Theodor: A Step Towards Smart Home Applications with Electronic Noses

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ABSTRACT
This paper presents preliminary results of the ongoing project TheOdor which explores the potential of electronic noses that make use of commodity gas sensors (MOS, MEMS) for applications in the smart home, for example to classify human activities based on the odors that activities generate. We describe the system and its components and report on classification results from first validation experiments.

CCS CONCEPTS
• Hardware → Sensor applications and deployments; Digital signal processing; • Human-centered computing → Ambient intelligence;

KEYWORDS
Electronic nose, Smart home, Odor, Scent, Sensor, Smell, MOS, MEMS

ACM Reference Format:

1 INTRODUCTION
Smart home technology has found its way into more and more households in recent years, turning ordinary homes into smart homes, and the technology is developing and spreading rapidly. The basic components of a smart home consist of actuators (e.g. power plug, light bulb, switching relay, door lock, ventilation, thermostat) and sensors (e.g. motion detector or light, contact, pressure, temperature, or humidity sensor) [6] which together form a causal relationship between cause (one or more sensors) and effect (one or more actuators) and thus implement a basic behavior [11]. For example, if a motion detector triggers and the light sensor indicates low light condition, then the light is switched on.

Ideally, the behavior or functions of a smart home should support an inhabitant’s daily routines or support the activities of an inhabitant. Necessary requirements to realize such behaviors are methods and approaches to recognize inhabitant’s activities by means of the sensors of a smart home among other data sources (e.g. time of day). Therefore, human activity recognition (HAR) plays an important role in smart home research to recognize activities of daily living [23], for example to assist in cooking tasks [22] or to help people with dementia with hand washing [13]. Most of the technologies used for HAR require inhabitants to wear a device with sensors, such as inertial sensors of a smartphone or smartwatch [18], or to have cameras mounted in the smart home [9]. A more unobtrusive way for HAR is to make use of sensors for the detection of odors that occur during activities, for example cooking, bath activities, or having a meal. Smart homes are particularly suitable environments for this approach, as these are mostly closed spaces compared to working environments or open interactive environments. In closed spaces, the odors of activities remain very long or until inhabitants ventilate them, making the use of HAR based on this approach more suitable than in open areas, where odors spread very quickly until they can no longer be measured. The research project and exploration platform TheOdor addresses exactly this area of application and investigates suitable machine learning approaches for HAR with prototypes that we built from scratch.

1.1 TheOdor Project
Our TheOdor project falls into the research of electronic noses for the recognition of human activities in smart homes. However, most research works on electronic noses are not concerned with the application in smart homes but rather for industrial use, for example for the determination of product quality [7, 14, 17] or bacterial cultures [12]. Recent research works, such as that at KIT [5], are taking a promising path by developing specialized sensors.
for the detection of odor molecules which may be the preference for HAR in future. Such developments are still in their infancy and not yet ripe for HAR research. If we focus on commodity gas sensors, Hirano et al. \cite{8} presented the system uSmell which made use of more recent commodity gas sensors to explore the classification of odors for UbiComp applications. They demonstrated the use of such sensors for the detection of different beverages by their odors using a decision tree classifier and achieved 88\% accuracy. Due to their promising results, we used their findings and considered them in the design of our exploration platform TheOdor as a first step towards our goal.

The ultimate goal of the TheOdor project is not only to recognize and distinguish beverages but to determine whether and how reliably human activities can be derived from recognized odors. Hence, the sensor array of TheOdor includes the sensors that previous work employed in addition to more recent MEMS sensors. TheOdor is part of a larger smart home research installation in which TheOdor also serves to investigate the environmental conditions in a smart home. Therefore, TheOdor also includes sensors that measure brightness or fine dust particles (e.g. PM2.5).

