Applying Convolution-Based Processing Methods To A Dual-Channel, Large Array Artificial Olfactory Mucosa

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Abstract. Our understanding of the human olfactory system, particularly with respect to the phenomenon of nasal chromatography, has led us to develop a new generation of novel odour-sensitive instruments (or electronic noses). This novel instrument is in need of new approaches to data processing so that the information rich signals can be fully exploited; here, we apply a novel time-series based technique for processing such data. The dual-channel, large array artificial olfactory mucosa consists of 3 arrays of 300 sensors each. The sensors are divided into 24 groups, with each group made from a particular type of polymer. The first array is connected to the other two arrays by a pair of retentive columns. One channel is coated with Carbowax 20M, and the other with OV-1. This configuration partly mimics the nasal chromatography effect, and partly augments it by utilizing not only polar (mucus layer) but also non-polar (artificial) coatings. Such a device presents several challenges to multi-variate data processing: a large, redundant data-set, spatio-temporal output, and small sample space. By applying a novel convolution approach to this problem, it has been demonstrated that these problems can be overcome. The artificial mucosa signals have been classified using a probabilistic neural network and gave an accuracy of 85%. Even better results should be possible through the selection of other sensors with lower correlation.

Keywords: Convolution, Signal Processing, Electronic Nose, Chemical Sensors
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INTRODUCTION

Over the past twenty years, significant advances have been made in the understanding of the mechanism by which odours are detected by the human olfactory system. This has led to the concurrent development of instruments designed to detect odours and commonly known as artificial or electronic noses (e-noses) [1].

However, sensor-based electronic noses today generally suffer from significant weaknesses that limit their ubiquitous application. Their sensing ability is heavily affected by a range of factors, including drift due to temperature, humidity variations and background electrical noise, sensor variations in production, aging and poisoning. These problems are increased by the frequent demand to detect very low concentrations (below PPM) of an odour in air [2, 3], making the design of an electronic nose difficult, even with expensive autosamplers and a carrier gas (e.g. zero-grade air, nitrogen and helium).

Faced with this challenge, novel instruments are being designed to tackle these issues and improve detection thresholds and classification success rates; examples include combining an electronic nose array with a commercial gas chromatography column or mass spectrometer unit.

More recently it has been suggested that chromatography plays a role in odour discrimination within the human olfactory system, known as 'nasal chromatography' [4]. This paper suggests that the aqueous layer covering the olfactory receptors in the

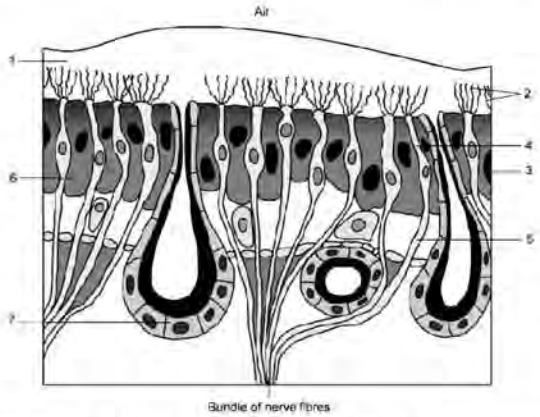

FIGURE 1. Schematic structure of the olfactory organ. (1) Mucous layer. Sensory cells consisting of olfactory cilia (2), cellular body (3), dendrite (4), and a neurite or axon (5). (6) Support cells. (7) Bowman's glands. [5]

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olfactory epithelium (Figure 1) acts as a retention layer to odours moving along and through it, functioning similar to a stationary phase coating channel in a gas chromatographic system. Hence different odours are partitioned and transported at different rates to olfactory receptor cells – leading to different temporal signatures. (Nb: this may even be further amplified by the use binding proteins to transport non-polar molecules through the mucous layer).

The signals produced by novel instruments mimicking this effect [6, 7] require a new approach to signal processing so that this information-rich environment can be fully exploited. One such method has been reported, where the spatio-temporal signals from matching spatially-separated sensors are combined and analysed using a convolution method [8]. This paper reports on the application of this novel processing approach to an artificial olfactory mucosa electronic nose.

