Odor Recognition for Intelligent Systems

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Abstract

An electronic nose (e-nose) is an intelligent sensing device that uses an array of gas sensors of partial and overlapping selectivity along with a pattern recognition component to distinguish between both simple and complex odors. To date, e-noses have had a variety of use in a number of applications from the food industry to medical diagnosis. A next stage in the development of e-noses is the consideration of artificial olfaction into integrated systems, working together with other sensors on more complex platforms e.g. a mobile robotic system or an intelligent environment. This paper presents an overview of the more critical challenges in the integration of this important sense into intelligent systems. We also present a mobile robot called Pippi, that uses different sensing modalities (cameras, sonar, tactile and electronic nose sensors) and high-level processes (planner, symbolic reasoning) to achieve a number of olfactory related tasks.

Keywords: electronic noses, machine olfaction, mobile robots.

Introduction

The ability to artificially replicate the biological sense of smell has been a topic of interest to the sensor community for several decades. Devices called electronic noses or e-noses made their debut in the 1980's and using an array of gas sensors together with pattern recognition techniques, e-noses have been used to distinguish a variety of odors [15, 6, 14]. In more recent years, advances in electronics, sensors and computing have made the manufacturing of compact electronic nose devices possible, and particularly suitable for integration onto platforms such as mobile robots or intelligent appliances [4, 2, 1].

Currently works in the field of e-noses have mainly considered the devices on their own as singular stand alone odor analysists. Few exceptions exist where electronic noses have been combined with other chemical sensors such as

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electronic tongues for quality evaluation [19]. This is an important combination which attempts to bridge the gap between the human perceptual system and the electronic counterpart. Another emerging area relevant to our discussions is mobile olfaction. Research so far in this topic has mainly focused on the use of gas sensors in mobile robotics for the purpose of odor based navigation strategies. Examples of these platforms include (but are not limited to): trail following, plume tracking, and odor source localization [9, 17, 8]. In these works, often single sources whose chemical composition is known a priori are used. The actual electronic nose per se, that is the ability to discriminate and recognize the chemical components have been considered in only a few cases [16, 13]. Yet, the integration of a complex odor recognition component with today's and tomorrow's robotics and intelligent systems offer a growing number of potential applications. A robot with the ability to discriminate odors could be used in a production line, testing the quality of products. A space exploration robot could collect odor samples from distant worlds and describe its perceptions back to the humans on earth. A home care robot for the elderly could identify when the milk has gone bad, throw it away and take out the garbage when it is time. In a future context, with advanced technologies working side by side with humans at home and in the industry, the possibilities for artificial olfaction are endless. Although we are still several years away from realizing these scenarios, the groundwork is now in place to start investigating the fusion of e-noses into robotic and intelligent systems. Our objective is to advocate the use of e-noses for this domain and highlight a number of novel challenges as well as benefits that arise as a consequence. This is, of course, a long-term objective that needs to consider a diversity of systems and platforms. In this article, we consider a special type of system, a mobile robot, which we presuppose as having a number of specific properties and investigate the integration of e-noses onto that platform.

Already electronic olfaction on its own is a challenging task. Sampling of an odor can range from several seconds to several minutes generating a complex pattern of artificial olfactory signals. In addition, the behavior of the sensing mechanism is not entirely understood, and there is an inherent uncertainty in the human perceptual domain of odors which make the integration of an olfactory module for any type of platform non-trivial. Furthermore, if we are to consider e-noses into today's and tomorrow's intelligent systems, it is important to examine the ingredients currently present in such systems. Sensing modalities such as vision, sonar and infrared are often used to collect a number of different properties about the external world. Planning and reasoning components are used to determine the appropriate responses to execute. The system can also perform actions which can then change the state of the environment. Using an electronic nose in a system containing these properties requires much more than simply mounting a physical sensor. In order for the system to really embody electronic olfaction, each level of the system architecture needs to be considered.

We begin our discussions with a presentation of the electronic nose. We then consider how an electronic nose can be used together with a mobile robot to perform a number of olfactory tasks. We follow with an outline of the system

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limitations and remaining challenges relevant to integration. Finally, we conclude this paper with a discussion on the future outlook for this exciting and new sensor.

Electronic Noses

The general accepted definition for an electronic nose is the following,

> "An electronic nose is an instrument which comprises of an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system, capable of recognizing simple or complex odors." (Gardner, [5]).

