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Human Based Sensor Systems for Safety Assessment

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Abstract – *The paper's focus on the assumption that sensor system for personal use has optimal performance if coherent with the human perception system. Therefore, we provide arguments for this idea by demonstrating two examples. The first example is a personal taste sensor for use in finding abnormal ingredients in food. The second application is a mobile sniffing system, coherent with the behavior of a biological system when detecting unwanted material in hidden structures, e.g. explosives in a traveling bag.*

Keywords – *Electronic nose, Electronic tongue, Human perception systems, Human based sensors*

I. INTRODUCTION

In this article a sensor approach to safety assessment and indication is presented and demonstrated in real world applications. It is based on the approach to find the coherent advantages similar to human perception since the safety aspects are very often related to the identification of hazardous situations. The human perception system has a remarkable ability to sense a dangerous situation by using sophisticated biological sensors (e.g. smell, taste, vision etc.) and merge this information with knowledge and earlier experience. Moreover, functional safety systems require that in the case of hazardous situations the result of the risk assessment is presented from a safe distance i.e., before getting in close contact with the human body. Therefore, a human-like ability to sense and indicate about hazardous situations is extremely well suited for safety assessment.

An important aspect in the design of any sensor based safety system is the response time and the ease of interpretation of the sensor response. If a danger is sensed, a warning must be issued as soon as possible. At the same time, humans (or other systems) should be able to easily interpret the warning so that the proper action can be taken. The interface should also consider that mainly non experts are interacting with the system. Therefore, a minimalistic yet effective output is favored over detailed information about the reasons for the warning.

In this paper, we propose an approach based on the sense of smell and taste as a contribution to human based safety assessment systems. The taste and smell detection has been identified to be very useful, especially in food safety assessment. In many cases significant deviation in food's taste, smell or appearance is a clear indication that the food is not safe to consume. Other areas of interest for this type of sensing systems are environment safety and detection of transportation of prohibited materials.

We begin our discussions with a general overview of the requirements in human based safety assessment systems. Two examples of such systems are then presented. In Section III.A a safety assessment system for food and water is demonstrated. The safety system is able to detect abnormal changes in the content of liquid substances e.g., baby food and drinking water. In Section III.B, an olfactory sensor system is used as human based sensor system for an intelligent sniffing system aimed for commercial detection of hazardous material in the transportation sector.

II. HUMAN BASED SENSORS

In this paper we focus on the goal to use artificial sensors to "extend" the human perception system. By extend, we mean to displace the point of sensing away from the human body. For example, instead of using our tongue to assess the quality of a food product, an electronic tongue placed in close proximity could provide an equal (or even better) evaluation. The consequence is a new generation of sensors built for individual local use that can provide fast and accurate warnings. In addition to large scale measurement systems used today for general protection and warning (e.g., tornado or earthquake monitoring), we also need individual monitoring (e.g., water quality evaluation at the tap). Figure 1 illustrates some simple examples of monitoring systems for safety assessment at both local and global levels.

An approach to the challenge to maintain individual safety and personal security can be to use artificial and biologically inspired sensors. Part of the motivation resides in their abil-

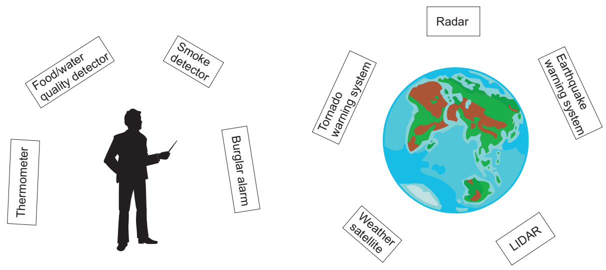

Fig. 1. Examples of sensors for *(Left)* individual warning and *(right)* global warning systems.

ity to provide non-destructive warnings. Another motivation resides in a growing ability for artificial sensing systems to exceed the human perceptual competence in accuracy and precision in detection. For example, the human perception system is not able to detect all chemicals or microorganisms in drinking water by taste alone and there is a benefit to an electronic system that can find abnormal or unsafe compounds before humans will drink it. Later in this paper, we present a system consisting of an electronic tongue that can detect both small changes in bacteriological content and chemicals.

