Learning Odors for Social Robots: The URBANO Experience

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***Abstract*— This paper presents the experience of the Intelligence Control Group of UPM in the design of URBANO, a tour guide robot. It is a cognitive system based on distributed agents. One of these agents is an ontology that contains the knowledge used by the robot. This knowledge is mainly developed for linguistic applications. Here it is described how to add odor experiences to some available concepts in the ontology. Odor experiences evolve in time so the learning process must be adaptive and supervised. Neural networks, fuzzy logic, recursive least squares, Mahalanobis distance and genetic algorithms are tested over a low-cost multi-purpose electronic nose in the URBANO environment. The obtained results show how to add odors to the emotional model of the robot help it to increase its performance as a social robot.**

Keywords: Cognitive systems; Social robotics; Neural networks; Fuzzy logic; Genetic algorithms.

I. INTRODUCTION

Electronic noses are artificial olfactory systems whose operation is based on an array of chemical gas sensors with partially overlapping sensitivities. A series of electronic adjustments are made to the electrical values provided by the gas sensors in order to enable computer processing. At this stage, a pattern recognition technique is applied to the data so that the electronic nose will, eventually, be able to identify, classify and/or quantify odors.

Over the last two decades, electronic noses have increased significantly in importance due to the different applications in which they can be used: agribusiness, security, medicine and environmental pollution. During this period a great deal of research has been carried out, some of which is mentioned by Moreno [1].

Emotion importance in human intelligence has been underlined in latest decades. Neuroscientist studies show that people with their traditional logical reasoning intact but with their emotions disconnected make poor judgments, finding strong impairments in taking appropriate decisions [2]. An emotional balance benefits the problem resolution in a flexible and creative way. Evidences show that emotional skills are basic for adaptation and taking decisions. In other words, emotional control is an intelligence factor. Emotional Intelligence [3], is defined as an ability to perceive, assess and manage the emotions of one's self and of others.

In human communication, emotions take an important roll, emotion recognition and emotion expression are essential for a complete communication. That is in fact, what Affective Computing studies: giving to machines an ability to recognize, model and interpret human emotions [4].

The tour-guide robot URBANO emotional model [5] does not intend to be a biological model, not trying to reproduce human brain. The aim of this project is to develop the necessary tools to let the robot URBANO show an emotional behavior that can be understood and accepted by humans. In other words, to give autonomy to the robot so that it is able to take decisions and to show a social behavior that leads to a satisfactory human-robot interaction. Emotional abilities, in particular the ability to recognize and show emotions, are essential for the natural communication with humans, because of that an emotional model is developed.

This paper explains the experience of the Intelligent Control Research Group of UPM, in order to include an olfactory system in URBANO, a tour-guide robot that is described in Section II, and how to integrate olfactory stimuli in the behavior of the robot, explained in Section III. The e-nose prototype is a low-cost multi-purpose designed for this project, which is described in Section IV. Section V presents the experiments developed and the obtained results. It has been paid special attention to the learning process as is depicted in Section VI.

II. URBANO, AN INTERACTIVE TOUR-GUIDE ROBOT

This section describes the URBANO robot system, its hardware, software and the experience we have obtained through its development and use until its actual mature stage.

URBANO robot is a B21r platform from iRobot [6], equipped with a four wheeled synchrodrive locomotion system, a SICK LMS200 laser scanner mounted horizontally in the top used for navigation and SLAM, and a mechatronic face and two robotic arms used to express emotions as happiness, sadness, surprise or anger.

The robot is also equipped with two sonar rings and one infrared ring, which allows detecting obstacle at different heights that can be used for obstacle avoidance and safety.

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The platform has also two onboard PCs and one touch screen.

The software is structured in a SOAP architecture with specialize agents in different functions: speaking, listening, navigating through the environment, moving his arm, responding to stimuli that affect its feelings. Some agents perform cognitive tasks.

The schedule for URBANO is defined by a diary with tasks. The way of making those tasks, the time when they are done and, in general, the behavior of URBANO while completing them will be based in its emotional state by optimizing its happiness function.

