

# The real-world localization and classification of multiple odours using a biologically based neurorobotics approach.

José María Blanco Calvo, Sergi Bermúdez i Badia, Hector Tapia Simó, Paul F.M.J. Verschure

**Abstract**—Autonomous robotic odour source classification and localization in real world environments is an essential step for applications such as humanitarian demining, environmental monitoring or search and rescue operations. However, at the moment this problem has only been solved by nature (e.g.: moths, bees, rats, dogs). Biological systems are capable and efficient at odour source localization in spite of the difficulties present in the real world such as turbulent environments, obstacles, predators or interfering odours. Here we aim at exploiting our understanding of the moth to solve this problem and we propose a biologically based model of moth behaviour. We implement our model on a robot that uses chemical sensors and we test its performance in a controlled environment. Further, we extend the behavioural model with a sensor front end that supports classification in order to deal with odour distractors. We show that our system is able to locate an odour source and map the chemical environment in the presence of distractors.

## I. INTRODUCTION

The olfactory system has not been studied as extensively as the visual or the auditory system but it is a crucial sense, especially for animals when foraging, looking for mates or avoiding threats. A deeper knowledge of biological olfaction can enable us to develop novel artificial olfactory technologies for applications such as search and rescue, environmental monitoring or humanitarian demining.

The main problem we face is how to make an autonomous robot detect a specific chemical blend within a complex background of mixed odours, distinguish it and also locate its source in a real world environment. This is known as the *specific odour coding and localization problem* [1].

In a real world situation, the dynamics of dispersion of a chemical plume make it difficult to locate its source. This dispersion, described by the Reynolds number, can vary a lot depending on the medium. At low Reynolds values, viscosity leads to diffusion producing monotonic decreases in chemical concentration as a function of the distance to the source, following a Gaussian distribution [2]. At medium and high

values, turbulence dominates: the substance is carried by a background fluid (advection). Although the plume has a complex fluctuating structure, in these conditions it can be assumed on average to approximate a decreasing concentration gradient from the source. However, local gradients of concentration cannot give reliable information on the location of the source [3]. These are the conditions faced by macroscopic robots that work above ground in air or underwater.

So far, the main approaches to the odour source localization problem for low Reynolds values exploit chemical information (chemotaxis) with reactive algorithms such as Braitenberg style algorithms [4], which use the instantaneous concentration to locate the source. These approaches obtain short mean path lengths but low reliability without flow information [5] [6] [7] [8]. Other approaches more suitable for high Reynolds values use vision, theories about fluid dynamics (fluxotaxis) [9] or Shannon information theory (info-taxis) [10]. Robot swarms have also been deployed for odour localization based on the idea that the use of a multi-robot system makes a more robust search since the probability of falling into local maxima is reduced. In particular, a modified Particle Swarm Optimization (PSO) algorithm was proposed to exploit chemotaxis and anemotaxis in what is known as Odor-Gated Rheotaxis (OGR) to find an odour source in a obstacle-filled environment [11]. Another variation of a PSO algorithm, called Probability-PSO, was proposed for ventilated indoor environments without obstacles [12].

A number of biological systems are able to solve the localization task very efficiently: lobsters, which use odour localization to locate food; dung beetles, which use it to locate faeces that are their primary material to feed or to build habitation; *Escherichia coli* bacteria uses it to locate nutrients; or moths that employ odour localization to find mates [8].

Some biomimetic algorithms exploiting chemotaxis combined with anemotaxis (wind flow information) have been proposed [8]. A model based on the Dung beetle uses an upwind zigzagging trajectory within the odour plume to locate the source [13], [14], [7]. Other approaches use predatory behaviour based on the combination of a global search strategy following a 'Z' shape trajectory combined with a local search [15]. A plume-centred upwind search has also been proposed where the robot moves towards the centre of the plume using odometry and its bilateral sensing history to continuously orient towards the higher concentrations [16] [17] [18] [19].

