Humanitarian Demining Using an Insect Based Chemical Unmanned Aerial Vehicle

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1. Introduction

Nowadays, there are about 100 million active landmines distributed around the world as the result of earlier conflicts (Habib 2007). These cheap and simple to manufacture weapons have a long lasting effect that cause injury to the civil population even decades after the conflict has ended. Their removal is very expensive, dangerous and time consuming, and it has a high social and economical impact. Hence, although demining is a necessity for the affected populations to recover, it poses fundamental technical challenges.

At the present time, the use of animals, i.e. biological sensors, still provides the highest accuracy and safety standards in demining tasks. A number of animal species including dogs, rats and bees have been successfully trained to detect and localize landmines following the minute chemical trails of leaking explosive compounds (Fjellanger et al. 2002; Bromenshenk et al. 2003; Verhagen et al. 2006). Insects, and in particular moths, are highly optimized chemical detection systems that are extremely proficient at the detection and localization of different chemical compounds, in particular pheromones, at very long distances, i.e. several hundreds of meters. Moths use pheromone signals for sexual communication and it has been shown that males are able to detect and distinguish minute amounts of female pheromones (as little as 10^4 molecules $\cdot cm^{-3}$) against a background of other chemicals in very irregular and unpredictable plumes (Wyatt 2003). As a consequence, the evolutionary pressure to detect pheromones has generated specific neural and behavioral adaptations to deal with this specific problem. Nonetheless, the chemical search task is not reduced to a unique olfactory process but is a multi-modal task that includes the integration of complex behavioral strategies with visual, olfactory and wind sensing information (Kennedy & Marsh 1974; Ludlow 1982; Charlton & Cardé. 1990).

In this chapter we analyze the relationship between the chemical detection and localization problem and its biological solution, and we will show how our understanding of the biological solution can be exploited to construct efficient autonomous chemo-sensing Unmanned Aerial Vehicles (cUAV). Firstly, we describe a blimp-based technology for a cUAV. Subsequently, we investigate the computational and behavioral principles underlying the opto-motor system of the fly and the locust, and we show that relying solely

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on vision, biologically constrained neuronal models of the fly visual system suffice for course stabilization and altitude control of a blimp-based UAV. Then, we augment this system with a collision avoidance model based on the Lobula Giant Movement Detector neuron of the Locust. A number of chemical search experiments are described with a mobile robot in a controlled wind tunnel environment. In these experiments, a number of chemical mapping strategies and behaviorally and biologically constrained models derived from the moth are tested and their performance is assessed. Finally, some of these solutions are evaluated in outdoor chemical detection, mapping and localization tasks using a cUAV. We show that our insect based approach that combines detailed biologically constrained models of the fly, locust and moth provides for a robust system and can constitute a viable approach towards the detection and localization of explosives and therefore be used for humanitarian demining. Moreover, our insect based cUAV demonstrates that the detailed understanding of biological solutions to real-world problems can provide for novel and robust artificial systems.

2. Technology

Sensor Technology

The effectiveness of the landmine detection process depends fundamentally on the sensor technology used and the target mine. The most commonly used sensors are metal detectors, electromagnetic, acoustic and seismic methods, and biological sensors (Bruschini & Gros 1998; Habib 2002; Gooneratne et al. 2004). However, the current technology is still too limited to deal with the great variety of mines available, and usually is rather specific to a particular kind of explosives or mines.

Aiming at mimicking the best sensors known so far, here we propose the use of an artificial nose sensor sensitive to a wide range of volatile compounds in combination with the current understanding of the best studied chemical detection system, the male moth (Pyk et al. 2006; Bermúdez i Badia et al. 2007a). The artificial nose sensor consists of a 6 grid array of broadly tuned thin film metal oxide chemo-sensors (Alpha MOS SA, France). The sensitivity of each of the individual sensors is controlled by variations in their dopants and semiconductor materials (Nanto & Stetter 2003; Pyk et al. 2006). These variations render variable binding properties of each sensor to chemical compounds and, hence, differential sensing capabilities. The interaction of the surface of each of the sensors with the odor molecules provokes a change in the bulk resistance of the semiconductor material, and this is then converted to voltage and measured (Nanto & Stetter 2003). To allow the release of bound compounds, the temperature of the surface of the sensor is regulated by an external circuit. Given that the compounds the sensor needs to detect are presented in the real-world in complex plume-like dynamics it is essential to also understand the dynamics of the sensor. We measured the time constants of the artificial nose sensor and showed a rise time of 2.0±0.77 s (mean±std, n=5) and a decay time of 3.1±0.84 s (mean±std, n=9) (Pyk et al. 2006). The low power consumption (of approx. 270 mW) and the lightweight and relatively high degree of miniaturization (2 x 3 x 0.38 mm) make it a suitable sensor for real-time use on an Unmanned Aerial Vehicle (UVA).

The different robotic platforms used in this project are equipped with lightweight and high-resolution cameras (628 [H] x 582 [V] pixels) ("Module 3", Conrad Electronics, Germany) fitted with wide-angle lenses (2.5 mm lenses, Conrad Electronics, Switzerland).

Subsequently, the obtained video stream from the cameras is broadcasted via compact PAL transmitters (SDX-21LP video transmitters on the 2.4 GHz band, produced by RF-Video, Canada). The robots use Lithium-Polymer rechargeable batteries (KOK 3270, Kokam, Kyunggi-do, Korea, www.kokam.com) that provide up to 5 times higher energy per unit of mass than regular Nickel Cadmium rechargeable batteries. On the ground station side, the camera images are received and processed by the neural simulator **iqr** (http://iqr.sourceforge.net/) (Bernardet et al. 2002). **iqr** is a software for the graphical design and control of large-scale neuronal models, and their interfacing to real-world devices in real-time. Our large-scale insect based neural models communicate with the robots via a wireless radio link in the case of the indoor blimp (BIM433-F transceivers, Wireless World AG, Switzerland), and Bluetooth in the case of the mobile moth robot.