EXPERIMENTS AND METHODS

The dual-channel artificial olfactory mucosa [7] has been realised by combining three large chemoresistive sensor arrays, employing composite polymer materials as the sensing layer (carbon black, Cabot corp. USA, mixed with 24 combinations of differing sensing polymers), and two plastic polymer-coated columns (Figure 3). Figure 2 shows the general arrangement of the system showing chemosensor arrays and two retentive columns.

Each large sensor array is laid out in a rectangular matrix configuration (12 columns × 25 rows) to reduce the pad count. This configuration allows us to get a total of 300 sensors per array, with a final chip size of 12 mm × 8.5 mm. This resistive based sensor is then coated with 24 different carbon black polymer composites to create a diversity of spatial responses (see Table 1). Multiple sensors are coated with each composite to provide redundancy that will be used to improve the accuracy of the data processing.

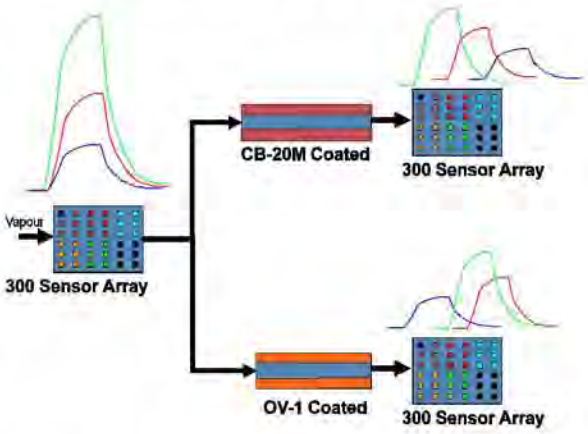

FIGURE 2. General layout of 900 sensor artificial olfactory system.

Each polymer composite solution was prepared by dissolving the polymer blend in 20 ml of solvent. Then the carbon black was added, and the solution shaken (Griffin & George flask shaker UK). Each group of 12

TABLE 1. Composition of sensing polymers.

No.	Polymer Composite	Polymer A (g)	Polymer B (g)	Carbon black (g)	Solvent (20 ml)
P1	Poly(stylene-co-butadiene) PSB	0.7	0	0.175	Toluene
P2	Poly(ethylene-co-vinyl acetate) PEVA	1.2	0	0.3	Toluene
P3	Poly(caprolactone) PCL	1.2	0	0.3	Toluene
P4	Poly(9-vinylcarbazole) PVC	0.7	0	0.175	Toluene
P5	Poly(ehtylene glycol) PEG	1.2	0	0.3	Toluene
P6	Poly(4-vinyl phenol) PVPH	1.2	0	0.3	Ethanol
P7	Poly(methyl methacrylate) PMM	1.2	0	0.3	Ethanol
P8	Poly(vinyl pyrrolidone) PVPD	0.7	0	0.175	Ethanol
P9	Poly(bisphenol A carbonate) PBA	0.7	0	0.175	Dichloromethane
P10	Poly(sulfane) PSF	0.7	0	0.175	Dichloromethane
P11	PSB 50% + PEVA 50%	0.35	0.6	0.2375	Toluene
P12	PSB 50% + PCL 50%	0.35	0.6	0.2375	Toluene
P13	PEVA 50% + PCL 50%	0.6	0.6	0.3	Toluene
P14	PEG 50% + PVPH 50%	0.6	0.6	0.3	Ethanol
P15	PSB 50% + PVC 50%	0.35	0.6	0.2375	Toluene
P16	PEVA 50% + PVC 50%	0.6	0.35	0.2375	Toluene
P17	PCL 50% + PVC 50%	0.6	0.35	0.2375	Toluene
P18	PMMA 50% + PSB 50%	0.6	0.35	0.2375	Toluene
P19	PMMA 50% + PEVA 50%	0.6	0.6	0.3	Toluene
P20	PMMA 50% + PCL 50%	0.6	0.6	0.3	Toluene
P21	PMMA 50% + PVC 50%	0.6	0.35	0.2375	Toluene
P22	PEG 50% + PVPD 50%	0.6	0.35	0.2375	Ethanol
P23	PVPH 50% + PVPD 50%	0.6	0.35	0.2375	Ethanol
P24	PBA 50% + PSF 50%	0.35	0.35	0.175	Dichloromethane

