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ODOR CLASSIFICATION IN MOTION: HOW FAST CAN THE E-NOSE GO?

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ABSTRACT

Odor classification for a moving olfactory system (e.g. an electronic nose carried by a mobile platform) presents specific challenges beyond those already posed by the static chemical recognition problem. Mostly, the new issues come from the fact that existing e-noses do not react instantaneously to the gas exposure but they have a considerable latency in both the response and recovery time, which prevents them to achieve the steady state and probably a sufficient signal level to be representative of the chemical at hand. These circumstances can make a substantial difference in the performance of any conventional recognition method. In this paper we present some first results of an experimental evaluation on this problem.

Index terms– Odor Classification, Robotics Olfaction, MOX sensors

1. INTRODUCTION

This work focuses on the classification of volatiles substances when the e-nose is directly exposed to the environment, and specifically, when it is being carried by a mobile platform, that is, performing the classification in motion. This presents specific challenges beyond those already encountered in the general chemical recognition field. Mostly, these come from the fact that existing e-noses do not react instantaneously to a gas exposure but they have a slow response and recovery time. Therefore, it may happen that the signal levels of the sensor array are quite different from their nominal, steady states, which were used for training the classifier. Works addressing the discrimination of odors under these circumstances can be found in the literature [1] [2], as well as preliminary studies of how different motion strategies impact the classification of odors [3]. Nonetheless, what is still missing in the olfactory robotic community is a deeper insight into how the motion of the olfactory system affects the classification performance.

We present here an experimental evaluation towards gaining a new perspective for the odor classification problem when the e-nose is on the move. The main questions we want to answer are: Does the e-nose motion really affect the classification performance? If so, how does the classification rate deteriorate?

2. EXPERIMENTAL SETUP

Uncontrolled environments are characterized by a high Reynolds number, which implies turbulent airflows and a chaotic nature of the gas dispersal. Thus, real robotic olfaction applications have to cope with such complex scenarios where the variables of interest are large and difficult (almost impossible) to monitor and control. This unavoidable leads to the need of repeating the same experiment several times in order to obtain data statistically representative of the phenomena under study.

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Having this in mind, the setup employed in this work consists of an array of 10 non-selective metal oxide (MOX) gas sensors mounted on a mobile robot which repeatedly monitors the volatiles present in a long corridor by performing a continuous sweeping strategy. Also, a photo ionization detector (PID) is employed because its fast response and absolute concentration measures, which are used to determine the real exposition of the e-nose to the volatiles. Two gas sources, namely ethanol and acetone, are continuously releasing volatiles at a fixed rate by means of two ultrasonic aroma diffusers. Fig.1 shows pictures of the robot, the sensors and the aroma diffusers, as well as a plot of the corridor and the robot path during the experiments. To avoid the mixture of the two volatiles, an airflow is forced perpendicularly to the robot path at the middle of the corridor by means of fans. Apart from this, all windows and doors in the corridor where kept closed to minimize the dispersion of gases.

To study the classification performance when varying the motion speed of the olfactory system, a Naïve Bayes (NB) classifier has been selected, because it has a reasonable good performance [4] while it is easy to implement. As previously stated, in order to obtain conclusions that can be generalized, for each motion speed to be analyzed the robot sweeps the corridor around 40 times, with a roughly travel distance of 1206m.

For all the experiments, the ground truth (GT) gas has been obtained by considering the spatial restrictions of our setup, that is, for each point (x,y) the GT label is defined as that of the closest gas source. Three different measures are then obtained to study the classification rate according to which samples are processed in the comparison with the GT:

GT-1: Only e-nose samples over a minimum threshold (set empirically) are processed. This avoids introducing errors in the classification rate when the gas source is not detected.

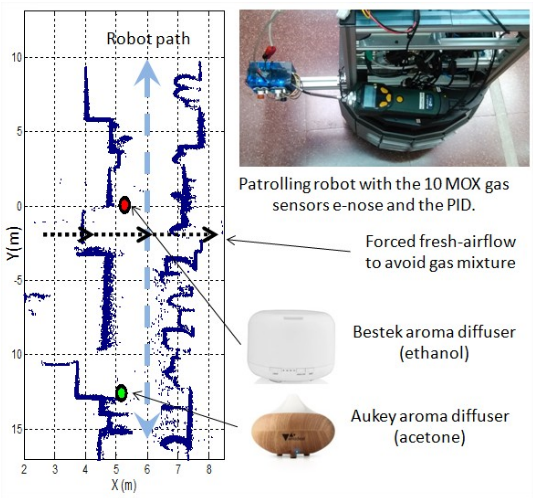

Figure 1. Experimental setup and pictures of the e-nose, the PID and the two gas sources. Blue dots represent the points-map of the environment, generated by an ICP-based method fed with the readings of the onboard robots' 2D laser scanners.