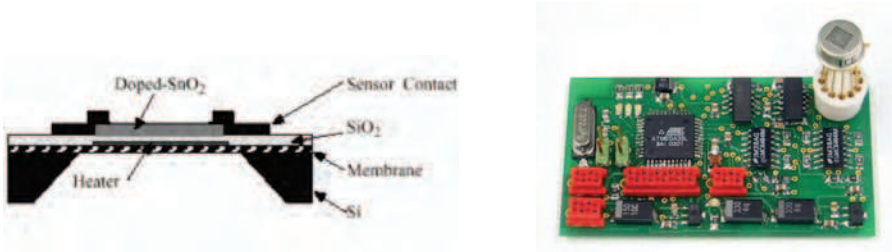

Fig. 1. The artificial nose sensor system. Left panel: schematic of each of the sensors of the 6 grid array including its main components. The size of a sensor is 0.18 x 0.2 mm (with x length), with an active area of 0.032 mm^2. Right panel: the full chemo-sensor package and its readout PCB. The sampling frequency of the PCB is 16.3 Hz, its dimensions 60 mm x 35 mm, and its weight 13.8 g. Adapted from Pyk et al. (2006)

The Robotic Platforms

Humanitarian demining clearly deviates from military demining in its objectives and approach. For humanitarian demining it is essential to locate and clean up every single mine in post-conflict areas for the recovery of the population. Seeking the highest accuracy and safety standards, many autonomous or remote controlled demining robots have been developed (Nicoud & Habib 1995; Nonami et al. 2000; Gonzalez de Santos et al. 2002; Marques et al. 2002; Santana & Barata 2005). Ideally, a robotic platform suitable to work in human non-accessible or unspecified environments with the highest degree of user safety is desired. Therefore, we propose the use of Unmanned Aerial Vehicle (UAV) technology since it provides a terrain independent solution and it is unable to detonate mines during inspection. In particular, the use of a blimp-based UAVs offers us a cheaper, more stable and easier to control solution than fixed-wing or helicopter like platforms. In addition, we need to consider that the sensing platform itself should not disturb the plume structure when it wants to localize the source.

We have developed a number of robots to approach the chemical localization problem from different angles. First, we constructed a blimp-based robot designed to work within indoor environments to study course control systems based on the understanding of the neuronal principles of insect visual navigation (Fig 2, left panel). This robot was constructed from a balsa wood structure, uses a lightweight Lithium-Polymer battery, and has independent control for altitude and translation (08GS - 8mm motors, API-Portescap, La Chaux-de-

Fonds, Switzerland, www.portescap.com) (see Bermúdez i Badia et al. (2007b) for further details).

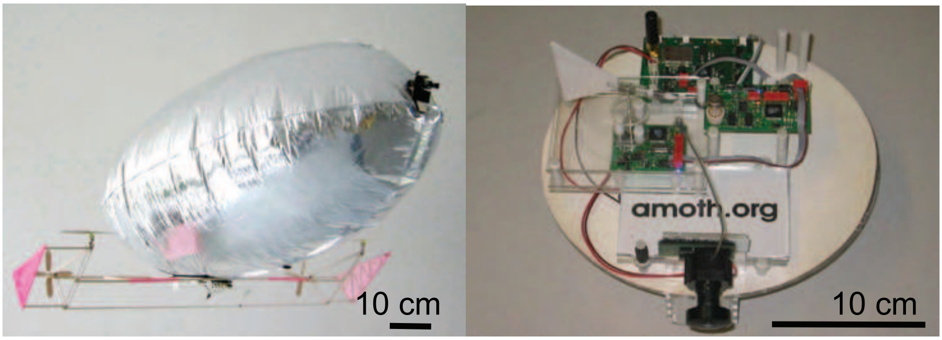

Fig. 2. The indoor artificial moth robots. Left panel: the blimp-based UAV consists of a 30 x 120 cm hull (radius x length) with a payload of about 250 g, a remote control board that provides with independent altitude and translation control, and 2 wide-angle wireless camera systems. Right panel: the ground chemosensory vehicle, of 20 cm diameter and 16 cm height, provided with, from top to bottom, a Bluetooth control board, a chemo-sensor, a wind direction sensor and a wireless camera equipped with a wide-angle lens. Right panel adapted from Pyk et al. (2006)

Subsequently, we developed a chemosensory ground vehicle as the first approach to study the odor mapping and localization problem in indoor and controlled environments (Fig 2, right panel). The robot is equipped with a chemo-sensor, a wind direction sensor and a wireless camera. The control board controls two motors, collects the sensory input from a chemo-sensor and a wind direction sensor and communicates with a ground station via a Bluetooth module. The wind direction detection sensor consists of a lightweight styrophore vane that is attached to a rotating shaft fitted with a small magnet. Then, a magnetometer is used to read out the orientation of the vane (MicroMag2, PNI Corporation, Santa Rosa, USA, www.pnicorp.com). All sensory boards are fitted with an ATmega32L microcontroller (ATmega32L, Atmel, San Jose, CA, USA, www.atmel.com) that makes local computations and interfaces the sensor with the robot infrastructure via a Two-Wire-Interface (TWI) bus. A Lithium-Polymer battery provides the robot with approximately 8 hours of autonomy.
To conclude, we constructed a blimp-based outdoor chemo-sensing UAV (cUAV) to perform field experiments (Fig. 3). One of the advantages of using a blimp-based cUAV is that it can carry additional sensors for conventional control, monitoring and analysis such as a GPS, accelerometers, altimeters, cameras, etc. In this case, the cUAV has a control board that interfaces a GPS, a 3D compass, 2 altimeters and a chemo-sensory board via a common TWI bus. The cUAV exchanges sensor readings and motor commands with a ground station via a 2.4GHz communication system (AC1524 transceiver, Aerocomm, Lenexa, USA). The total weight of the electronics is 90 g. 8 Lithium Polymer cells with a capacity of 13 Ah provide up to 2 hours of run time in moderate wind speeds. Based on the sensor readings, a control layer was developed to allow for unsupervised cUAV operation (see Bermúdez i Badia et al. (2007a) for further details).

Our custom developed cUAV consists of a PVC hull filled with helium (4.5m long, 1.2m diameter, 6m^3 volume) with an approximate payload of 3 kg. Four independent DC motors are fixed on a modular and scalable carbon fiber frame of about 3 kg (Fig. 3, right panel). Each of the propellers fixed to a DC motor generates a thrust of approximately 620G. The resulting mass/power ratio turns the cUAV into a more unstable platform than conventional blimps, while faster in dynamic responses. To solve the instability problem, the motor frame is constructed around the hull as opposed to be attached exclusively to its lower part as in the case of conventional blimps (Fig. 3). The arrangement of the motors is such that the forces are applied directly at the center of mass of the cUAV, hence reducing the oscillatory behaviors that result from fast flight maneuvers. The distance between the motors used for rotation is significantly increased, meaining that greater torque forces can be generated by the same thrust. Furthermore, fins of about 0.2 m^2 are used as a passive stabilization mechanism. As a result, our design of the motor frame renders the cUAV more stable and with better maneuverability than standard off the shelf solutions.

