Artificial Neural Network Prediction of Specific VOCs and Blended VOCs for Various Concentrations from the Olfactory Receptor Firing Rates of *Drosophila melanogaster*

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***Abstract*— In our previous work, we have investigated the classification of odorants based on their chemical classes only, e.g. Alcohol, Terpene or Ester, using Artificial Neural Networks (ANN) as the signal processing backend of an insect olfactory electronic nose, or e-nose. However, potential applications of e-noses in the food and beverage industry which include the assessment of a fruit's ripeness, quality of wines or identifying bacterial contamination in products, demand the ability to predict beyond chemical class and to identify exact chemicals, known as specific Volatile Organic Compounds (VOCs) and blends of chemical that present themselves as aromas, known as blended VOCs (BVOCs).**

In this work, we demonstrate for the first time how it is possible to predict such VOCs and also BVOCs at varying concentration levels. We achieve this goal by using ANNs in the form of hybrid Multi-Layer Perceptrons (MLPs), to analyze the firing rate responses of the model organism *Drosophila melanogaster's* odorant receptors (DmOrs), in order to predict the specific VOCs and BVOCs. We report for the raw and noise injected data how the highest MLP prediction for specific VOCs occurred at a 10^{-4}mol.dm^{-3} concentration in which all the VOC validation vectors were identified and at a concentration of 10^{-2}mol.dm^{-3} for BVOCs in which 8/9 or 88.9% were identified.

The results demonstrate for the first time the power of using MLPs and insect odorant receptors (Ors) to predict specific VOCs and BVOCs.

I. Introduction

The electronic nose (e-nose) market is estimated to be worth $4 billion a year, leading to much interest in new research and development opportunities in the industry [1]. Through their odor and flavor detection capabilities, e-noses have numerous applications such as detection of illegal contraband, medical diagnosis and food quality inspection [2]. A number of studies [3, 4] have found success in the implementation of biological olfactory receptors for the sensory array of an olfactory biosensor.

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In this work, we are particularly interested in the odor detection of fruit's ripeness and the qualities of wines, so we have elected to use *Drosophila melanogaster* fruit fly odorant receptors. The *D. melanogaster* olfactory system is capable of recognizing thousands of odors and tastes which assists their feeding, mating, and supplementary behaviors. Odor detection involves the Olfactory Receptor Neuron (ORN) located on the hair-like sensilla of the antennae and maxillary palp olfactory organ. Interaction of odorant molecules results in a unique change in the resting potential of the ORN. Recombination gene technology can be used to record the odorant receptors (Ors) responses that are ectopically expressed in a mutant 'empty' ORN [5]. ORNs are known to exhibit a combinatorial model of odor coding in which individual odorants activated subsets of Ors and certain Ors responded to subsets of odorants [5]. Artificial Neural Networks (ANNs) are powerful adaptive filters which can learn the essential features of the combinatorial odor coding present in a data set. Olfactory recognition studies in particular, can utilize ANNs to identify the complex relationships that exist in the data.

In our previous work, we have successfully employed the ANN architecture of Multi-Layer Perceptrons (MLPs) for analyzing *D. melanogaster* odorant receptors (DmOr) [6, 7] and *Anopheles gambiae* mosquito odorant receptors (AgOr) [8] firing rate responses, and chemical descriptor values [9], to classify odorants into their chemical classes, e.g. Alcohol, Ester or Terpene. In this work, we use hybrid MLPs to study the responses of DmOrs for the prediction of specific Volatile Organic Compounds (VOCs) and blended VOCs of fruit odors (BVOCs) at various concentration levels.

II. Method

A. VOC and BVOC data & pre-processing

In this work, we analyze the spontaneous firing rate responses from 24 *D. melanogaster* Ors (which we term, DmOrs) from two data sets obtained from the work of Hallem [5]; spontaneous activity is calculated based on the number of spikes recorded in 1 second of spontaneous activity [10]. The two data sets consist of: a set of 10 specific VOCs and a set of 9 BVOCs [5]. The 10 specific VOCs comprise of Ethyl Acetate, Pentyl Acetate, Ethyl Butyrate, Methyl Slicylate, 1-Hexanol, 1-Octen-3-ol, E2-Hexenal, 2,3-Butanedione, 2-Heptanone and Geranyl Acetate which are presented at four different concentration levels of 10^{-2}mol.dm^{-3}, 10^{-4}mol.dm^{-3}, 10^{-6}mol.dm^{-3} and 10^{-8}mol.dm^{-3}. The BVOC data set consists of Apple, Apricot, Banana, Cherry, Mango, Peach, Pineapple, Raspberry, and Strawberry

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presented at a pure, 10^{-2}mol.dm^{-3}, 10^{-4}mol.dm^{-3}, and 10^{-6}mol.dm^{-3} concentration. Prior to analysis, both data sets were de-meaned and normalized [6] to improve classification performance, which leads to more efficient network training to minimize network output error [11].