The traditional architecture for the identification of odors is summarized in Figure 1. The basic principle is that each odor leaves a characteristic pattern or fingerprint of certain compounds. Based on this assumption, the process begins by collecting the signal responses from the each sensor, which occurs by converting the chemical reaction into an electrical signal. Many chemical sensors exhibit a response profile for several analytes. The degree of selectivity and the type of odors that can be detected largely depend on the choice and number of sensors in the sensor array.

The sensors are often mounted in an air tight chamber containing gas inlets and outlets to control the gas flow. The signals from each sensor are measured and processed, usually by a analog to digital conversion that is performed by a computer. After the signal processing, the data is transformed by a variety of pre-processing techniques designed to reduce the complexity of the multi-sensor response. From this point, pattern recognition can be applied to differentiate substances from one another or train a system to provide a classification based on a collection of known responses.

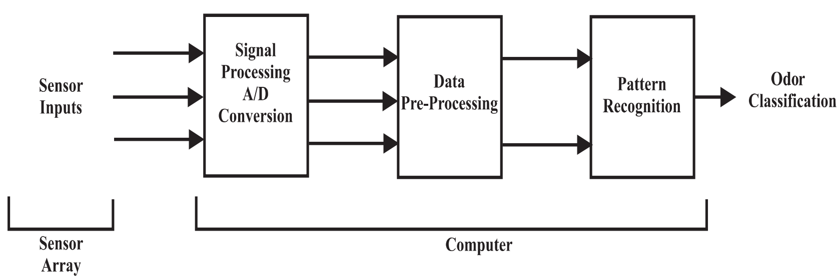

Figure 1: An Odor Classification System.

The term "electronic nose" is rather general and consequently can be misleading as far as its capabilities. In short, electronic noses are designed to mimic the human sense of smell by providing an analysis of individual chemicals or chemical mixtures. They offer an efficient way of analyzing and comparing

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odors. Electronic noses have yet to reach the capability of decomposing odors into their chemical components.

Today, a variety of sensing technology is available ranging from metal oxide gas sensors to optical sensors. An equal if not larger variety of data processing techniques have been used with electronic nose data such as artificial neural networks (ANN), principal component analysis (PCA) and fuzzy based techniques. The possibility to quickly and effectively analyze odors has given rise to a number of industrial and research applications such as the monitoring and control of industrial processes, medical diagnosis, and control of food quality.

Our Approach

The platform we have used for our investigations of integrating an electronic nose into an intelligent system is a mobile robot. Present within the system architecture are a number ingredients common to the intelligent systems such as heterogeneous sensing modalities, high-level reasoning, and learning. Additionally, we consider the inclusion of a human in the loop and a number of interfaces allowing the user to interact with the robot. The robot can run in two modes, either autonomously or tele-operated by a human. Our motivation for choosing a system with these ingredients is twofold. First, the system architecture is common thereby promoting the feasibility of integration without needing specifically tailored processes for olfaction. Second, certain ingredients within the architecture are necessary in order to effectively employ the electronic nose. This is due in part to a number of properties relating to the current technology of electronic nose devices and to the general properties of odor transport. Examples of such properties are the following:

- Sampling process of an odor is long and expensive. The sampling of a single odor can take up to 2 minutes. The length of this procedure depends primarily on the method of sampling where a baseline is normally collected in order to reduce the effects of drift as well as capture and provide as much information about an odor, so that the pattern recognition process can distinguish among a small collection of different substances.

- Localization of an odor source is a difficult problem with odor sensors. In systems with vision modalities, odor source candidates may be identified first using spatial information. Still however, there is a conceptual problem concerning the validity of associating a dispersed odor in the air to an object physically located at a distance from the actual point of detection. This problem becomes particularly difficult when multiple odor sources are present, see Figure 3.

- Resource consumption for the operation of an electronic nose is high. The delivery system often consists of pumps and valves which rely on independent power sources. The sensing arrays also require heating to high temperatures for correct operation. Particularly for mobile systems with

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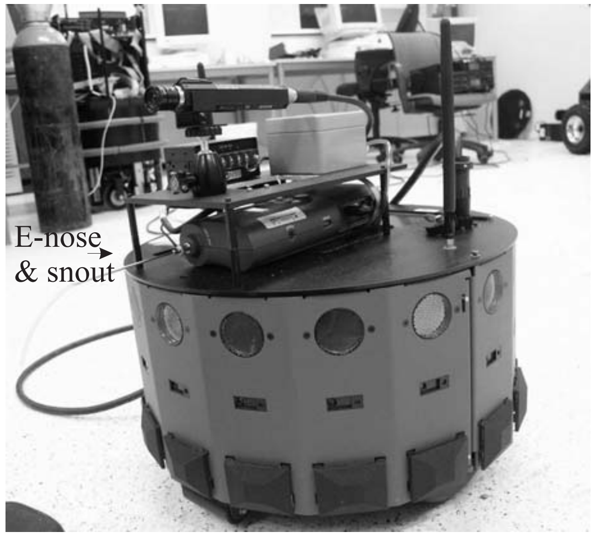

Figure 2: The robotic platform, Pippi, with an electronic nose, Cyranose 320.

limited battery, the sensing cost given the power requirements needs to be considered.