Is intended that, the identification of certain odors act as another stimulus and affect to its decision making. For example, if the person that is interacting with URBANO smells to cigarette, then it can exhort to quit smoking. Also URBANO can identify a person by his perfume.

A new agent has been developed in order to manage the odor information that controls the electronic nose and the classification algorithms.

This new agent collaborates directly with other agents: Knowledge Server and Emotional Model.

The knowledge server consists of a Java application developed using the libraries of Protégé-OWL API [7]. The tool is capable of reading and editing files in ".owl" format where the knowledge is stored in the form of ontologies and the management of the information from the kernel is made by means of messages that codify the request of specific information, and the reply is obtained from the server or the introduction of new data.

The functions of the knowledge server are: loading and saving ontologies; creating, renaming, and deleting classes or instances; displaying properties of a class; showing subclasses or superclasses; showing or entering the value of a property; integrating one ontology into another; handling queries.

III. EMOTIONAL MODEL IN URBANO

In order to reach a nearer approximation to human emotional system, the proposed model makes use of dynamic variables to represent internal emotional state. The model follows the classic diagram showed in Fig. 1, being the system stimuli *u(k)* considered as inputs variables, emotions *x(k)* as state variables and task modifiers *y(k)* as output variables.

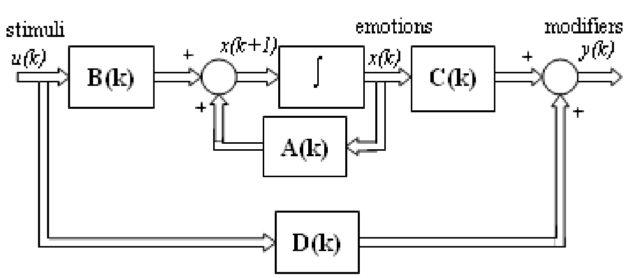

Figure 1. Emotional state model.

Following the classic state variable model, four matrices have to be defined.

A-matrix represents the model dynamic, the influence of each emotion over itself and over the other emotions. In other words, how the emotional state at the time *k* influences the emotional state of the next time *k+1*. Let us call the A-matrix *emotional dynamic matrix*.

Stimuli influence the system in a different way depending on its actual emotional state, i.e., the sensitivity information contained in the B-matrix. Let us call it *sensitivity matrix*.

C-matrix has the information of how emotional state influences modifiers. Let us call this matrix the *emotional behavior matrix*.

D-matrix contains the information of how the stimuli influence directly the task modifiers. Let us call the D-matrix *direct action matrix*. We usually consider it to be null, nevertheless its use would be analog to the rest of the state matrices.

Due to the difficulty of finding an analytic calculation for the matrices coefficients, a fuzzy rules set is used to obtain each coefficient. The matrices coefficients are function of time *k*, giving dynamics to the system. Because of that coefficients are calculated for each time *k*. To define fuzzy rules is a simple task; the information contained in the rules can be obtained from experts in emotions. The use of fuzzy knowledge bases opens the opportunity to a future automatic adjustment, e.g., genetic algorithms.

Model equations are analog to the equations used in multivariable systems and shown in (1) and (2).

$$\xi(\kappa+1) = \mathrm{A}(\kappa)\ \xi(\kappa) + \mathrm{B}(\kappa)\ \upsilon(\kappa) \tag{1}$$

$$\psi(\kappa+1) = \mathrm{X}(\kappa)\ \xi(\kappa+1) + \Delta(\kappa)\ \upsilon(\kappa) \tag{2}$$

The operation sequence follows the next steps:

1. <u>Read stimuli</u> *u(k)*. Stimulus is considered as an impulse: it appears and at the next time it disappears.
2. <u>Stimuli and emotions fuzzification</u>. Stimuli and emotions intensities are normalized in the range [0,100]. In order to transform these determinist values of stimuli and emotions into fuzzy values, following considerations has been done. Three linguistic terms have been considered: HIGH, NORMAL, and LOW. A triangle membership

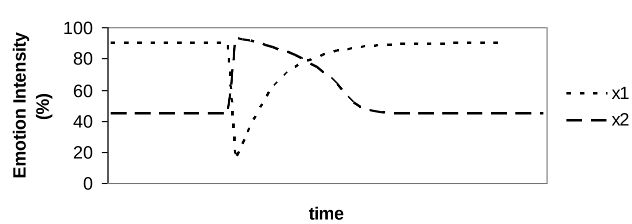

Figure 2. Time dynamics for different emotions.

