Indoor Localisation using Aroma Fingerprints: A First Sniff

Published in
2017 14th Workshop on Positioning, Navigation and Communications (WPNC)

DOI
10.1109/WPNC.2017.8250046

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***Abstract*—Electronic noses (eNoses) can detect and classify a large variety of smells. They are, in general, much more sensitive than the human nose. Could they identify different indoor locations based on the locations' characteristic combinations of airborne chemicals? We study in this paper how well location can be determined in an indoor environment using only measurements from an ion mobility spectrometry eNose and a K nearest neighbour (KNN) classifier. Based on the results of test with real-world data eNose-based localisation seems to have potential but there are several questions and issues that still have to be addressed. This paper provides therefore a discussion of questions and issues that have to be studied in the future, and proposes potential solutions.**

I. Introduction

Indoor localisation, the technology enabling people to navigate in environments where satnav does not reach, has received a lot of attention in the research community and in the industry over the last decades. However, no single indoor localisation technology has emerged to dominate the field. A variety of radio signals, such as cellular networks, wireless local area networks (WLAN), ultra-wideband (UWB), Bluetooth and Bluetooth low energy (BLE), have been used. Alternative sources of used measurements include data from, for example, inertial measurement units (IMUs), laser range scanners, floor maps, and magnetic fields [1], [2].

A source of measurements that to our knowledge so far has not been investigated for localisation are electronic noses (eNoses). They are used in artificial olfaction, which is the science of gas sensing with sensors. An eNose mimics the biological sense of smell and its communication with a biological brain [3]. An eNose consists of a sensor array, a signal-processing unit, pattern recognition software, and reference databases [4]. Traditional eNoses have gas sensor arrays, but ion mobility spectrometry (IMS) technology can be used in a similar way. IMS-based eNoses have the advantage, compared with gas sensor-based eNoses, that their sensors and electrodes do not age. Therefore, we focus in this paper on IMS-based eNoses.

Electronic noses are rapidly becoming more portable, cheaper, and more sensitive. They are already much more sensitive than the human sense of smell, and also measure airborne chemicals that are odourless. The question arises, are they able to detect and distinguish different indoor locations based on the locations' existing characteristic scents? This paper is a first exploratory look at this question.

There are reports in the literature about the use of eNoses for localising gas sources, for example, on landfills using a mobile robot (see [5] and references therein). This application is different from the application studied in this paper, because here we want to use the eNose to tell the user where they are. In [5] (and other similar papers) the aim is to find the source of a certain scent. Thus, it does not use eNose for (self-) localisation. The three robots used for tests in [5] rely instead on either laser range scanners or an IMU for localisation.

For localisation using eNose measurements we focus in this paper on nonparametric fingerprint-localisation techniques. These nonparametric methods use a database that contains measurements taken at known locations, so-called fingerprints, that are collected in the offline (aka training) phase [6]. In the online (aka localisation) phase the measurements from the user's unknown location are compared to these fingerprints in order to infer the user's location. Common algorithms used for localisation are nearest neighbour (NN) and K nearest neighbour (KNN), which we will use in this paper. Overviews on additional nonparametric fingerprint-localisation methods can be found in [7] and references therein.

The contribution of our paper is twofold. First, we provide test results that show that eNose-based localisation has potential but requires still a lot of research. Second, we discuss problems and questions that have to be solved in order to being able to use eNoses for positioning. We also present potential solutions for solving these issues.

This paper is organised as follows. In Section II we explain briefly the eNose we use for our tests and how it works. Section III describes the KNN and how it is used for localisation. We present and discuss test results using real-world data in Section IV. Finally, open questions and issues, and potential solutions are discussed in Section V.

Notation: In this paper a denotes a scalar, $\mathbf{b}$ denotes a vector, and $\mathbf{C}$ denotes a matrix.

presented at WPNC 2017, 25/26 October 2017, Bremen, Germany

Fig. 1: ChemPro100i handheld chemical detector from Environics with ruler showing values in centimetres.

