Enhancing Vapor Sensor Discrimination by Mimicking a Canine Nasal Cavity Flow Environment

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"Artificial noses" are vapor detection systems that mimic key principles of vertebrate olfaction. Unlike the selectivity characteristic of most biological interactions, such as enzyme/substrate binding, vertebrate olfaction relies on cross-reactive receptors that respond to many odors, generating unique response patterns.[1] By creating a "fingerprint" for each odor, humans can discriminate thousands of compounds, even though they only have 500−1000 odorant receptor genes.[2] Artificial nose systems utilize cross-reactive sensing elements, akin to the primary odorant receptors, that generate response patterns when exposed to odorants. Responses are identified by pattern recognition algorithms, analogous to cortical processing that enables odorant recognition.[3] While the cross-reactivity and pattern recognition aspects of vertebrate olfaction have been exploited in artificial nose systems,[4] olfactory flow dynamics have been largely overlooked. Several papers reported the use of catalytic surfaces in a flow chamber to induce changes in the concentration profile of analytes presented to a series of identical sensors. The sensors detected local changes in the concentration profile, and the differences were used to enhance analyte discrimination;[5] however, the flow environment itself was not responsible for the enhancement. Here we show that improved discrimination is obtained when identical sensors are exposed to the complex flow environment in a model nasal cavity, demonstrating a novel method to enhance the discriminatory ability of vapor sensors.

In vertebrates, the nasal cavity plays an important role in odor discrimination by influencing the distribution of odorant molecules to olfactory receptors through several mechanisms.[6] First, the lining of the nasal cavity acts in a manner similar to that of a gas chromatography column, separating molecules on the basis of their partition coefficients into the mucosal layer along the length of the cavity.[7] The nasal cavity's second major influence is on the flow dynamics. The interiors of vertebrate nasal cavities are typically convoluted, creating distinct flow paths and generating eddies and currents that result in uneven distribution of odorants to the receptors in the anterior and posterior regions of the cavity, physically patterning odors.[8,9] There are also pockets of receptors that are not in the main airflow, where diffusion is the only mechanism for exposure. In these regions, analyte molecules are detected exclusively on the basis of their diffusion rates.[9] All of these mechanisms may play a role in odor perception and discrimination in vertebrate olfaction, and these mechanisms could be a rich area to exploit in developing sensor diversity.

In this paper, we use a nasal cavity model to investigate how the complex flow dynamics through a cavity can affect odor discrimination with an optical vapor sensor. A sensor in this study is defined as an individual single-core fiber with its distal tip coated with an adhesive to affix thousands of vapor-sensitive fluorescent microspheres.[10] The microspheres are impregnated with Nile Red, a solvatochromic, fluorescent indicator that responds to polarity changes by shifting its emission maximum. Sensors incorporating
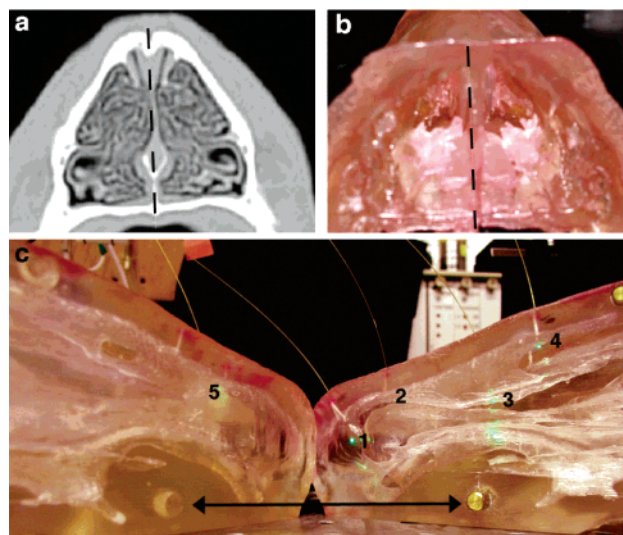

Figure 1. (a) CT scan slice showing the interior structure of a canine nasal cavity. (b) Back view of the nasal cavity model with the dashed line indicating the model halves. (c) Cross-sectional interior view of the model with example sensor positions marked. Position 1 is in a front nostril, and the other positions are in passageways in the nasal model. The model halves are joined via a pin and hole mechanism indicated by the arrow.

this indicator are termed "cross-reactive", because the dye responds to any analyte that affects its environmental polarity.[11] The temporal fluorescence response of each sensor is recorded with a CCD camera before, during, and after an analyte pulse is delivered to the sensors. We hypothesized that by distributing *identical* fiber optic sensors in a complex flow environment, the sensors would experience different exposure conditions, and therefore would respond differently to the same analyte. To test this hypothesis, we fabricated a complex cavity by translating a computed tomography (CT) scan of a canine nasal cavity (Figure 1a) into a 2× scale plastic model (Figure 1b,c). The nasal model, while not as intricate as an actual nasal cavity due to fabrication restrictions, has many passageways, creating a complex flow environment. Identical sensors were fabricated and then placed into different positions within the nasal cavity model. Vapor was pulsed through the nasal cavity by a vacuum/sparge system. The flow rate during the pulse was approximately 1000 mL/min, which corresponds approximately to that of a dog, taking into account the 2× scale of the model.