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function with a uniform distribution, as shown in Fig. 4, has been used.

3. Fuzzy inference. Let us consider two stimuli {u_1, u_2}, two emotions {x_1, x_2} and the three linguistic labels named previously. In that case, A-matrix would be a 2x2 matrix, with the coefficients a_{11}, a_{12}, a_{21} and a_{22}. For each coefficient there is a fuzzy knowledge base that contains the fuzzy rules to apply depending on the emotion fuzzy values.
4. Defuzzification to obtain the state matrices coefficients. The method of gravity centre is used as defuzzification function simplifying the calculation by equidistant membership functions which do not overlap. After this step, the matrices A(k), B(k) and C(k) are known.
5. Calculation of next time emotional state and task modifiers, x($k+1$) and y($k+1$). Knowing the state matrices at time k, $u(k)$ and $x(k)$, value of emotions and task modifiers at next time are obtained applying equations (1) and (2).

Nor the higher emotions number neither the higher number of linguistics terms would increase the complexity of the model. It would work with the same efficiency but with a higher computational work.

Task modifiers are used in the development of the tasks. This "way of being" is valued by the public through a poll. If the results are not satisfactory it is necessary to correct the robot "way of being", i.e., fuzzy rule bases that determine the matrices A, B and C. The proposed model adjusts in the way described by means of a genetic algorithm. The algorithm makes use of the information collected of other tried behaviors. It changes the fuzzy rules looking for an optimization of a desired function.

Human do or try to do things that make them happy, for that reason happiness would be an appropriate function to be optimized. Happiness understood no as an emotion but as an abstraction that indicates the personal fulfillment of the subject. Happiness used to be considered associated to the fulfilling of some norms in the development of our vital activities. The norms or scale of values are not the same for all humans, it exists differences. Helping to others produce happiness but we used to help more to friend than to enemies.

In order to implement this capacity in URBANO, it is necessary to define a scale of values or *robotics laws*. Done a task, a mathematical function calculates the fulfillment degree of these norms and a happiness value.

IV. Electronic Nose Hardware

Most of electronic noses comprise three modules: chemical, electronic and software The chemical module prepares the sample and takes the measurement made by the sensors; the electronic module prepares the electrical signal obtained at the sensor output and extracts the traits and electrical characteristics given by each of the sensors of the array; the software performs the signal recognition and produces the corresponding visualization in the system.

Electronic nose design depends on the applications in which the nose is to be used. The electronic nose under discussion is intended for use, mainly, in agribusiness. This intended purpose meant that it would be appropriate to use a wide range of chemical odor sensors. Therefore, MOS technology chemical odor sensors from Figaro Inc. [8] were chosen, from the TGS series, with target gases as organic solvents, ammonia, air pollutants, etc. These sensors are used in common applications such as monitoring air quality, detection of toxic gases, etc.; they are inexpensive and readily commercially available. In addition to these sensors, four temperature sensors, a relative humidity sensor and an atmospheric pressure sensor were fitted to the electronic nose with the aim of observing the effects of changes in the aforementioned parameters on the measurements produced by the electronic nose.

The different components that have been chosen for the design and construction of the electronic nose, have been selected based on the type of chemical odor sensors chosen for the sensor array.

The electronic nose constructed contains three modules, and it is small, facilitating the integration on a mobile robot.

