NOVEL CONVOLUTION BASED SIGNAL PROCESSING TECHNIQUES FOR A SIMPLIFIED ARTIFICIAL OLFACTORY MUCOSA

J.W. Gardner[1] and J.E. Taylor[2]
[1]University of Warwick, School of Engineering, Coventry, UK
(Tel: 02476 523695; E-mail: J.W.Gardner@warwick.ac.uk)
[2]University of Warwick, School of Engineering, Coventry, UK
(Tel: 02476 574494; E-mail: James.E.Taylor@warwick.ac.uk)

Abstract: As our understanding of the human olfactory system increases, so does our ability to design novel architectures in order to mimic the biological system. The concept of an artificial olfactory mucosa represents a new development in the field of biomimetics. Here we analyse the signals produced by such a biomimetic system that contain a spatio-temporal element not previously encountered within the field of machine olfaction or so-called electronic noses. This paper explores the use of convolution-based signal processing methodologies to exploit this richer data-set and ameliorate the well-known problems of sensor noise and drift. We show that, under certain conditions, an artificial mucosa combined with a convolution based classifier performs better than a conventional electronic nose.

Keywords: Electronic Nose, Signal Processing, Convolution, Artificial Olfactory Mucosa

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1. INTRODUCTION

Over the last decade, there has been significant increase in our understanding of the human olfactory system. This advance in knowledge has led to the design of artificial instruments to identify odours, more commonly referred to as an electronic nose (e-nose) [1].

The limitations of classical sensor based electronic noses have been identified, such as poor specificity, and this has lead to the development of enhanced instruments, such as combining an e-nose with either a gas chromatograph [2] or mass spectrometer. However, this approach makes the system much less portable, more complex, more expensive and harder to use (e.g. needs gas supply).

However, these analytical instruments do recognise the value of chromatography and such a phenomenon has recently been proposed as a possible mechanism in biological olfaction and is known as nasal chromatography [3, 4]. It has been suggested that the aqueous layer coating the olfactory receptors in the olfactory epithelium (see Figure 1) act as a retentive channel like a conventional chromatographic system, causing differential partitioning of odorous molecules within the mucosa.

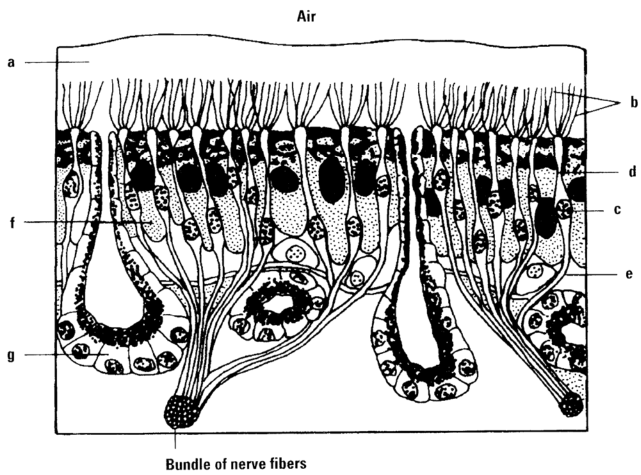

Figure 1: Diagram of the human olfactory epithelium, showing (a) the aqueous mucous layer covering (b) the olfactory receptors [4].

Recently, a novel approach was reported [5] that involves the development of what we call an artificial olfactory mucosa - based upon an array of sensors distributed along a channel coated with a retentive material (Figure 2).

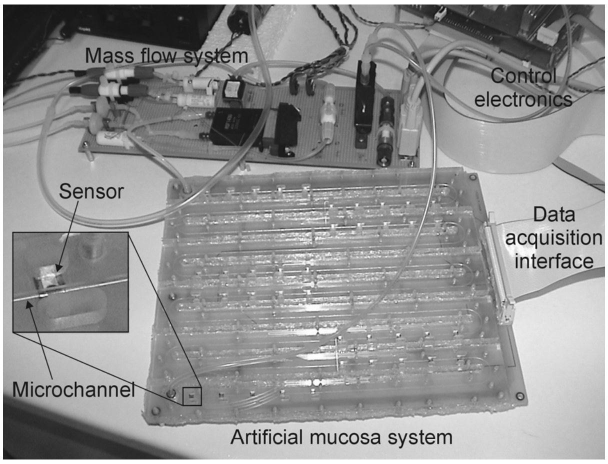

Figure 2: Photograph of the artificial olfactory mucosa with 40 sensors along a meandering coated channel [5].

The number and type of sensors selected for this distributed system then determines the performance of the proposed e-mucosa. Figure 3 shows the concept of an e-mucosa (employs all sensors), a traditional e-nose (first column only) and a z-nose (retentive row and last column). The signals generated by the sensors are now more complicated and information rich, with features extracted/selected not only from the spatially-separated outputs from different sensors, but also from the temporal differences from the outputs of identical sensors at different locations. Common processing techniques currently in use within the field of e-noses are not designed to exploit the new level of information contained within these spatio-temporal signals.