One sensor was placed in the nostril of the nose model (position 1 in Figure 1c), and the rest were distributed through the cavity. The flow environment effect on sensor responses was determined by comparing the discriminatory ability of the sensor in position 1 relative to the discriminatory ability of the array of five sensors distributed in the nasal cavity. Because all five sensors were identical, the only difference in the discriminatory ability of the one sensor versus five should be due to additional information
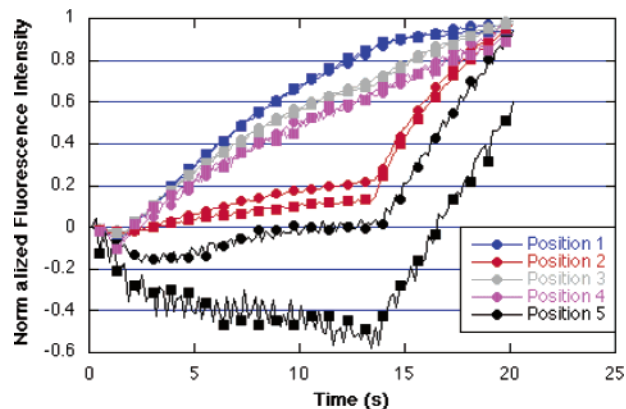
Figure 2. Average response patterns for ethanol (●) and rum #2 (■) at five sensor positions.

Table 1. Individual Increases in Percent Classification Rates for Three Odor Discrimination Tasks[a]

	rums	perfumes	vodkas
experiment 1	14	6.0	14
experiment 2	5.7	10	8.0
experiment 3	8.6	4.0	2.0
experiment 4	13		
experiment 5	1.4		
average increase in % correct	8 ± 5	7 ± 3	8 ± 6

[a] Each experiment had 10 observations of every analyte.

encoded by the different sensor environments. The discriminatory ability of the one sensor as compared to the array was determined through singular value decomposition (SVD) for feature reduction followed by classification of analytes based on the shortest Euclidean distance of each sample to the analyte clusters.

The first question was a simple odor discrimination task to identify air (control), ethanol, methanol, and propanol. A 100% correct classification was obtained for both the single anterior sensor and the five distributed sensors. A much harder task was to identify five individual rums, ethanol, and air (seven-class problem). Figure 2 shows typical responses from the distributed sensors to ethanol and rum 1. Using only the position 1 sensor response, we found that it is not possible to distinguish the two analytes. The responses from all five distributed sensors, however, revealed differences between these two analytes, improving their discrimination. On average, an increase in the rum classification rate of $8 \pm 5\%$ was obtained when the five-sensor array was used relative to the one sensor (Table 1). No response curve feature selection was performed prior to SVD; yet this simplistic method led to improved discrimination. Weighting particular sensor positions for certain analytes could potentially further improve discrimination. For example, in the experiments discussed here, it was found that a sensor in the third position on average correctly identified rum #5 36% more of the time than a sensor in the first position (see Supporting Information). These increases indicate that the change in the sensor flow environment affects the sensor response pattern, leading to the enhanced discriminatory ability of the system.

In addition to the rum classification problem, we also looked at two other odor recognition tasks. Again, sensor position 1 was compared to the five-sensor array distributed throughout the nasal cavity. We challenged the system with a five-class problem to discriminate between air, ethanol, and three perfumes, and an average increase in the classification rate of $7 \pm 3\%$ was obtained. A harder five-class problem was discriminating between air, ethanol, and three brands of unflavored vodka, for which an average increase of $8 \pm 6\%$ was obtained. While the overall classification for each problem was relatively low, only a single sensor type was employed,

Table 2. Average Percent Correct Classification Rates for Three Odor Discrimination Tasks

	average % correct (one sensor)	average % correct (five sensors)
rums[a]	46 ± 5	55 ± 7
perfumes[b]	56 ± 2	63 ± 1
vodkas[b]	56 ± 9	64 ± 4

[a] Average of five experiments. [b] Average of three experiments.

and this lack of sensor diversity led to the low percentages (Table 2). Improvements in the perfume, rum, and vodka problems were statistically significant at the 99, 95, and 80% confidence levels, respectively, as determined by the standard t test. Discrimination between vodkas was the hardest task and therefore had the lowest confidence. These results explicitly show that a complex flow environment can provide improved discriminatory power with even a single sensor type.

The preliminary results of the nasal cavity study show that the flow environment not only affects sensor response, but also enhances discrimination by increasing the amount of information available from the sensor array. Vertebrate systems may enhance discrimination by weighting particular receptor positions over others, and it is highly likely that discrimination can be tuned by weighting particular sensor positions for a given analyte, thereby further increasing the discriminatory ability of the sensors for some odor recognition problems. The use of a complex flow environment, such as a nasal cavity, to provide additional discriminatory information from sensors is a novel and potentially powerful method of generating sensor diversity in artificial nose systems. In the future, this type of nasal cavity system could also be used as a simple model for studying the role of flow dynamics in vertebrate olfaction by isolating flow effects from other factors such as the nasal mucosa and cilia present in biological systems.

Supporting Information Available: Experimental procedures for data collection and analysis (PDF). This material is available free of charge via the Internet at http://pubs.acs.org.

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