sensors were then deposited with an Iwata CP-30 airbrush by spraying through a mask with a set of (4 × 3) 200 μm square holes. The sensor resistance was controlled during deposition to have a value between 1 kΩ and 5 kΩ.

In order to mimic the 'nasal chromatograph' effect such as in the mammalian olfactory system [9], two retentive columns like nares but with different retentiveness were used (Figure 3). Each column was of similar size (0.38 mm × 0.25 mm × 2000 mm) and coated with a different coating. In this experiment, the first column is coated with a 5 μm thick layer of OV-1 (a non-polar stationary phase), while the second column is coated with a 5 μm thick layer of Carbowax 20M (a polar stationary phase). These two differently coated columns produce different retentive responses to the same analyte, producing a set of spatio-temporal signals.

In this experiment, we are discrimating between four essential oils: Lemon Grass, Cinnamon, Ylang Ylang and Lavender. Each vapour test had a duration of 450 s, consisting of 50 s of laboratory air followed by a 100 s pulse of essential oil vapour mixed with laboratory air, with a flow rate of 20 ml/min. The tests were performed at a temperature of 22°C, and each vapour was repeated 5 times.

FIGURE 3. Warwick stackable plastic retentive columns.

RESULTS

The data obtained from the experiment were analysed using the methods reported in [8]. This processing approach takes related signals, such as a signal from before the retentive channels (S_F) and another from after passing through a retentive channel (S_C), and combines them into a new characteristic signal using the convolution transform (Equation 1). This characteristic signal is then used for processing and analysis.

$$S_F(t) * S_C(t) = \int_{\tau=-\infty}^{\tau=\infty} S_F(\tau) S_C(t-\tau) d\tau \quad (1)$$

Samples of the relative responses from the sensor arrays are illustrated in Figure 4. With 3 sensor arrays, it is possible to pair up the arrays in three possible ways when performing the convolution: front array * OV-1 array (F*O), front array * carbowax array (F*C), or OV-1 array * carbowax array (O*C). Each of these pairings was considered.

Each sensor in the first array was paired with their counterpart in the second array. In cases where one signal was either saturated or too weak (less than a 1% response), the pair was censored and would not be used further in the processing process.

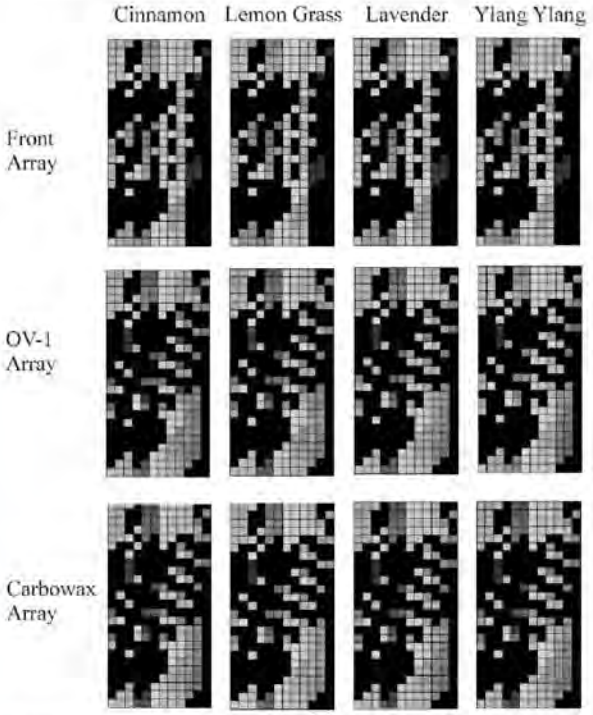

FIGURE 4. Illustration of relative response from each sensor array. Black cells show signal saturation, white cells show weak signals and greyscale shows relative peak magnitude of sensor response. It is evident that there is considerable correlation in the arrays.