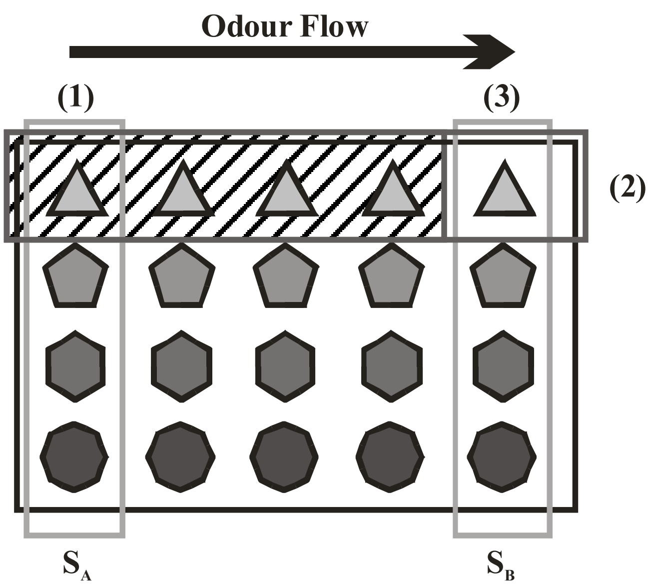

Figure 3: Cartoon of an artificial olfactory mucosa with 20 sensors. Other configurations: (1) Basic e-nose system; (2) A GC column; (3) A GC-coupled e-nose system; (1) and (3) Simple mucosa or tandem electronic nose.

Here we have been exploring the performance of a sub-system employing only the first and last sensor columns that could be thought of as a simple e-mucosa or a tandem electronic nose system (e-nose/column/e-nose). This reduces considerably the dimensionality of the problem to solve. The aim is to use a new convolution based signal processing algorithm to classify odours better than conventional sensor-based e-noses.

2. PROCESSING METHODS

There are different methods by which the two signal arrays in Figure 2, S_A and S_B, could be analyzed. Different combinatorial functions will produce different characteristic signals. Convolution is commonly used in signal processing for determining the similarity between two signals, such as matched filtering [6]. Figure 4 illustrates an example of such a characteristic signal.

$$y(t) = \int S_B(\tau) S_A(t-\tau) d\tau \,. \qquad (1)$$

A second method, the simple product of the two signals, will also produce a characteristic signal. To preserve the dimensionality of the signal, the root of the magnitude of this product is taken. As the sign may include important information, this is preserved after the root.

$$y(t) = sign\left(S_A(t) S_B(t)\right) \sqrt{\left|S_A(t) S_B(t)\right|} \,. \qquad (2)$$

Thirdly, the two signals could be subtracted from each other, producing a difference signal which will reduce common interference effects.

$$y(t) = S_A(t) - S_B(t) \,. \qquad (3)$$

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These characteristic time-dependent signals can be used to represent the spatio-temporal data contained within the data-set provided by both sensor arrays used, and are suitable for feature extraction and use in further processing and classification methods.

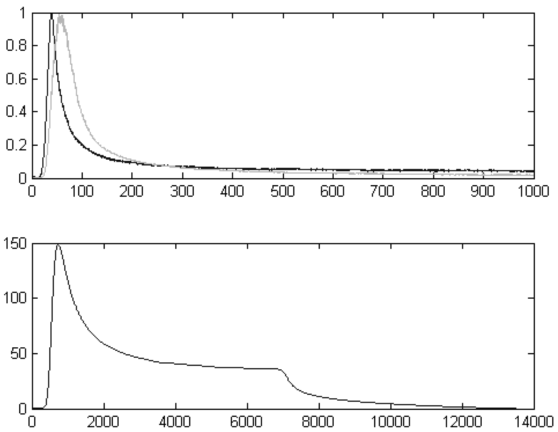

Figure 4: (Top) Normalised response from two sensors in the artificial olfactory mucosa [5] to a 25 second pulse of toluene vapour in air. (Bottom) Characteristic signal generated by the convolution of the two sensor responses.

3. SIMULATION

To compare these differing methods, existing computational simulations of the artificial olfactory mucosa [5] were subjected to three types of noise: sample variance (SV), a noise effect altering the global magnitude of a signal; a random additive noise source with a defined signal-to-noise ratio (SNR); and baseline drift (BD), a common noise effect to each signal, which translates the response baseline value. All noise was Gaussian distributed and applied at a level of 5% of the peak magnitude. The combinations of two different noise sources were also investigated.