The warning system must have an interface that is easy to understand for most humans. A simple example could be a warning system inspired by the traffic light concept. A green light corresponds to safe consumption and a red light indicates impurities of high concentration in the drinking water. The yellow light corresponds an ambiguity i.e. cannot guarantee safe consumption and further analysis may be needed. Representing the results as traffic light makes it easy for the user to understand the outcome of the safety system.

Certain situations are best detected by either local or global warning systems. A typical example of a local warning system is human based sensors, e.g., smoke detector, while for example an earthquake warning system is an example of a global warning system. A local warning system is more effective in applications when the scope is limited to a particular place or small group of people. Global systems has the problem of transmitting information to all people that might be in danger. In contrast to a local warning system that immediately warns the humans, information from a global warning system must be transmitted to the right place so that people in danger can receive the warning in time. This requires well developed infrastructure, otherwise the global warning system is considered to be useless.

Also information from the sensors may need to be sent to other systems (e.g. the control of a mobile robot). In which case, this information should be significant so that the proper actions are taken. Later in this paper, we shall present a mobile robotic sniffing system with an electronic nose whereby an uncertainty in an odour classification will affect the plans generated by the autonomous agent. The result could be calls to extra perceptual actions in order to improve reliability in gas identification.

Certain demands must be fulfilled for the system to be useful. The sensor system must among other things be small, fast and user-friendly. Both the electronic tongue and the electronic nose easily fulfil the first demand since they are small in size. Other requirements may be the online analysis of data, robustness (e.g. resistance to sensor drift), low computational and power requirements and ease of maintainance.

III. Two Examples of Human-Based Sensor Systems

In this section we present two examples of human based sensor systems used for safety assessment. Both examples use biologically inspired sensors, namely the electronic tongue and nose.

A. The electronic tongue system

The electronic tongue has a somewhat different perception than the human perception. While taste is often described as sour, sweet, bitter, etc, the presented electronic tongue normally provides a total estimation of the quality depending on the samples content. However, in real applications the quality evaluation of substances using taste employ more elaborate descriptions. For example, flavor is given by the taste, the texture, odor and even the consistency of a substance. Humans usually do not express flavor as “a little sweet” and “more sour”, rather we identify by experience a taste that correspond to a specific known food product. The electronic tongue can be seen as a simple but effective perception of specific taste as it reacts to the quality changes in a sample, i.e., the sensor is normally detecting differences in abnormal samples. The sensing principle used in most electronic tongues is based on electrochemical methods such as potentiometry [1], [2] and voltammetry [3]. There are also principles based on optical methods and impedance [4]. Some electronic tongues are developed to mimic the basic taste sensations experienced by humans [5].

The electronic tongue system used in our experiments is based on an electrochemical method called voltammetry and has previously been presented in [6]. The sensor is based on a two-electrodes configuration and consists of a stainless steel references electrode and two working electrodes made from wires of gold and platinum, seen in Figure 2. A potential is applied at the reference electrode and the arising current is measured.

The measured response is composed of two currents, the faradaic current and the charging current. The faradaic current reflects the redox activity that occurs when a potential is applied. The charging current is due to the electrical double layer that is established at the interface between the electrode surface and the solution. This layer will give the electrodes a

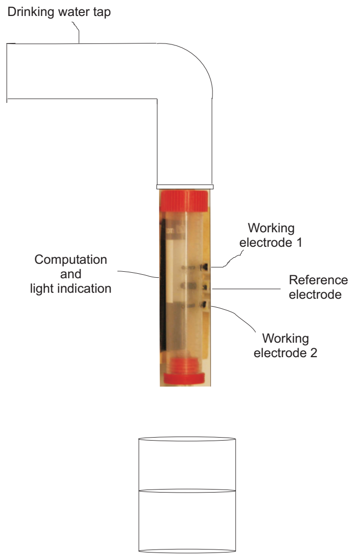

Fig. 2. An electronic tongue mounted on the water tap.