II. ChemPro eNose

In this paper we use the ChemPro100i handheld chemical detector (displayed in Fig. 1) from Environics, which is an eNose based on ion mobility spectrometry. It was originally developed for field detection and classification of chemical warfare agents [8]. For example, it is been used by fire departments to detect gas leaks and find hazardous objects in buildings. We are using it for scent classification.

The ChemPro100i analyses the air in a certain location by separating and identifying ionised molecules in the gas phase based on their mobility. The ChemPro100i yields data from 16 ion electrodes. We use data from 14 of these 16 channels, namely ceramic electrodes 1 to 7 and 9 to 15. Electrodes 8 and 16 are used only to control the air flow speed, and thus cannot be used for analysing the air. More details about the ChemPro100i can be found at [8].

The ChemPro100i is rather bulky and expensive, costing around 8 000 EUR when it was purchased in 2016. However, it is important to note that for localisation we only need its IMS part. Recently substantial improvements in the development of ion mobility spectrometers have been made, which have reduced both the cost and the size of IMS chips significantly. For example, Owlstone launched the field asymmetric ion mobility spectrometer, which is "fabricated on a single microchip with dimensions under a centimetre" [9].

III. Description of KNN-based classification

For localisation in Section IV we use a K nearest neighbour (KNN) classifier (see e.g. [10, p. 174 ff.] for a detailed discussion). The idea behind the KNN classifier is to return a location estimate based on a sample from the eNose at that location by finding the K closest samples from a database containing N IMS measurement samples $\mathbf{x}_i = [x_{i,1} \ \dots \ x_{i,14}]$, $i = 1, .., N$ with known locations.

This means, in our case the 14 IMS measurements $\mathbf{x}^{(\mathrm{UL})} = [x_1^{(\mathrm{UL})} \ \dots \ x_{14}^{(\mathrm{UL})}]$ from the unknown location (UL) of the eNose are compared with the 14 IMS readings of each sample in the database. The closeness between the new sample and the ith training sample is computed as the Euclidean distance[1] between the two, which is defined as

$$d_{\mathrm{E}}(\mathbf{x}^{(\mathrm{UL})}, \mathbf{x}_i) = \sqrt{\sum_{j=1}^{14} \left(x_{ij} - x_j^{(\mathrm{UL})}\right)^2}. \tag{1}$$

Based on the locations to which the K closest samples belong the location estimate is chosen. If the K nearest neighbours belong to different locations then the estimate is chosen by majority vote. In case of a tie we choose the label of the nearest neighbour as location estimate.

The KNN classifier's only parameter, besides the distance function, is K. Because N is, in general, finite, we need to find a compromise between all K neighbours being close to $\mathbf{x}^{(\mathrm{UL})}$, which favours small K, and the location estimate being reliable, which favours large K [10, p. 184]. We therefore test in Section IV with $K = \{1, 3, 5, 7\}$.

Because we use the Euclidean distance for measuring the closeness between the UL's sample and the training samples, we have to standardise all samples. This has to be done because the absolute values and the fluctuations of IMS readings on the 14 channels differ significantly. Details on the standardisation procedure are given in Subsection IV-B.

IV. Results from classification

This section assesses whether data from our electronic nose could be used for localisation in indoor environments. For localisation we use the K nearest neighbour classification algorithm described in Section III.

[1]Other distance measurements such as Mahalanobis, Chebyshev or Minkowski distances could be tested alternatively.

TABLE I: Location numbers, location types, and number of measurements for (almost) empty buildings, for buildings in which people were present, and in total.

loc. no.	location type	measurements (empty)	measurements (crowded)	measurements (total)
1	office room	629	618	1 247
2	coffee room	643	631	1 274
3	open space	616	618	1 234
4	open space	609	614	1 223
5	corridor	630	646	1 276
6	open space	608	637	1 245
7	open space	626	611	1 237
Σ		4 361	4 375	8 736

A. Explanation of the data

Our data was collected in May 2017 with Environics' ChemPro100i Handheld Chemical Detector in seven different indoor locations at the campus of Tampere University of Technology, Finland. One of them is a small office room (location 1), one is a coffee room (location 2), one a corridor connecting two buildings (location 5), and four are large open areas (location 3, 4, 6 and 7). Locations 6 and 7 are next to restaurants that have lunch buffets available during weekdays.

