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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 the odors present in an environment as perceived by humans. They provide a convenient mean to assess the smellscape of urban areas, determine regions with heavy impact on the population, and measure the reach of industrial emissions. However, their use is not widespread because they are laborious to generate and easily outdated, as they rely on in-place human annotations of the perceived smells. In this work we study the feasibility of automatizing the generation of smell maps by means of a wearable electronic nose (e-nose) as replacement for the human sense of smell; being our main objective the analysis of whether this technology can be employed to map the subjective information inherent in smells. We have collected to that end a dataset composed of more than 450 labeled samples of 10 different smells with a wearable e-nose, and performed a thorough comparison of several machine learning algorithms to evaluate their suitability for this task. As a second contribution, we present a smartphone application developed to record (in situ) e-nose measurements and GPS coordinates as well as the human perception of smells (using a form-based input method). Finally, we present an illustrative example with several automatically generated smell distribution maps and discuss their accuracy.

Keywords. electronic nose, artificial olfaction, machine learning, smell distribution map, bio-inspired sensing

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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 urban areas, understood as the subjective perception of both pleasant and unpleasant odors, has been neglected until quite recently despite its psychological impact on the mood and well-being of residents [2]. For instance, sulphur based gas emissions from waste-water treatment-plants are regulated by law to protect the health of nearby population, whereas the highly unpleasant odors of the exposed sewer water remains an unaddressed issue and source of complaints.

New initiatives like *smellwalking* [3], the localization of smells on a map, aim to change this situation by assessing the smellscape of major cities. However, it is an arduous task that requires an elevated number of human *sniffers* and constant updates to be meaningful [4]. In this regard, we propose to automate the task of *smellwalking* by introducing an electronic nose (e-nose) as replacement of the human sense of smell.

It must be noticed that opposed to pollution monitoring [5,6], we are not interested in the concentration measurement of chemical volatiles (e.g. CO, H_2S, o_3, etc), but in perceiving gases in such a way that can be matched to the human perception of smells. In this regard, e-noses are good candidates because they consist 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 their identity [7]. Of course, the spectrum and concentration of volatiles an e-nose can detect is much lower than that of a human, yet it is usually enough to recognize simple odors like garbage or tobacco smoke [8].

Still, recognizing smells with an e-nose remains a challenging problem. One major constraint is the elevated, and sometimes immeasurable, number variables that affect our sense of olfaction, like climatic conditions [9] (e.g. temperature, humidity, air pressure) or emotional factors [10] (e.g. pleasantness, exposition time, subjective connotations).

Accordingly, this work studies the feasibility of training an e-nose classifier to recognize simple odors. We have collected to that end an extensive dataset of continuous and geo-referenced sensor readings of an e-nose, labelled according to the the subjective perception of the person who carried it and recorded at different locations (promenades, residential areas, etc). We also compare the performance of some common machine learning algorithms [11] when classifying e-nose readings in order to choose one among decision trees (DT), linear discriminant analysis (LDA), support vector machines (SVM), and convolutional neural networks (CNN). Through this, we pretend to test and validate the generation of automatic smell distribution maps under the most favorable conditions.

The remainder of this paper is organized as follows. Section 2 describes the e-nose and data acquisition system, followed by a report of the collected dataset in Section 3. Next, Section 4 discusses the best classification algorithms for odor classification, and Section 5 employs it for the automatic generation of various urban smell maps. Lastly, Section 6 offers a summary of conclusions and suggests possible improvements for future research.

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2. Data Acquisition System

This section is devoted to our data acquisition system: a *smellwalking* app and a wearable e-nose for smartphones. Together, they enable the wearer to easily tag any encountered smell, creating over time a labeled dataset of the e-nose's transient response.

Our design goal was to keep the system as unobtrusive and lightweight as possible, which led to a wearable design that exploits the widespread use of smartphones. Accordingly, the hardware on the e-nose was kept to the bare minimum (i.e. gas sensors, OTG-communications, and a battery), while most of the functionality was relayed to the app, including user interface, data storage and GPS localization.

2.1. Wearable Electronic Nose

All measurements were recorded with the e-nose shown in Figure 1. It is based on an modular architecture for e-noses [12] that integrates heterogeneous gas-sensor technologies and auxiliary peripherals (e.g. battery, communications) in a customizable design. It was consequently very easy to adapt to our project's needs, specially in terms of size and portability.