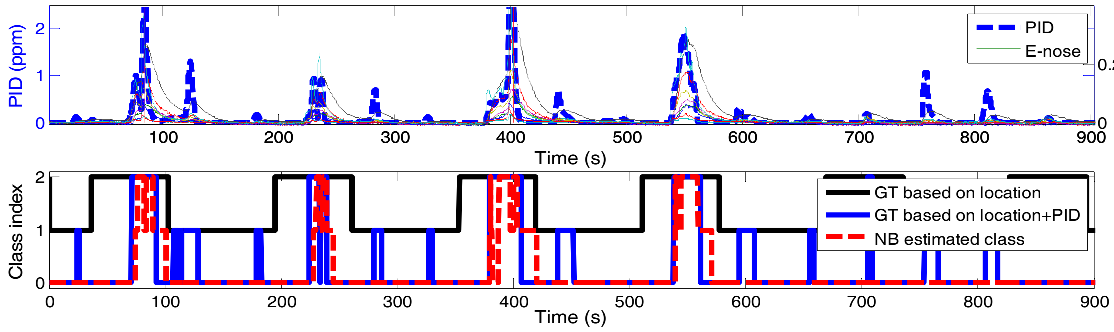

Figure 2. Readings and classification results of a portion of the data collected for a robot motion speed of 0.37m/s.

GT-2: Similar to the previous case, but only processing samples where the PID measures are over a minimum threshold. This additionally avoids the processing of samples corresponding to the long recovery of the MOX sensors, which does not correspond to the presence of any volatile.

GT-3: Finally, the third case only considers samples fulfilling the two previous restrictions. This is to ensure that both detection systems have been able to respond to the volatile excitation in a representative way, and then to avoid introducing errors due to the faster response of the PID.

3. RESULTS AND CONCLUSSIONS

Figures 2 and 3 plot the gas readings (e-nose and PID) of a portion of an experiment corresponding to an average robot motion speed of 0.37 m/s. Both, temporal and spatial representations are provided, as well as the class label estimated by the NB classifier. For training the classifier, separate sampling experiments have been carried out where only one gas was released at a time. The gas source (acetone or ethanol, respectively) was placed 1.5m away from the e-nose in a static configuration, leaving the natural airflows of the environment to spread the gases. This setup (easily realizable in a laboratory) allows us training the classifier with dynamic information due to the mechanisms of gas dispersion, while not considering the motion effect of the e-nose.

As can be noticed from the y-axis plots in Fig. 3, the e-nose is exposed several times to the same gas sources, but different responses are obtained each time due to the chaotic nature of gas dispersal and to the robot motion. This is also noticeable in the output of the NB classifier (see Fig. 2), which in many occasions has not enough information to perform the classification (providing a 0 class index). Finally, Table 1 shows the classification accuracy for two different robot motion speeds. From these results some conclusions can be drawn: first, as could be expected, a decrease in the classification rate is observed when the motion increase. Mostly, this is due to the aforementioned latency of the gas sensors and the consequent lower levels of the MOX sensors response. Second, the classification rate is notably superior when the e-nose and the PID have a minimum response level. This suggests that a PID o similar device is useful for classification tasks, discarding the classification when no gas is present or, as suggested in [2], updating the posterior probabilities with concentration information. Also, it is noticeable how GT-2 gives, in general, worse classification rates than GT-1, possibly due to the different response times of both sensors, which make a direct comparison problematic.

In summary, the experimental results suggest, as expected, that the motion speed of the e-nose has an important impact on the overall classification accuracy. Nevertheless, these preliminary results should only be considered as an initial

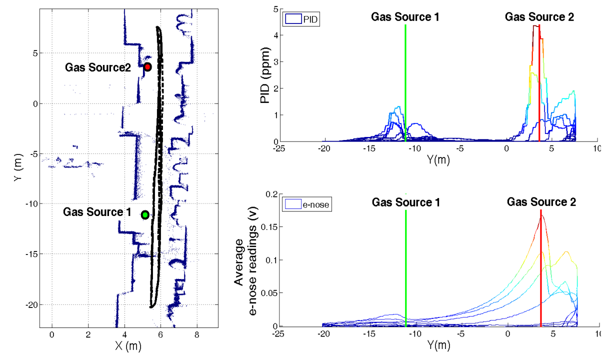

Figure 3. Spatial representation of a portion of the data collected for a robot motion speed of 0.37m/s. (left) Points-map of the environment with the robot path. (right) Readings of the PID and e-nose with respect the y-axis.

evaluation of the phenomena. Not only a deeper study is necessary, but to cope with a series of problems that arise when carrying real olfaction experiments such as the saturation of the gas sensors due to the initially unknown concentration of the volatiles and to the different sensitivities among the gas sensors in the array, or the use of complex setups to avoid gas mixtures.

Table 1. Classification results of the NB classifier for two different motion speeds.

Average Motion Speed (m/s)	Classification rate (%)		
	GT-1	GT-2	GT-3
0.37	67.95	67.69	71.87
0.46	66.77	62.65	66.76

4. REFERENCES

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