Improving Odorant Chemical Class Prediction with Multi-Layer Perceptrons Using Temporal Odorant Spike Responses from *Drosophila melanogaster* Olfactory Receptor Neurons

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Abstract—**In this work, we examine the possibility of improving the prediction performance of an olfactory biosensor through the use of temporal spiking data. We present an Artificial Neural Network (ANN), in the form of an optimal hybrid Multi-Layer Perceptron (MLP) system for the classification of chemical odorants from olfactory receptor neuron spike responses of the *Drosophila melanogaster* fruit fly (DmOrs). The data used in this study contains the responses to 34 odorants from 6 individual DmOrs, of which we exploit the temporal spiking responses of a 500ms odorant stimulus window.**

We report, for the first time, the difference between the classification performance of the temporal spiking data to an equivalent spontaneous scalar dataset that we have reported previously. We demonstrate that a higher prediction (%) was obtained when using the temporal data, in which a greater number of validation odorants are identified to their correct chemical class. This work presents a novel technique to improve the classification performance of an olfactory biosensor, whilst maintaining a limited sensory array of 6 DmOr receptors.

I. Introduction

An electronic nose (e-nose) biosensor is a device capable of discriminating various odors by using pattern recognition methods to analyze the response data of a sensory array. E-noses present advantages over traditional odor analysis (sensory panel) as they are quick, safe and non-destructive to the recorded samples [1]. Typically, the pattern recognition methods implemented in an e-nose utilize spontaneous or scalar sensor responses [2]. An alternative method for achieving an improved discrimination capability of the biosensor is to use temporal data recorded over a period of time. Temporal data can provide additional information of a sensor's responses, which may improve the biosensors odorant detection capability.

A. Insect Odorant Detection

The antenna and maxillary palp olfactory organs of insects (Fig. 1) are used for detecting numerous chemicals. These organs contain hair-like sensilla that house Olfactory Sensory Neurons (OSNs) that upon their dendrites contains Olfactory Receptors (Ors) capable of receiving odorants. Interactions with odorants are characterized by changes in the resting potential of OSNs by an order of approximately 20mV [3]. This change in membrane potential induces a propagation of an action potential to the higher centers of the insect brain for processing.

Recombinant gene technology has been successfully used by Hallem [4] to ectopically express odorant receptors (DmOrs) in a mutant 'empty' *Drosophila melanogaster* OSN allowing for the insect's spontaneous responses to odorants to be recorded. The *D. melanogaster* has been found to express a combinatorial mode of odor coding [4], in which individual receptors respond to a collection of odorants and individual odorants have been found to activate a collection of receptors. This provides the possibility of using classification techniques to identify specific odorants from the unique responses of DmOrs [5].

Figure 1. Profile of the Drosophila melanogaster captured with a scanning electron microscope [8]. Highlighted are the olfactory organs of the antenna (arrowhead) and maxillary palp (arrow).

B. Odorant Prediction Model

The motivation of this work is to predict the chemical class of an unknown odorant, based on the firing rate of *Drosophila melanogaster* odorant receptors (DmOrs). We have successfully used the Artificial Neural Network (ANN) approach in our previous work for predicting descriptor values of unknown chemicals [6], identifying chemical classes of unknown odorants [7-11] and predicting odorants and fruit blends of varying concentrations [5]. Thus far, we have used the spontaneous scalar data of receptor responses to odorants [4]. For this study, we investigate the temporal spiking data of receptor neuron responses to odorants as temporal or time-series data is known to increase the generalization capabilities of an ANN system [1]. Using an

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ANN in the form of a hybrid system of Multi-Layer Perceptrons (MLPs), we compare the difference in prediction performance between using temporal and spontaneous DmOr responses to odorants.

II. METHOD

A. Data Used in the Study

In this work, we use the data recorded by Hallem [4], consisting of 6 *Drosophila melanogaster* odorant receptor (DmOr) responses to 34 odorants. The DmOr receptors used are: DmOr9a, DmOr22a, DmOr67a, DmOr82a, DmOr85a and DmOr85b. A mutant olfactory receptor neuron (ORN) was used to house the Ors and record their responses to the odorants. We grouped the 34 odorants into 4 different groups defined by their chemical class (with the number of chemicals listed in parentheses): Lactone (5); Aldehyde (4); Ester (14) and Alcohol (11). Prior to the MLP operation, both temporal and spontaneous data were preprocessed by zero-mean and normalization to enhance network learning [12].

