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Gas Discrimination for Mobile Robots

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Abstract Robots with gas sensing capabilities can address tasks like monitoring of polluted areas, detection of gas leaks, exploration of hazardous zones or search for explosives. Most of the currently available gas sensing technologies suffer from a number of shortcomings like lack of selectivity (the sensor responds to more than one chemical compound), slow response, drift in the response, and cross-sensitivity to physical variables like temperature and humidity. The main topic of this dissertation is the discrimination of gases, therefore the scarce selectivity and slow response are the limitations of direct concern. One of the possible solutions to overcome the poor selectivity of a single sensor is to use an array of gas sensors and to interpret the response of the whole array using signal processing techniques and pattern recognition algorithms. This is an established technology as long as the sensors are placed in a measuring chamber. However, discrimination of gases with a mobile robot presents additional challenges because the sensors are directly exposed to the highly dynamic environment to be analyzed. Given the slow dynamics of the sensors, the steady-state of the response is never achieved and therefore the discrimination has to be performed on the transient phase. The contributions presented in the summarized thesis focus around the design of algorithms for gas identification in the transient phase, thus they are particularly suited to mobile robotics applications.

Keywords Mobile Robotics Olfaction · Gas Discrimination · Pattern Recognition

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1 Introduction

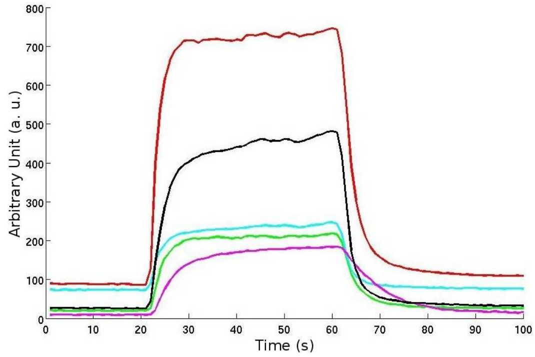
The ability to monitor and identify gases is required in a variety of applications ranging from air pollution monitoring, food and beverage quality assessment, medical diagnosis, exploration of hazardous areas, and search and rescue operations [1]. Various technologies for gas sensing are available, and the gas sensors can be deployed in many different setups in order to fulfill the application dependent requirements. Metal oxide (MOX) gas sensors are the most common gas sensing technology since they have, compared to other gas sensing technologies, a high sensitivity to the compounds of interest, a fast response time, they show a good stability of the response over time, they are commercially available, and they are inexpensive. Though, one of the crucial limitations of MOX gas sensors is the scarce selectivity. This means that MOX gas sensors do not respond only to the compound for which they are optimized but also to a multitude of other compounds. The selectivity of MOX gas sensors can be enhanced by building an array of sensors with different, and partially overlapping, sensitivity, and then analyzing the response of the array with a pattern recognition algorithm. This concept, introduced in the early 1980s, is known in literature as electronic nose (e-nose) [1]. An electronic nose is constituted by three functional parts: the sensor array, the sampling system that is the system that handles and delivers the gas sample to the sensor array, and the pattern recognition algorithm that interprets the response of the sensor array and identifies the sample. This abstract summarizes the achievements presented in the doctoral dissertation [2], where an e-nose suited for mobile robotics applications is developed and analyzed.

2 Problem Statement

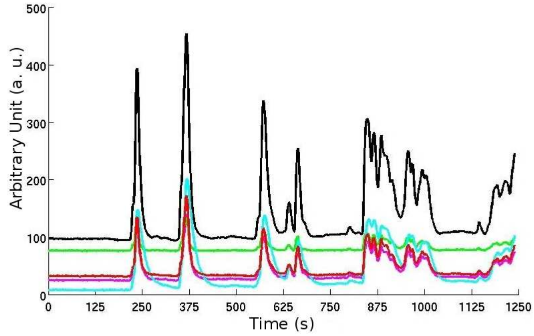
For applications where the main challenges are the localization of a source of pollution [3] or the creation of a map of the gas distribution [4], e-noses are deployed either in a sensor network that covers the area of interest or on a mobile platform that can transport them. In these scenarios, the gas sensors of the e-nose are most often directly exposed to the environment they are analyzing and perform continuous measurements (open sampling system). This is mainly due to the fact that gas sampling systems are bulky and many platforms would not be able to transport them. Also, it is possible that the dynamic response of the sensor when directly exposed to the environment contains information about the nature of the plume. This information, which is useful to perform tasks such as gas source localization, is unavailable if the sensors are enclosed in a chamber (closed sampling system). Moreover, a setup with sensors that continuously sample the environment is more suited to meet time constraints that arise in certain applications, for example when a robot continuously moves and cannot stop for collecting gas samples.