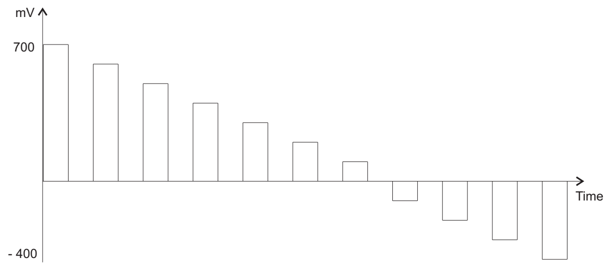

Fig. 3. The measurement cycle.

natural capacitance and when the applied voltage is changed, a current is required to adjust the electrode voltage.

The potentials can be applied in different waveforms. In these tests a method called normal pulse voltammetry is used, where pulses of varying amplitudes are applied following a predetermined measurement cycle as seen in Figure 3. All compounds that are electrochemically active below the applied potential will contribute to the redox response. By using pulses of different amplitudes the sensitivity is increased due to the shape of the response current. The charging current creates a peak when the pulse is applied and decreases fast while the faradaic current slowly decreased. Hence, the end of each pulse will hold the most information about the redox activity in the sample. The electronic tongue response is a large amount of data regarding the content in the measured sample, as seen in Figure 4. Data analysis including signal processing and classification is necessary to interpret the sensor response and detect if a change has occured.

Our food quality assessment system consists of an electronic tongue for measurements and a signal processing part for classification. In the analysis of the data, abnormal presence or lack of ingredients that may be dangerous for humans can then be detected.

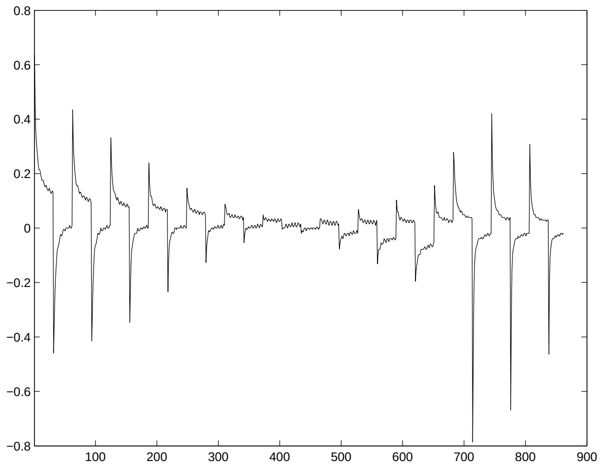

Fig. 4. A typical sensor response where the number of samples is shown on the x-axis and the current on the y-axis.

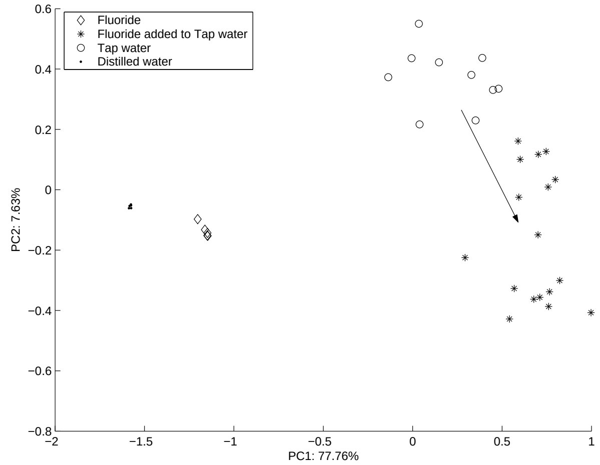

Fig. 5. A contamination is added to tap water and the sensor reacts immediately.

The signal processing part has mainly been solved using principal component analysis (PCA) [7][8]. Other techniques seen in the literature are wavelet transform [9], [10] and artificial neural networks [11] and [12]. Irrespective of which technique is used, the important aspect is to quickly and correctly detect abnormal ingredients in a sample.

The following experiment tests samples of drinking water which may have deteriorated from the purification plant to the consumer. This is a major concern, for although drinking water is normally guaranteed to be drinkable, there are several points where this guarantee may fail due to bad pipes, temporary contaminations etc. These deteriorations can be difficult to locate and they might not be detected before causing illness since a temporary contamination has often subsided by the time the problem has been diagnosed. Therefore, the main concern is that the water should be safe at the consumer and not only at the purification plant. Online monitoring is also of importance because of the rapid subsidence of a temporary contamination.