Table 1: Sensors used in TheOdor

<table>
<thead>
<tr>
<th>Model</th>
<th>Type</th>
<th>Main sensitivity (secondary)</th>
<th>Power (mW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MQ2</td>
<td>MOS</td>
<td>Methane (Butane, LPG)</td>
<td>~800</td>
</tr>
<tr>
<td>MQ3</td>
<td>MOS</td>
<td>Alcohol</td>
<td>~750</td>
</tr>
<tr>
<td>MQ5</td>
<td>MOS</td>
<td>Propane (LPG)</td>
<td>~800</td>
</tr>
<tr>
<td>MQ9</td>
<td>MOS</td>
<td>Carbon monoxide</td>
<td>~350</td>
</tr>
<tr>
<td>MICS 6814</td>
<td>MEMS, MOS</td>
<td>Ammonia, Carbon monoxide, Nitrogen dioxide (Hydrogen, Hydrogen sulfide, Nitrogen monoxide, Isobutane, Ethanol, Propane)</td>
<td>~100</td>
</tr>
<tr>
<td>AS MLV P2</td>
<td>MEMS, MOS</td>
<td>Volatile organic components</td>
<td>~200</td>
</tr>
<tr>
<td>TFA</td>
<td>NDIR</td>
<td>Carbon dioxide</td>
<td>~300</td>
</tr>
<tr>
<td>DHT 22</td>
<td>Polymer</td>
<td>Temperature, humidity</td>
<td>~3</td>
</tr>
</tbody>
</table>

In the following, we present the results of the first step, that is the design and implementation of the exploration platform TheOdor and the validation of the gas sensor array.

2 SYSTEM DESIGN OF THEODOR

In contrast to the system uSmell \cite{8}, we designed TheOdor as a compact and mobile stand-alone system that does not require a desktop PC. This allows TheOdor to be placed anywhere where odors occur without restrictions for experiments. TheOdor consists of two closed measuring boxes with sensors, each connected to and controlled by a Raspberry Pi 3 single-board computer as depicted in Figure 1 and Figure 2. Access to TheOdor is realized via WiFi, so that TheOdor only requires a power socket to start its work.

2.1 Measuring Boxes and Sensors

The measuring boxes were printed with a 3D printer and are designed to have a fan mounted on top of the box which blows air into the box on demand, see Figure 1. Furthermore, the boxes were printed with mounts in the box to optimally accommodate the sensors within the environmental conditions in a smart home. Therefore, TheOdor also includes sensors that measure brightness or fine dust particles (e.g. PM2.5).

In order to validate the gas sensor array of TheOdor for this step, we adapted the classification approach that \cite{8} applied for validating their system. By this means, we made sure that the implementation (without our extensions) is valid in terms of previous findings. However, for HAR tasks, we believe that there are more suitable machine learning approaches (than statistical classification) to cope with the idiosyncrasies of gas sensors, such as sensor drift \cite{10} or temperature / humidity dependencies \cite{16, 19}. In future steps, we consider the sensor array of TheOdor as receptors of an electronic nose in which the electronic signals of the receptors generate multivariate time-series data. For such kind of data, a series of recent research works has shown great potential of deep neural networks in comparison to other approaches \cite{12, 15, 21}, in particular to compensate for sensor drift \cite{10}. However, these works have not addressed human activity recognition in smart home environments.

\footnote{Volatile Organic Components}
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Theodor, a novel system, is designed to capture and analyze various sensor arrays to recognize different activities. Theodor comprises MOS sensors, which provide distinct odor data with labels representing actual activities that happened at that time.

**Odor Data and Environmental Parameters**

To ensure accurate readings, Theodor samples both temperature and humidity in order to compensate for their dependencies. MOS sensors' response varies with humidity, necessitating a humidity sensor that offers high precision. Theodor also incorporates temperature sensors to ensure dependable readings.

**Sensor Arrays**

Theodor arrays include MOS sensors, a Non-Dispersive Infrared (NDIR) CO\(_2\) sensor, and an AMS VOC sensor. The NDIR sensor is based on spectroscopic mechanisms, enabling precise CO\(_2\) concentration measurement. The AMS VOC sensor, self-contained, offers volatile organic compound detection. A Passive Infrared (PIR) sensor, measuring an auxiliary motion parameter, ensures motion recognition.

**Operational Environment**

Theodor operates within a controlled environment. The room is periodically aired with a fan to reset gas concentrations, temperature, and humidity. The ambient concentration of CO\(_2\), humidity, and an auxiliary motion parameter are periodically sampled.

**Data Collection**

Data collection involves placing each foodstuff sample in the center of a container with sufficient space for a glass of beverage or food. Each container is sealed with a lid, and the odor data are sampled for ~180 seconds. A measuring box of Theodor is placed inside the containers for the designated period.