Since our purpose is to classify urban smells, we chose sensors that should be specially sensitive to chemicals present in smog (e.g. CO, SO_2, ammonia) [13] as well as others for more generic organic compounds (e.g. hydro carbons, VOCs).

Concretely, the e-nose hosts 7 gas sensors: 1 Electrolytic SO_2 sensor by AlphaSense, 3 MOX sensors by Figaro (TGS2600, TGS2602, and TGS2611), and 3 MOX sensors by SGX (dual MICS-4514, and MICS-5524), plus 2 temperate (integrated within the MSP430f5309 MCU) and 1 relative humidity sensor (HIH-4000). Under this configuration the e-nose works at an output rate of 20Hz, drawing about 1.300 W from a 1100 mA 3.3 V, and yielding approximately 2.5 hours of continuous application.

We must stress that the size of the e-nose was kept to a minimum. Thus, data logging is only possible with the smartphone application (i.e. the e-nose carries no memory module), and communications are only possible over the OTG-USB cable, as the Bluetooth module would imply a greater footprint size as well as additional energy consumption.

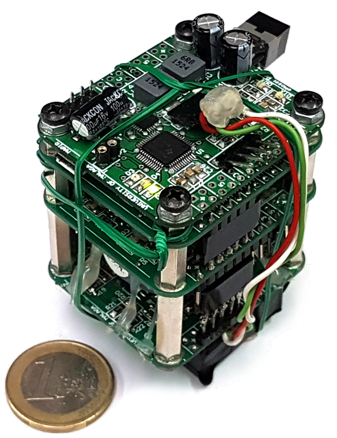
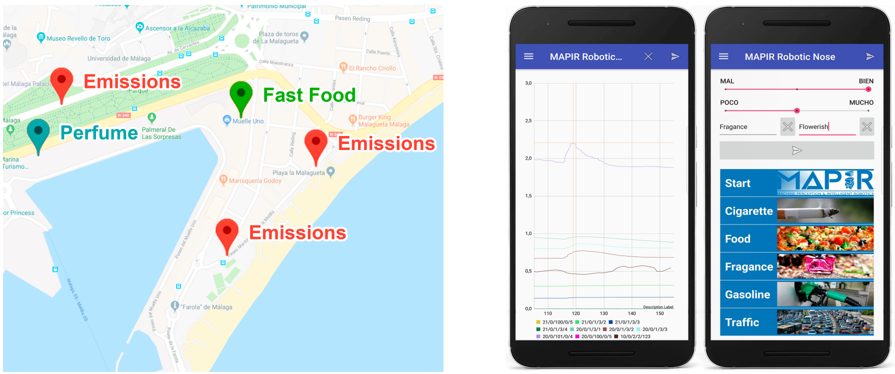


Figure 1. Wearable e-nose



(a) Geotagged map

(b) Smartphone application

Figure 2. *(a)* the app’s main window that shows the locations of previously tagged smells, and *(b)* screenshots of the sensor’s real-time monitor (on the left) and the smell labelling menu (on the right).

2.2. *Smartphone Application*

Our smartphone app enables the user to log smells in a simple and intuitive way, while it continuously records the e-nose sensors over OTG-USB and stores them in a database. In addition, the app exploits the smartphone’s hardware (GPS, temperature, pressure...) to obtain information from internal sensors to further enrich the aforementioned e-nose data.

When the electronic nose is connected, the app shows a map with all the smells introduced during the session as shown in the left screenshot of Figure 2a. This allows to obtain an overview of the route followed and the labelled smells. Advanced users can also monitor the signal of each sensor through a real time graph, as shown in the left screenshot of Figure 2b. This allows the detection of errors in the hardware, avoiding the log of incorrect data.

When the user detects a smell, he only has to fill in a small form shown in the right screenshot of Figure 2b. Each encountered smell can be labelled to a smell-category (i.e. flower, garbage, etc) and tagged according to its pleasantness and intensity [14] (both in a scale between very low and very high). Plus, the user may add an optional comment to the label for consideration during any subsequent data processing (e.g. information about surrounding events, like traffic).

Also, the smartphone app features some utilities to facilitate smell identification and aid during cooperative data acquisition (i.e. smell mapping from several users); such as a label-name manager, automatic prompts when the sensors exceed a configurable threshold, or a service to send the database by email.