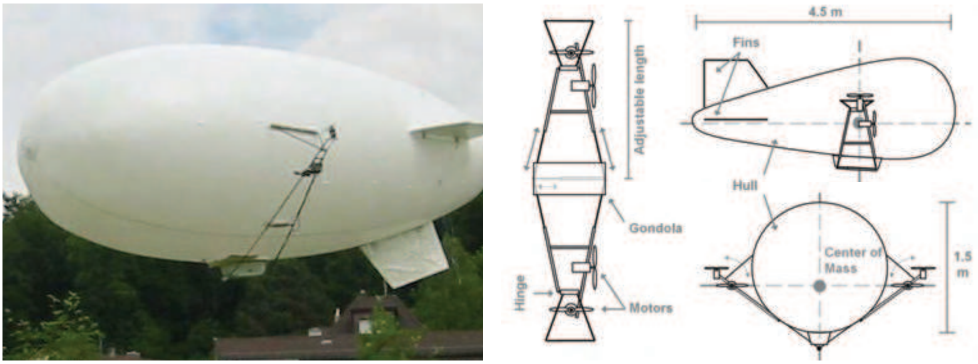

Fig. 3. The outdoor artificial moth robot. Left panel: the cUAV during autonomous flight. Right panel: scheme of the cUAV. It includes 2 pairs of motors, a carbon fibre frame that builds around the hull of the blimp, and a hinge and a variable length mechanism that makes it adjustable to different hull sizes. Adapted from Bermúdez i Badia et al. (2007a)

The Wind Tunnel and the Odor Delivery System

In order to investigate the responses of our sensor technology to different chemical stimuli and a number of moth based localization algorithms, we constructed a wind tunnel suitable for mobile robot experiments. The wind tunnel measures 3 x 4 x 0.54 m and was constructed out of wood and transparent plastic sheets. The front part of the wind tunnel was left open to let the air in. Four ventilators with adjustable wind speed were placed at the back to generate a negative pressure and create an air flow of about 0.7 m · s^{-1} from front to back, and to adjust for a uniform and symmetric velocity profile. Then, the air sucked out of the tunnel goes into an exhaust tunnel where it is removed.

As delivery system for the chemical substances we used an ultrasonic release system (Mist of Dreams, XrLight, Zhongshong City, China) that generates a rapidly evaporating mist at a rate of about 3.33 ml min^{-1}. The vaporizer was enclosed in a 40 x 30 cm chamber and the delivery from this chamber was controlled via an impeller (CGW/EDF-50, GrandWing Servo-tech C0, Ltd, Taiwan). Unless otherwise is specified, a solution of fixed concentration of ethanol and distilled water (20% ethanol) was used for all the chemical search experiments. The delivered rate of ethanol was approximately 0.8 ml · min^{-1}.

3. Insect Based Flight Control

In order to deal with the accessibility challenge faced in humanitarian demining we propose to use a flying platform. The first property of such a system is that it can autonomously maintain a specific course and compensate for perturbations. Insects localize odour sources by using multiple sensor modalities including: chemosensing, vision, anemotaxis and mechano-sensing. It is for this reason that this particular behavior observed in the moth is referred to as ***opto-motor anemotactic*** behavior (Kennedy & Marsh 1974). Hence, for the moth, vision is as important as olfaction since they cannot orient without visual cues (Kennedy & Marsh 1974; Charlton & Cardé. 1990). In a brain of about $1mm^3$, insects incorporate principles for visual navigation that are not only efficient in their implementation but also robust and reliable (Posey et al. 2001)**.** Generally in insects, about two thirds of their brain is dedicated to visual processing to support navigation (Strausfeld 1976)**.** Visual processing is mainly done by feed-forward neural structures dedicated to extract wide filed directional optic flow that is believed to be used for flight control (Hausen 1982a; Hausen 1982b; Egelhaaf & Borst 1993a; Krapp et al. 1998; Franz & Krapp 2000; Douglass & Strausfeld 2003; Higgins et al. 2004). In later processing stages, this information is integrated and used for landing, course and altitude control and collision avoidance (Rowel 1971; David 1982; Rind & Simmons 1992; Egelhaaf & Borst 1993b; Srinivasan et al. 1996; Srinivasan et al. 2000; Tammero & Dickinson 2002; Higgins et al. 2004).
In the particular case of the moth, it is believed that vision is used to assess the wind direction by computing the optic flow caused by drifts in position generated by the wind airflow (Ludlow 1982). Moreover, vision is also known to be used to control the flight speed and set it to a constant ground speed (Kennedy & Marsh 1974; Kennedy et al. 1978).
Here we look into the flight control question in relation to the computational and behavioral principles of the opto-motor system of the fly and locust. We choose these two preparations since they are the best studied species with respect to opto-motor behaviors. An important question is to what extend these insect based principles of visually guided 3 dimensional navigation can generalize to man made flying platforms (Srinivasan et al. 1999; Franceschini et al. 2007). From the technological point of view, the idea of using insect based task oriented models for flight control appears appealing because of their computational efficiency and flexibility. Consequently, we aim at providing a flight control infrastructure based only on biologically plausible and realistic neuronal models of the insect opto-motor system that can bring in the essential capabilities for the autonomous navigation of a flying robot.

Course and Altitude Control

The visual system of insects is commonly seen as a feed forward system with clearly defined functional and anatomical divisions (Strausfeld 1976). These divisions, known as neuropils, process the visual information at different levels, from a contrast enhancement to visual motion extraction (Fig. 4). Our synthetic insect visual system models the first three neuropils (Lamina, Medulla and the Lobula complex), and starts with the capture of visual information by means of a video camera, mimicking the photo transduction that takes place in the photoreceptors. The first process on the visual input is a compression of the luminance levels (Fig. 4a), followed by an edge enhancement (Fig. 4b). These 2 simple operations render the system more robust to changes in illumination (Dubs 1982). At the level of the Medulla we find the first visual motion sensitive neurons (Borst & Egelhaaf 1993; Douglass & Strausfeld 2003). Since the 60s, when Reichardt first proposed the, so called, correlation model, insects are believed to possess neurons that are capable to compute local directional motion, the Elementary Motion Detectors (EMD), and that they use this information for navigation purposes (Reichardt 1961) (Fig. 4c). Furthermore, at the level of the Lobula complex a number of wide field neurons have been identified in many species that provide motion information on horizontal and vertical displacement, as well as on rotations and collisions in the full visual field (Krapp et al. 1998; Gabbiani 2004). In the case of the fly, the neurons known as the Horizontal and Vertical System (HS and VS) can extract this information from the optic flow and have been suggested to be used for flight control (Egelhaaf & Borst 1993a; Franz & Krapp 2000; Tammero & Dickinson 2002).

