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Olfactory Interfaces: Recent Trends and Challenges of E-Noses in Human–Computer Interaction †

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Abstract: An electronic nose (e-nose) is an electronic device composed of one or more odor sensors, a microcontroller, electronic components, and software that acquire and analyze a gas or volatile organic compound (VOC) present in an environment. E-noses attempt to identify the gas or VOC based on their chemical composition, sending electronic data about the detected odor signature to a computer, akin to an animal nose identifying odors and sending electrochemical signals to an animal brain. Then, the computer attempts to identify the perceived odor. E-noses have been used in human–computer interaction in specialized computing applications containing a user interface (UI) with a purpose: supporting its user to identify an odor and its properties and communicating information about the odor on the UI.

Keywords: e-nose; olfactory interfaces; smell; odor; sensor; human–computer interaction; microcontroller

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1. Introduction

An electronic nose (e-nose) is an electronic device that attempts to identify one or more olfactory fingerprints (signatures) of gases or volatile organic compounds (VOCs) from an odor sample obtained from an environment [1]. For an e-nose to identify an olfactory fingerprint, the e-nose needs to be trained [2], providing it with a reference dataset of olfactory signatures related to the intended odor signature that the e-nose sensor is capable of detecting.

E-noses have been applied for supporting human–computer interactions (HCIs) in specialized computing applications. For example, physicians and medical researchers have used e-noses in computers for diagnosing illnesses from patients' breath samples in medical devices [3]. A user interface (UI) [4] can present e-nose data to the user through different computer–human modalities, for example, visualizing alphanumeric text or graphics.

1.1. Background on E-Noses

Odor is a substance property capable of stimulating the user's sense of smell. This stimulus occurs when odor molecules reach receptors located on the olfactory epithelium in the human nasal cavity. The origin of commercial e-noses dates to the 1960s, when the company Bacharach Inc. built Sniffer, a device that consisted of a single gas sensor; however, it was not considered a true e-nose at that time because of its odor-detection limitations [5]. The first electronic system designed to mimic a biological olfactory mechanism was built in 1982 [6]. A new e-nose definition appeared in the nineties, stating that an e-nose is an electronic instrument that has a set of chemical sensors capable of detecting specific odors and a pattern-recognition system and that can recognize simple or complex odors [7].

Nowadays, e-noses have received more attention during the past decade because of their diverse applications derived from multidisciplinary research among several fields [8].

1.2. Composition of E-Noses

An e-nose is composed mainly of one or more odor sensors, a microcontroller, odor-recognition software, and a UI for presenting odor-recognition data to a user. Figure 1 shows a block diagram of a generic e-nose device and its UI.

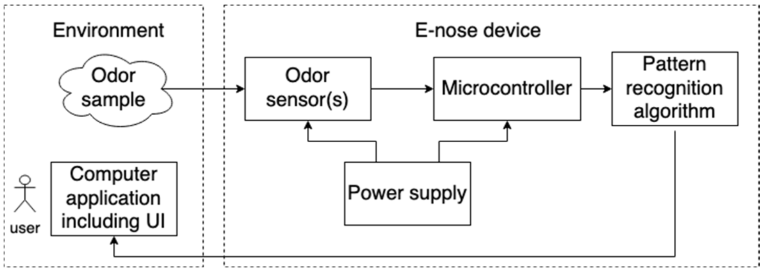

Figure 1. E-nose device containing hardware and software elements used for identifying an odor.

As depicted in Figure 1, one or more odor sensors from the e-nose device detect an odor when its molecules contact the sensor(s) reactive surface, producing analog electrical signals that are read by a microcontroller (a small self-contained computer on a chip [9]). The microcontroller analyzes the sensor signals and determines the odor properties (such as the type of odor and its concentration in parts per million, or PPM). The odor sensor can be part of a tiny microcontroller board module, running the pattern-recognition algorithm on it. The pattern-recognition software can also run on a computer connected to the sensor module. The e-nose sends the odor information to a computer application (or shows the information on the microcontroller board) for its use.

Artificial intelligence techniques such as fuzzy logic have been used for estimating the odor intensities of a mixture of gases [10]. Fuzzy logic has also been used for odor classification in industrial applications [11] and video games [12]. Other analysis techniques include artificial neural networks (ANNs) [13]. Moreover, genetic algorithms (GAs) have been used in e-noses for optimizing data obtained from odor-sensor arrays [14].

1.3. HCI in E-Noses

E-nose information can be communicated to the user through different information presentation modalities using practically all the human sensory channels. In the context of HCI, a modality is considered a single independent input/output sensory channel between a human and a computer [4]. Odor fingerprint results generated by the e-nose can be presented visually on a GUI and aurally through a buzzer. Other sensory modalities can be used, such as haptics, through a vibration motor that can be perceived with the sense of touch.

E-noses can be applied in human–computer interactions in several ways:

1. Odor information sensed by the e-nose can be presented to the user visually [15].
2. The odor data can be sonified and presented in an auditory display [16].
3. E-noses can be used to support sensory substitution, for example, in users with anosmia (the full or partial loss of smell) caused by COVID-19 [17].
4. E-noses can be used in wearable computing [18], supporting user mobility.
5. E-noses can work seamlessly as ubiquitous computing in an environment, working in the background for the service of users [19].

2. Recent Trends in E-Noses

Recent advances in the development of e-noses have been extensive, as the literature from recent years can testify. This section describes some of the current e-nose development projects impacting people through HCI.

