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Toward the Generation of Smell Maps: Matching Electro-Chemical Sensor Information with Human Odor Perception

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Abstract.
Smell maps are geo-localized representations of odors as perceived by humans, and are a convenient tool to assess the smellscape of urban areas. However, they are laborious to generate and easily outdated, as they need to be recorded and updated by individuals during repeated excursions to the regions of interest. In this work we propose to employ a compact and wearable electronic nose (e-nose) to automate the task of smell map generation by training it to recognize certain urban odors according to human subjective perception. To that end, we have collected with a smartphone application a labeled dataset of the e-nose's response to common smells (e.g. garbage, tobacco, flowers), that we subsequently used as input for various machine learning algorithms. In particular, we report on our systems ability to recognize the smell of traffic emissions, and present an example of an automatically generated smell map of places affected by it.

Keywords. electronic nose, artificial olfaction, machine learning, smell map

1. Introduction

General awareness regarding smog and urban air pollution has greatly increased during the past decade due to their negative impact on public health as well as on the environment [1]. Still, the smell itself of urban areas has been neglected until quite recently despite of its psychological impact on mood and general well-being of residents [2]. New initiatives like *smellwalking*, the geo-localization of smells, aim to change this situation by assessing the smellscape of major cities [3]. However, it is an arduous task that requires an elevated number of human *sniffers* and constant updates to be accurate. In this regard, we propose to automate the task of *smellwalking* by means of an electronic nose.

An e-nose consists of an array of non-selective gas sensors that respond indistinguishably to various chemicals, but whose combined output can be processed by a classification algorithm to recognize specific volatile substances [4]. Naturally, the spectrum

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and concentration of volatiles an e-nose can detect is much lower than that of a human, yet it is enough to recognize simple odors like garbage or tobacco smoke [5].

Therefore, to use an e-nose for automatic urban smell map generation, it first needs to be able to match odors to human perception. This in turn requires to train the e-noses' classification algorithm with a sufficiently large and varied set of samples. Accordingly, we contribute in this work with a dataset that contains the raw readings of a wearable e-nose (gas sensors and spatio-temporal references), thoroughly labeled with each smell encountered by its carrier. We employ relatively few gas sensors for this task to keep the e-nose as lightweight and portable as possible, and record all data from various outdoor locations on a custom smartphone application for later processing.

Finally, this data serves to train a classification algorithm to recognize certain urban smells, and subsequently, generate continuous smell maps that also include untagged locations. In particular, we resort to the classifiers that are most common in literature [6], including support vector machines (SVM), decision trees, linear discriminant analysis (LDA), and deep learning; which we train, as an illustrative example, to recognize the odor of urban transportation emissions.

2. Data Acquisition System

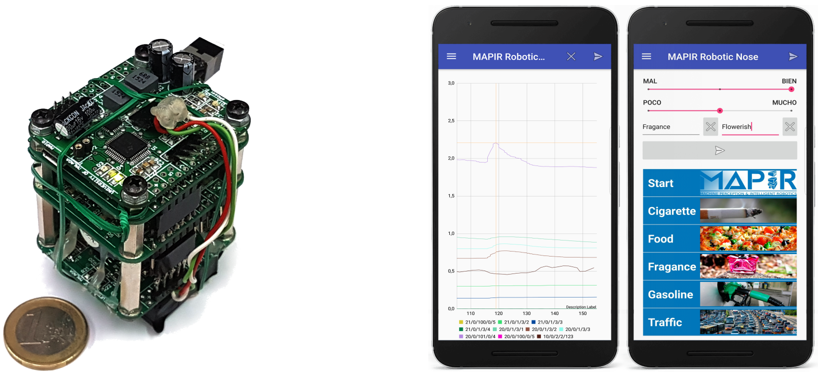
In order to collect the training dataset, we developed a smartphone application that connects to our wearable e-nose and enables its user to log all encountered smells. It records at 1Hz all sensor outputs from the e-nose (gas measurements, plus temperature and humidity), as well as from the smartphone itself (GPS coordinates and ambient pressure), and labels them with the type of smell perceived by the user, including general pleasantness and intensity.

