS

Confidence level calculations and experimental results show a consistency in recognizing and declaring a fire source while minimizing the possibility of a false alarm or non-declaration.

As a result of the adoption of single sensor detection mode and also using single sensor non-possibility mode, the accuracy of detecting a fire increased. Also, this improvement was achieved while not compromising on the ability to detect suppressed or noisy targets.

Good source detection results were achieved by the introduction of the sinusoidal movement strategy. This increased the angle of peripheral vision to 180˚ improved the detection probability by helping the detection of a stronger source and, at the same time, by bringing weaker sources into visible range.

Introduction of comparison of stronger signals while avoiding the obstacles resulted in a decrease of the detection times.

The above combined improvements made the detection system more reliable, more robust and more accurate in tracking and in declaration of indoor fires.

The system is also able to distinguish between a reflected and direct signal coming from the source based on the readings of different variables at the approach of an obstacle.

REFERENCES

Karter, M. J. Jr., 2013, NFPA's Fire Loss in the United. States during 2012, September.

Klein, L. A., 2004, Sensor and Data Fusion, a Tool for. Information Assessment and Decision Making, *SPIE. Press*, 2nd edition.

Zervas, E. et al., 2009, Multisensor Data Fusion for Fire. Detection, Information Fusion, 12, pp. 150–159.

Khoon, T., 2012, Autonomous Fire Fighting Mobile. Platform, IRIS 2012, *International Symposium on. Robotics and Intelligent Sensors*, issue 4, pp. 1145 – 1153.

Viswanathan, R. and Varshney, P. K, 1997, Detection with. Multiple Sensors: Part I – Fundamentals, *Proc. IEEE*, vol85, issue 1.

Sasiadek, J. Z., 2002, Sensor Fusion, Annual Reviews in. Control, *IFAC Journal*, No. 26, pp. 203-228.

Lilienthal, A. et al, 2006, Gas Source Tracing with a. Mobile Robot Using an Adapted Moth Strategy, WSI, University of Tubingen, Sand 1, 72074 Tubingen, Germany.

David, C. T., 1982, A Re-Appraisal of Insect Flight. Towards a Point Source of Wind-Borne Odour, *Journal of Chemical Ecology*, issue 8, pp.1207–1215.

Ishida, H. et al., 1994. Study of Autonomous Mobile. Sensing System for Localization of Odor Source Using Gas Sensors and Anemometric Sensors, Sensors and Actuator, vol. 45, pp. 153–157.