Our approach to odor sensing on the robot is to navigate to potential odor sources using extroceptive and proceptive sensors and when close to a source take an odor sample. The electronic nose is mounted directly under the camera on our robot. In this way, line of sight and line of smell are coordinated. In previous work, we have empirically verified that odors are best discriminated at a distance no further than 20 cm distance from the source (when no dominant airflow is present) [12].

Pippi - the Mobile Robot

Let us introduce Pippi, a Magellan Pro indoor mobile robot, whose name is inspired by the Swedish fictional character Pippi Longstocking, best described as unconventional and assertive (not unlike our robot). Pippi (the robot) is approximately 0.25 m high with a diameter of 0.4 m , see Figure 2. The motion of Pippi is driven by a 2-wheel drive with differential steering. The robot has a rear balancing caster and is equipped with a number of sensing modalities which include: Odometry sensors on the two wheel motors, 16 tactile sensors placed at the lower base of the robot, 16 sonar ranging sensors placed at the upper base of the robot, a fixed color CCD camera fixed at the top of the robot, 16 infrared (IR) proximity sensors and an electronic nose.

Pippi is equipped with an on-board computer with a 550Mhz Pentium III

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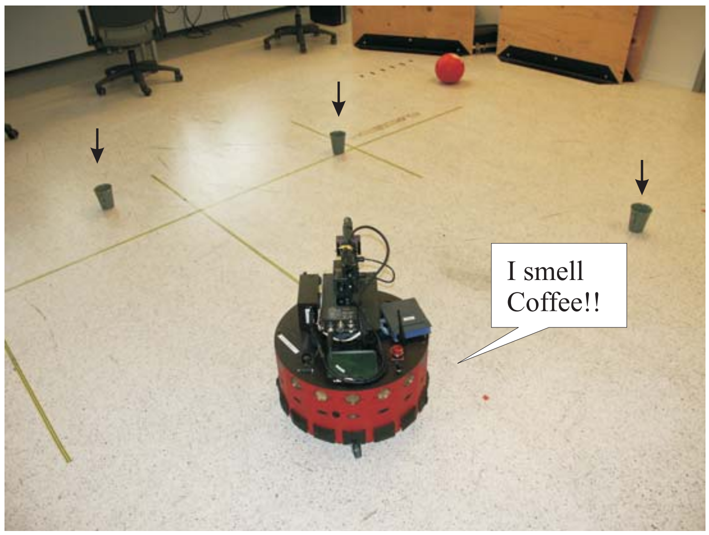

Figure 3: A situation where active sensing may be needed. Here the robot in the middle of the image detects an odor using the gas sensors but sees several candidate odor sources. Planning can be used to first approach each candidate and then actively engage a thorough odor sampling process in order to determine the character of each object and resolve the ambiguity.

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processor running Linux. On this computer a number of processes for low level control and perception is running, communicating with high level decision making processes through a TCP/IP protocol. Furthermore, the robot is equipped with a wireless network so that we can monitor the robot and run the high level functions from other computers. Many of the components on Pippi used for control and navigation rely on standard techniques for mobile robotics. Consequently, these components shall be outline in brief. Focus in this work is rather placed on the integration of the olfactory module with a standard robotic system.

For image processing, the captured images are pre-processed using standard filters and segmented using mean shift segmentation in the *Luv* color space [7]. After segmentation each segment is examined and pattern matched against the contours of a number of predefined objects. For each found object we extract a number of properties such as color, size and relative position using different heuristics. The system is designed to work for single colored, convex objects standing on the floor. Images are received once every second taking into account the total execution speed of the image processing when executed together with all other processes. The percepts from the vision processing are sent over TCP/IP to a perception process. This perception process is using the percepts in order to build a database of perceived objects, attempting to match percepts to earlier seen objects or creating new objects for completely new percepts. Together with some simple filtering this gives a representation of time persistent objects as opposed to percepts only valid for one frame.