A snapshot of the experiment is seen in Figure 5, where the system reaction on contaminated water was tested. At the top right corner of the figure tap water can be seen and a fluoride solution containing 1.3 mg F/l is also shown. At first, 8 ml of the fluoride solution was added to the tap water and the sensor immediately reacts to the abnormalities in the drinking water. Fluoride was added at several different times in the tap water and the concentration of the contaminant growth stronger. The increase in the fluoride contamination is shown in the figure by the downward arrow. As a reference distilled water is also shown in the figure.

With some minor adaptations this can be applied to food quality assessments as well. Before measurements can be conducted the sample must be provided in liquid state. Mixing samples of the food product with distilled water produces a measurable liquid.

In the example of food products we often know what kind of food product we have and our main concern is then to identify if the product's quality is sufficient or if it contains unknown substances that can be dangerous for humans. The quality of the product can be affected if something fails in the production process. There can also be substances dangerous to humans added to a food product in purpose to poison the consumer. A food detection system can detect such abnormalities and secure the food safety. An experiment on baby food has been performed with the purpose of detecting changes in quality. The tests mainly was directed towards quality monitoring but the results can be applied to monitoring the overall quality in terms of correct amount of ingredients etc.

Today much of the research is focused on quality control for different kinds of liquids or beverages but can with some modifications be used as personal safety equipment. Experiments has been conducted using drinking water [13] and the results has shown the electronic tongues ability as a quality-monitoring device.

B. The mobile intelligent sniffing system

The mobile sniffing system consists primarily of a commercially available electronic nose which contains 32- carbon black polymer sensors and the respective hardware such as pumps and valve to facilitate the sampling of an odor [14]. Although the nose is equipped with an onboard classification component, the classification is performed on the robotic system, which also contains an electronic repository of odors. The robotic system consists of a Magellan Pro robot , 12 sonars, a CCD camera, tactile sensors and infrared sensors. The robot also has processes for behavior based control, high-level and symbolic processing and reasoning components (including a conditional planner). Since much of the detail of the robotic system is not directly related to the theme of this paper, it shall be omitted, however more information can be found in the respective references [15], [16], [17]. Several challenges emerge in the integration of olfaction onto robotic platforms. The two challenges that we are most concern with are the cooperation between the different sensing modalities and the electronic nose in order to accomplish odor related tasks; and the ability to communicate electronic perceptions of odors to a human user. To address the later challenge, a classification module which is able to preserve its own concept of odors is used. This approach is motivated by several reasons. The first reason deals with the challenge for humans not only to conceptualize but to describe odor character [18]. The second reason is motivated by the desire to have intelligent sensors capable of measuring perceptions outside the human perceptual domain, thus giving us more information about our environment [19]. Therefore in the design of the classification we denote new odors by a tuple $< \mu, L >$, where L is the symbolic categorization of an odor (e.g. ethanol, 3-hexanol, etc) and μ is fuzzy similarity degree representing membership to the given class. This is in fact a natural method to odor classification but more importantly, by explicitly representing the uncertainty in odor classification, the mobile system may reason about perceptions and take active decision to gather more information.

The problem of coordinating sensing modalities deals specifically with being able to budget between sensing resources (given a mobile robot with limited power and battery), and also fusing the information from different modalities. We solve this problem using two components. The first is an internal data structure, an anchor, which is able to maintain perceptual information relating to a specific object [20] . The second is a reasoning component which decides between which modality to use, when to use it, and how to best position the robot in order to obtain optimum data quality from the sensors. These ideas are very much in concordance with active perception often used in vision based systems [21].

In the scenario showed in Figure 6 a suspicious package is detected by the robot, in order to ascertain if the package is dangerous the robot needs to acquire an odor sample to examine any traces of substances. The olfactory module is pre-trained to detect samples of cleaning detergent (our stand-in for a more dangerous substance). Using this pre-trained knowledge that accords with human perception combined with a classification system which represents uncertainties, the planner can reason about the nature of the package and if needed plan for additional sensing actions. These sensing actions occur by approaching the suitcase at another angle and taking additional "sniffs". From the planner's perspective, each sampling attempt has a certain probability p to fail ($\approx 20\%$), and therefore the accumulated probability of n consecutive failures ($1 \leq n \leq 4$) is p^n. When the accumulated probability reaches a threshold decided by the user, the robot stops performing perceptual actions and informs the user of the state of the object.