Particularly, male moths have been widely studied since

José María Blanco Calvo, Sergi Bermúdez i Badia and Hector Tapia Simó are with the Synthetic, Perceptive, Emotive and Cognitive Systems group in the Department of Information and Communication Technologies, University Pompeu Fabra of Barcelona, Institute of Audio-Visual Studies (IUA), Communication-Poblenou Campus (LA NAU building). Roc Boronat, 138. 08018 Barcelona, Spain (phone: +34 93 542 13 66; email: josemaria.blanco@upf.edu, sergi.bermudez@upf.edu, hector.tapia.upf@gmail.com ).

Paul F.M.J. Verschure is a Catalan Institute of Advanced Research (ICREA) research professor and he is with the Synthetic, Perceptive, Emotive and Cognitive Systems group in the Department of Information and Communication Technologies, University Pompeu Fabra of Barcelona, Institute of Audio-Visual Studies (IUA), Communication-Poblenou Campus (LA NAU building). Roc Boronat, 138. 08018 Barcelona, Spain (phone: +34 93 542 13 69 email: paul.verschure@upf.edu).



activity, generating the appropriate timing for the oscillation of the counterturning behaviour. This is a kind of moth flip/flop neuron as described in [33] that shows a switching high/low firing rate state. Two other inhibitory connections from neurons excited by the spontaneous activity neuron decrease periodically their activity, reducing the frequency of counterturning. The output activity of the *Casting and Surge* process, excites the motor neurons in a rate based fashion (Figure 2, point 3), being the responsible of controlling the robot motors through the *In/Out Motor Output* process.

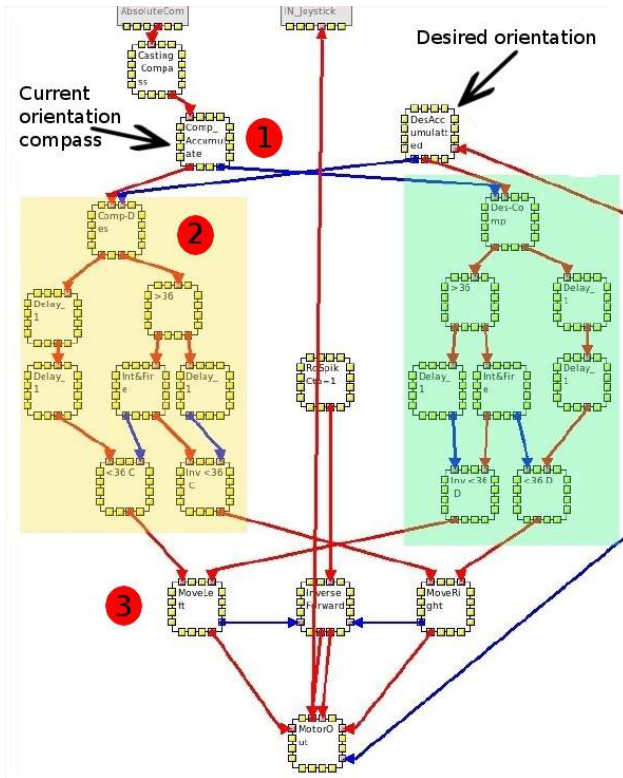


Fig. 2. Detail of *Casting and Surge* process implementation in *iqr* [34]. Every square represents a group of neurons. Red lines indicate excitatory connections and blue lines inhibitory. The picture shows two shaded sets of neuronal groups. These are responsible of calculating the minimum angle from current orientation to desire orientation to turn the robot to the appropriate direction.

There is a module that resolves conflicts when two processes try to access common resources (*Process Control*). Basically, it regulates the motor commands that are sent to the robot. This is implemented using a winner take all neuronal net, where only the active process with highest priority can send motor commands at a moment, while the motor decisions from other processes are inhibited. The process *In AnTS Tracking* gets information from a vision based tracking system that is used to calculate the position and orientation of the robot in the *Compute Direction* process. The process *Collision Detection* uses the position of the robot in the test environment to avoid collisions with its boundaries sending high priority motor commands to the robot. The *Odour Detection/Classification* process analyses the raw data obtained by the chemical-sensor, and performs classification

and detection.