3. Urban Smell Dataset

This section describes the collected smell dataset, recorded with the previously described e-nose and labelled on the smartphone app according to the users’ subjective perception. It has been gathered in Malaga, Spain, at different locations that are representative of specific urban life-styles. These include various quite residential and commercial areas, a

Table 1. Distribution of the user-entered smell label in the dataset

	Clean air	Traffic emissions	Tobacco smoke	Garbage	Animal wastes	Chemical	Perfume	Air-freshener	Plants and flowers	Food	Others	Total
Count	95	126	24	15	9	43	31	17	24	50	23	457

touristic sea-promenade (El Muelle Uno), an open-air shopping mall (Plaza Mayor), and our university campus; all visited under different ambient conditions to obtain a varied range of samples.

We labelled all encountered smells with a common set of objective categories [10], like the smell of food or tobacco smoke, to establish a reasonably impartial naming convention. This includes an explicit label for places with clean and fresh air (i.e. no smell at all) as well, which is intended to register the e-nose's response in the absence of odors. Furthermore, all *smellwalks* were performed with the e-nose hanging like a key-chain on our backpacks, which ensured that the recordings contained the general smell of the ambient air, and limited to a maximum duration of 1 hour to account for human olfaction numbness [15,16].

In the end, we recorded more than 48.000 e-nose measurements over a period of 6 months, accounting for 13 hours of continuous data, a travel distance of 47 km, and 457 user-entered smell labels (shown in Table 1). These are the final result of manually purging the data from incongruent user-entries, like removing all labels that had missing attributes (e.g. smell intensity). The final dataset is available for download at our webpage[2].

4. Matching Odors with Chemical Data

In principle, all that is needed for an efficient urban smell recognition with an e-nose is a classification algorithm trained with an appropriately labelled smell dataset. However, this is not an easy task due to the inherent complexity of smells. Even if it were feasible to label the immeasurably wide range of urban odors to train a classifier, it would still be impossible to distinguish them with the current gas-sensor technology. The sensory capabilities of e-noses (and specially that of our wearable version with only 7 gas-sensors) remain below of human olfaction [17,8], reason why most e-nose applications are only targeted at a narrow set of substances (e.g. classification of wines [18], dairy products [19], or olive oil [20]).

Still, our intend remains to study the feasibility of employing an e-nose to map urban odors, which in turn requires an estimate of how many individual smells can be recognized with our wearable version. We have trained to that end a CNN (one of the proposed classifiers) with different smell grouping strategies, ranging from grouping similar tags together to training with all of them separately as shown in Table 2.

On account of these results, we addressed the classification task by grouping the labels from our dataset into three large categories to represent the overall characteristics

[2] `http://mapir.uma.es/mapirwebsite/index.php/277-labelled-e-nose-dataset`

Table 2. Tentative classification results depending on the number of smell categories into which the individual smell labels can be grouped.

Number of categories	Accuracy		Precision		Recall	
	μ	σ^2	μ	σ^2	μ	σ^2
3 Categories	0.7203	3.360e−04	0.7940	3.145e−04	0.7748	1.615e−03
4 Categories	0.4601	1.115e−03	0.5821	2.399e−03	0.6138	3.724e−04
6 Categories	0.3112	4.957e−04	0.5705	7.295e−04	0.5648	8.730e−03
8 Categories	0.2442	4.899e−05	0.3867	1.617e−03	0.4055	9.682e−03
All dataset labels	0.1245	4.269e−05	0.2579	6.050e−04	0.2617	1.506e−03

of urban air. These are: (i) clean air with no smell at all, (ii) traffic emissions and smog, and (iii) any other smell (e.g. food, garbage, flowers, etc.).

It must be noticed that although we employed a CNN classifier to establish the number of smell categories, it may be possible that other algorithms achieve better results. We proceed therefore with the extraction of features from the samples, as required by common classifiers, followed by a detailed comparison of their classification performance.

4.1. Signal Preprocessing and Feature Extraction

Given the slow response time of e-noses (usually in the range of seconds [21]), we took a 30 seconds wide time-window around each user-label to excerpt a sample of the e-noses transient response. This ensured that we no longer depended on whether the user and the e-nose detected the smell at exactly the same moment, and provides more information for the feature extraction [22] than instantaneous e-nose readings alone. Concretely, for each of the 7+3 sensors in our e-nose we extracted 4 features from fitting their response to a 4th degree polynomial curve [23], and 4 features from their Fourier transform [24]; yielding a total of 80 features per labelled e-nose sample. In addition, we further reduced these 80 features through Principal Component Analysis (PCA) to generate a second and optional feature dataset. Our intention was to retain only the subset of features that carried the most significant information, and thus tested the effect of removing redundant information from the training data [25] to seek the best possible smell classifier.