The results of 40 trials showed that the robot was able to correctly assess the suitcase 81.16% of the trials when an odour

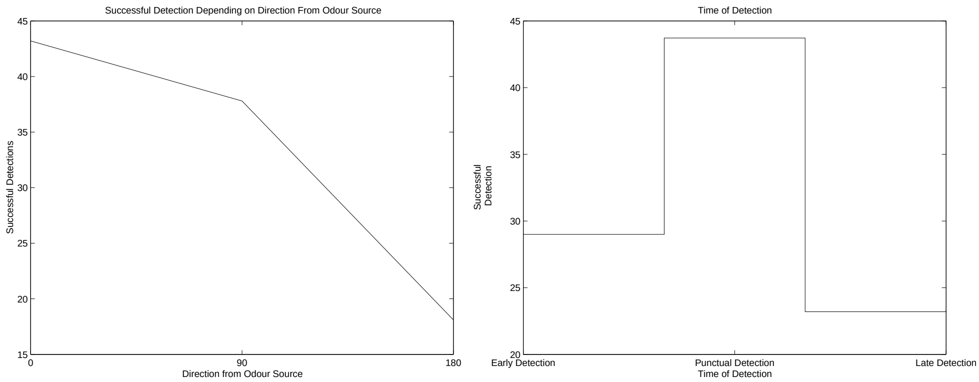

Fig. 7. *(Left)* Successful rate of detection depending on the angle of approach. *(Right)* The rate of successful detection given a fixed emission angle and the fact that the robot may not choose that angle for first inspection.

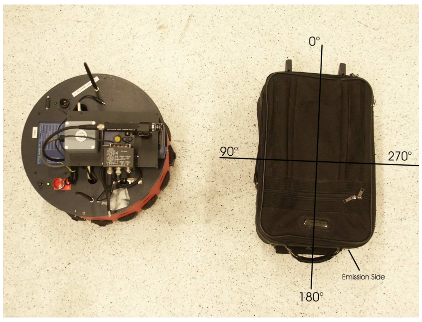

Fig. 6. Illustrates a robot performing careful inspection of a suitcase. The angles are the possible direction from which the smell odour will be obtained. The planner's task is to determine the best strategy to smell, given a higher uncertainty of detecting false negatives (i.e. no odour with one present) than false positives (i.e. odour when none present).

source was present, and 100% when no odour was present. Most often the optimum detection of an odour would occur when the robot approached the object from the emission side. However, of the 81.16% successes, about 37% found an odour when the robot was placed 90° from the emission point and 18% when the robot was placed 180° (on the opposite side of the suitcase). By planning for additional sensing actions, the performance improved by 23% since late detection of a substance was possible, Figure 7 (Right). For more detail on the planning, olfactory and anchoring modules, readers are referred to original publications on this work [17]. The emphasis here, however, is to show an example where an olfactory system working in accordance with human perception can combine a priori knowledge together with explicit uncertainty from the sensing component to then reason and act for the benefit of ensuring a safe environment.

IV. CONCLUSIONS

In this work we showed how an electronic tongue and an electronic nose could be used to provide assessment of different substances for the purpose human safety applications. A number of key issues regarding the integration of such sensing systems were discussed. Problems regarding, userability and reproducability were highlighted and considered as important ingredients for any sensing system in close contact with humans. Another important issue is the integration of intelligence in the human based artificial sensor systems which can improve their performance. Ultimately, human based artificial sensors provide an important and unique means to perceive our environment and therefore are valuable components for many safety assessment systems.