1) Temporal Receptor Neuron Odorant Response Data

The temporal data used was taken from 11 second recordings of DmOr activity, within which there was a 500ms window of odorant stimulus. Fig. 2A presents the spikes recorded over the 11 second recording of receptor DmOr9a; two vertical dotted lines represent the 500ms stimulus window of Ammonium Hydroxide. For the MLP analysis, we only use the spike response within the stimulus window (Fig. 2B). The stimulus window is typically within 2 seconds to 2.5 seconds of the total 11 second recording.

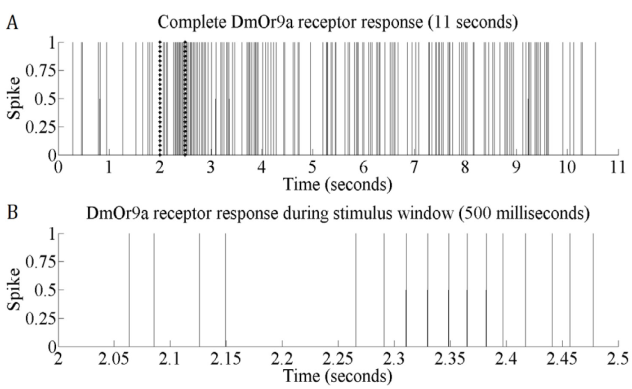

Figure 2. Spike response of DmOr9a receptor from Ammonium Hydroxide odor stimulus: (A) complete 11 second recording and (B) odorant stimulus window of 500 milliseconds. The vertical dotted lines in (A) represent the 500 millisecond stimulus window.

We utilize the recorded time of each *t*-th spike event across the DmOr receptor array for the MLP input data. Fig. 3 illustrates how we acquired the data of each spike event timestamp. It was determined that approximately 200 spikes were the maximum number of spikes a receptor may elicit over the 500ms stimulus response; Thus, we have elected to apply a 0-value (a form of zero-padding) when a spike was not found. Table 1 provides an overview of the temporal data: the explicit spike event times recorded, in seconds, of each *t*-th spike used and the 0-value used if a DmOr receptor does not present a *t*-th spike.

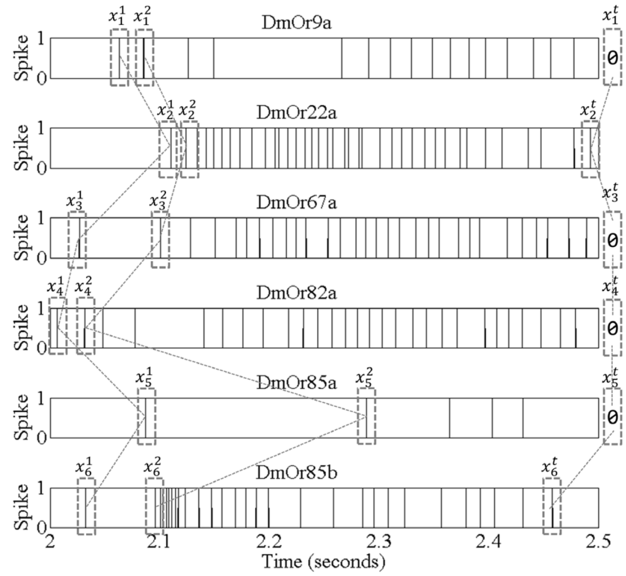

Figure 3. Acquiring MLP input vectors from the temporal data. The notation x^t_n represents the *t*-th spike of input node *n* of the MLP.

TABLE I. TEMPORAL DATA: SPIKE OCCURANCE OF THE DMOR RECEPTOR ARRAY IN RESPONSE TO AN AMMONIUM HYDROXIDE ODORANT STIMULUS.

Receptor	Spike Occurrence (seconds)			
	Spike - 1	***Spike - 2***	**…**	***Spike - t***
DmOr9a	2.063	2.085	…	0.000
DmOr22a	2.111	2.124	…	2.493
DmOr67a	2.027	2.101	…	0.000
DmOr82a	2.007	2.032	…	0.000
DmOr85a	2.087	2.289	…	0.000
DmOr85b	2.032	2.096	…	2.458

2) Spontaneous Receptor Odorant Response Data

Recordings of the spontaneous activity are quantified by the number of spikes recorded in 1 second of spontaneous activity [4]. This scalar value representing DmOr responses was used to represent receptor characteristics [4, 13, 14] and used for analysis in our previous work [5, 7, 9-11, 15]. The spontaneous data contains the same 34 chemical odorants, 4 chemical classes and 6 DmOrs used in the temporal data.