B. Artificial Neural Network Architecture

The Artificial Neural Network (ANN) architecture employed in this work was a feed forward Multi-Layer Perceptron (MLP) with binary sigmoidal activation functions [6-9]. Thorough rigorous initial experiments, we determined that a double hidden layer MLP with 75 neurons in the first hidden layer, 5 neurons in the second hidden layer and a single neuron in the output layer provided optimum network output. A VOC input vector that consisted of the 24 DmOr responses was then fed into the MLP. Weighting functions between each layer were obtained from a symmetric Gaussian distribution with a zero mean and variance of unity. The network was trained via back-propagation under supervised learning. To increase the convergence rate and avoid stagnation at local minima, a momentum function was included [12]. The series of hybrid MLPs derived for the VOC data is shown in Fig. 1. A separate set of hybrid MLPs was trained under the same method as described for the BVOC data.

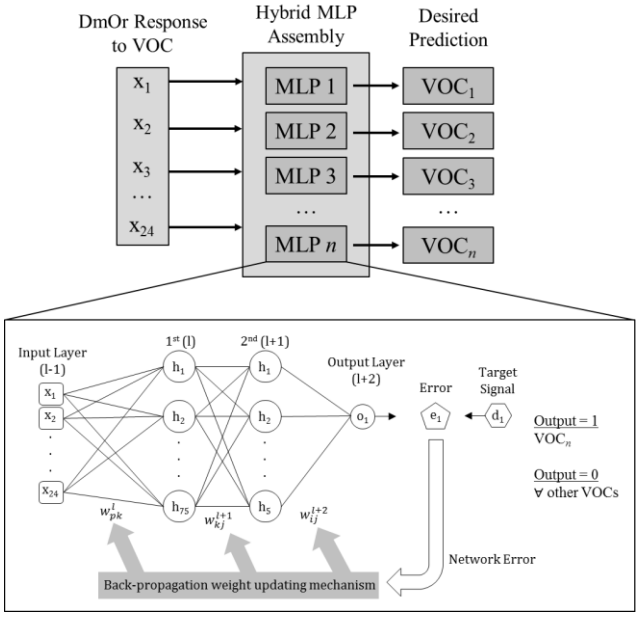

Figure 1. Schematic of an assembly of hybrid MLPs. The highlighted MLP is of the VOC$_n$ class, where the MLP is trained to provide an output of 1 for a VOC$_n$ input vector and an output of 0 for all other VOCs. A similar hybrid MLP scheme was implemented for the BVOC dataset.

C. ANN Training Procedure

Investigation into the the VOC and BVOC data sets were performed separately. For the VOC case, MLP simulations were conducted using 40 specific VOCs (i.e. 10 VOCs at 4 concentration levels) and a similar procedure for the BVOC case, using 36 BVOCs (i.e. 9 BVOCs at 4 concentration levels). Training of the system involved a training set consisting of all vectors except for the vectors of the concentration level being assessed. For example, the BVOCs at 10^{-4}mol.dm^{-3} involved a training data set of 27 vectors (of 9 BVOCs) of the pure, 10^{-2}mol.dm^{-3}, and 10^{-6}mol.dm^{-3} concentrations. Consequently, the validation set consists of 9 BVOC validation vectors at 10^{-4}mol.dm^{-3}. Thus, the prediction (%) of the validation vectors represented the ability of the MLP to identify the unseen VOC/BVOC at the concentration of interest. It should be noted that error bars of the validation vectors were not included as the two data sets used did not allow for cross-validation or bootstrapping techniques. Extensive experimental runs identified that a total of 200 epochs was necessary for sufficient training of the system. This value was found to provide sufficient classification performance, an output error above the desired 0.01 threshold, whilst avoiding excessive computational simulation time.

D. Noise Injection

A method known as noise injection [13] was also implemented as it can sometimes aid to improve the generalization of the network [7, 9, 14, 15]. We applied a standard uniform 10% additive noise to the raw data set [16]. The raw vectors of each data set were presented with noise to form 10 noise injected realizations. Consequently, the VOC training data increased from 30 to 300 vectors, while the BVOC training data increased from 27 to 270 vectors.

III. Results

Investigations were performed using both VOCs and BVOCs, in which good prediction performance from the hybrid MLP system was observed. We hypothesize that this was due to reducing the output layer to a single neuron; reducing the complexity of the network results in an efficient and enhanced rate of convergence due to smaller number of weights [17]. Also, the additional hidden layer allows for the extraction of higher-order relationships present in the data [18].