For each location two data sets of approximately 10 minutes have been collected with a measurement frequency of 1 Hz. The data sets for any specific location have been collected on two different dates with a gap of 2 or 3 days respectively. The first sets were collected on a Saturday, to ensure that the buildings were (almost) empty. At locations 6 and 7 the restaurants were closed and no food was on display. The second sets were collected during weekdays when people were present and walked by the eNose. In addition, at locations 6 and 7 food was on display. Table I summarises the locations, their type and the number of samples. For each location we have a similar amount of samples, which helps to avoid a skewed class distribution.[2]

B. Validation Accuracy of the KNN classifier

In the first test we determine the validation accuracy of the KNN classifier, i.e. how accurately our classifier will perform on new data. We use all data sets, meaning that we train the KNN classifier on data from both empty and crowded locations.

We standardise our data by centring it and dividing it by the standard deviations of all measurements for any IMS channel. This means, for IMS channel j we first compute empirical mean μ_j and standard deviation σ_j using all measurements on channel j. Then we compute standardised IMS measurement

$$\bar{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \tag{2}$$

[2]Skewed class distribution means that the number of samples for each location differ significantly. In extreme cases this can cause the KNN to pick training samples belonging to a false location as nearest neighbours because they are among the K closest samples to the UL's sample just due to their large amount [11].

TABLE II: Validation accuracies and classification losses for test in IV-B.

K	validation accuracy	classification loss
1	99.98%	0.02%
3	99.91%	0.09%
5	99.87%	0.13%
7	99.84%	0.16%

TABLE III: Misclassification rates for tests in IV-C.

training data	test data	K	misclassification rate
empty	crowded	1	71.50%
		3	71.61%
		5	71.79%
		7	71.75%
crowded	empty	1	62.46%
		3	62.62%
		5	62.55%
		7	62.55%

where x_{ij} is the original ith measurement on IMS channel j.

Because we have only a small amount of data for training our KNN classifier, we use 10-fold cross-validation [10, p. 483 f.] to prevent over-fitting and to increase the validation accuracy (aka lower the validation error).

We test the NN algorithm (i.e. $K = 1$) and the KNN algorithm for $K = \{3, 5, 7\}$. Table II contains the values for the validation accuracy and classification loss averaged over the 10 folds by the corresponding KNN classifier.

As we can see, the value of K has no significant influence on validation accuracy and classification loss. More importantly, the validation accuracy is almost 100%, which means that eNose-based localisation by a KNN algorithm has potential.

C. KNN-based localisation

Here we analyse how a KNN classifier with the same features as in the previous subsection performs when it is used for localising new samples that are taken under different conditions than the samples used for training the classifier. Therefore, we divide our data described in Subsection IV-A into training and test data. We first use the data from empty locations for training and the crowded locations for testing the classifier. In the second run we use data from crowded locations for training and data from empty locations for testing.

We again test the NN algorithm (i.e. $K = 1$) and the KNN algorithm for $K = \{3, 5, 7\}$, and normalise the training samples using (2). For normalising the test samples we use (2) with $\{\mu_j\}_{j=1}^{14}$ and $\{\sigma_j\}_{j=1}^{14}$ computed from all training samples.