The dataset was recorded in Malaga (Spain) and its surrounding, and includes an open-air shopping mall (Plaza Mayor), a touristic sea-promenade (Muelle 1), our campus surroundings, and several residential areas. It was collected during several *smellwalks* of two different participants, and subsequently processed to remove labels what were incongruent or taken too close in time (to account for the slow recovery of the gas sensors). The result is a dataset with well over 10 hours of recorded sensor data and 600 labels for 16 distinct smells.

2.1. Wearable Electronic Nose

To acquire the raw sensor readings for the dataset, we carried the e-nose shown in Figure 1a like a keychain hanging on our backpacks. Note that it is based on a completely modular architecture for e-noses [7] that enables the integration of different gas-sensor technologies and transducers, as well as auxiliary sensors and peripherals (i.e. battery, communications, data logging) in a configurable and compact format.

Because we were targeting urban smells, we chose to use sensors that should be sensitive to some of the chemicals present in smog (e.g. CO, SO_2, ammonia) [8] as well as other more general organic compounds (Hydro Carbons, VOCs). Specifically, the e-nose hosted 1 Electrolytic SO_2 sensor by Alpha-Sense, 3 MOX sensors by Figaro (TGS2600, TGS2602, and TGS2611), and 3 MOX sensors by SGX (dual MICS-4514, and MICS-5524), plus 2 temperate and 1 relative humidity sensor.



(a) Wearable e-nose (b) Smartphone application

Figure 1. *(a)* shows the physical appearance of the wearable e-nose, and *(b)* shows the real-time sensor data view (left) and the screen for logging new smells (left).

2.2. Smartphone Application

Our smartphone application enables the user to log smells in a simple and intuitive way, as well as continuously record the e-nose's measurements over OTG-USB or Bluetooth (not implemented yet). It features to this purpose two windows: one is as a map-like view with the GPS-localized position of all previously tagged smells, and the other is a real-time plot that shows sensor's readings (if the e-nose is connected).

As for tagging encountered smells, the user can add new labels through the input-menu shown in the right screenshot of Figure 1b, along information about the smell's intensity, overall pleasantness, and an optional description. Furthermore, to ease the task of generating datasets, the application offers tools to notify the user if any sensor rises above a configurable threshold, and an option to conveniently send its whole logged database over email.

3. Smell classification results

In order to generate smell maps with an e-nose, we first have to train a classification algorithm to match odors according to human perception. However, the sensory capabilities of e-noses, and specially that of our wearable version (with only 7 gas-sensors), is way below of human ability to perceive complex smells. We therefore chose to classify and map more simple odors like that of traffic emissions, which make up a significant part of urban smog. In this regard, we propose no new machine learning technique or algorithm for e-noses, but resort to SVM, decision trees, LDA, and deep neural networks.

Our current results show that it is possible to classify transportation emissions from the other smell labels with an average 80% success ratio. These results were obtained with a deep neural network (5 convolutional and 2 fully connected layers), which offered slightly better results than the other tested machine learning techniques, using 70% of the dataset for training and the remainder for evaluation. In any case, we are confident that we will be able to further improve the classification success ratio by increasing the dataset's size (more training examples) and by fine-tuning the characteristics of our classifiers in the future.

(a) Raw e-nose response mesaurement (b) Predicted locations of engine exhaust odors

Figure 2. Maps of the smell distribution around Muelle 1 (Malaga, Spain), showing in *(a)* the e-nose’s raw sensor responses (heat gradient) and the user’s labels for smelled engine-smoke (red pins); and in *(b)* the prediction of places with engine-smoke after training the e-nose with deep learning.

4. Generation of Urban Smell Distribution Maps

In order to generate transportation emission distribution maps, we process all raw e-nose measurements with the classifier from Section 3 and plot all those labeled as *engine-smoke* in Figure 2. We have no means to verify how exact this prediction is, nevertheless, notice that the smell map *(b)* highlights both underground-garage entrances and the roundabout in the left, in addition to most of the already labelled places.

5. Conclusions and Future Work

This work shows that it is possible to create relatively precise smell distribution maps for engine exhaust odors with a compact, wearable e-nose. The only requirements are a labelled training dataset, which we collected with a smartphone application, and an appropriate classification algorithm, like a deep neural network. In this regard, our future work is aimed at training our classifier for the detection of additional odors, and in turn, the generation of more complex smell maps.

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