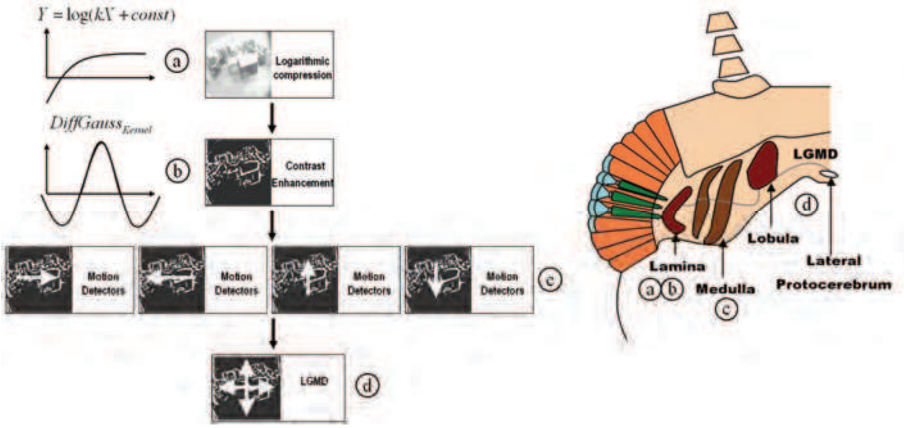

Fig. 4. The main functional and anatomical components of a prototypical insect visual system based on the locust. See text for further explanation. Adapted from Bermúdez i Badia et al. (2007b)

A course stabilization and altitude control system should make sure that the flying device follows a desired trajectory, and corrects for eventual drifts and altitude changes. Indeed we find that the HS and VS neurons of the fly exactly provide reliable information for the above mentioned functionalities (Krapp et al. 1998; Haag et al. 2004). These neurons have been widely modeled using the correlation model proposed by Reihardt to extract local directional motion information (Borst & Egelhaaf 1993; Egelhaaf & Borst 1993b; Franz & Krapp 2000; Haag et al. 2004; Bermúdez i Badia et al. 2005; Harrison 2005; Bermúdez i Badia et al. 2007b) (Fig. 5). Conceptually, the model performs a time delayed-spatial correlation to compute time dependent correlations on the normalized and enhanced input pixel values, and as such extracts local motion information (see Bermúdez i Badia et al. (2007b) for model details). Subsequently, all the correlations computed per pixel are summed to extract wide field motion information (Fig. 5). Therefore, depending on the two parameters that define the spatio-temporal correlation (δ and spatial shift), wide field neurons can be modeled to be sensitive to different kinds of optic flow such as the ones generated for horizontal and vertical displacements during flight (Fig. 5).

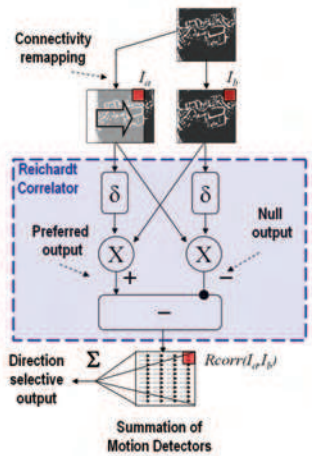

Fig. 5. The functional principles underlying a model of the Horizontal System neuron that extracts directional motion information from the optic flow based on the, so called, Reichardt correlator. In this particular case, the model is maximally sensitive to rightward motion (preferred direction). δ represents a delay, x the multiplication operation and – the subtraction operation. See text for further explanation. Adapted from Bermúdez i Badia et al. (2007b)

To detect rotations and altitude changes from the optic flow of the video stream broadcasted from the cameras of the indoor UAV, wide field HS and VS neurons are modelled. In order to map displacements detected by the HS and VS systems we used a P control system (proportional) that executed a motor command proportional to the responses of the HS and VS neurons, and in the opposite direction. The P system was chosen since it is the simplest solution and the one that makes the least assumptions on the computations that an insect brain could perform.

A blimp has a very prototypical and inconvenient dynamics caused by the added mass and Coriolis forces that prevent it from following a straight course. In order to evaluate the performance of our altitude and course control systems, we implemented them in the neural simulator **iqr** and we recorded synchronously the motor commands, UAV position and neuronal responses of our model. The effects caused by the added mass and Coriolis forces seem to disappear after applying our model to the UAV (Fig. 6, left panel). Several test flights were performed with the UAV to quantify the performance of the model. A maximum off-course deviation of 15° with respect to the perfect trajectory, with a mean deviation of 7.05°, was measured. During all these tests, a mean velocity of 0.62 $m \cdot s^{-1}$ was maintained. In addition, we used the same method to quantify the performance of the altitude control system to support a constant altitude. The examination of the responses of the UAV shows that the motor compensation forces of the altitude control system are tightly coupled to the variations of the altitude of the UAV (Fig. 6, right panel). Hence, we observe that the altitude control system is compensating the upwards and downwards displacements of the UAV with strong motor responses proportional to the vertical displacement detected by the neural model (Bermúdez i Badia et al. 2007b).