In order to maintain and predict sensed objects currently outside the camera's viewpoint, an odometry based localization is used so that objects not currently perceived can be remembered. For limited movements, the system can easily reacquire objects based on their stored position. During navigation obstacles are avoided using visual information about objects' location, sonar and IR data.

The control and navigation system is organized in a three layer hierarchical structure and consists of sensing modules (odometry, sonar, and vision, etc.), a fuzzy behavior-based controller, and a navigation planner. The fuzzy behavior based controller proposed by [18] uses fuzzy logic to determine activation levels of different behaviors such as obstacle avoidance. The main behaviors used in our experiments are: "Go-Near" behavior, which approaches an object to obtain a good odor sample; "Avoid" which performs obstacle avoidance; "Orient" used to orient the robot towards a particular object or corridor: "Follow-Corridor" which uses the sonar readings to remain within in the corridor. The navigation planner is based on standard search techniques and decides what sequence of behaviors should be active to reach a specific target or goal. Plans are generated in the form of a set of "situation $\rightarrow$ behavior" rules. These are called B-plans and are used by the top-level plans to formulate actions.

A planner is used to autonomously decide which tasks to perform. The presence of the planner is especially important to co-ordinate smelling actions with other perceptual and navigation tasks. PTLplan is a planner for partially observable domains with uncertainty (probabilities) [10]. It searches in a space

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of epistemic states, or e-states for short, where an e-state represents the agent's incomplete and uncertain knowledge about the world at some point in time. An e-state can be considered to represent a set of hypotheses about the actual state of the world. Each sub-state in the e-state consists of a set of value-assignments to properties or state variables, where a property might represent for instance the shape or smell of a particular object: (shape b1 = cup), (smell b1 = ethanol). Sub-states are also associated with degrees of probability. The planner can reason about perceptive actions, such as looking at or smelling an object, and these actions have the effect that the agent makes observations that may help it to distinguish between the different hypotheses. Each different observation will result in a separate new and typically smaller e-state, and in each such e-state the agent will know more than before. It is also possible to represent sensor errors — observations need not always coincide with the actual state.

The planner we use is a forward-chaining planner, which basically adds one action at a time, introducing conditional branches whenever several observations are possible, and keeping the search space down by the use of strategic knowledge formulated as logical formulae. It searches for a plan with a probability of success above a given threshold, and returns such a plan as soon as it is found. Certain situations may arise where recovery planning may be necessary. This may require the robot to gather more information about the different perceived objects in order to resolve ambiguities or reacquire existing objects.

From this task, the planner can generate both top-level plans and recovery plans (if necessary). The plan executor receives the plans and performs the required actions, while monitoring their execution. Actions involving movement are sent to the navigational planner and controller.

Finally, an anchoring module is a novel component which functions to maintain the link between high level symbols and low level sensor data that refer to the same object. Since the planner used in our experiments generates plans in symbolic form, such as **(1 smell cup-87)**, an internal data structure is needed which maintains the link between the symbol (cup-87) and its perceptual signature (sensor data referring to relative position of the cup, shape, area, etc.).

An anchor, α_t, is created during the perceptual process, in other words, when the system detects an object of interest from the sensing modalities (vision or sonar). Existing anchors are either updated at each t perceptual cycle or by certain events such as after the odor sampling of an object. Each anchor contains several fields: a symbolic name (cup-87), a symbolic description (color:red,smell:ethanol) and a perceptual signature [3]. The perceptual signature and symbolic description are obtained from the respective sensing modules. In this way, the anchoring module not only functions to maintain the symbol-data link but also provides a means to maintain all the properties of an object in a singular structure - even when the properties are coming from different sensing modalities at different times. Each anchor that is added is also added to current world model so that the planner can reason about objects. Currently in this system interesting objects are pre-defined in the vision module.

In addition to the computations mentioned above for control, perception and

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autonomy, the system also has a number of processes for displaying the internal state of the robot as well as its current model of the external world. This model of the external world includes locally perceived objects and a gridmap of the environment built from sensor data, shown in Figure 6 and explained in the experiment.

Pippi's Olfactory Module

Pippi's olfactory module consists of a Cyranose 320 Electronic Nose, classification module and an electronic repository of odor signatures. Both the classification module and repository are adaptable and different pattern recognition algorithms can be used. The repository can also be tailored for application specific testing. For example, in cases where we might be interested in a quality evaluation of a particular substance, only the relevant training samples are loaded in the classification module.

