TIME-SERIES PREDICTION OF SUBJECTIVE EXPERIENCES RECORDED USING THE TEMPORAL DOMINANCE OF SENSATIONS METHOD VIA RESERVOIR NETWORKS

Hiroharu NATSUME*[a], Shogo OKAMOTO[a]

[a] *Tokyo Metropolitan University, Japan*

ABSTRACT

The temporal dominance of sensations (TDS) method records the time-series evolution of multiple sensory changes during experiences such as eating food. We obtained TDS data on sensory changes while eating strawberries using this method. We utilized two sensory groups for the experiment: primary sensations and complex sensations. The former group comprises sensations such as sweetness and sourness, whereas the latter group includes sensations such as ripeness and richness. We then established a reservoir network model to estimate the complex sensations from the primary sensations. The reservoir network, a type of neural network, is suitable for time-series data and demonstrated high estimation accuracy. Reservoir networks provide robust capabilities to predict sensory profiles of food products.

Keywords: temporal dominance of sensations, reservoir computing, sensory evaluation, strawberry

1 INTRODUCTION

Temporal dominance of sensations (TDS) method is used to record multiple sensory changes during the consumption of food (ISO, 2016). This method is becoming a standard sensory evaluation technique in the field of food science and is gaining popularity in other domains as well. In this study, we aim to estimate changes in complex sensations, such as ripeness and richness of food tastes, from changes in primary sensations, such as sourness and sweetness,

* Corresponding author.

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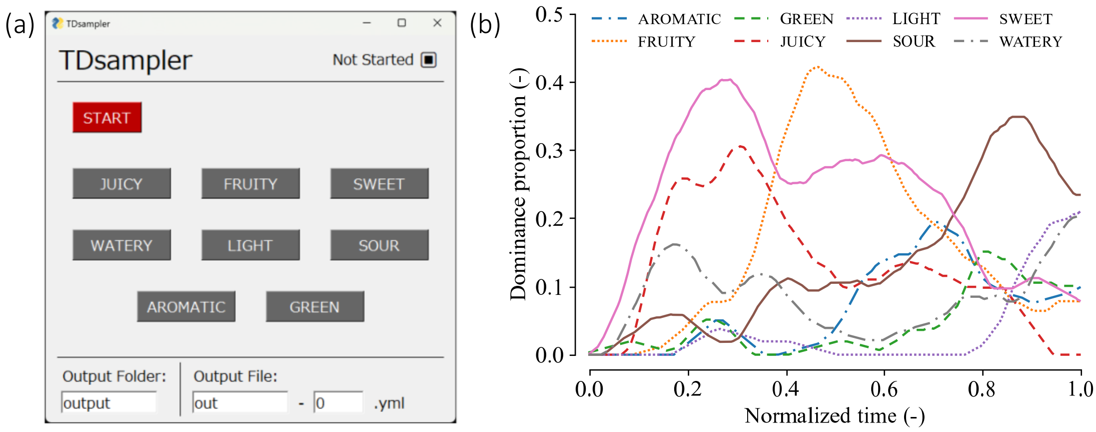

Figure 1. Temporal dominance of sensations method. (a) User interface used in the task. Adapted from (Natsume et al., 2023). (b) Example of TDS curves of primary sensations when eating strawberries.

exemplifying strawberries. Automatically estimating human experiences while eating foods can substantially reduce the costs associated with sensory evaluation tests. To achieve this, we utilize a reservoir network model. Reservoir networks are a type of recurrent neural network used for the prediction and generation of time-series data and are recognized for being fast and lightweight machine learning methods (Tanaka et al., 2019). In a previous study, we estimated changes in food preferences using reservoir networks (Natsume and Okamoto, 2024); however, no attempts have been made at inter-sensory estimation.

2 TEMPORAL DOMINANCE OF SENSATIONS METHOD

The TDS experiment was conducted using a computer application. The user interface (Figure 1(a)) displayed buttons with attribute words such as *sweet* and *juicy*. An experimental participant (panel) placed a food sample into their mouth and began the TDS task. The panels pressed the button corresponding to the attribute that best described their current sensation. While eating the food, the panelist reselected buttons each time the dominant sensation changed. Multiple buttons could not be selected simultaneously. The task concluded when the food sample was swallowed.

We utilized the TDS data collected during our previous study on eating strawberries (Natsume et al., 2024). Thirty-one university students participated in the study, and two different sensory attribute groups were employed. The first group comprised primary sensations with eight attributes: *aromatic*, *fruity*, *green*, *juicy*, *light*, *sour*, *sweet*, and *watery*. The second group consisted of complex sensations with five attributes: *fresh*, *mild*, *refreshing*, *rich/deep*, and *ripe*. These attribute lists were selected through a user study by Shimaoka et al. (2022).

The TDS curve represents the average time-series of a particular attribute across all trials. It illustrates the evolution of the dominance proportion, which is the percentage of trials in which the attribute is selected at a specific time. For visual clarity, TDS curves are smoothed using a moving average filter. Figure 1(b) presents the TDS curves for strawberries. The time axis is normalized between 0 (the start of the task) and 1 (the end of the task).

3 PREDICTION OF TDS CURVES VIA RESERVOIR NETWORK

We employed an echo state network, a typical reservoir model, which consists of three layers: input, reservoir, and output. The reservoir layer is a recurrent neural network with randomly connected nodes and fixed weights between nodes. To train the model, we adjusted only the weights from the reservoir to the output layer.