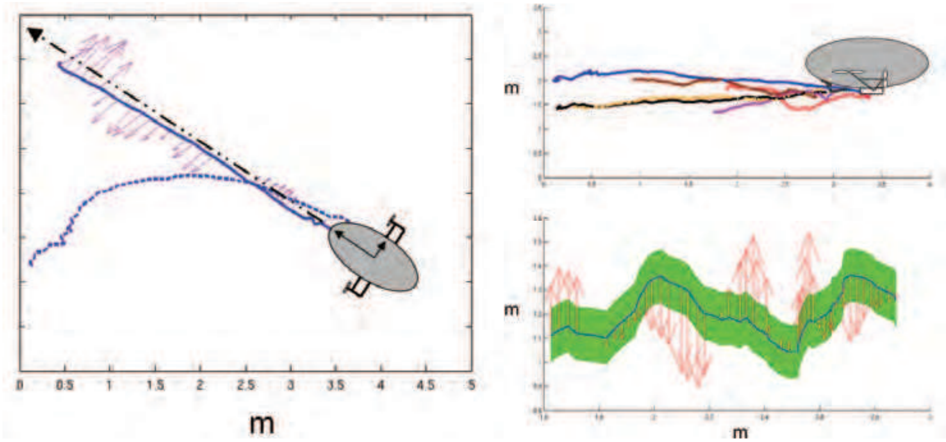

Fig. 6. UAV behaviour under the control of the proposed biologically based neuronal models for course stabilization. Left panel: top view comparison of a trace of the blimp-based UAV without the course control system (dashed line) and a trace of the UAV controlled by the neuronal models. Top right panel: side view of 6 UAV traces under the control of the altitude control system. Bottom right panel: side view showing the compensation motor forces (arrows) and the standard deviation (filled area) of an example trace. Adapted from Bermúdez i Badia et al. (2007b)

Collision Avoidance

A collision avoidance system is a must for any autonomous navigation system. Many sensors, from ultrasonic, infrared and laser sensors to vision have been applied to this purpose, although no general solution has been found (Fox et al. 1997; Surmann et al. 2003; Harrison 2005). The neural correlate of collision avoidance has been identified in many insect species, and due to its impressive performance and accessibility it has been subject of abundant research (Rowel 1971; Gabbiani 2002; Tammero & Dickinson 2002; Krapp & Gabbiani 2005). The best studied collision avoidance system in insects is the one of the Locust, known as the Lobula Giant Movement Detector (LGMD), which relies exclusively on vision. The LGMD has been shown to robustly signal collisions with objects independent of their size, texture, shape and approaching angle (Gabbiani et al. 1999; Gabbiani 2001; Gabbiani 2002; Gabbiani 2004).

Previous studies shave shown that a system that extracts visual expansion, i.e. looming sensitive, based on Reichardt's correlation can account for many aspects of the responses generated by the LGMD at the same time it is a suitable system for a robot implementation (Indiveri 1998; Blanchard et al. 2000; Bermúdez i Badia & Verschure 2004; Harrison 2005; Bermúdez i Badia et al. 2007b).

Relying on the same principles as the course and altitude control models, the local computation of motion, our LGMD model computes motion in a radial outward fashion (Fig. 7, left panel). This alignment of EMDs makes the system looming sensitive. Looming is greater when it is caused by faster approaching objects or by closer ones. Thus, the level of the looming signal is used to trigger collision detections as opposed to be used to estimate distance-to-contact or time-to-contact. All the neural responses of the specifically arranged EMDs are integrated by the excitatory pre-synaptic fan of the LGMD and inhibited by a global motion signal (Rowel 1971; O'Shea & Williams 1974; O'Shea & Rowell 1976) (Fig. 7, right panel). This connectivity converts the LGMD neuron into a looming sensitive system (excitatory pathway) with a normalization signal that regulates the looming sensitivity of the system with respect to the properties of the visual input (inhibitory pathway). The regulatory signal is crucial since more activity at the input level generates more spurious activity at the EMD level, which may lead to random correlations and therefore to more false positives. After the integration of the activity of the inhibitory and excitatory synaptic connections, a threshold operation is used to decide when the looming signal is high enough to be considered a collision (see Bermúdez i Badia et al. (2007b) for model details).

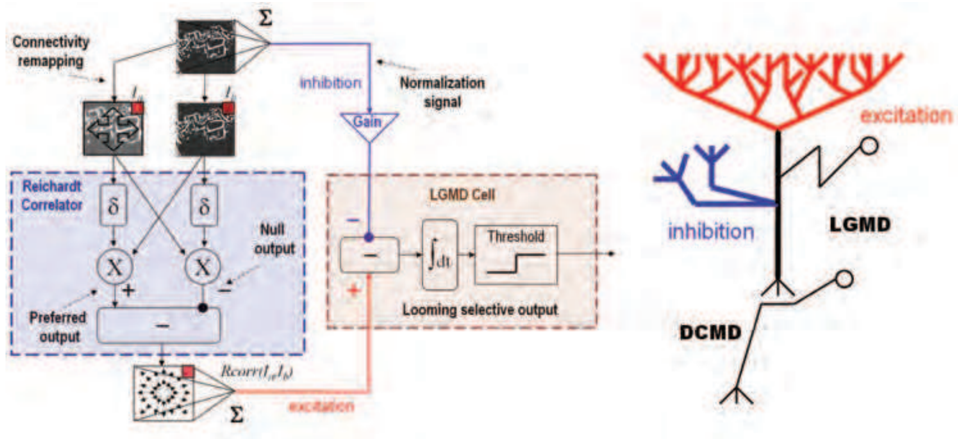

Fig. 7. The functional principles of our model of the Lobula Giant Movement Detector, that extracts expanding motion information from optic flow, and the morphology of its biological counterpart. δ represents a delay, x the multiplication operation and – the subtraction operation. See text for further explanation. Adapted from Bermúdez i Badia et al. (2007b)

To successfully avoid collisions, the UAV not only has to reliably detect approaching objects but also do it at a prudent distance. This is also critical for fast moving vehicles, vehicles with slow reaction times or when inertial forces play an important role. To test the performance of the proposed model of the LGMD, we implemented it in **iqr** and employed it to trigger avoidance manoeuvres on the indoor UAV whenever a collision was detected. The avoidance manoeuvre was triggered in the opposite direction of the collision detection, and with a rotation speed proportional to the amplitude of the looming measure provided by the model

The tests were run in an empty room (~ 5 x 4 m) equipped with curtains with random black filled squares to provide visual cues. An analysis of the system showed robust collision detection and a correlation between detection distance and translational speed where later responses were observed for high speeds, being in the worst case at a distance of about 1.75

m. In addition, the peak response always occurs before the collision takes place, largely independent of the approaching speed (Bermúdez i Badia et al. 2007b). This system allowed for successful autonomous navigation of the UAV with a minimal number of collisions (~ 90% correct detections) (Fig. 8). Most missed collisions occurred at very shallow angles where the cameras and their optics do not capture sufficient visual information.