The chemical module of the electronic nose consists of one chamber were the sensors are located. It contains a simple acquisition system for sampling the volatile components of the sample, in comparison to other more complex systems [9], [10], which include air pumps, reaction tubes, purge and trap systems etc., or other systems that keep the sample chamber completely separate from the sensor chamber [11]. The sensor chamber and the sample are separated by a cover, that can be open, and a small ventilation unit that draws the odor sample gas molecules from the sample chamber into the sensor chamber. After the sensors are exposed to the odor samples, this chemical signal is transferred, as an analog signal, to the next module, in this case, the electronic module, where the signal is amplified, filtered and converted into digital values; these will be used in the final module, where an algorithm has been developed based on neural networks, which will classify the odor that has been detected by the electronic nose. When the sample has been taken the nose open a backdoor and active another ventilation for cleaning the chamber.

Each sensor has been mounted on a separate card so that it can be easily removed or changed by the user.

V. Experiments and Results

A series of experiments was performed in order to validate the design and the use of the electronic nose; all testing was done indoors.

A. *Tests to improve signal stabilization*

Since the signal from the sensors received by the computer shows a significant degree of oscillation, an adjustment to that signal by means of the computer program was proposed.

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The aim of the adjustments to the program is to filter the signal as far as possible, without losing relevant information, in order to later apply the pattern recognition algorithms. Therefore, the filtering of the signal obtained at the point of output of the electronic module was performed using different averages (10, 20, 30, 40 and 50) in the data. Ten data readings were taken, their average was calculated, a further reading was taken, and the average was re-calculated using the 10 most recent values, and so on. Using this technique means that the average value of the most recent 10, 20, 30, 40 or 50 values is always used, both for the display in graph form and for the application of the pattern recognition algorithms.

The average value that produced the best signal filtering was 50, and this is the average that was used to perform all the tests.

B. Tests on odor detection in semi-circles

Tests were carried out to determine the maximum distance at which the electronic nose is still capable of significantly detecting an odor. These distances were measured from the central point of the sample chamber and were arranged to form a semi-circle with different radii. The measurements used for the radii were 15, 20, 30, 40 and 50 cm.

In the first stage of this test, the sample chamber remained in its original location; in addition, two ammonia sensors were used, adjusted to different gains.

In the second phase of this test, the sample chamber was removed, thereby allowing the odor to disperse in the open air. The values measured by the sensors declined sharply as the distance of the odor source from the electronic nose was increased. Comparing the results of this phase with the previous phase, the measured values were lower than the corresponding values. It is interesting to note that, for radii very close to the electronic nose, whatever the position of the sample, the values measured by the sensors were equal or better than those obtained using the sample chamber.

The final results of this test demonstrated experimentally the need to use the sample chamber to carry out the odor measurements and that the best position for odor detection is locating the odor source in front of, or diagonal to, the electronic nose.

C. Test carried out to investigate the effect of temperature on electronic nose performance

In one of the tests performed for classification between red wine and white wine, data was obtained at a temperature of approximately 25ºC, and network training was initiated. However, when the tests were performed to verify the network learning, the values measured by the sensors were observed to be different from those obtained during the training phase. The possibility of achieving good classification was therefore minimal. The only condition that had altered with respect to the training phase was the ambient temperature, which had risen by three degrees Celsius.

This test demonstrated that changes in temperature affect the repeatability of the sensors. A change was therefore suggested in the computer program for odor classification.

D. Odor classification test

The aim of this test was to verify the effectiveness of the electronic nose at distinguishing between the odor given off by a glass of white wine and air molecules under normal conditions.

Before training the neural network, sensors were chosen that best reacted to the odor samples: three volatile organic compound sensors and one organic solvent vapor sensor. The selection of the sensors was based on the fact that the olfactory fingerprint obtained by a few sensors facilitates learning by the neural network. Subsequently, 50 measurements were taken in clean air, and 50 from white wine, and neural network training was performed.

The network was then verified with a further 200 samples, (100 air and 100 wine): with 100% of success. This same experiment was repeated using a glass of white wine and a glass of red wine. It was observed that using all the sensors complicated the network learning, and again, only the most representative sensors were chosen.