**Data Storage**

Readings are stored together with a timestamp in a local log file on an SD card. Timestamps are synchronized to a local clock over NTP. Readings are then pushed over the network to a server if available. In the absence of a server, readings are stored in a SQL database.

**Classification**

Theodor provides data for classification approaches. A deep learning approach was validated to recognize different types of food. Theodor and its PIR-based motion detector are used to capture a series of activities, with each activity labeled for recognition.

**Conclusion**

Theodor promises a step towards smart home applications, offering a new approach to activity recognition with electronic noses. Through careful design and validation, Theodor demonstrates its potential in recognizing various activities in a home environment.
Figure 4: Classification results of different sensor data combinations and classes. For all classifications WEKA's C4.5 (J48) decision tree classifier with a 10-fold cross-validation was used. The data set consisted out of about 80 samples per class.
Table 2: Foodstuff used for gas concentration measurements. Beverage names, that are bold, are comparable with the beverages used in [8]

<table>
<thead>
<tr>
<th>Foodstuff</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>apple</td>
<td>fruit</td>
</tr>
<tr>
<td>banana</td>
<td>fruit</td>
</tr>
<tr>
<td>black tea</td>
<td>hot drink</td>
</tr>
<tr>
<td>buttermilk</td>
<td>dairy product</td>
</tr>
<tr>
<td>carrot juice</td>
<td>vegetable juice</td>
</tr>
<tr>
<td>chardonnay</td>
<td>white wine</td>
</tr>
<tr>
<td>coffee</td>
<td>hot drink</td>
</tr>
<tr>
<td>cola</td>
<td>soft drink with CO₂</td>
</tr>
<tr>
<td>dornfelder</td>
<td>red wine</td>
</tr>
<tr>
<td>emmenthaler</td>
<td>cheese</td>
</tr>
<tr>
<td>garlic</td>
<td>vegetable</td>
</tr>
<tr>
<td>grapefruit juice</td>
<td>fruit juice</td>
</tr>
<tr>
<td>green tea</td>
<td>hot drink</td>
</tr>
<tr>
<td>herder’s cheese</td>
<td>cheese</td>
</tr>
<tr>
<td>hot tap water (no chlorine)</td>
<td>water</td>
</tr>
<tr>
<td>merlot</td>
<td>red wine</td>
</tr>
<tr>
<td>milk</td>
<td>dairy product</td>
</tr>
<tr>
<td>onion</td>
<td>vegetable</td>
</tr>
<tr>
<td>orange juice</td>
<td>fruit juice</td>
</tr>
<tr>
<td>pear</td>
<td>fruit</td>
</tr>
<tr>
<td>quark</td>
<td>dairy product</td>
</tr>
<tr>
<td>sparkling wine</td>
<td>white wine with CO₂</td>
</tr>
<tr>
<td>tap water (no chlorine)</td>
<td>water</td>
</tr>
<tr>
<td>tomato juice</td>
<td>vegetable juice</td>
</tr>
</tbody>
</table>

of 1 Hz. The time-series data were then segmented into 5 second frames (each consisting of 5 samples) with no overlap. For each of the frames, the following features were calculated: average, linear regression and variance. For classification, we combined the time-series data of both sessions which resulted into about 80 frames for each class (type of foodstuff sample).

The classification was carried out with the C4.5 (J48) decision tree classifier implementation in the WEKA machine learning toolkit (version 3.9.2) [20] and a 10-fold cross-validation with stable random seed for all evaluations.

3.3 Results

The experiment included the MQ sensors used in previous work and additionally with more recent MEMS sensors as well as with additional odors of food. In the following, we use confusion matrices to discuss what effects the types of sensors and the number and type of odors have on the classification. To create the confusion matrices, the classifications were only performed with the time-series data of the selected sensors and odor types given in the discussion.

3.3.1 Comparison with uSmell. For the comparison with [8], only the data of the MQ sensors and the humidity sensor for the odors of the beverages were used. The results are shown in the confusion matrix in Figure 4 a). Compared to the sensor combination of uSmell, our selection of MQ/MOS sensors contains three fewer sensors. Therefore, this comparison is not fully comparable. Nonetheless, the weighted averaged recall (88.6%) and precision (88.7%) are similar (marginally better) to the results of uSmell (88.1% / 88.2%).