These noisy signals were normalized using auto-scaling, and used to generate characteristic signals by the above methods. The area (time integration of response to odour pulse) was extracted as a feature for use in processing. For comparison, the same simulation method was used to simulate a traditional e-nose (S_A) and a GC-coupled e-nose (S_B). The feature extracted during pre-processing in these cases was the peak magnitude of the sensor response. Also investigated were 'cross-convolutions', convolutions between pairs of sensors selected from the same sensor array.

4. CONCLUSION

A qualitative assessment of the results obtained for different signal processing methods is summarised in Table 1; based on the linear separability of the clusters that resulted from a basic principle component analysis (PCA) of the feature sets. Two examples of the PCA plots are shown in Figures 5 and 6.

In the cases where significant levels of sample variance and signal-to-noise were present, the basic e-mucosa coupled with a convolution based or product based signal processing showed a significant improvement over the tradition e-nose system. However, significant baseline drift impacted on the performance of these two methods. The difference method performed

Table 1: Qualitative comparison of the linear separability of analyte groups when using differing signal combination methods and processed using principle component analysis. 'oooo' – very good separability, 'ooo' – good separability, 'oo' – average separability, 'o' – separable, 'x' – inseparable

Noise Type	Conv. (1)*(3)	Diff. (1)-(3)	Prod. (1)×(3)	E-Nose (1)	GC + E-Nose (3)	Cross-convolution (1)	GC + Cross-convolution (3)
SV	ooo	o	oooo	oo	oo	ooo	ooo
SNR	oooo	oo	oooo	oo	oo	oooo	oooo
BD	o	oo	o	oo	oo	o	x
SV + SNR	oooo	oo	oooo	oo	oo	oooo	oooo
SV + BD	x	oo	o	oo	oo	o	o
SNR + BD	x	oo	o	oo	oo	o	o

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comparably to the e-nose in all of the test cases.

These simulation results show that using characteristic signals, such as those generated by combinatorial functions (such as convolution, product and difference), are suitable for use in data processing and classification systems. The performance of the classification system was comparable, if not better, that a traditional processing methodology using a classical e-nose system.

However, the results obtained here indicate a particular weakness to a baseline drift in the value of the sensor outputs. The common mode effect and high value of the baseline drift analysed here may have overestimated the problem experienced in general, because the actual drift between the response of the first set and last set of sensors in a few seconds should be considerably less than 5%.

In conclusion, we believe that an artificial mucosa coupled with a convolution-based signal processing methodology offers significant advantage over a conventional electronic nose. Further work on more complex odorants than ethanol and toluene mixtures has been carried out and suggests that the system is also capable of discriminating between essential oils and other complex odours.

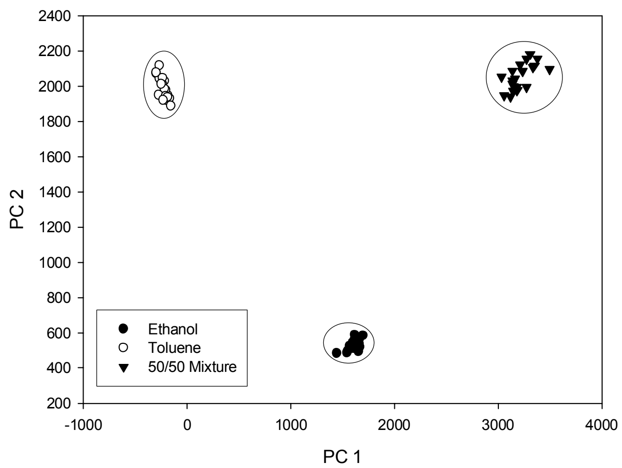

Figure 5: PCA Plot of 5 second pulses of ethanol, toluene and a 50/50 mixture of the two, processed using normalized sensor responses and the convolution of two sensors as the feature for analysis. Simulation noise: 5% sample variance.

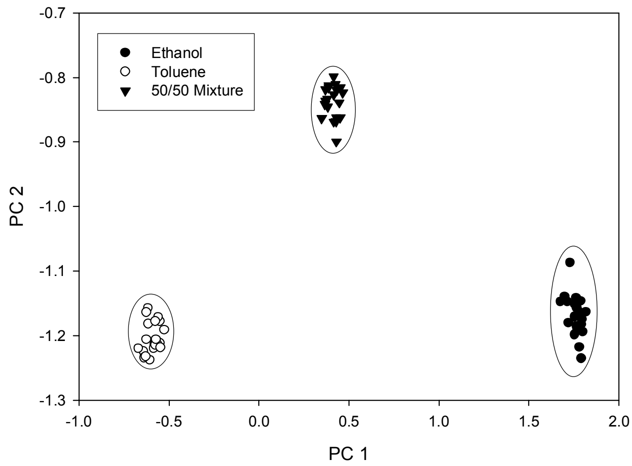

Figure 6: PCA Plot of 5 second pulses of ethanol, toluene and a 50/50 mixture of the two, processed using normalized sensor responses and peak response as the feature for analysis. Simulation noise: 5% sample variance.

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