Notice that we only employed the e-nose's sensor-readings during the feature extraction stage, leaving the smartphones' ambient sensors out (e.g. pressure and temperature). Not only because their availability and response characteristics varied too much between our different smartphones models, but also because they were very unreliable and noisy, which would encumber the subsequent training stage.

4.2. Classifier comparison

The purpose of this section is to compare the classification capabilities of the aforementioned machine learning techniques, namely decision trees (DT), linear discriminant analysis (LDA), support vector machines (SVM), and convolutional neural networks (CNN). We train them to that end with our dataset and compare their performance in terms of accuracy, precision, and recall to choose the fittest for smell classification.

All tested techniques other than CNN were implemented with scikit-learn [3], a machine learning library for Python, and trained with both the complete and the PCA-

[3] http://scikit-learn.org

filtered feature datasets. For CNN, on the other hand, we employed Tensorflow [4], a machine learning framework that works with Python as well, but which is better suited for neural networks and our NVIDIA high-performance GPU. We must stress that in this case, instead of using the extracted features from the procedure described above, we trained with the raw dataset as the self-learned kernels of a CNN extract their own features [26].

In all cases, we validate the classifiers with 50 cross validation runs [27] and repeatedly dividing the samples into 70% for training and 30% for testing. Thus obtaining a better estimation of the true performance of the classifiers, which were configured as follows:

- **Decision Tree:** the DT training was performed in a top-down fashion using the Gini impurity criterion to split the branches to a maximum depth of 10, which proved to offer the best results. Analogously, the PCA filter was set to 10 dimensions.
- **Linear Discriminant Analysis:** we trained LDA with an singular value decomposition (SVD) solver and, when applicable, the 15 most significant features of the PCA dataset.
- **Support Vector Machine:** after testing different configurations, we obtained the best results for SVM with a linear kernel and gamma set to default. Again, PCA was set to 15 dimensions for best results.
- **Convolutional Neural Network:** The design of the CNN follows a variation of the standard CNN architecture[28], with 7 convolutional layers, some of them consisting in separated vertical and horizontal filters, followed by two Fully Connected layers, and a softmax function applied over the last one. Because the main data types which a CNN works with are images [29,30], all e-nose measurements (vectors with the output of the individual sensor) were rearranged into matrices by aggregating adjacent samples. This way, each label gets associated not only to the e-nose's instantaneous response, but to its transient evolution. Lastly, we optimized the hyperparameters with a grid search, exploring slightly different architectures and layer depths.

After running the cross validation test for our three target categories (clean air, emissions, and others), we obtained the results that are shown in Figure 3. The classifiers that were trained with the 80-features dataset, namely DT, LDA and SVM, behave similarly

[4] https://www.tensorflow.org/

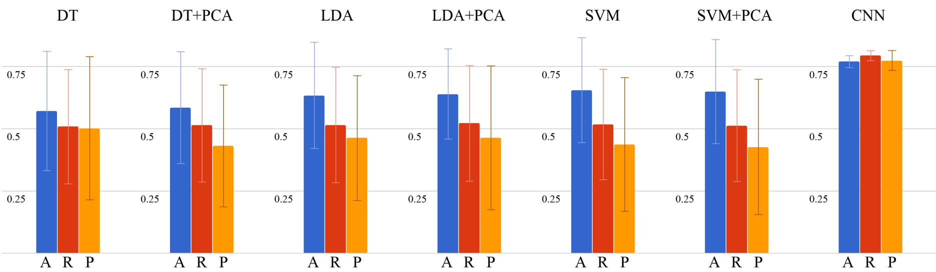


Figure 3. Accuracy, Recall and Precision of the tested classifiers, showing the average (bars) and standard variation (rods) for 50 cross validation runs.

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in all three performance measurements. They have an average accuracy of 65%, a recall of 55%, and a precision of 45% (all with a standard deviation of 20%), which slightly increase by 2% when trained with PCA-filtered feature dataset. SVM+PCA stands particularly out, as this combination is very unreliable yet achieves the highest test result of all classifiers. As for the CNN classifier, it attained higher average performance indices (above 74% for all three measures) with a much lower standard deviation (less than 4%), which translates into highest reliability and robustness.