This architecture has been implemented using *iqr*, a multi-level neuronal simulation environment that provides a tool for graphically designing large-scale real-time neuronal models [34] and allows to test them in real-time using a real world systems such as robots. *iqr* runs on a desktop computer and it is interfaced to the robot via a bluetooth connection. It acquires data from the robot sensors, processes it and sends motor commands at run time. The vision based tracking system sends the data to *iqr* via a direct UDP connection.

### B. Robotic platform and chemical sensors

The robot we use for the experiments is called *SPECS M2* (Figure 3). Since the robot does not have a wind direction sensor and we generate a strong airflow of known direction inside the wind tunnel, we use the tracking information of the robot to simulate the wind direction sensor. The odour blend is measured by means of chemical sensors that are placed at front of the the robot and connected to its main board.

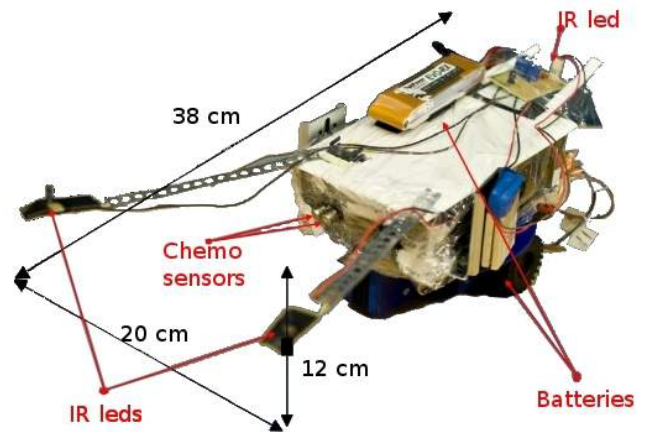


Fig. 3. *SPECS M2* robot with Figaro chemical sensors. It is a mobile platform with two motors driving the rear wheels and an omni-directional wheel at the front. It is controlled by a Arduino Mega board (SmartProjects, Italy) with Bluetooth wireless connection. The robot is powered by a 2-cell LiPo battery of 7.4V (Flightpower, United Kingdom). Three IR leds form an isosceles triangle that is detected by the vision based tracking system to compute both robot position and orientation.

We selected three different chemical sensors provided by Figaro Engineering Inc (Osaka, Japan). These are the TGS 21802, which respond to water vapour, the TGS 260010 for low concentrations of gaseous air contaminants such as hydrogen and carbon monoxide, and the TGS 262010 for vapours of organic solvents as well as other volatile vapours (e.g.: CO or Ethanol).

A chemical sensor varies its resistance proportional to the concentration of chemical substances that binds to its surface. The sensors are mounted on a PCB that controls their operating temperature and digitizes the output voltage. To compute the change of resistance due to a specific compound, and consistent with previous studies ([22]) we use the *Fractional Change in Conductance* (FCG):

$$FGC(t) = \frac{G_{stimulus}(t) - \langle G_{nostimulus} \rangle}{\langle G_{nostimulus} \rangle} \quad (1)$$

$G_{stimulus}(t)$  is the conductance of the sensor in the presence of chemical stimuli at time  $t$ .  $G_{nostimulus}$  is the mean conductance in the absence of any stimuli [23]. Different known concentrations of a set of solutions are used to normalize the amplitude of the FCG. This allows us to exploit more subtle information to enhance the differentiation of different substances, and therefore robustness.