However, the problem that arose for this experiment is that the temperature affected the values measured by the sensors, resulting in different values being registered by the sensors during the training phase and at the verification phase. These drifts in response arise in the medium and long term.

Different algorithms have been used with different objectives. The Mahalanobis distance has given excellent results in the identification of the ripeness cherry states, green-mature-out. The use of back propagation neural networks and the recursive minimum squares allows an appropriate generalization in the classification. Because of the great influence of the temperature different categories it has been added for different temperatures which have significantly improved the identification.

E. Odor search test

The objective of this test was the validation of URBANOs capacity to locate the odor source. It starts by presenting the robot a sample of a particular odor, to then ask the robot to find a position in the workroom where the odor seems very similar to the sample.

Keep in main that the olfactory fingerprint will have an influenced distribution by the air movement in the workroom so keep a history of measurements may not provide any advantage.

Simply algorithms were proved were the robot measures in semicircles (-90, 0, 90 degrees) and advance in the direction where the samples mean square error is minimum. For the cases were local minimums are found it has been used the relaxation technique. To reduce the time to find the source location the algorithm has been modified so that progress, without checking the smell of 90 ° and -90 ° when the error decreases. This algorithm has been simulated in Matlab to verify its performance against abrupt changes of the fingerprint while the search. The results show that certain

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forms can significantly delay the location. The following figures show some examples of these simulations.

In the use of the algorithm on a real robot has shown that the time required to clean and stabilize the new measured value is high in the developed prototype, about a minute from one sample to another. If cleaning is not carried out the measurement quality decreases and the robot can pass through the vicinity of the source without finding a better error.

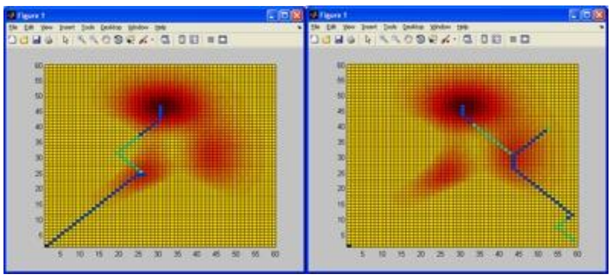

Figure 3. Matlab simulations of the odor search.

The algorithm described works and sources are located but must be combined improvements in design for easy cleaning and in the algorithm to try to estimate the best direction.

The photos below show the platform used for testing.

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Figure 4. Urbano and the electronic nose with mobile plataform.

F. Odor identification test

Important tasks for URBANO are the location of an odor and the position of the odor source. To achieve this goal it is necessary to define the concept of "odor experience".

An odor experience is the set of available sensor values that characterize an odor for a period of time as well as an identifier for that odor.

The robot URBANO, in a normal performance, gets periodically samples of odor.

This process starts with cleaning of the chamber by circulating a stream of air by opening the two lids and turning on both fans, then, it is closed the back cover and rear fan is turned off, so a new sample enters in the camera, after settling time the sensor values are read. If the sample is identified as "similar" to one of the registered it is associated with the corresponding identifier and URBANO informs that it has detected the smell, except that corresponds to the sample labeled "clean air" or what is the same "odor default".

If it has a refutation by the "user that interacts" informing it that the odor is different, it verifies it knows the identifier and it adjusts the algorithm including that sample in the appropriate category, if it is unknown creates a new category with the single sample.

To validate the identification process, it has been used two basic techniques: back propagation neural networks and minimum squares. The results have been good with a success rate above 94%.

VI. Learning Odors

As already stated the ultimate goal is to equip the robot URBANO with the capacity to learn odors and relate them to certain activities. This learning involves:

- Odor experiences
- Odor identifiers given by the supervisor
- Tasks to be associated to an odor identification

The supervisor is the system administrator.

It has been designed a new agent in the URBANOs architecture that performs the functions for measure odor, the identification and the proposal of appropriate tasks to that odor. In the following sections it is described with more detail this process.