As can be observed, the overall classification performance is relatively low, even with the classification task simplified to three categories. This is probably due to the reduced number of available gas-sensors on our e-nose, and to the wide range of possible responses they may produce depending on the intensity of the target smells as well as the ambient conditions. These results also show that the manually extracted training features can not compete with the CNN kernels, which learn to produce their own. So while we could try to extract better features, leaving the CNN learn its own filters seems to be the best option.

In light of this, we can conclude that the CNN achieves the best results, despite not reaching more than 75% accuracy. Still, it should be enough to generate coarse maps of urban smell distribution.

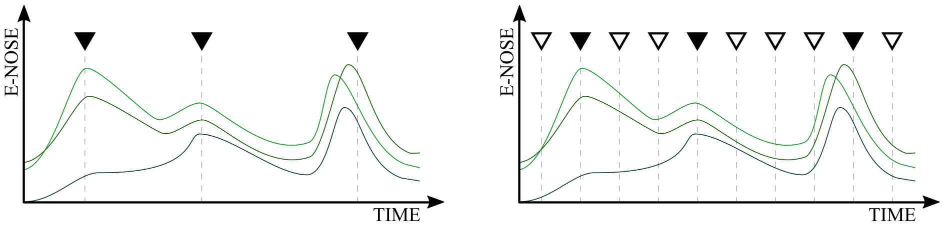
5. Generation of Urban Smell Distribution Maps

This section discusses the generation of smell maps with the recorded e-nose data and, given the results of the previous section, the CNN classifier. Our intention is to test whether the smell classification was successful (beyond the numeric classification results) by comparing these maps to the user-entered labels.

As opposed to the training stage, where we only fed the classifier with user-labelled data (Figure 4a), we now process all e-nose measurements in a continuous fashion to identify their smell (Figure 4b). Concretely, we treat the output of the CNN as a categorical probability distribution (since the last layer uses a softmax function) rather than a binary label, such that it may be represented as a linear combination of the output categories. Accordingly, Figure 5 shows the classification results of some of the recorded *smellwalk* as an RGB combination of colors; where the red component refers to the probability of belonging to traffic emissions, blue to clean air, and green to other smells. The maps show this way primary colors at all locations where the classifier is confident, and smooth transitions (like yellow or white) between them. We also plot the user-labelled smells to serve as ground truth and therefore assess the accuracy the generated maps. They are displayed with the same color code, but with a different shape (to distinguish them) and varying size (depending on their perceived intensity).

Overall, the classified e-nose measurements seem to be consistent with the recorded smell labels and with their physical surroundings. For example, samples classified as ”traffic emissions” appear at bus stops (Figure 5a), around parking entrances (Figure 5a), at avenues with high traffic flow (Figure 5c) or at slopes where cars have to accelerate (Figure 5b). Likewise, ”fresh air” appears at the promenade (Figure 5a) and quite residential streets (Figure 5b).

There are however several mismatches. Figures 5a and 5b show false-positives of ”traffic emissions” at restaurant areas and, surprisingly, near bronze sculptures in Fig-



(a) User defined labels

(b) User and automatic labels

Figure 4. Conceptual interpretation of how the original labels *(a)* get augmented by the classification algorithm *(b)* to create continuous smell maps. The information gap between the user-entered labels (filled triangles) are filled out with smell predictions (empty triangles) to represent their actual extend, and to detect other smells that were possibly overlooked.

ure 5a; and the southern motorway in Figure 5c gets missclassified as ”others” instead. This is probably caused by the limited number of available gas-sensors and the lack of more training data to improve our classifier. Also, changes in ambient conditions also affect the results, despite our best efforts to compensate them with the e-nose's humidity and temperature sensors.