### C. Set-up

The wind tunnel (Figure 4) is built of wood and covered with transparent low density polyethylene, divided in three modules. The first one comprises four exhaust ventilators that generate a wind flow inside the tunnel. The other two modules form the tunnel and create a controlled space where the robot can move freely. The vision based tracking system (*AnTS*) is placed above the tunnel. To disperse the compound we use an ultrasonic source that generates a mist at the entrance of the wind tunnel (for clarification purposes, the entrance or the beginning of the wind tunnel is where the odour source is placed and the exit or the end where the fans are located. For more details check Figure 4). Then the negative pressure created by the four fans creates a plume that moves across the whole wind tunnel from the entrance to the exit where the air is extracted out of the experimental environment.

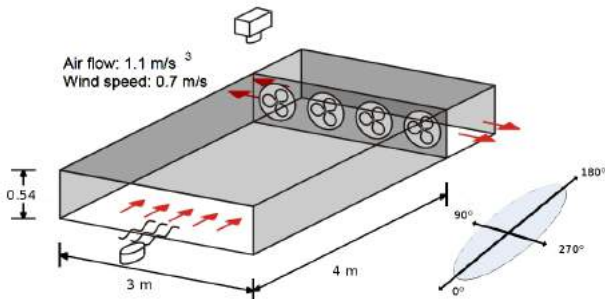


Fig. 4. Wind tunnel schematics including the position of the camera of the vision based tracking system. A compass taken as absolute reference for robot orientation during experiments is also drawn. Red arrows show the wind flow direction from the entrance of the wind tunnel where the odour source is placed towards the end where four fans absorb the flow and extract it out of the tunnel. Adapted from [23].

For the calibration of the sensors, the reconstruction of the plume and the odour source localization task we used a 5% ethanol solution with distilled water. To reconstruct the plume we took static measurements at 25 positions inside the wind tunnel when delivering the ethanol solution. The equidistant measuring points cover the whole area of the wind tunnel. At every point, the robot is placed with the chemical sensors facing the entrance of the tunnel ( $0^\circ$  in wind tunnel coordinates) and samples the air during 3 minutes. No sensor data obtained during the transition between points is used. With those values, we calculate the mean FCG norm

of the three sensors array, taking as  $G_{nostimulus}$  the one obtained solely with distilled water according to:

$$FGC_{sensor\ array} = \sqrt{\sum_{i=1}^3 FGC_{sensor\ i}^2} \quad (2)$$

For the odour source localization experiments, a 5% ethanol solution was used as odour source. We placed the robot at the end of the tunnel in different positions, trying to randomize not only the initial position but also its orientation. We made 17 runs of the experiment where the robot performs casting and surge search behaviour until it finds the source or exits the wind tunnel.

To test the feasibility of the robot dealing with interfering substances, we use two classification methods and data gathered dynamically by the robot within the wind tunnel. For these experiments three water solutions were selected: 5% ethanol, 11% acetone and 20% ammonia. The robot explored the whole wind tunnel in two different trajectories for each of those solutions separately. The measured data has been used for training the classifiers. Then, and to assess the performance in case of interference, we used two different odour sources (pairs of the above mentioned substances) separated by 1 meter, and the robot made a complete exploration in the wind tunnel. If the robot is able to classify adequately a plume formed by two different substances and identify each one separately, we demonstrate that our current technology allows the robot detecting an specific chemical within an interfering chemical background. To evaluate the classification performance we use two benchmarks, a K-Nearest Neighbours algorithm and a second order linear classifier. K-Nearest Neighbours computes the distance between every point in the training data set and each one of the test set. Then the minimum distances will determine the category for each point in the test set [35]. Since we are using three dimensional data, the second order classifier uses the training set to compute second order surfaces that separate the space of data into subspaces that represent categories. Then, each point of the test set is classified into one of these subspaces, belonging to a specific category then [36].

After the acquisition of the data by the robot, we perform an offline analysis in Matlab (The MathWorks, Inc., Massachusetts, USA) to assess the quality of the classification. Since the robot samples data at 80 Hz, we use a time window of one second to reduce noise and improve the classification. Additionally, an exploration of the tunnel without any odour source is used to compute the baseline responses.