In an open sampling system, however, variables like exposure of the sensors to the analyte, temperature and humidity that are controlled in a closed sampling system, can only be observed but not controlled. These factors make the gas discrimination problem significantly harder. A typical signal collected with an e-nose mounted on a mobile robot (open sampling system) and a signal collected with the same e-nose in a small chamber using the traditional three-phase strategy (closed sampling system) are compared in Figure 1. The main difference between the two signals is that the signal collected with the robot (open sampling system) does not have the three phases typical of a signal collected by an e-nose with a closed sampling system. This is because there is no step in the concentration of the compound induced by a sampling mechanism, but the changes in concentration are due to the turbulence and advection of the airflow that predominantly transports the gas in environments characterized by a high Reynolds number. These changes in concentration have a much faster dynamics than the MOX gas sensors themselves and therefore the gas sensor response never reaches a steady state. Consequently, an algorithm for performing gas discrimination or quantification in such a setup has to be able to extract information from the transient response of the sensors.

The lack of a controlled exposure of the sensor array to the target gases, that in closed sampling systems allows segmenting the signal into three phases, introduces the additional complication of not having any trivial segmentation strategy. The task of the segmentation algorithm is to isolate the parts of the signal that contain the information useful for identifying the compound interacting with the sensors. The segmentation policy presented in this dissertation is based on the assumption that every patch of gas that hits the sensor array causes a peak in the response. The responses to the different gas patches are segmented and then fed to the subsequent parts of the algorithm. The implication of having a segmentation step will be discussed more in depth in Section 4.



(a) Closed sampling system



(b) Open sampling system

Fig. 1 Response of a sensor array composed by 5 MOX gas sensors. In sub-figure (a) the sensors are in a small chamber and the three phase sampling strategy is used. During the first 20 seconds the sensors are exposed to a reference gas, then for the subsequent 40 seconds the sensors are exposed to the gas sample and finally the sensors are exposed again to the reference gas in order to recover the initial state. In sub-figure (b) the sensors are mounted on a mobile robot and are placed in an actively ventilated tube.

3 Methodology

Before introducing the algorithmic contributions of the dissertation, it is important to focus the attention on the experimental design, probably one of the most crucial aspects of research in electronic noses with an open sampling system. Technical difficulties in designing experiments that enable to study and develop systems for airborne chemical monitoring are due to various reasons. One reason is that the dispersion of chemicals in natural environment is difficult to observe since most chemicals produce an invisible plume. Plus, given the chaotic dispersal of a gas in natural environment, the plume is also difficult to predict in a non-trivial setting. Moreover, environmental conditions are often very variable and therefore experiments are hard to repeat. Thus, it is difficult to obtain a ground truth that can be used to validate experimental results.

In order to overcome these limitations, experiments are often carried out under partially controlled conditions that enable to obtain a ground truth that simplifies the analysis of the experimental data. Another advantage of controlling experimental conditions is that the repeatability of the experiments is increased. On the other hand, it is hard to predict how the results obtained in experiments carried out under controlled conditions extend to uncontrolled environments. Experiments performed with uncontrolled environmental conditions are interesting because they constitute a good benchmark for the system to be developed. Indeed the ultimate goal of research in electronic noses with an open sampling system is to produce systems that can be deployed in a multitude of settings where environmental conditions are not controllable (e.g. environmental monitoring in towns). The experimental setup is often a result of a trade-off between controlled experimental conditions, that enable deep insight in the data and ease of analysis, and uncontrolled experimental conditions, which enable the collection of data more similar to those that the final system would have to cope with.

Two kinds of experiments are presented in the outlined dissertation. One set of experiments was carried out in a room with controlled airflow where the electronic nose is placed on the floor at a known distance from a gas source. This allows a partial ground truth on the compound (and its concentration) that is interacting with the gas sensors in any phase of the experiment. The gas source emits the compound according to different emission strategies where the compound identity/concentration is abruptly changed. This enables the analysis of the sensor response when the sensors are exposed to abrupt changes and the quick identification/quantification of the compound is not trivial. A second set of experiments was carried out with the electronic nose mounted on a mobile robot together with an anemometer for measuring the instantaneous airflow. The mobile robot is deployed in different experimental locations, ranging from an enclosed large indoor room to an open courtyard, where the environmental conditions experienced large variations across different experimental runs.