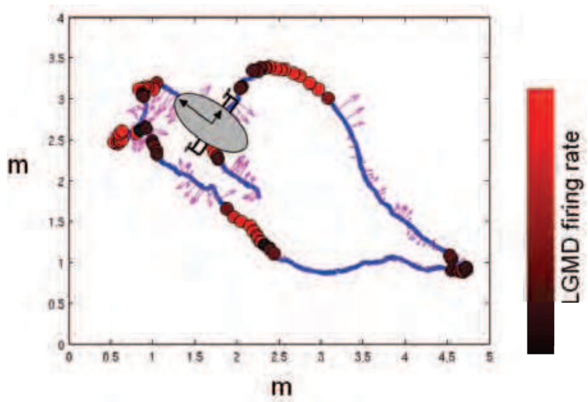

Fig. 8. Trace example for one minute of flight controlled by our LGMD neural model. The blue line represents the position of the UAV within the test area, the arrows represent the motor commands of the course stabilization model, and the filled dots indicate when a collision is detected. The intensity of the red colour is proportional to the amplitude of the model's response. Adapted from Bermúdez i Badia et al. (2007b)

4. Localization Strategies

Usually, the study of mine clearance is reduced to the investigation and development of sensor technology that can detect a number of mines. However, the ultimate sensor technology does not yet exist among the technologies of potential use to this problem. Moreover, demining does not only depend on the selection of the appropriate sensor technology but more aspects play a role. Often overlooked, the efficiency of the clearance process largely depends on the chosen localization strategy. This becomes more relevant when the mined areas are very large or unknown, or when clearance is urgently required. Thus, there is a need for an efficient explosive localization strategy that is not only able to locate possible explosive artifacts but that performs this task in an efficient way.

Our target model, the moth, has developed the appropriate sensor neural structures to be extremely sensitive in the detection of chemical signals (Kennedy & Marsh 1974). In addition, via evolution it has developed a behavioral strategy to optimize success rate when tracing a particular odor in a plume of complex dynamics and within complex odor blends (Kennedy et al. 1978; Baker & Kuenen 1982; Baker 1990). Therefore, the understanding of the origin of the high sensitivity of moths to pheromones is very valuable when studying optimal odor encoding and processing mechanisms, and developing a real-time mine localization robot. Hence, the objective is to learn the key elements from the neural substrate of the systems of the moth involved in the odor localization task, and to present the according biologically constrained models of our cUAV.

Mapping of an Area

The first and most straight forward approach for localization is to perform a mapping of the area to be examined. The objective of mapping an area is to generate a density plot in which sensor measures are associated to specific locations in space. There are many ways to generate such maps, by means of numerous static sensors located at specific points in space, by means of a dynamic scanning of the full area, a random search within the area, etc. The resulting maps contain information that, independent of the sensor technology used, can be used to derive the probability of having an explosive at specific x and y coordinates. Interestingly enough, this approach has been also used to locate explosives with bees. Bees trained to detect certain chemical compounds were released in a mined area, and then the measured density of bees $\cdot$ m^{-2} was used to estimate the position of the mines (Bromenshenk et al. 2003).

Mapping using multiple sensors and parallel measures speeds up the process but it becomes unfeasible when the sensor technology is very expensive. Alternatively, the scanning of an area may lead to the best results but requiring a long time to explore the entire surface, becoming then impracticable for very large areas. A trade off would be to use a mapping strategy that maximizes the area coverage per unit of time. In particular, a random search strategy applied on larger areas explores initially a larger surface per unit of time but then it requires an infinite amount of time to explore the entire area. Thus, depending on the time and surface area constraints, a strategy has to be chosen to maximize coverage, i.e. probability of mine detection (Bermúdez i Badia et al. 2007a).

The mapping of known areas or environments can also be used as a way to characterize the sensitivity, reliability and dynamic responses of our sensor technology. This is a necessary step to assess the limitations of the sensor technology and therefore its applicability to a particular task, in this case the autonomous chemical search by means of a cUAV. The first question that arises is whether our metal thin oxide sensor technology can reliably measure a chemical plume and reconstruct it. In order to assess that, we constructed a 3 x 4 m wind tunnel in which we generated a chemical plume using an ultrasonic delivery system with a 9.4% solution of ethanol in distilled water and a wind speed of 0.7 m $\cdot$ s^{-1} (see section 2).

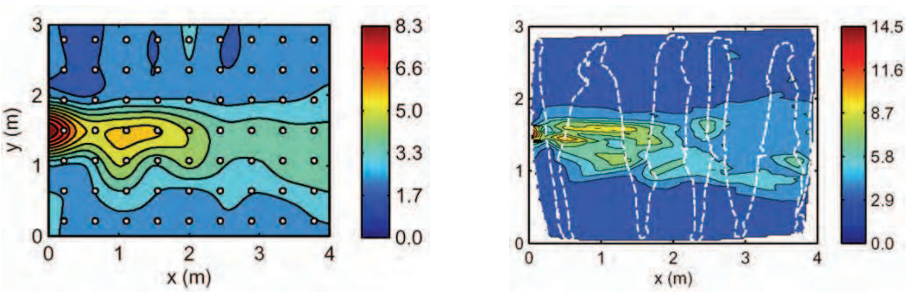

Fig. 9. Wind tunnel chemical mapping experiments by means of static (left panel) and dynamic (right panel) measurements of a chemical plume. Both maps are generated by the sensor responses to a 9.4% solution of ethanol in distilled water delivered at position (0 m, 1.5 m). The map was smoothened using a bi-cubic filter and divided

into 11 contours. The dots represent the sensor location, the trace the position of a remote controlled mobile robot, and the color bar the sensor response strength. Adapted from Pyk et al. (2006)

In order to investigate the effect of the sampling strategy on the accuracy of a chemical map we performed windtunnel experiments comparing static and dynamic smapling approaches. The chemical plume generated in the wind tunnel was sequentially measured during 2 min using a single sensor placed at 9 times 7 equally spaced locations which were interpolated to generate a map (Fig. 9, left panel). The resulting map shows that the static mapping of a controlled chemical plume can be done using our sensor technology, clearly displaying the ethanol distribution in the wind tunnel. Moreover, as a control experiment, the wind tunnel was remapped using the same procedure but this time with a distilled water plume, this demonstrated that the sensor was responding exclusively to the ethanol content of the plume (see for Pyk et al. (2006) further details).