## III. RESULTS

In order to assess the performance of our system, we performed sensor calibration tasks, odour source localization experiment, a classification of different odours and the reconstruction of a complex chemical plume with two different odour sources.

### A. Sensor calibration and plume reconstruction

We choose values for the load resistances of the electronic circuit of the chemical sensors that maximize the dynamic range of the sensors within the wind tunnel. Through simulation using PSpice17 (Cadence Design Systems, Inc. California, USA) and additional tests with 5% ethanol solution, the following values were chosen (Table I).

TABLE I  
CHEMICAL SENSORS RESISTANCES CALIBRATION: VALUES LISTED ARE SPECIFIC TO THE SENSOR AND THE COMPOUNDS.

Sensor model	Sensitive to	Resistance (kOhm)
TGS 262010	Solvent Vapours	1.8
TGS 260010	Air Contaminants	5.6
TGS 21802	Water Vapour	100

The results of computing the FCG norm during plume reconstruction experiments (Figure 5) show that there is a clear increase of the FCG when the robot is approaching the source. From the centreline to the lateral edges of the wind tunnel there is also a pronounced decrease of the response. This decrease is also perceived when moving downwind from the source, confirming other results [3].

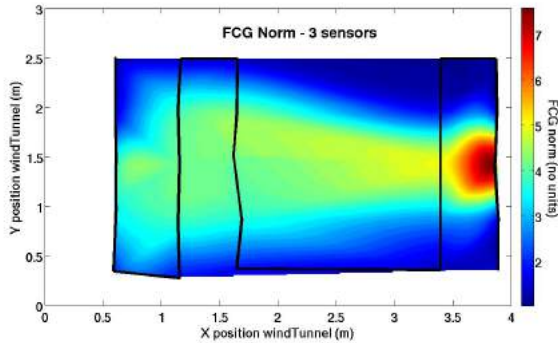


Fig. 5. Plume concentration gradient in the wind tunnel constructed by means of computing the norm of the FCG measurements using ethanol (5%) as the chemical cue. Axis X and Y show the coordinates in the wind tunnel. The odour source is at the right hand side of the picture (perfectly shown by the red colours). The black line joins the different positions where the robot was placed to obtain the data. The robot's sensors pointed to the beginning of the wind tunnel, i.e.: right hand side of the picture.

### B. One source odour localization

Subsequently, we tested the odour localization strategy implemented in our robot. In these experiments, the mean search time is  $303 \pm 125.4$  seconds (normally distributed, Lilliefors test). To give a reference, the time the robot takes to cross in a straight line through the tunnel is 86 seconds (28%). If the robot reaches the odour source within 40 cm (two times robot size), we consider that the robot has properly localized the odour source. According to this criterion, out of a total of 17 trials, 13 were considered successful, i.e. a final success rate of 76%. This value is slightly above the 70% reported by [8] using a moth based behavioural strategy. Thus following a moth based strategy

and its biomimetic implementation we are able to achieve robust localization of single odours.

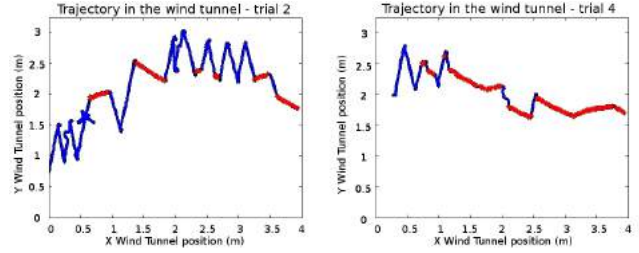


Fig. 6. Robot moth based search behaviour: Illustrative trials of odour source localization where the robot combines casting and surge to find the source. Blue lines indicate casting and red lines surge.