The confusion matrix reveals that the class chardonnay was most often confused with the class merlot and the other way round. This happens also with the other two alcoholic beverages dornfelder and sparkling wine, although not often. In uSmell, especially the class champagne was confused with the class chardonnay and the class merlot and in part also the other way round indicating that there were also some problems with alcoholic beverages.

3.3.2 MQ sensors vs. MICS sensor. The MICS sensor is a compact MEMS sensor which consumes only a fraction of the power that only one MQ sensor requires (see Table 1). The three independent sensors in the package covers most of the gas-molecule (primary and secondary) that the four MQ sensors are sensitive of. Therefore, it is advantageous to use the MICS sensor instead of the MQ sensors, which would lead to greatly reduced power consumption and less heat generation and thus increase mobility of the electronic nose. To compare the classification performance with the MICS sensor, we conducted the same calculations as in Section 3.3.1 with the time-series data of the MICS sensor.

The results are given in the confusion matrix in Figure 4 b). Recall and precision were nearly identical at 87.7% which is about one percent less than with the MQ sensors. Compared to the MQ sensors, the classification of the time-series data of the MICS sensor shows fewer problems with false classification of alcoholic beverages but confines the two hot beverages with caffeine with each other, that are coffee and black tea.

3.3.3 Classifying all foodstuff classes. Our extension of the original experiment for uSmell includes eight additional food samples and two more beverages (tomato juice and green tea) with the aim to test the approach also for food and other beverages. For this classification, we compared the time-series data of the MQ sensors against the MICS sensor. Both data sets also included the time-series data of the humidity sensor. The confusion matrices are given in Figure 4 c) and Figure 4 d). For both matrices, recall and precision are slightly worse in comparison to using fewer classes (MQ + humidity: recall: 87.8% / precision: 88.1%; MICS + humidity: 86.4% / 86.2%). Figure 4 c) and Figure 4 d) show that alcoholic beverages (in part) still get confused with each other. The beverages involved are also the same as in Section 3.3.2 (MQ: chardonnay / merlot; MICS: coffee / black tea).

3.3.4 CO₂ NDIR sensor. Instead of the power-hungry MOS sensor MG-811 for CO₂, we included the more precise and energy-efficient NDIR CO₂ sensor from TFA. Adding the time-series data of the CO₂ sensor to the two sensor combinations (MQ + humidity / MICS + humidity) gives the confusion matrices shown in Figure 4 e) and Figure 4 f). The MQ sensor combination receives a recall of 96.2% and a precision of 96.2% while the MICS combination receives a recall of 94.7% and a precision of 94.8%. Both combinations achieve about 8% higher recalls / precisions after adding the CO₂ sensor and all classes show much higher recognition rates.

3.3.5 MICS, MQ, CO₂ and humidity sensor. If we do not care about power-consumption and combine MQ and MICS sensors
MQ + MICS + humidity + CO₂ (recall: 97.1 % / precision: 97.2 %)

apple banana cereal bread butter milk chardonnay cola dornfelder emmental grapefruit juice herder's cheese coffee garlic mustard milk orange juice sparkl. wine tap water hot tap water onion prediction actual class

0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0 1 1.2 1.3 1.4 1.5 1.6 1.7 1.8 2 2.1 2.2 2.3

Figure 5: Classification result for the combination of MICS, MQ, humidity, and CO₂ sensor.

together with the humidity and CO₂ sensor, then we receive the confusion matrix given in Figure 5. The confusion matrix shows that the combination results in even better recognition than the other combinations with a recall of 97.1 % and a precision of 97.2 %.

The VOC sensor of AMS was not included for the previous comparisons, as it was not present in uSmell either. For the combination of all sensors in this section, we also tried to include the VOC sensor in the classification. However, this resulted in only very little improvement of the classification results (recall: 97.2 %, precision: 97.3 %).

4 DISCUSSION AND CONCLUSION

Based on our exploration platform TheOdor, we performed several comparisons with different combinations of sensor types and food types. In general, recognition rates can be increased by including more recent MEMS sensors and more precise (NDIR) sensors. Our extension to the experiment in [8] has demonstrated that the application of the approach also works for food samples. The comparison of MQ sensors and the MEMS sensor revealed only few differences in classification performance. If power-consumption is an issue, then the use of MEMS sensors instead of the MQ sensors help drastically reduce power-consumption at marginally lower classification performance.

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REFERENCES