The remaining pairs were then normalised and subjected to a convolution integral transform. This produced an array of characteristic signals that could be used for classification. The feature extracted from these signals was simply the area of the convolution integral. Figure 5 illustrates a sample of these signal arrays after normalisation.

These feature arrays were then classified using a probabilistic neural network (PNN). Due to the limited quantity of replicated data available, a bootstrap train

and test method was used. A set of samples (1 of each test analyte) was omitted for testing, and the remainder used to train the PNN. The overall performance of the system was judged once all the 20 samples had been omitted once.

Due to the redundant (correlated) nature of much of the data, a subset of sensor results was used. A search-forward feature selection method was combined with a random sampling of sensor feature space.

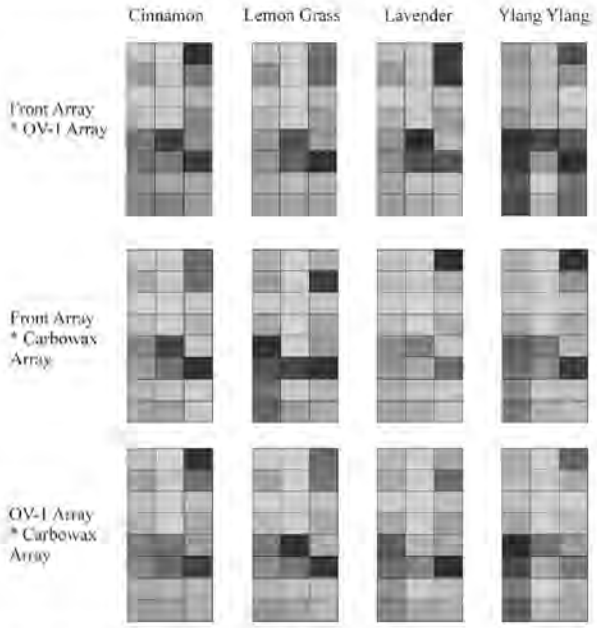

FIGURE 5. Illustration of normalized areas extracted from characteristic signals. Less correlation is observable than in the raw data.

Table 2 summarises the results obtained from optimization of the feature subset.

TABLE 2. Accuracy results from a PNN classified when utilising an optimal subset of sensors.

Array pair	Train and Test Accuracy (%)					Avg. (%)
F*O	50	75	75	75	100	75
F*C	100	100	100	75	50	85
O*C	75	75	75	75	25	65

CONCLUSIONS

A novel convolution integral transform based method, as proposed in [8], has been applied to a novel odour sensing instrument that combines 900 sensors with two mucous-like retentive channels. The unique design and size of this novel instrument has been exploited to classify different odours in air with an accuracy of about 90%.

The accuracy of the instrument can be substantially improved in a number of different ways: firstly, by the selection of other sensors that are less correlated to those employed here. Secondly, the choice of convolution feature (area) can also be extended to use height, shape etc. And thirdly, the process of selecting the sensor subset is basic and neither exhaustive nor even comprehensive - and more advanced search methods exist that utilise fewer restrictions in subset selections and sensor pairings. These methods are being explored and should provide further improvements to accuracy.

Interesting, it is not uncommon in biological olfaction for odour binding proteins (OBP) to capture and transport odorant molecules to the olfactory receptors (ORs). This mechanism may improve selectivity more than by simple diffusion alone and allow hydrophobic molecules to be sensed without the need for a non-polar mucous layer.

Finally, it should also be noted that the convolution approach has also be applied with some success to a single set of different sensors (cross-convolution), i.e. a conventional e-nose.

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