Table III contains the misclassification rates for both runs and all four values of K. As in the previous test, the influence of K on the misclassification rate is marginal. The misclassification rates for both runs are disappointingly high. Thus, let us check the results in more detail. Fig. 2 shows

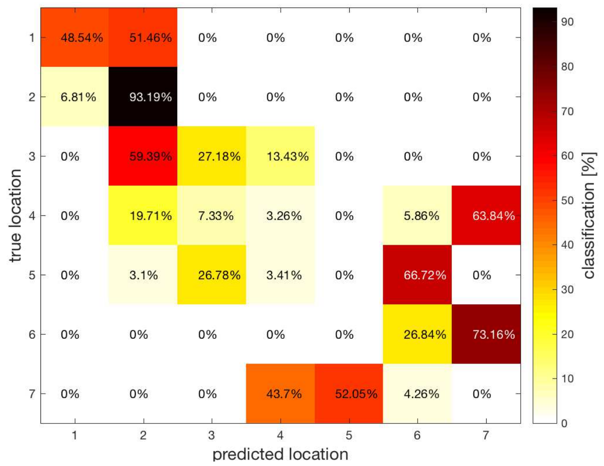

Fig. 2: Relative confusion matrix using NN classifier for test with empty training and crowded test data. Values in each row sum up to 100%.

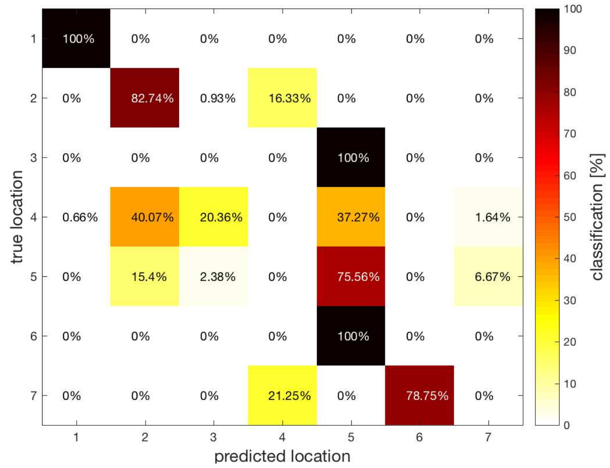

Fig. 3: Relative confusion matrix using NN classifier for test with crowded training and empty test data. Values in each row sum up to 100%.

the relative confusion matrix of run 1 (empty training and crowded test data) for $K = 1$. The confusion matrices for the other values of K differ only insignificantly. For each row of the matrix the values sum up to 100%. Ideally the elements on the matrices' main diagonal are 100% and all other elements are 0%. However, in our first run this is not the case. We see that only few samples from location 2, the coffee room, get misclassified as location 1 (office room). For location 1 around half of the samples are classified correctly, and the other half gets misclassified as location 2. Both of these locations are closed spaces that could only be entered through a door, and for both locations there was only one person in the room when training data was collected and several people when test data was collected. This might explain why samples from these two locations are not misclassified as being from locations 3 to 7, which are larger open areas.

All test samples from location 5, the corridor between two buildings, were misclassified, mostly as locations 6 and 3, which are also open spaces. While in the training phase only one person was static in the corridor, people moved through the corridor all the time in the test phase. The samples from open spaces (locations 3, 4, 6 and 7) are misclassified in general as samples from other open spaces. The exception are samples from location 3, of which 59.39% are misclassified as location 2. One similarity between locations 2 and 3 is that both contain coffee machines. Furthermore, location 3 is somewhat smaller than the other three open spaces, which might explain why such a large amount of test samples get misclassified as samples from location 2.

The confusion matrices for run 2 (crowded training and empty test data) for $K = 1$ is shown in Fig. 3 (confusion matrices for the other Ks differ only slightly). Here we see three major differences to run 1. First, all samples from the office room are classified correctly. Second, the majority of samples from the corridor (location 5) are classified correctly. And third, all samples from location 6 (open space) are misclassified as samples from the corridor.

Thus, we can conclude that it is important to have training data that is collected in various conditions to ensure that the KNN algorithm can classify a location correctly with high probability. A more thorough discussion of these results can be found in the next section.

V. Discussion and Outlook

This paper tries to provide initial answers to the question whether electronic noses could be used for localisation. Based on the results from Subsection IV-B localising with a KNN classifier using IMS measurements from an eNose has potential. However, the results in Subsection IV-C show that there are still many issues that have to be resolved, and many questions have to be answered before IMS measurements can be used for reliable localisation.