B. The Artificial Neural Network

In this work, we employed a feed forward Multi-Layer Perceptron (MLP) architecture [5-11] consisting of a double hidden layer hybrid MLP system (Fig. 4). Both temporal and spontaneous datasets utilize the DmOr receptor array response as the input layer of the MLP; the temporal data consists of the timestamp of spike responses within the 500ms stimulus window, while the spontaneous data is a single scalar value of receptor activity during odorant stimulus. The MLP operation begins by feeding the input vector, which is subsequently fed into the proceeding layers of the network. A supervised back-propagation learning scheme was utilized, incorporating a momentum function to ensure that training of the MLP avoids local minima [16]. A symmetric Gaussian distribution with a zero mean and variance of unity was used to produce the initial values of the network's weighting functions. To enhance optimization of the 'weight' decay regularizer, we defined small weighting function values, which also prevents over-fitting during the training process [8]. A sigmoidal activation function was employed and an output value close to 1 was used to identify an odorant associated to the chemical class and similarly 0 for an odorant of every other class. Preliminary simulations identified that a training length of 150 epochs provided a satisfactory error prediction below the desired 0.01 threshold value.

C. *Identifying Optimal MLP Architecture*

A basic MLP structure [17] was initially used for both temporal and spontaneous data. Additional simulations involving different numbers of hidden neurons were performed to determine an optimal MLP architecture that produced the best classification performance. A double hidden layer architecture was found to be favorable, the temporal data utilized a 10-neuron first hidden layer and 15-neuron second hidden layer structure, while the spontaneous data utilized a 15-neuron first hidden layer and 15-neuron second hidden layer MLP structure; both MLP systems using a single neuron output.

The hybrid MLP system consists of 4 independent MLPs corresponding to each of the chemical classes present. As described earlier, a desired value of 1 was used to identify the input odorant of the associated chemical class and a 0 for an odorant not belonging to that class. By combining MLPs into a hybrid system, we can address the multiclass problem associated with odorants of different chemical class [18]. From our previous work [5, 8, 10, 11], we have found that a hybrid MLP architecture consisting of single-output double hidden layer MLPs to outperform single hidden layer MLPs with multiple output neurons.

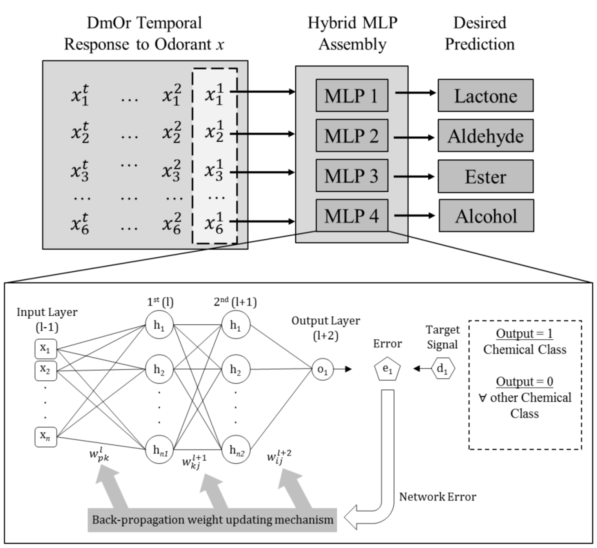

Figure 4. Schematic of the hybrid MLP structure showing the use of an independent MLP for chemical class. The graphic insert presents MLP training to produce an output of 1 for the chemical class of the input odorant and an output of 0 for all other chemical classes.

D. *Training and Validation Data Sets*

Training and validation data sets were created for both temporal and spontaneous data sets. Approximately 90% of each chemical class was used to train the respective MLP systems and the remaining 10% reserved for validation. The chemicals used for MLP validation are (chemical class in parentheses): G-Hexalactone (Lactone), Pentanal (Aldehyde), Ethyl Butyrate (Ester), Isopentyl Acetate (Aldehyde), 1-Penten-3-ol (Alcohol) and E2-Hexenol (Alcohol). The chemical odorants for validation were selected randomly and are identical for both temporal and spontaneous validation data sets to ensure unbiased comparison of results.