The Cyranose 320 is a portable unit containing 32 conducting black-polymer sensors and the additional pumps and valves required to draw a sample to the sensing array. Sampling of a single odor occurs in three phases. A baseline phase samples a reference gas which is mounted on the physical robot (duration 30 seconds). A sampling phase draws an odor through Pippi's snout and exposes the sensors to the analyte (20 seconds) and finally a purging phase cleans the inlets of odor traces (30-50 seconds). Each sensor's reaction can be expressed in terms of the maximum resistance change caused by exposure of the odor in relation to the baseline. Both normalization and auto-scaling techniques are then applied to the sensor data for classification. An example of the real-time responses for all sensors is shown in Figure 4 where the e-nose is exposed to Ethanol and the resistance value R_t across each sensor is measured.

Many pattern recognition techniques have been applied to e-nose data when on static and singular platforms. A good review of such techniques can be found in [14]. Currently our classification module uses a combination of fuzzy clustering methods. More detail on the clustering algorithm can be found in [11], however to briefly summarize, the classification of each odor is given as a tuple: $< \mu, \mathcal{L} >$. $\mathcal{L}$ is a linguistic label that identifies the odor (such as ethanol, hexanal) and μ is a non-linguistic degree of membership to $\mathcal{L}$. The output of the olfactory module currently only outputs the class to which an odor has the highest degree of membership. The tuple is then stored in the anchoring module which is further described, where the $\mathcal{L}$ forms part of an object's description and μ may be later used by the planner to represent uncertainty. For example, if an unknown sample has low membership to any class or appears to be anomalous, the planner may execute another smelling action, and/or better position the robot before the next smelling action.

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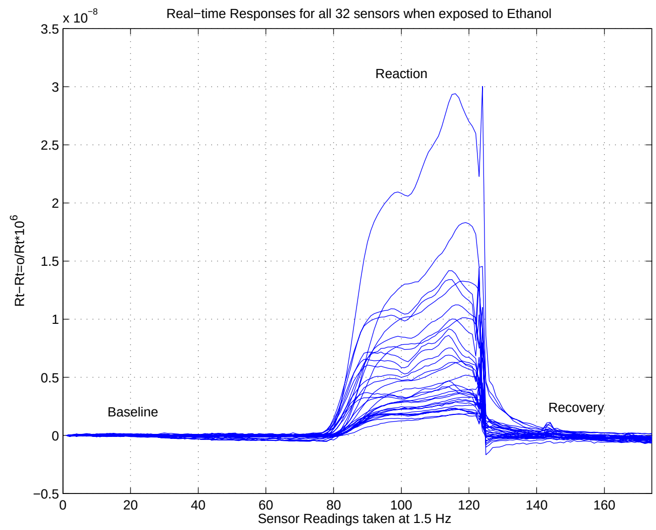

Figure 4: Real-time response from the 32 gas sensor array when exposed to Ethanol.

Demonstration of the Corridor Inspector

The corridor inspector provides a good experimental setup in which to test the many components of Pippi's architecture. The principle objective is to patrol the university corridor and monitor the odor quality of objects. A number of objects are placed outside office doors as shown in the center of Figure 5. The challenges that Pippi faces are to maintain a coherent perceptual notion of an object given that each object has a number of properties and that some of those properties may change over time. Pippi must also be able to service the requests of humans. Pippi can perform the requested task and then resume the patrolling of the corridor.

The user can request a number of different tasks to be performed during the experiment. A request may be made to acquire an object given a list of those object properties, for example, "Find Gar-1" where Gar-1 is defined to be a green garbage can that smells Hexanal (resinous). Here Pippi, will need to search its current knowledge to find a match, if no match is available or if its knowledge is out of date, a plan will be generated to visit any potential candidates. Visual properties are used first since the cost of smelling is higher, but in case of visual ambiguities the olfactory module will be used. Instead of giving Pippi a symbolic description of the target object, an artifact with similar odor of the target can be presented. Pippi samples the artifact storing its odor signature online, and then explores the corridor for an object with a matching odor.

The task to thoroughly inspect an object using smell can be requested. Here

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the planner uses the uncertainties from the odor classification module to reason about probabilities that an odor classification is erroneous. The robot will then take additional odor samples of the same object, but each time docking at the object from a different angle. In this way, an uneven odor distribution around the object due to air currents, or the shape of the object itself can be accounted for. This task is quite analogous to using active vision and planning to observe an object from different angles.

Finally, the user may take Pippi off autonomous mode and control the robot through a series of interfaces shown in Figure 6. Pippi can then resume the task of patrolling the corridor and inspecting objects when placed back in autonomous mode.