### C. Classification

In the analysis of the two classification methods proposed, we compute the percentage of success or failure based on the number of measurements of the sensor responses that are above their baseline values. An analysis of the raw data taken by the three chemical sensors when acquiring the training data shows that the classification of the different odours is possible, although it becomes extremely difficult at very low concentrations due to an excessive overlap of the sensor responses (Figure 7).

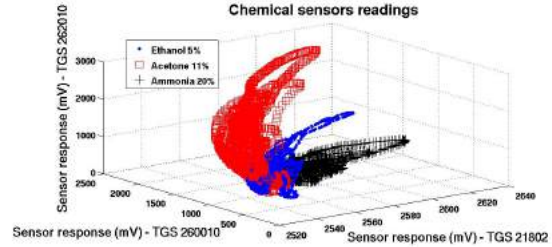


Fig. 7. Robot odour classification: Raw data acquired by the three sensors (three axes) when using three 5% ethanol (blue), 11% acetone (red), 20% ammonia (black) separately. The robot moves with low speed during exploration of the wind tunnel. These data is used as training set for the classifiers.

When analysing the results with both classification methods, we computed the percentage of points recognized as a specific substance (rows in the tables) when we used a specific substance as the odour source (columns). The results of the k-nearest neighbours (KNN) method, after training, when using two different chemical sources placed at two different points at the beginning of the wind tunnel, show that KNN is able to classify the substances appropriately (Table II). However, in case of Ammonia plus Acetone KNN shows lower performance. This can be explained by the enormous difference of sensor responses between Ammonia and Acetone increases the probability of wrong classification when they are used simultaneously for the experiment.

Although KNN algorithm is computationally expensive (it compares each query point with the whole database), it has the advantages of its simplicity and also that there are some

TABLE II  
K-NEAREST NEIGHBOURS SUCCESS RATES: 77.9% CORRECT CLASSIFICATION.

Recognized	Ethanol-Ammonia	Ethanol-Acetone	Ammonia-Acetone
Ethanol	25.7%	22.9%	20.7%
Acetone	13.4%	50.1%	39.4%
Ammonia	17%	1.1%	7.5%
No odour	43.7%	25.6%	32.4%
Success	76.1%	98.5%	59.1%

neural implementations of it. This is important because it provides us a lower bound on what we can expect the moth will be able to do in terms of classification.

We also made a test with a second-order classifier ( $2^{nd}LC$ ). This method creates second-order functions from the training data to divide the feature space in different regions where the incoming data will be classified. In our case, we have three dimensions, one per sensor. The results of testing the classifier with the training data are shown in Table III. The values show the percentage of points that have been identified with the recognized substance (each row) when using the two odour sources showed in each column. They show that the classifier has a good performance with one odour source. The results of the second-order lineal classification when using two odour sources are shown in Table IV.

TABLE III  
SECOND-ORDER LINEAR CLASSIFICATION TEST.

Recognized	Eth-1	Eth-2	Ace-1	Ace-2	Amm-1	Amm-2
Ethanol	33.3%	29.7%	2.2%	3.3%	6.7%	3.3%
Acetone	0%	0%	40.3%	48.2%	0%	0%
Ammonia	7.9%	0%	0%	0%	93.3%	72.4%
No odour	58.7%	70.3%	57.5%	48.5%	0%	24.4%
Success	80.8%	100%	94.9%	93.6%	93.2%	95.7%

TABLE IV  
SECOND-ORDER LINEAR CLASSIFICATION TEST: 80.73% CORRECT CLASSIFICATION.