However, it is not clear how time-averaged static measurements generalize to measurements performed by sensors in behaving artifacts. Therefore, we repeated the experiment using our mobile robot equipped with a thin metal oxide chemo-sensor. In this case, the robot was manually driven scanning the wind tunnel from back to front at a speed of 10 $cm \cdot s^{-1}$. Its position was tracked using a custom made visual tracking system called AnTS. The map generated using the dynamical measurements is consistent with the previous one, and shows that the chemo-sensor provides a rapid and reliable measurement of the ethanol concentration while the robot is moving. Hence, we can conclude that this technology seems suitable for an on board implementation in our cUAV that performs dynamic mapping (Fig. 9, right panel).

A Moth Behavior Based Localization Strategy

The problem of odor localization is considerably more complex than the one of mapping since the chemical cues are carried by filamentous plumes of a complicated structure and dynamics that are unpredictable and follow complex patterns (Murlis 1986). Localization, as opposed to mapping, can be less time consuming and does not necessarily require the exploration of the complete area.

In nature we can find a large amount of animals that solved the localization problem of odor cues as an effective way of chemical communication (Kennedy & Marsh 1974; Thorp & Ammerman 1978; Johnston 2003). Female moths release extremely low concentrations of sex attractant chemical signals (pheromones) that male moths are capable of tracing over large spatial scales (hundreds of meters). Therefore, the understanding of the mechanisms underlying moth chemical communication would allow human made robots to reproduce their accuracy, sensitivity and strategies adapted to a number of applications such us fire detection, environmental monitoring, demining, etc.

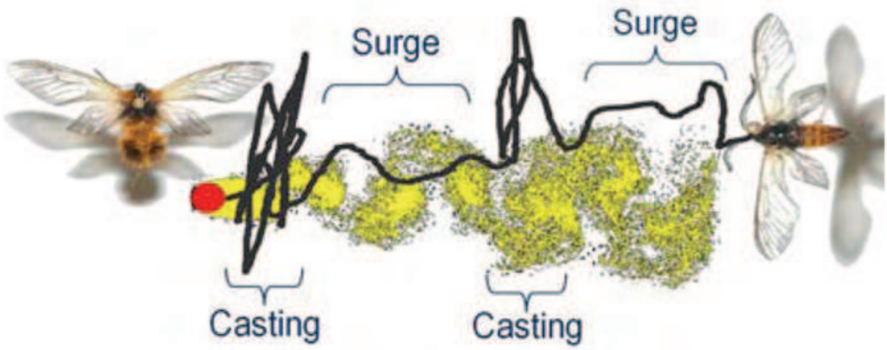

Fig. 10. An actual moth trace (black line) following upwind a pheromone plume (in yellow) released by a female moth (left). The male moth displays two stereo-typical behaviors, surge up-wind and casting cross wind. The red dot represents the location of the release point

The remarkable performance of the male moth in the chemical location task has been largely attributed to the alternation of two behaviors that help it to sample the pheromone plume. The surge behavior consists of a relatively straight upwind flight believed to be triggered by the contact with a pheromone filament. Instead, the casting behavior is a zigzagging crosswind movement triggered in this case by the absence of pheromone contact (Kennedy et al. 1978; Kennedy 1983; Baker 1990; Olberg 1993; Balkovsky & Shraiman 2002).
Based on the moth chemical search behavior, many models have been proposed and tested in both simulations and robot experiments (Kennedy et al. 1978; Kennedy 1983; Baker 1990; Olberg 1993; Balkovsky & Shraiman 2002). We have proposed a model augmented with the previously introduced opto-motor course stabilization and the collision avoidance system based on the LGMD neuron of the locust. This model of the opto-motor anemotactic behavior of the moth is based on the surge and casting behavioral modes observed in the moth, and the switches between them are triggered by the contact with the targeted chemical compound. Additionally, the LGMD collision avoidance system overwrites any of those behaviors triggering an avoidance maneuver whenever an imminent collision is detected (Fig. 11). As a result, the model requires of a chemo-sensor, wind direction information for the upwind and crosswind flight (anemometer), and a partial insect visual system to detect collisions (wireless camera system). All these sensor systems are integrated in our mobile platform (Fig. 2, right panel), and a biologically plausible neural implementation of the opto-motor and chemical search model, consisting of 7082 neurons, aggregated in 97 groups, and 180 connections with 11887 synapses, is simulated in real-time using iqr (see Pyk et al. (2006) for further details).

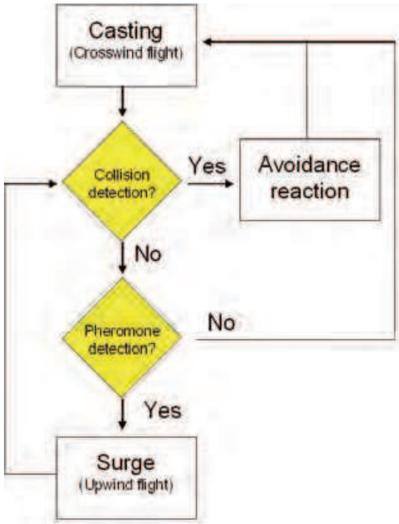

Fig. 11. Block diagram of the moth opto-motor anemotactic behavior model augmented with a collision avoidance system. Adapted from Pyk et al. (2006)

The previous mapping experiments described earlier demonstrated that the chemo-sensor technology proposed provides a functional signal for the detection of ethanol. Further, the wind vane sensor provides the wind direction to the chemical search model. We tested the performance of the proposed moth behavioral model in our wind tunnel in two test and two control conditions. 37 trials were performed and for each trial the robot was placed around 3.5 m downwind from the source on an arbitrary y-coordinate.

Firstly, the model was tested without the collision avoidance system to evaluate the performance of the chemo-sensing mobile robot for an ethanol plume. Two chemical concentrations were tested (17 trials on 9.4% and 20 trials on 23.5%) of water ethanol solution. In all the cases the robot was able to locate the ethanol delivery point, and it required of a median time of 74.2 s (Fig. 12, top left panel) (see table 1 for details). The search times did not differ significantly between the two conditions (Wilcoxon rank sum test for equal medians), being the performance not dependent on the chemical concentration. We observed that the casting mode can be distinguished from the surge mode without difficulty because of the zigzag pattern, lower sensor readings and smaller upwind displacement (Fig. 12, top left panel).