A. Step 1: Identifying the odor

The process starts with de odor identification. After cleaning the camera and waiting to stabilize the sensor measures it is performed the average of 50 measurements. These values are used as inputs of the neural network that will result the similarity of the sample with other identified odors. The neural network provides outputs that can determine that a sample seems partially to various odors. Then it is "reacted" to that odor.

B. Step 2: Reaction to known odors

If the odor identified clearly (the response of the network is close to 1) belongs to the category of alarm it is activated the corresponding task, likewise the odor is introduced, as stimuli in the emotional model of the robot causing emotions of WORRY, FEAR.

If this is not an alarm is then introduced as a stimulus in the emotional model generates variations in the emotions and the behavior modifiers. For example, an unpleasant odor will produce and increment in the emotion value of DISGUST, which means that will mean that the task "TOUR GUIDE" will be performed in less time because the robot movement speed will increase and the modifier amount of information provided during the visit will be decremented.

For same odors will be activated tasks that, normally, involve an interruption to the task that is being performed for: greet the person to which it relates, to comment that is near a certain object or make a comment about the odor.

C. Step 3: Unkown odors

In this case, a task is activated that, by a dialogue with the supervisor, tries to get the information needed to incorporate the knowledge of the robot. If at that time there is no supervisor, the smell is stored as historical data.

In the performed demonstrator, as well as maintaining a question-answer dialogue is possible to complete a form by the supervisor, the voice recognition does not always work correctly.

The supplied information by the supervisor is:

- Odor ID.
- Category to which belongs. This will generate a default behavior for that type of odor. It can, also, assign a specific behavior relating a specific task for the smell or an additional task in addition to the standard category.
- The stimuli values when the odor is identified.
- If the category is new, it is necessary to propose the standard task, and if it were necessary to define a new one for the specific odor.

Considering that, during learning, the dependence of the robot's supervisor is very high, it has been proposed a class-based design that allows a very effective default behavior. The LEMON odor will belong to the class FRUITS, that inherit from PLEASANT_ODORS, so the identification of the ORANGE odor will only require by the supervisor to say that it belongs to the category FRUITS. Experimentally has been tested the feasibility of assigning an unknown odor without ID to an ODOR generic category, and has been given it a default behavior. The public appreciates the fact of recognizing the smell, but in general, requires identification.

The tasks performed by URBANO are defined in an own interpreted language, UPL. This language is C-Like and has features appropriate to the characteristics of URBANO, i.e.:

Say(“Hello”); Produce the synthesizing with the current voice of “Hello”.

SayDB(“Welcome”); Produce the synthesizing of a welcome message selected from the available database.

URBANO has, in its ontology, a hierarchical structure of tasks that can be performed; to facilitate the association of odors detected tasks has been created some basic tasks more, as: ESCAPE, ALARM_WARNING, GREETINGS, PLEASANT_ODOR_MSG, UNPLEASANT_ODOR_MSG, etc.

The genetic algorithm designed to optimize the performance of the emotional model, now lead the best use of possible tasks associated with a smell and how they are used, for it, only needs the public opinion. Since learning is based on the experience some performances of the robot may be inappropriate.

VII. CONCLUSIONS

This paper presents a successful experience in the use of an electronic nose on a service robot. On the path towards the final demonstrator it has been tried different classification algorithms on different elements (fruit, wine, etc.), likewise, it has been verified that it is possible to detect and locate the odor source for products or dangerous situations.

It is proposed a mechanism for identifying odors that fires robot activities. These tasks are related to security or they can help with the interaction with the public by identifying people, or simply noticing good or bad smells.

The incorporation of the ontology that relates linguistic concepts, which are used by the robot in their explanations, with certain smells greatly enriches the knowledge and facilitates public acceptance. The performed tests have shown a malfunction occurred as expected, with several categories of odors that are not detected by the 16 sensors selected. For example, infusions, tea, coffee, were not detected by our system.

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