III. Results

To ensure we used an optimal MLP architecture unique for both temporal and spontaneous data sets, complete simulations were performed on almost 800 hybrid MLP systems of different double hidden layer sizes. By determining the optimal number of neurons in the hidden layers, the MLP is capable of capturing more of the complex relationships in the data, which ensures classification of unknown validation odorants with high accuracy [16, 17].

Classification performance of the hybrid MLP using temporal and spontaneous data sets is presented in Fig. 5. For the temporal data, we present the average prediction (%) of a validation odorant within the 500ms stimulus window; error bars are included to illustrate the range of best and worst-possible prediction (%) values. On the other hand, the MLP validation results from the spontaneous data are presented as a single prediction (%) value; spontaneous data is a single scalar value representing odorant-receptor responses.

To quantify the prediction capability of the MLP, a threshold value was implemented. The probability of selecting the correct chemical class of a validation odorant vector is ¼ or 25%. With an added 5% safeguard, a 30% conservative threshold was used and is presented in Fig. 5 as the dotted horizontal line. We define any prediction (%) above the threshold value as successful classification.

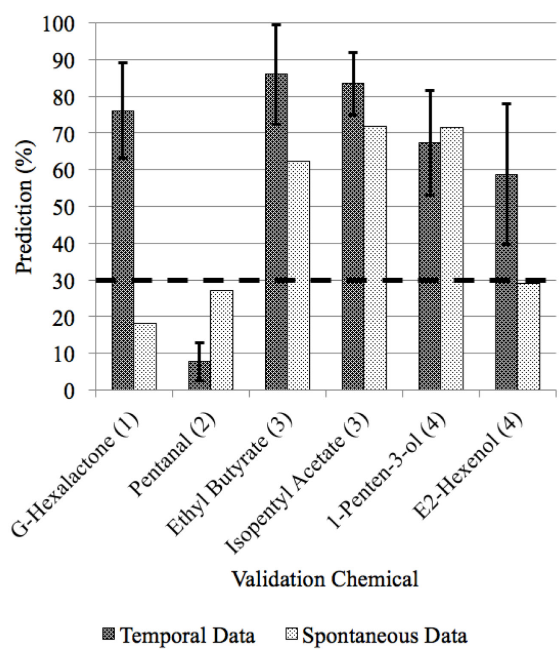

Figure 5. Prediction performance of the hybrid MLP system when using the time series data and spontaneous data. The numbers in brackets denote the chemical class of the validation chemical: (1) Lactone, (2) Aldehyde, (3) Ester and (4) Alcohol.

For the temporal data, the MLP system on average correctly identified the chemical classes of 5 out of 6 unknown validation odorants. These 5 odorants presented a high average prediction of at least 58.73%, comfortably surpassing the defined 30% conservative threshold value. The single validation odorant below the threshold is pentanal, which presented low prediction results with an average prediction value of 7.79%. On the other hand, with the spontaneous data only 3 of 6, or 50% of validation odorants were correctly classed. The correctly predicted odorants presented high prediction values of at least 62.36%. However, three validation odorants were below the threshold (prediction % in parentheses): G-Hexlactone (18.29%), Pentanal (27.17%) and E2-Hexenol (29.16%).

IV. Conclusion

There is an inherent need for a reliable and fast-acting biosensor tool to detect chemical odorants. In this work, we present a unique method of temporal data acquisition for the successful identification of odorant chemical classes. This was accomplished by training an optimal hybrid Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) system on the firing rate responses of *Drosophila melanogaster* odorant receptors (DmOrs).

For our analysis, we utilized the responses of 6 DmOrs. The temporal data consists of spike response timestamps elicited within a 500 milliseconds stimulus window. The spontaneous data is a single scalar value of the number of spikes recorded in 1 second of spontaneous activity. We observed an improved classification performance when using the temporal data compared to the spontaneous data. The hybrid MLP system correctly classified 83% odorant vectors compared to 50% odorant vectors when using the spontaneous data. We hope this work presents new possibilities for improving odorant detection of biosensors and novel classification techniques.

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