We have run the corridor inspector experiment over a 4 day period. When batteries were low, Pippi would inform the user and be guided to the charging station. During the evenings no experimental runs were made. A typical run through the corridor would first consist of an inspect behavior of moving to the end of the corridor and collecting the spatial properties of each object. These spatial properties were stored in the anchors. For each anchor, a plan to gather the olfactory property was made. After the gathering of the olfactory properties of all objects, another inspect of the corridor was done and the process was repeated. Depending on the number of objects present, the amount of movement done by the robot and the number of odor samples taken, the batteries would last an average of 2-4 hours before charging was required. A number of different odors were used: ammonia, ethanol, linalool and hexanal, also "ventilated air" used as a baseline can be considered as a fifth odor. These odors were placed (lightly spraying) on each of the objects located in the corridor. Over 70 odor samples were collected during testing. Throughout the autonomous inspection of the corridor, each of the specific tasks was requested, each task being initiated 20 times.

Results and System Limitations

The successful classification rate for each odor can be seen in Table 1. The classification results were obtained offline, after all the odor samples were collected, the data set was divided into a training and testing set. For the Ethanol, clean air, and ammonia, the classification results were acceptable giving a result of 81.3 percent, 85 percent and 100 percent respectively. The linalool and hexanal had a lower classification performance. Misclassified hexanal was classified as linalool and vice versa. This suggests an inability for the e-nose to discriminate between these two substances. This problem is most likely due to a sensing limitation. The possibility that the error is due to dynamic changes in the substance concentration is reduced by performing offline classification. In an offline context, the training set represents samples of odor throughout the entire experiment. In an online classification scenario, however, it would be necessary to take into account concentration decrease of a substance in the identification process. It may also be possible that a larger training set could help distinguish

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Table 1: Classification Performance

Odor	Classification Success on Pippi
Ethanol (C_2H_6O)	81.3%
Hexanal 98% ($C_6H_{12}O$)	62.5%
Linalool 98% ($C_{10}H_{18}O$)	65.0 %
Ammonia (H_3N)	100 %
Clean Air	85%

Table 2: Task Performance limitations

Task	Failure in Completing Task (%)
1 - Find object by smell artifact	20
2 - Find object by symbolic description	30
3 - Successful identification of an object after thorough inspection	25

the two substances of hexanal and linalool, however, another possibility would be to compensate the odor sensing unit with an appropriate sensor targeted towards either one of those odors.

Table 2, shows the limitation of the system to perform different tasks. The sources of error in the task evaluations stem from the sensing modalities, in some cases these errors are a result of visual and odometric errors in which the robot is incorrectly oriented (e-nose is not directed at the object) or it is too far from the odor source. Such visual errors occur when the object is not perceived during a patrol of the corridor, its corresponding anchor is not updated and the positional information is not updated. Other sources of errors in the task performance are due to olfactory errors alone that arise from misclassification of odors. An important aspect that addresses the limitations of the system is to examine which errors are attributed to olfactory errors and which are caused by vision in the evaluation of a task. We have considered this problem in a previous publication [12]. In this evaluation the more objects we attempt to discriminate the weaker performance is obtained from the e-nose. The visual errors on the other hand are more or less maintained at 20 percent. This could be explained by the fact that in an experiment with several objects more movement is required by the robot and thus increasing the chance of perceiving an object again and updating its anchor and position. In this way, we see that the anchoring module, besides being used as an internal container for different object properties is also beneficial for maintaining updated information of any one specific object property (e.g., location).

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Critical Challenges

The corridor inspector has showed that an existing robotic framework could be used together with an electronic nose in order to equip the robot with an olfactory perception. In our investigations, a number of critical challenges emerged whose solutions are non-trivial.

Training of the e-nose and identification of unknown odors. Currently, classification of an odor is done by collecting a set of training data. The training data can either be collected offline or online. The validity of the training data when testing new odors depends on a number of factors. These include temperature, humidity and time. The fact that the sensors are subject to drift is a current problem for the gas sensors. In some cases the effects of drift can be compensated by regular re-training of the data set. It could therefore be advantageous to automate the process collecting training data. For an intelligent system to effectively make use of an odor repository over a long term, re-training needs to be done at regular intervals and a mobile robot could assist in such tasks.