[1] K. Toko, "Electronic tongue," *Biosensors and Bioelectronics*, vol. 13, pp. 701–709, 1998.
[2] C. Di Natale, E. Mazzone, A. Mantini, A. Bearzotti, A. D'Amico, A. V. Legin, A. M. Rudnitskaya, and Y. G. Vlasov, "Electronic tongue distinguishes different mineral waters," *Alta Frequenza Rivista Di Elettronica*, vol. 11, no. 2, pp. 88–90, 1999.
[3] F. Winquist, P. Wide, and I. Lundstom, "An electronic tongue based on voltammetry," *Analytica Chimica Acta*, vol. 357, pp. 21–31, 1997.
[4] A. Riul Jr., R.R. Malmegrim, F.J. Fonseca, and L.H.C. Mattoso, "An artificial taste sensor based on conducting polymers," *Biosensors and Bioelectronics*, vol. 18, no. 11, pp. 1365–1369, 2003.
[5] K. Toko, "Taste sensor with global selectivity," *Materials Science and Engineering*, vol. 4, no. 2, pp. 69–82, June 1996.
[6] M. Lindquist and P. Wide, "Virtual water quality tests with an electronic tongue.," in *Proc. IEEE Instrumentation and Measurement Technology Conference*, Budapest, Hungary, May 2001, vol. 2, pp. 1320–1324.
[7] C.M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press Inc, New York, 1995.
[8] K. Esbensen, S. Schönkopf, and T. Midtgaard, *Multivariate Analysis in Practice*, CAMO AS, Trondheim, 1st edition, 1994.
[9] L. Robertsson and P. Wide, "Analyzing bacteriological growth using wavelet tranform," in *Proc. IEEE Instrumentation and Measurement Technology Conference*, Como, Italy, May 2004, vol. 2, pp. 854–859.
[10] T. Artursson and M. Holmberg, "Wavelet transform of electronic tongue data," *Sensors and Actuators, B: Chemical*, vol. 87, no. 2, pp. 379–391, 2002.
[11] F. Winquist, C. Krantz-Rulcker, P. Wide, and I. Lundstöm, "Monitoring

of freshness of milk by an electronic tongue on the basis of voltammetry," *Mess. Sci. Technology*, vol. 9, pp. 1937–1946, 1998.

[12] A. Legin, A. Rudnitskaya, L. Lvova, Y. Vlasov, C. Di Natale, and A. D'Amico, "Evaluation of italian wine by the electronic tongue: Recognition, quantitative analysis and correlation with human sensory perception," *Analytica Chimica Acta*, vol. 484, no. 1, pp. 33–44, 2003.

[13] M. Lindquist and P. Wide, "New sensor system for drinking water quality.," in *Proc. Sensors for Industry Conference*, New Orleans, Louisiana, USA, January 2004, pp. 30–34.

[14] Cyranose Sciences Inc., "The cyranose 320 electronic nose," 2000, User's Manual Revision D.

[15] A. Loutfi and S. Coradeschi, "Forming odour categories using an electronic nose," in *Proc. of European Conference in Artificial Intelligence (ECAI 2004)*, 2004, pp. 119–124.

[16] A. Loutfi, S.Coradeschi, L. Karlsson, and M. Broxvall, "Putting olfaction into action: Using an electronic nose on a multi-sensing mobile robot," 2004, pp. 337–342.

[17] A. Loutfi and S. Coradeschi, "Improving odour analysis through human robot interaction," in *To Appear In Proc of the IEEE International Conference on Robotics and Automation (ICRA 2005)*, Barcelona, Spain, 2005.

[18] D. Dubois, "Categories as acts of meaning: The case of categories in olfaction and audition," *Cognitive Science Quaterly*, vol. 1, pp. 35–68, 2000.

[19] M. Siegel, "The sense-think-act paradigm revisited," in *International Workshop on Robotic Sensing ROSE*, 2003, pp. 1–5.

[20] S. Coradeschi and A. Saffiotti, "Perceptual anchoring of symbols for action," in *Proc. of the 17th IJCAI Conf.*, Seattle, WA, 2001, pp. 407–412, Online at http://www.aass.oru.se/˜asaffio/.

[21] G. Wasson, D. Kortenkamp, and E. Huber, "Integrating active perception with an autonomous robot architecture," in *Proc. of the 2nd Int. Conf. on Autonomous Agents (Agents)*, 1998, pp. 325–331.