Ethanol source	Mode	Median [s]	Percentile 10% [s]	Percentile 90% [s]
9.4%, n=17	Casting	39.90	28.37	45.72
	Surge	33.10	17.91	103.66
	Total	74.97	62.35	121.89
23.5%, n=20	Casting	32.32	16.42	61.73
	Surge	31.88	14.23	136.53
	Total	67.83	45.50	174.37

Table 1. Performance analysis of the chemical search neural model. Median, 10% percentile and 90% percentile total search time for the two plume conditions

Secondly, the experiment was repeated with an obstacle and the collision avoidance system enabled. The robot behavior demonstrated a successful integration of the moth anemotactic chemical search model with the insect based collision avoidance model, being capable of finding the odor source even in the presence of objects obstructing the direct path (Fig. 12, top right panel).
Finally, two control experiments were performed in the absence of a chemical plume and in the absence of wind flow (Fig. 12, bottom). In the first case, the robot was unable to detect the ethanol plume and therefore displayed exclusively the casting behavior (Fig. 12, bottom right panel). In the second case, the robot not only could not detect the chemical trail but it was unable to measure the wind direction, and thus unable to find the source direction. This resulted in an erratic behavior without a clear movement direction or target direction (Fig. 12, bottom left panel). This demonstrates that both airflow and chemical stimuli are required for the robot to complete the localization behavior.

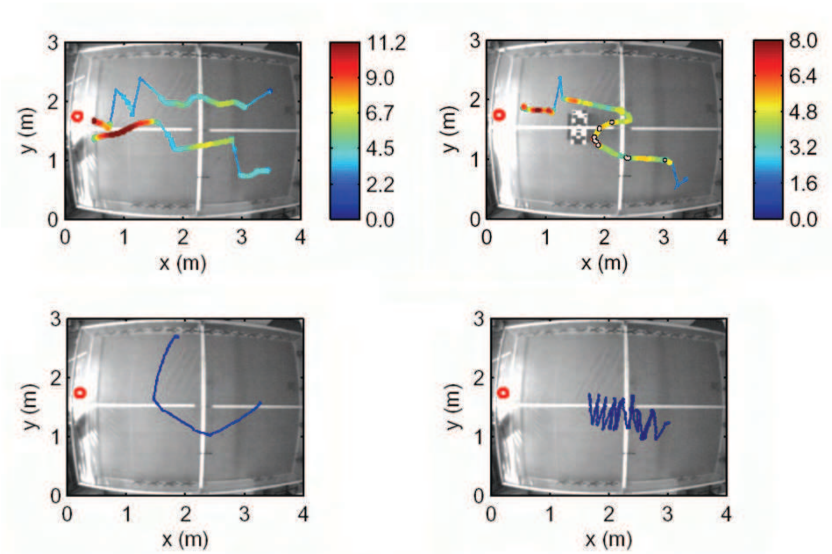

Fig. 12. Prototypical robot trials for the chemical search experiments using the moth behavior based localization model. Top left panel: two trials of the chemical search model with the collision avoidance system disabled. Top right panel: example trial of the chemical search model augmented with the collision avoidance system in the presence of obstacles. Bottom left panel: example trial of the chemical search model in the absence of airflow. Bottom right panel: example trial of the chemical search model in presence of airflow and absence of chemical plume. The thick robot trace indicates surge mode whereas the thin one indicates casting mode. The color of the trace represents the amplitude of the sensor readings of the robot in that particular position. The white dots indicate collision detection and the red dot indicates the position of the ethanol delivery system. Adapted from Pyk et al. (2006)

Consequently, the moth based search behavior model seems to be a comparatively faster odor localization strategy than mapping. Moreover, its success rate demonstrates not only the reliability of this model to successfully localize the odor source under turbulent conditions, but also the matching between chemical plume dynamics and sensor readings, and its integration and enhancement with the LGMD collision avoidance model.

A moth Neural Based Localization Strategy

It has been very difficult to assess more detailed aspects of moth chemotaxis directly because of the impossibility of visualizing a plume without interfering with the flight behavior of the moth. Hence, it is still not quantitatively established whether the moth responds to a chemical gradient, filament contact or uses a more complicated behavioral strategy. However, experiments have been performed where a male moth was equipped with a third antenna with a wireless transmission system to approximate what it would sense (Kuwana et al. 1999). Although the results of this approach were technologically interesting and challenging, it is insufficient for a proper characterization of the relationship between the stimuli the moth is exposed to and the behavior it displays since it does not directly measure from the real antennae.

As shown by our behavior based model, a simple strategy switching between upwind (surge) and crosswind flight (casting) can be very successful in solving the localization problem. Nevertheless, the moth developed some neural systems to deal with the specific characteristics of the structure of the pheromone plume that are not exploited in our behavior based strategy. For instance, it is known that the temporal structure of the stimulus is encoded in the responses of the nervous system of the insect, and that this structure is crucial to keep the moth flying upwind in the direction of the source of pheromone (Murlis & Jones 1981; Vickers & Baker 1994; Mafra-Neto 1995; Kuwana et al. 1999; Quero et al. 2001; Justus 2002). In this case, the frequency of the odour filaments has been shown to have a strong impact on the behavior of the moth, where the moth appears to be tuned to respond maximally to a specific detection frequency (Willis & Baker 1984; Vickers & Baker 1994; Vickers 1996).

The question arises whether a model based exclusively on phenomenological observations of the moth can fully account for its behavior without taking into account the neural substrate that regulates it. Hence, we aim at constraining our localization model with the current knowledge of the odor processing stages in the moth and identified neuronal mechanisms.

Our neural based model relies on two important hypotheses, the use of ***stereo information*** and the ***pheromone frequency dependency***. The first hypothesis is supported by the, so called, flip/flop neurons (Kanzaki et al. 1989)**.** These are, so called, Descending Neurons of the protocerebrum that arborize in the Lateral Accessory Lobe, and that show a bi-stable high and low frequency response. The activity of these, so called, flip/flop neurons is directly correlated with the body orientation and zigzagging of the moth while tracing a pheromone trail. Moreover, the orientation switches appear to be caused by the difference of pheromone concentration in the anteanne (Olberg 1993; Mishima & Kanzak 1998; Wada & Kanzaki 2005). Therefore, olfactory stereo information is used in our model to trigger the orientation changes whenever the sensor reading difference of two chemo-sensors is above threshold (Fig. 13).