When, where and how to use e-nose in the context of a multi-sensing system. In odor classification, an odor's signature is stored based on its reaction to an analyte with respect to a reference gas. Each odor sample is a comparison from the sensors' baseline condition to the reaction to the gas. It is important that after sampling an analyte the sensors recover from exposure. Therefore, a determination of *when* and *where* the sensor should be activated needs to be made. Furthermore, since electronic noses take point measurements which means that the odor molecules need to come into contact with the sensing array for detection, the quality of an odor sample is dependent upon the position of the sensing unit at the time of sampling. Maintaining a consistence in sample quality is important both in the training stage and when new samples are being classified. Also when multiple sensing modalities are being used, properties corresponding to the same object may be collected at different times, for example, given a robot with the ability to see and smell it is possible that visual percepts related to objects will be obtained before olfactory percepts. This means, that specific calls to perceptual actions may be necessary to acquire more information about given objects. Furthermore, these calls should be done with caution as certain modalities such as the electronic nose may require additional demands on the power supply, as well as require time for sampling and data processing. The "cost" of using certain modalities may be higher than others. Considering this fact, when integrating an electronic nose with other modalities it is important to have processes in place which co-ordinate their activation. In this work we use a high level planner which combines domain knowledge and probabilistic reasoning to determine which sensing actions are appropriate and when they should be instantiated in context of a multi-step plan.

Maintaining coherent perceptual information Conceptually, objects cannot be localized using olfaction alone. This is because the point of detection of an odor will not always correspond to the location of the source (due to wind/air currents). Instead, to confirm the presence of an object, sensors which

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can provide structural information (vision, lasers, sonar) are needed. One challenge is how to combine the information from different sensing modules to form a coherent perception of an object.

Communication of olfactory data to a human user. The communication of olfactory data to a human user is a difficult task. Several factors complicate the communication of olfactory data. One factor is the fact that the sensor data from the electronic nose is multivariate and in many ways unintuitive. For example, to compare with vision, we can easily examine the stream of a video and understand what the camera is sensing but as seen in Figure 4, it is difficult to relate the sensor readings from a gas sensor to a particular odor character. A possibility is to develop scales or transformations for which to translate odors into a human perceptual domain. However, there are no generally accepted standards to odor classification upon which humans agree. Instead a description of an odor can be very subjective and depends on culture, past experience and linguistic factors. For humans the most useful tool to communicate olfactory perceptions has been language. Often the hedonic tone is used to better describe a character or the name of the source is used e.g. smells like banana.

The Future for Electronic Noses

The development that we expect is that artificial olfaction technologies will mature and be standard equipment on many systems, from field robots detecting hazardous gases to smart environments. It is important that this development focuses on all aspects of artificial olfaction, from navigation strategies in odor localization to classification and discrimination of odors on robotic platforms. In this work, we focused on the latter and showed how a multi-sensing robotic system could benefit from the integration of an electronic nose. We also addressed important issues relating to this integration in the particular context of a complete system with autonomous processes working over extended periods of time. Currently the mobile system we have developed uses crude methods for localization and object recognition. Our immediate future plans will be integrate better techniques and investigate performance improvement. It is also possible that in a future context, ambient environments will play a larger role and consequently will alleviate some of the major problems that mobile robotic systems face today. For example, a network of cameras can relay information to the robot as to its position. This is an exciting avenue particularly for olfactory robots where a network of simple gas sensors located at tactical locations could trigger an alarm and consequently dispatch a robot such as Pippi. Pippi who is equipped with a much more sensitive e-nose could then provide a thorough analysis of the object. This is not only a cost effective solution since the e-nose is typically a much more expensive device than a simple gas sensor, but also could increase classification performance. Today it is within our ability to tag objects and using a priori knowledge of which objects are being sampled, it is possible to constrain the training set in the classification algorithm. For example,

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if we know that we are sampling milk, we can then load into the classification algorithm different training samples of milk quality, thereby using context (see Figure 7). Instead of assuming an almighty olfactory robot, a sensing network together with the mobile robot can be used to provide a total olfactory impression of an environment. This type of intelligent system is another example which we are currently investigating in future works.