Recognized	Ethanol-Ammonia	Ethanol-Acetone	Ammonia-Acetone
Ethanol	33.3%	41%	34.6%
Acetone	10.7%	43.8%	43%
Ammonia	30.3%	3.9%	10.6%
No odour	25.7%	11.3%	11.7%
Success	85.7%	95.7%	60.8%

Comparing the results with the KNN, we can see that on average second order linear classifier performs slightly better (80.73% success rate for  $2^{nd}LC$  and 77.9% for KNN). This suggest that this method is a good candidate to perform the real-time classification implemented in the robot. Although the table only shows absolute values for classification, it is also very important to see how the points have been classified spatially inside the wind tunnel. To do it, we add to each classified point (by the second order linear classifier) its spatial

position obtained while the robot was exploring. In this way we can obtain the spatial distribution of the classification and hence be more confident with its quality. This process show effectively that the classifier gets a coherent spatial distribution of the plumes, taking into account that there are some interferences between them, specially in the centre line of the plumes where the probability of wrong classifications increases (Figure 8). To appreciate better the distribution of the substances along the wind tunnel, we performed an spatial interpolation over the same data set (Figure 9). Results show that this methodology can be applied for real time classification in the robot.

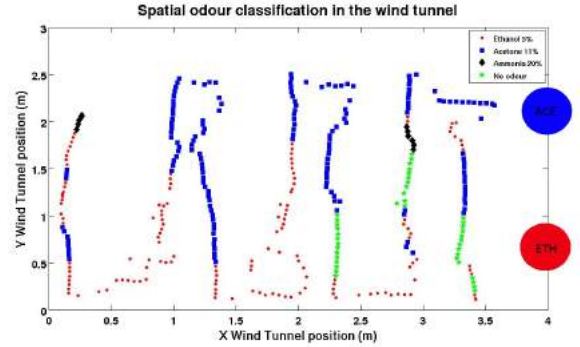


Fig. 8. Trajectory of the robot inside the wind tunnel. Every point represents the combination of measurements of the three sensors during 1 second (they have been measured with a frequency of 80 Hz). The colour represents the substance assigned to each measurement by the classifier. Red: ethanol ; blue: acetone; black: ammonia and yellow: no substance. The substances used as odour sources for this experiment were ethanol and acetone, represented with circles at the beginning of the wind tunnel. In this case we obtained a 95.7% of success classification.

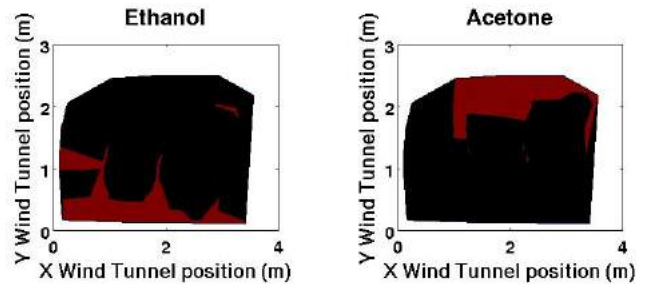


Fig. 9. Contour plot where each subplot shows the spatial distribution of the classification for each substance. The recognized substance is coloured in red. The substances used for this experiment were 5% ethanol and 11% acetone. Distribution of ammonia or no odour is not presented due to their minimum influence.

#### IV. CONCLUSIONS

This research aims at providing a solution to the problem of location and discrimination of odour sources by means of autonomous artificial systems. The approach we have taken starts using a macroscopic mobile robotic platform equipped with broadly tuned chemical sensors in a turbulent medium, such as air with strong airflow. We have based our design on a biological behavioural model of the male moth tracing female pheromones. We have calibrated the chemical sensors and

tested them, showing that they can be used to reconstruct the plume in a way that allows for a source localization task. To assess the performance of the casting and search behavioural model we have run 17 odour source localization experiments with high successful performance rates. Then we have used the chemical sensor data of the robot exploring the tunnel in presence of different substances and performed successful odour classification.

In the future, online classification neuronal algorithms will be tested that will be closely based on our understand of the antenna lobe of the moth [37]. Additionally, we will add more chemical sensors to the robot and explore whether stereo chemotaxis can improve the robot performance. The most ambitious improvement we must face is to implement a learning method that allows the robot to explore freely an environment and learn to distinguish untrained new odours.

#### ACKNOWLEDGMENT

This project has been supported by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 216916 for NEUROCHEM and EU SYNTHETIC FORAGER (FP7-217148) projects.

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