To quantify the classification prediction (%) of the MLP, we employed a conservative threshold value obtained from the probability of correct identification of a validation vector [6-9]. For the VOC data set, this value was 1/10 or 10%, with an added 5% safeguard, a 15% conservative threshold value was established. Similarly, for the BVOC data set, the value was 1/9 or 11%, which produced a 16% conservative threshold once the 5% safeguard was included. The benefit of employing a conservative threshold is that any validation vector that supersedes the value can be regarded as successful classification.

Classification performance of the MLP system using the specific VOC data set is presented in Fig. 2. At a concentration level of 10^{-2}mol.dm^{-3} (Fig. 2A), training with the raw data correctly identified 8/10 or 80% of the validation set, while using noise injection identified 50%. At a concentration of 10^{-4}mol.dm^{-3} (Fig. 2B), training with the raw data identified all validation vectors, whilst 90% were identified with noise injection. For the 10^{-6}mol.dm^{-3} and 10^{-8}mol.dm^{-3} concentration levels (Fig. 2C and Fig. 2D), training with the raw data identified 60% and 40% of the validation set, noise injection on the other hand, identified 60% and 30%. In machine learning, Receiver Operating

Characteristic (ROC) graphs are used to visually present the performance of classifiers, by expressing the balance between true positive and false positive rates of classifiers [19, 20]. ROC graphs are presented for the raw data and noise injection data across the various concentrations in Fig. 2A – 2D. The Area Under the Curve (AUC) scalar value included in the ROC graphs represent the probability of the MLP classifier ranking a randomly chosen positive instance higher than a randomly chosen negative instance [21]; the larger the AUC, the better average performance can be said of the classifier. Similar to the classification prediction results, it appears that a concentration of 10^{-4}mol.dm^{-3} produced the highest AUC. Lastly, the average prediction (%) of the validation set, when using both raw and noise injected data to train the MLP, appeared to decrease below 10^{-2}mol.dm^{-3} (Fig. 2E). This suggests that dilution of the VOCs negatively impacts MLP classification and can be attributed to the weakened DmOr response at lower concentration levels.

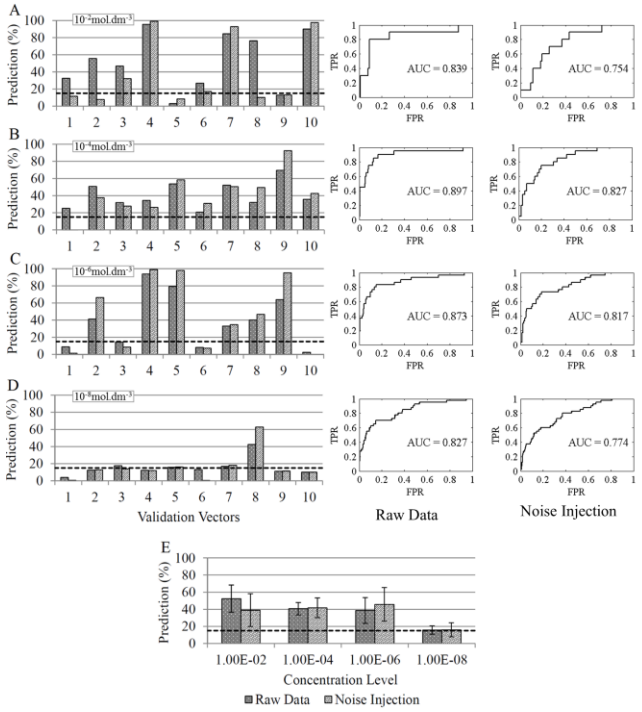

Figure 2. Classification performance of the specific Volatile Organic Compound (VOC) data set: 1) Ethyl Acetate, 2) Pentyl Acetate, 3) Ethyl Butyrate, 4) Methyl Slicylate, 5) 1-Hexanol, 6) 1-Octen-3-ol, 7) E2-Hexenal, 8) 2,3-Butanedione, 9) 2-Heptanone and 10) Geranyl Acetate, across the different concentration levels: A) 10^{-2}mol.dm^{-3}, B) 10^{-4}mol.dm^{-3}, C) 10^{-6}mol.dm^{-3} and D) 10^{-8}mol.dm^{-3}, from training with raw data (left bar) and training using the noise injected data (right bar). Raw data and noise injection Receiver Operating Characteristics (ROC) graphs of A – D include the AUC scalar value representing the area under the curve of each ROC plot. E) The average prediction (%) of the validation set across the 4 concentration levels. The horizontal broken lines represent the 15% threshold value.