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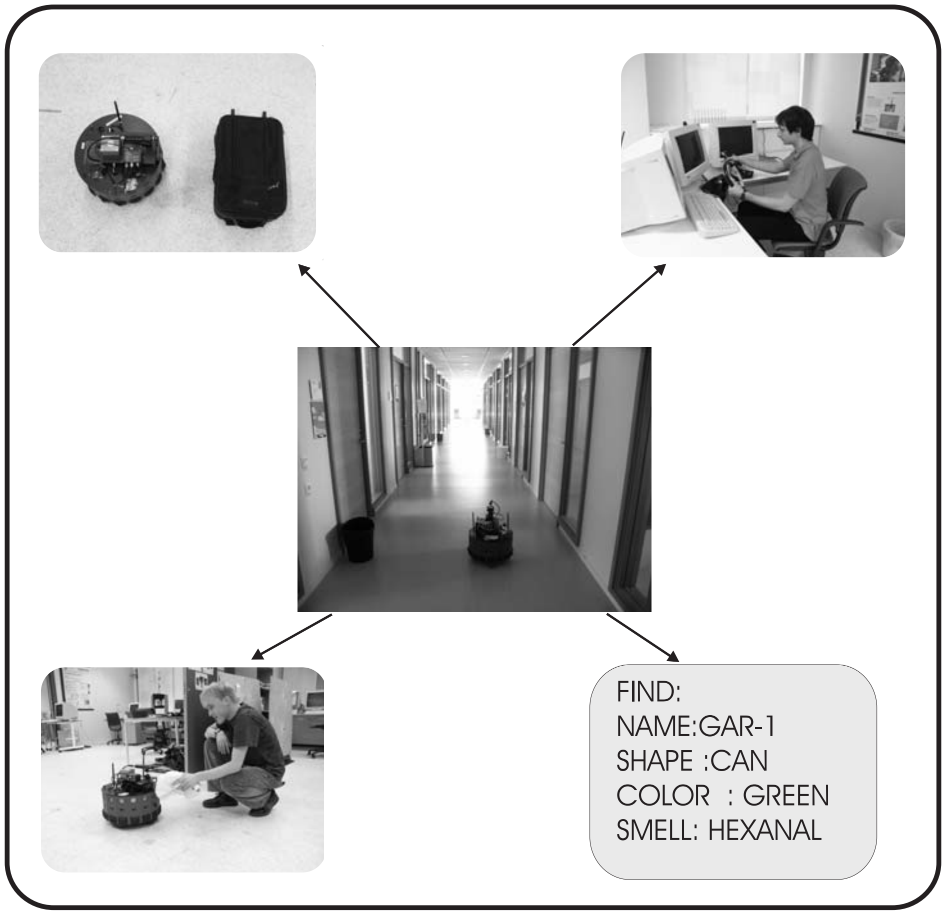

Figure 5: The corridor inspector in the center of the figure. Additional tasks can be performed when requested from the user. Upper left shows a thorough investigation of an object (suitcase). In the upper right image the user is tele-operating the robot. In the lower left image, the human and robot cooperate to find an object that matches the artifact presented by the human. In the lower right, a symbolic description of an object is given and the Pippi will attempt to find an object in the corridor matching the description

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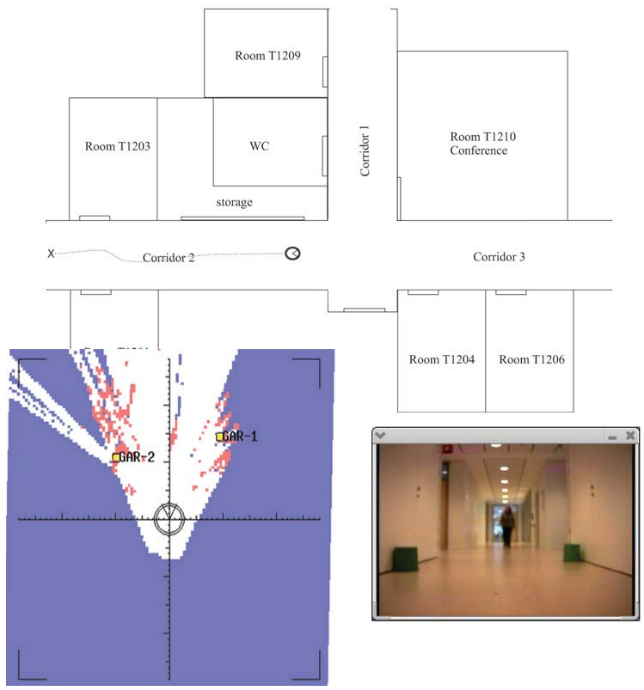

Figure 6: The interface of the robotic system, the upper image shows a rough map of the environment provided by the system. Lower left is the local perceptual space, shaded areas have yet to be explored, and recognized objects such as garbage cans are placed inside the space. The lower right image shows the live camera feed from the robot.

Figure 7: A future prospect for artificial olfaction for an intelligent environment. By tagging objects with RFID tags and using information about their properties a mobile robot with an e-nose can better constrain the classification context in order to improve performance. In this example, Pippi could be used to better inspect objects with the e-nose inside a refrigerator after a simple alarm has been generated.

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