We constructed a model to predict the TDS curves of complex sensations from those of primary sensations. Continuous TDS curves were discretized into 1000 vectors, with each vector having the same dimensions as the number of sensory attributes, to facilitate model handling. The dimension of the input layer corresponded to the number of primary sensory attributes, i.e., 8, and the dimension of the output layer corresponded to the number of complex sensations, i.e., 5. The number of reservoir neurons was set to 256. Other principal parameters included leaking rate, spectral radius, and input scaling, which were set to 0.0109, 0.7616, and 0.1772, respectively. We used *reservoirpy* (ver. 0.3.11) for the implementation. We employed a bootstrap resampling method (Okamoto, 2021) to generate the dataset for training and testing. From all the TDS trials, we produced 100 sets of TDS curves for model training and 20 sets for validation.

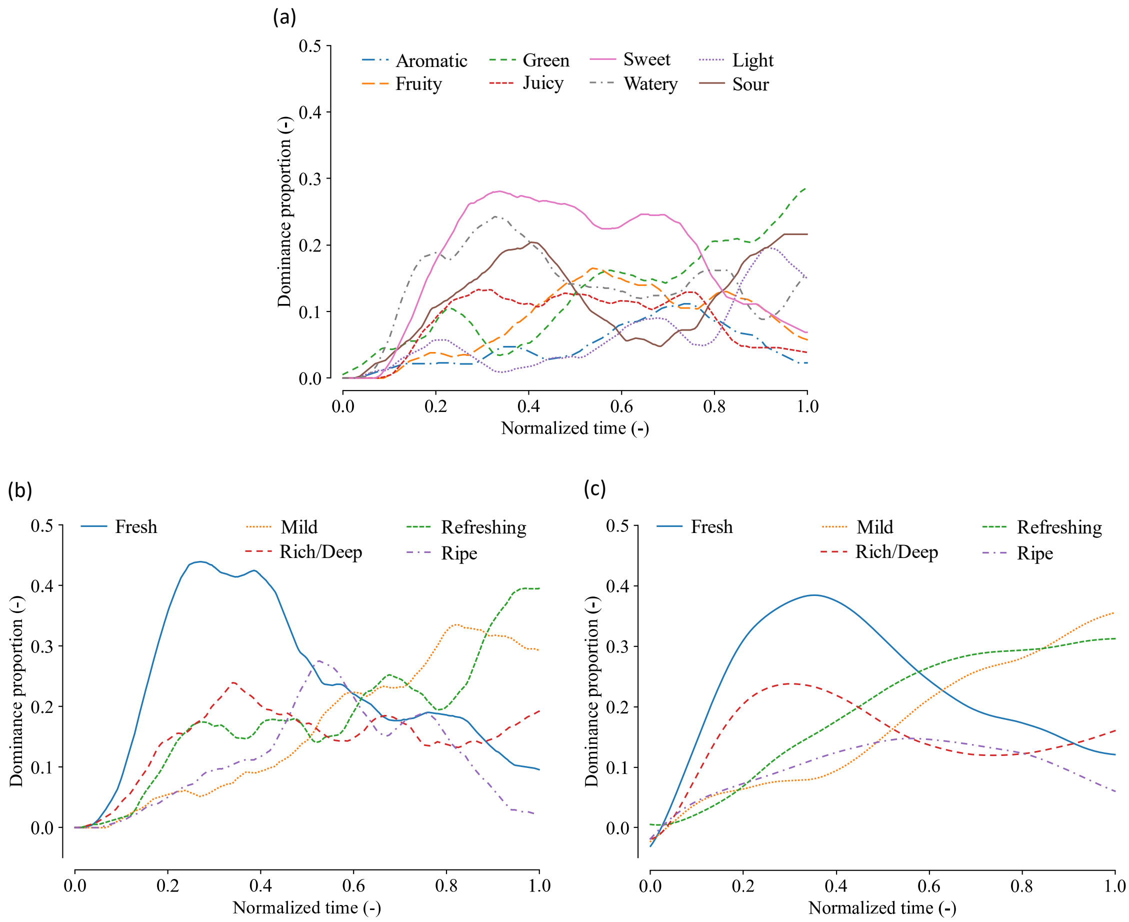

Figure 2. TDS curves with the highest estimation accuracy ($R^2 = 0.8551$, $RMSE = 0.0405$). (a) TDS curves of primary sensations as inputs to the reservoir network. (b) Observed TDS curves of complex sensations corresponding to (a). (c) TDS curves of complex sensations predicted by the model from (a).

4 RESULTS

The established model successfully predicted the TDS curves of complex sensations from each of 20 sets of TDS curves of primary sensations. The coefficients of determination ranged from 0.367 to 0.855, while the root mean squared errors ranged from 0.0405 to 0.0768. Figure 2 illustrates the TDS curves for primary and complex sensations with the highest estimation accuracy. Specifically, Figure 2(a) presents the primary sensation curves used as input to the model, and Figure 2(c) shows the output, or the predicted complex sensations. Figure 2(b) shows the curves of complex sensations when provided with the primary sensation curves from Figure 2(a). The curves in Figures 2(b) and 2(c) are comparable, with a root mean squared error of 0.0405.

5 DISCUSSION AND CONCLUSION

The constructed model predicted the changes in the dominance proportions of complex sensations with mean deviations ranging from 0.0405 to 0.0768. When five options are involved, the chance of selection is 0.2, and the theoretical 95% confidence interval is 0.141 with the number of samples being 31. The errors of our model are smaller than this value, suggesting a fair performance. Predicting complex sensory responses from basic ones will allow us to lower the costs of sensory evaluation. However, predictive models using neural networks cannot be simply formulated, and interpreting the relationships among multiple sensory changes is left to the analysts. Future research should focus on improving the explainability of such networks.

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