Seesaard et al. [20] developed an e-nose that detects people's body odor, intending to detect possible health problems. It was implemented by adding chemical gas sensors to a shirt to achieve self-monitoring for the wearer. The human–computer interaction was built as a wearable device developed with the special version of Arduino for these types of developments: LilyPad. For data communication, a ZigBee wireless module was used. The validation tests confirmed that the device could track changes in the person's odor print, showing its potential for health monitoring by discriminating the odor print of a healthy person.

Another critical threat to human health that electronic noses can help solve is indoor air pollution, as it represents a significant cause of deaths worldwide [21]. The project reported in [22] reports the use of a low-cost e-nose system capable of measuring different air pollutants and various variables such as temperature and humidity. The data collected by the sensors is sent to the cloud to monitor the indoor environment's state in real time. This is clearly a ubiquitous system capable of being deployed in various locations within a smart environment. Therefore, the selected user interaction was the so-called small-screen interface. These interfaces allow the display of dynamic information from systems such as the one mentioned in this scenario.

The predominant user-interaction model in electronic noses is the graphical user interface (GUI). The e-nose is connected to a personal computer, and through a screen, users can view and analyze the information generated from the hardware. This type of interaction has been used in the following projects.

The food industry has been one of the biggest beneficiaries of advances in electronic noses. An example is the case of the adulteration of camellia seed and sesame oils. Because of the high demand for these oils' nutritional value, the adulteration process generates substantial economic benefits. However, unfortunately, these oils are frequently adulterated with other cheap oils to obtain higher profits, which destabilizes the economies of the original producers [23]. Hai et al. [24] developed an electronic nose to detect corn oil adulteration in camellia and sesame seed oils to solve this problem. Using an artificial neural network (ANN), they achieved results with an accuracy of 83.6% for detecting the olfactory signatures of camellia seed oil and 94.5% for detecting those of sesame oil.

E-noses have shown high accuracy in analyzing food in a non-invasive way. For example, in [25], an e-nose was used to classify bacteria according to aromatic compounds during the milk fermentation process. Fermented foods generate aromatic compounds that are associated with probiotic bacteria. This principle demonstrates that aroma monitoring in the fermentation process is a reliable method for classifying bacterial strains during milk fermentation.

The adulteration of alcoholic beverages generates health risks for people and economic losses for manufacturers. A trained human expert can identify adulterated drinks, but that is difficult to perform and is inaccurate. An e-nose odor analysis can identify whiskies, differentiating between brands and origin. Therefore, e-noses have a high potential to identify fraudulent drinks. The work presented in [26] used an e-nose to identify six different whiskies, achieving 96.15% accuracy in identifying the brand, 100% in identifying its origin region, and 92.31% in identifying its style, confirming the effectiveness of this technology for benefiting the health of people and the economy of producers.

3. Challenges of E-Noses in HCI

There are several technical challenges that may affect e-nose performance and their use in HCI:

1. Odor sensors need a calibration process when used for the first time [27], where sensor manufacturers recommend a time interval for calibrating the sensor. This may require an extra task for either the e-nose (when the calibration is performed automatically by the e-nose algorithm) or its users (performing the calibration manually) if this has not been completed before using the e-nose.

2. Sensor drift may affect the e-nose accuracy in HCI, generating false positives in the odor recognition. Fortunately, sensor drift can be compensated by applying artificial intelligence techniques such as deep learning [28].
3. A mixture of odors present in the user environment could affect the e-nose performance and recognition because one odor can enhance or weaken another [29], and thus this may affect the HCI.
4. Some types of e-noses may not work fast enough for a timely rendering of data to a UI depending on the type of odor sensor [30], affecting the user experience (UX) with the UI interaction.
5. In some cases, e-nose data can be difficult to visualize on a GUI due to their amount or complexity, e.g., measuring many types of odors concurrently [31]. HCI techniques such as auditory display techniques (the use of auditory parameters to represent data, e.g., [32]) could be used in UIs, which may help identify and comprehend the odor identification data.
6. The e-nose's UI should clarify the measurement unit notation used in the e-nose application, e.g., clearly show if the odor data are presented as parts per million (PPM) or parts per billion (PPB) [33] to avoid user confusion.

4. Conclusions and Prospects

This paper describes electronic noses (e-noses), which are electronic devices composed of one or more odor sensors, a microcontroller, electronic components, and software that acquire and analyze a gas or a VOC present in an environment. AI techniques have been successfully applied in e-noses to identify one or more olfactory fingerprints. The identification takes place after an odor sample is obtained from an environment. Many e-noses incorporate a UI with the purpose of presenting useful information to the user. We argue in this paper that e-nose information about the detected odor can be presented to the user through different sensory modalities, namely, visually, aurally, haptically, and/or olfactory, exploiting practically all the human senses. In addition, the e-nose information can be presented as a multimodal human–computer interface, fusing all the types of information presentation. There is the potential for future work on the development and testing of e-noses that display information through sound parameters using sonification, as well as incorporating e-noses into olfactory displays. We have discussed applications of e-noses in HCI and their challenges that may affect e-nose and user performance.

The design and development of e-noses that incorporate UIs is often a multidisciplinary activity, involving different areas such as human–computer interaction itself, interaction design, electronics, computer science, ergonomics, and others. Future e-nose designs will require non-complex and low-cost instrumentation and usable user interfaces designed for mobile and everyday use [34].

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