First of all, we should check in detail differences of IMS readings between full and empty buildings, but we could also check the variations of IMS readings during different times (e.g. morning, noon, afternoon and evening) of a working day. It seems that the readings of some channels react more strongly to people in the eNose's vicinity. Thus, we will study if we can reduce the misclassification rate by either using only sensitive channels, which fluctuate strongly, or stable channels, whose eNose readings differ only slightly or not at all for empty and crowded buildings. This is crucial when we want to define under which conditions training data should be collected. For the latter case it might be enough to collect data in an empty building, and still being able to localise the user correctly with high probability inside a crowded building.

The second issue related to the channel readings is that the KNN might be fooled by irrelevant channels. This means, channels that display similar values for all locations. Furthermore, some of the IMS channels may be correlated. Thus, feature transformation and/or feature selection methods should be tested. As an example, the principal component analysis

(PCA) could be used to transform the measurements from the IMS channels into measurements from artificial, uncorrelated channels. PCA, in general, reduces the amount of channels that are used for classification significantly, thus reducing the computational demand notably. The drawback of PCA is that it is more difficult to interpret the artificial channels.

In order to further reduce the computational demand for classification one should study alternative methods for searching the K closest training samples to a new sample from an unknown location. Currently, we use the exhaustive search algorithm, which compares the new sample to all training samples. Obviously this will be too slow if our database of training samples becomes larger. An alternative search method is the k-dimensional (k-d) tree search [12]. In this method a tree is generated from the training data in the offline phase and the new sample is only compared to a small fraction of training samples in the online phase, which speeds up the classification process significantly. One of its drawbacks is that it works only with low-dimensional data. Thus, it should be tested together with the PCA, which would reduce the dimensionality of our data from 14 to between 2 and 5. Another drawback of k-d tree search is that it might miss the true nearest neighbour(s). Thus, it remains to be tested if this will affect the misclassification rate negatively.

An advantage of k-d tree search is that it possible to add new nodes to an existing k-d tree [12], which means that we do not need to retrain the whole tree when updating our training database with measurements from new locations. Updating the training database will be a major task, because for real-world applications the flexibility to add data from new locations, and remove or update data from existing locations in the training database will be crucial. Therefore, using the KNN classifier is a good choice, as it does not require any retraining as the training database is modified. This does not hold, however, if the data is transformed by PCA or if a k-d tree is used for searching the nearest neighbours, as discussed before.

In addition, it should be investigated if the classification accuracy can be improved by using a time series of IMS samples instead of a single sample from the unknown location. For positioning based on radio signal strength or magnetic fingerprinting this approach proved to be successful [6], [13].

Furthermore, we could study if it is possible to improve the positioning accuracy by using a denser grid of points in which training samples are measured, and how other nonparametric and parametric fingerprint-positioning methods (see e.g. [6] for a recent survey) perform in this case. In addition, the fusion with other information, for example, from an inertial measurement unit, wireless area networks, and bluetooth low energy networks should be studied.

Possible device heterogeneity is another issue that has to be studied. We need to compare the IMS readings of different eNoses at the same locations at the same time. If significant device heterogeneity is detected then we have to find calibration methods that mitigate its influence. In the literature, manual (e.g. [14], [15]) and automatic (e.g. [16], [17]) calibration techniques for received signal strength heterogeneity have been proposed. These methods might also work for IMS heterogeneity, but at least we could use them as starting point for finding a suitable calibration method for IMS devices.

Finally, we want to stress that this paper is an explanatory study for the future when IMS chips will be cheaper and more widespread. This future seems to be not that far away. For example, Owlstone's ion mobility spectrometer with dimensions of less than a centimetre (see [9] for details) could in principle already today be incorporated into mobile devices such as smartphones.

VI. Acknowledgement

This research was financially supported by the Academy of Finland under grant number 295433.

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