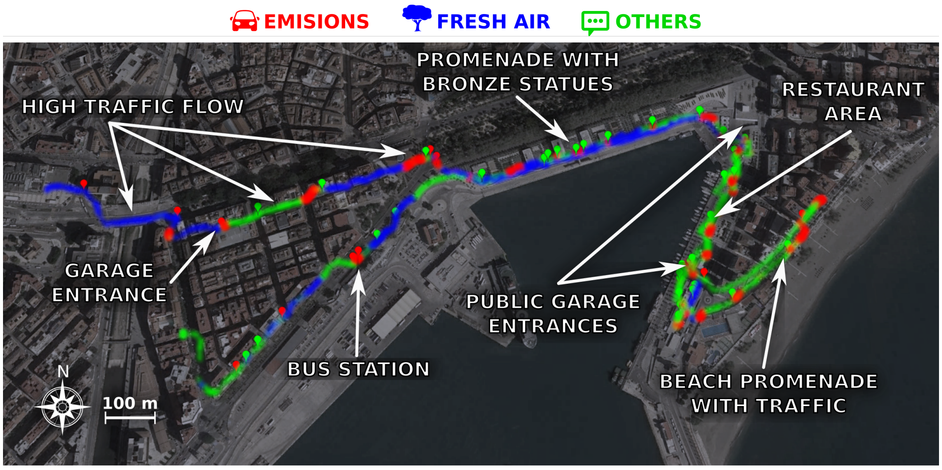
The samples classified as ”other” (green) are of a very disparate nature: they include nice smells, like perfume and flowers, unpleasant odors such as garbage, and neutral aromas, such as food and chemical compounds. Their strong presence on all maps suggest that the e-nose is able to detect more smells than the human *sniffers* aware of, a reflection of the complex background of urban smells we have unconsciously learned to ignore.

Overall, the accuracy of the smell maps is consistent with the performance results of the employed classifier (see Section 4.2). This reflects the sensing limitations of the available e-nose technology, as well as the intrinsic difficulty of matching odors according to a subjective perception. Even so, the accuracy of the obtain maps is sufficient to identify locations that suffer from smog related odors together with places that possess clean air with no smell at all. Meaning that the employment of e-noses is indeed feasible but limited to the generation of coarse smell distribution maps.

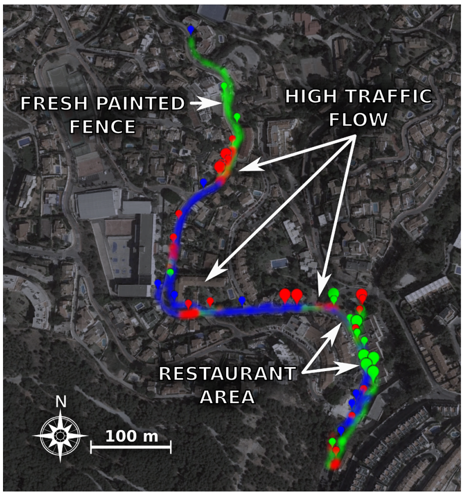
6. Conclusions

This work shows that the generation of reasonably accurate smell distribution maps with an e-nose is feasible. The only requirements are a labelled dataset of the e-nose's response to the target smells and an appropriate classification algorithm. In this regard, we have tagged over 450 urban smells with a smartphone application, and recorded over 47 km of continuous e-nose measurements. Also, we have conducted an extensive comparison of several popular classifiers, among which Convolutional Neural Networks ranked first to produce distributions maps for traffic emissions, clean air, and other urban smells at three different locations in Malaga (Spain).

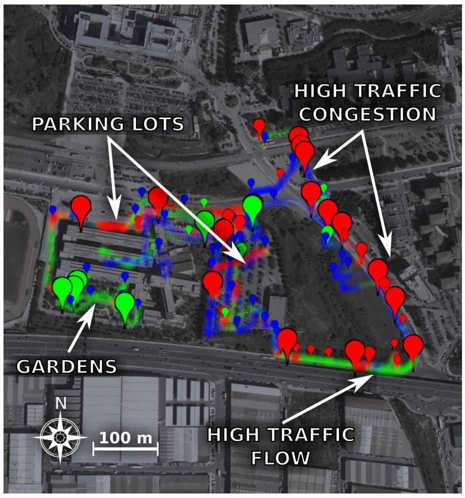
Admittedly, the accuracy and resolution of these maps remain below of those generated by human *sniffers*. However, they are a first step toward the development of an automatic tool to assess the smellscape of major cities in real time. In any case, we are confident that we will be able to further improve the classification success ratio by increasing the dataset's size (more training examples) and by fine-tuning the characteristics of our CNN classifier in future research.



(a) Sea promenade El Muelle Uno (N36°71′ W4°41′).



(b) Residential area (N36°72′ W4°38′).



(c) HTS Computer Science (N36°71′ W4°47′).

Figure 5. Visualization of the user-defined labels (pins) and the output of the CNN smell classification (continuous path) at three different locations. Each color represents a smell category, although gradual transitions may exist. In particular, red stands for traffic emissions and smog, blue for clean air (i.e. no smell at all), and green for any other smell. The size of the pins represents the user-perceived intensity, where bigger means more prominent smells.

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