4 Results

The first set of experiments performed with the partially controlled setup indicate that, once the sensor has passed the transient phase due to a substance or source intensity change, the sensor response fluctuates due to small variations in concentration caused by the turbulent airflow. These fluctuations, though, do not prevent the compound from being identified just from a snapshot of the sensor response. For what concerns the transient phase immediately after a compound or source intensity change, a snapshot of the sensor response is not enough for performing reliable gas discrimination. Therefore, either a notion of state (for example the substance to which the array has just been exposed), or a feature extraction technique that can capture the dynamics of the sensor response is needed for performing gas discrimination under this condition. It is important to notice that in the experiments under controlled conditions the long exposure needed for the sensor response to stabilize fluctuating around a value could be achieved by introducing a stable unidirectional airflow, but in environments where the airflow is uncontrolled this long exposure time cannot be guaranteed. Therefore, it is important to perform the identification when the sensor is in the transient phase that occurs just after the exposure of the sensor to a substance, even if the sensor has been previously exposed to a different compound without the possibility of recovery between the two exposures.

Given this consideration, for the scenarios in which the electronic nose is mounted on a mobile robot, the attention is moved to algorithms that perform feature extraction from the dynamics of the sensor response. As already pointed out in Section 2, the first challenge is to identify the parts of the signal that contain the information for performing the identification. The basic observation is that when a patch of gas hits the sensors it causes a response, and a simple approach based on the first derivative of the signal can isolate the responses due to the gas patches. Once the segmentation is performed, different feature extraction methods (FFT, DWT, and polynomial curve fitting), baseline manipulation techniques (differential, fractional, relative) and normalization techniques (vector normalization, vector autoscaling, dimension autoscaling) are used. A comparison of these methods can be found in [5]. An additional comment is needed on the segmentation policy. The proposed approach that isolates the responses due to gas patches is not optimal since it is not guaranteed that all the gas patches contain enough information to be correctly identified. Therefore the gas discrimination algorithm presented in [5] provides not only a decision, but also an estimation of the posterior probability of each sample belonging to the classes of interest. This posterior probability can be used as a confidence measure on the classification outcome. For example, it is possible to introduce a threshold that, if not met by the maximum of the posterior probabilities, the sample is rejected and not classified.

Another major issue of chemical sensing in mobile robotics is that chemical and airflow sensors, the sensing modalities that have been mostly used, take point measurements. This means that, unlike range sensors, the variable of interest can be measured only at the location of the sensor. Therefore the mobile robot serves an important role to bring the sensors to an area where good measurements can be obtained. On the light of this consideration, an algorithm that performs on-line gas discrimination has been developed and presented in the dissertation. This algorithm provides to the path planner information that can optimize the exploration, achieving a quicker and more robust identification of the polluting substance.

The last point investigated in the dissertation is the influence of the experimental conditions, namely the location of the experiment and the robot moving strategy, on the signal collected by the mobile robot. In particular, it is observed that the experimental conditions heavily influence the signal collected by the mobile robot degrading the gas discrimination capability of a robot trained under specific experimental conditions and then deployed in a different location or performing a different moving strategy. Two different solutions have been proposed to this problem, an ensemble of classifiers or a feature selection strategy. The most general of these two solutions, namely the feature selection, finds a feature subset that show regularity across the experimental setups while providing enough discrimination between different chemical compounds [6]. The measure chosen to formulate this concept is the mutual information. Mutual information has its origin in information theory and provides a measure of mutual dependence of two random variables. The dependency between a feature and the compound label can be considered a measure of its discriminative power and therefore it is a positive feature, while the dependency between a feature and the experimental setup label can be considered a measure of the variability of a feature across different experimental condition, which is something to be penalized. Two feature selection approaches, one filter and one wrapper have been proposed. The wrapper, that is the approach that obtained the best performance, is a modification to the Backward Elimination algorithm. One of the weak points of the Backward Elimination algorithm is that many features would be good candidates for elimination since the performance of the subsets of the remaining features does not drastically change. Therefore, rather than performing an uninformed choice on which feature to eliminate (since they are equivalent with respect to the considered criterion), the features which obtain a comparable classification accuracy are isolated. These features are then ranked according to the mutual information with respect to the experimental setup and the highest ranked feature is permanently eliminated.

5 Conclusions and Future Directions

This abstract analyzes the problem of gas discrimination with an array of partially selective gas sensors, paying particular attention to applications where the sensors are mounted on a mobile robot. The presented contributions range from principled experimental design to formulation of new algorithms. Future research will center around the integration of the gas discrimination algorithms developed in this dissertation with algorithms for gas source localization, gas distribution mapping, or gas plume tracking. This will enable the robot to address tasks like localization of a specific gas source, creation of a distribution map of multiple gases, and tracking a specific gas plume in presence of interfering gas plumes.

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