Fig. 3 presents MLP classification using the BVOC data set. At a pure BVOC concentration (Fig. 3A), MLP training using the raw data resulted in 6/9 or 66.7% classification of the validation set, whilst noise injection produced 44.4%. An increase of *n* correct vectors was observed at a concentration of 10^{-2}mol.dm^{-3} (Fig. 3B), in which using raw data presented 88.9% classification and 66.7% using noise injection. At the lower concentrations of 10^{-4}mol.dm^{-3} and 10^{-6}mol.dm^{-3} (Fig. 3C and Fig. 3D), the raw data presented 55.6% and 11.1% classification of the validation set, while using noise injection resulted in 44.4% and 11.1% classification. A concentration of 10^{-2}mol.dm^{-3} revealed the highest AUC value of a ROC graph for both the raw and noise injected data. Finally, the average prediction (%) of BVOCs decreased as the concentration was diluted (Fig. 3E). This supports our hypothesis that a weakened DmOr response due to dilution of the VOCs/BVOCs negatively impacts the overall classification performance of the MLP system.

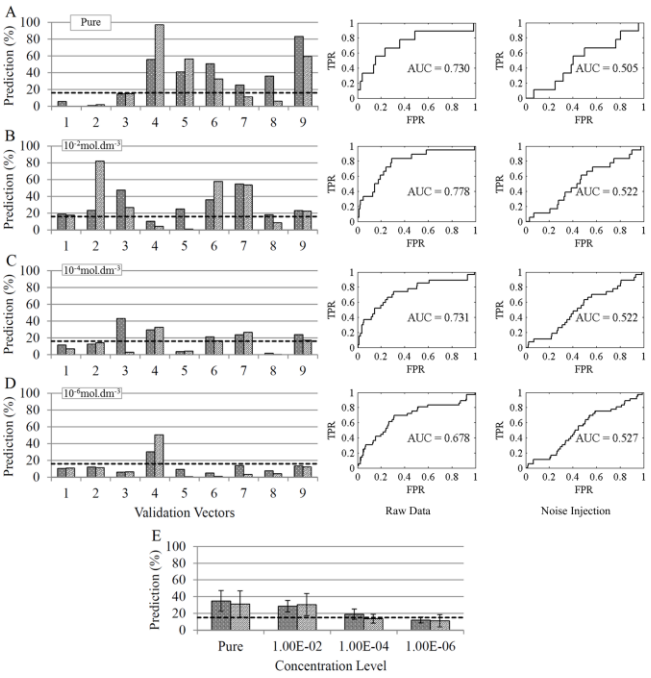

Figure 3. Classification performance of the Blended Volatile Organic Compound (BVOC) of fruit odors data set: 1) Apple, 2) Apricot, 3) Banana, 4) Cherry, 5) Mango, 6) Peach, 7) Pineapple, 8) Raspberry, and 9) Strawberry, across the different concentration levels: A) pure, B) 10^{-2}mol.dm^{-3}, C) 10^{-4}mol.dm^{-3}, and D) 10^{-6}mol.dm^{-3}, from training with raw data (left bar) and training using the noise injected data (right bar). Raw data and noise injection Receiver Operating Characteristics (ROC) graphs of A – D include the AUC scalar value representing the area under the curve of each ROC plot. E) The average prediction (%) of the validation set across the 4 concentration levels. The horizontal broken lines represent the 16% threshold value.

Finally, the VOC data set presented high prediction (%) of certain validation vectors compared to the BVOC data set, which suggests that compared to BVOCs, the MLP was able to predict specific VOCs with a higher certainty. This observation is also reflected by the higher average prediction of VOCs (Fig. 2E) compared to the average prediction of BVOCs (Fig. 3E) across the four concentration levels tested.

IV. Conclusion

In this work, we demonstrate for the first time how it is possible to predict specific Volatile Organic Compounds (VOCs) and blends of fruit VOCs (BVOCs) at varying concentration levels. We achieved this goal by using Artificial Neural Networks (ANNs) in the form of a series of

hybrid Multi-Layer Perceptrons (MLP), to analyze the firing rate responses of the model organism *Drosophila melanogaster's* odorant receptors (DmOrs) in order to predict the specific VOCs and BVOCs. Additionally, a noise injection technique was implemented to enhance network training and generalization capabilities of the network. We observed that using the raw and noise injected data, the highest MLP classification for VOCs was found at a 10^{-4}mol.dm^{-3} concentration in which all validation vectors were successfully identified, and at a concentration of 10^{-2}mol.dm^{-3} for BVOCs in which 8/9 or 88.9% were identified. A reduction in classification performance at more dilute concentrations was observed and can be attributed to the weakened DmOr response toward the VOCs/BVOCs. The results demonstrate for the first time, the power of using MLPs and insect odorant receptors (Ors) to predict specific VOCs and BVOCs.

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