State-Space Modeling of Temporal Dominance Responses to Stimuli: A Case Study Using Strawberry

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Abstract. Our perceptual and affective responses change in a dynamic manner upon experiencing some stimuli; however, there are few mathematical models describing their dynamics. In this study, we propose state-space modeling as a method to represent their relationships based on time-dependent perceptual and affective responses acquired by the temporal dominance (TD) method. We used canonical variate analysis to compute and define the state variables. For this purpose, the TD responses were bootstrap-resampled to generate a sufficient amount of training data. We applied this method to the TD responses to the strawberries reported in our previous work. The estimated model could represent the temporal evolution of some affective responses with a good accuracy index. The proposed model consists of three latent variables, and the meaning of each of these could be reasonably interpreted.

Keywords: Canonical variate analysis · Affective dynamics · Latent variables

1 Introduction

The perceptual and affective responses in humans are known to evolve in a dynamic manner upon exposure to stimuli. These dynamic changes in multiple subjective experiences are recorded by the temporal dominance (TD) method [1–3] in the food industry. This sensory evaluation method enables the study of evolution of perceptual (gustatory, osmatic, and textural) and affective responses during food intake. However, since this method has been in use only in recent years, there exists few mathematical approaches to model the time-series data acquired by the TD method. For instance, thus far, methods based on Granger causality [4, 5], Markov model [6, 7], or principal motion analysis [8] have been reported.

In a typical TD task, approximately 10 types of perceptual or affective responses are evaluated. If a TD task for perceptual responses or affective responses is conducted separately for a single type of food, a maximum of 20 types of responses should be accounted for in a single model. This large number of variables has deterred our intuitive understanding of the model and responses to food. Therefore, a method that represents the entire model in a reductionist manner is required. The aforementioned methods [4–7] are not amenable to the reductionist treatment of time-series data

H. Shoji et al. (Eds.): KEER 2020, AISC 1256, pp. 139–148, 2020.
https://doi.org/10.1007/978-981-15-7801-4_14

acquired by the TD method, although the method in [8] was capable of decreasing the model dimensions by using a few non-time-series latent parameters. In the present study, by using state variables, we established relationships between perceptual and affective time-series responses. Usually, the number of state variables is smaller than the number of perceptual and affective responses evaluated in the TD task. The state variables could therefore be utilized for a reductionist representation of the entire model. We then utilized the TD data for strawberries [4, 5] to test the state-space modeling method reported here.

Fig. 1. Example of a graphical user interface used in TD tasks.

2 Temporal Evolution of Perceptual and Affective Responses on Eating Strawberries

2.1 Temporal Dominance (TD) Method

In this study, we used the TD method [1–3] to measure the time evolution of perceptual and affective responses. The TD method enables the simultaneous measurement of multiple types of subjective responses while assessors ingest food. Here, we briefly introduce the method, and more details can be found in previous reports [1–3].

In the TD method, a graphical touch panel interface is used, as shown in Fig. 1. An assessor presses the start button when he or she puts a piece of food into the mouth. S/he then selects a button on the touch panel, the label of which corresponds to the feeling of the assessor on food intake. The selected label is not necessarily the one with the highest subjective intensity. The assessor selects a corresponding button each time the dominant feeling changes and presses the stop button when the sensations in their mouths disappear. The same button can be selected more than once, and not all buttons need to be selected at least once.

TD tasks record the time at which the buttons are selected in each trial, as shown in Fig. 2(a). TD curves are subsequently calculated, as shown in Fig. 2(b), by integrating the records from all the trials and assessors. These curves are smoothened for later computation. The TD curves represent the dominance rate obtained by dividing the total number of times each button is selected by the total number of trials. The temporal base represents the time normalized to the period spanning the beginning of each trial to the moment of disappearance of all sensations in the mouth.

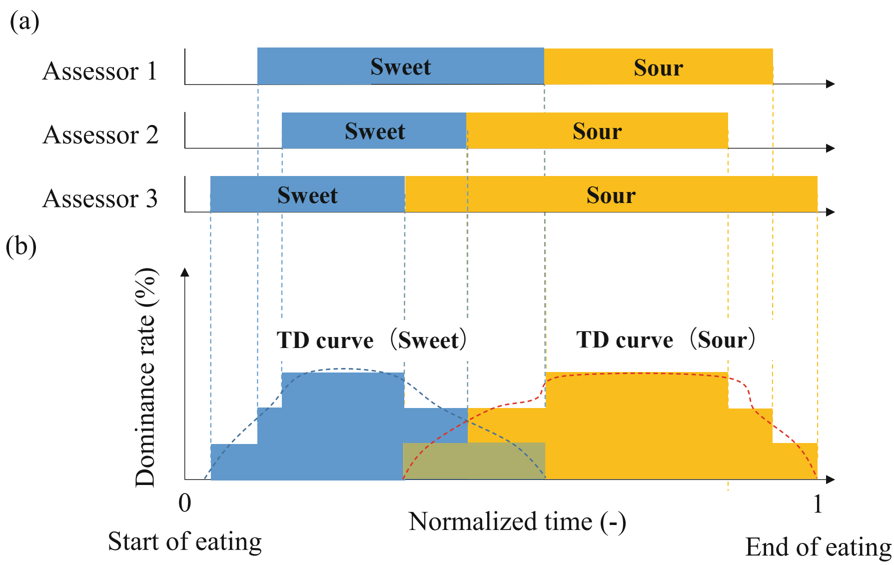

Fig. 2. Calculation of the TD curves. (a) Binary data obtained from the TD method for each assessor or trial. (b) TD curves are calculated by accumulating and smoothening the binary responses shown in (a).

Table 1. Terms used to represent perceptual and affective/evaluative responses in [5].

Perceptual	Affective/evaluative
Sweet	*Like*
Sour	*Delicious*
Watery	*Happy/satisfied*
Refreshing	*Fresh*
Juicy	*Flavorsome*
Melty	*Natural*
Soft	*Elegant*

2.2 TD Curves for Strawberries

In this study, we used TD curves obtained on eating strawberries [4, 5]. These studies employed the sensory and affective/evaluative labels listed in Table 1, and the acquired TD curves are shown in Fig. 3. For the purpose of the present study, we removed the responses to *melty*, *soft*, *happy/satisfied*, *natural*, and *elegant* from the original data because their dominance rates were small and statistically insignificant. We then used the remaining nine types of responses in the present study.

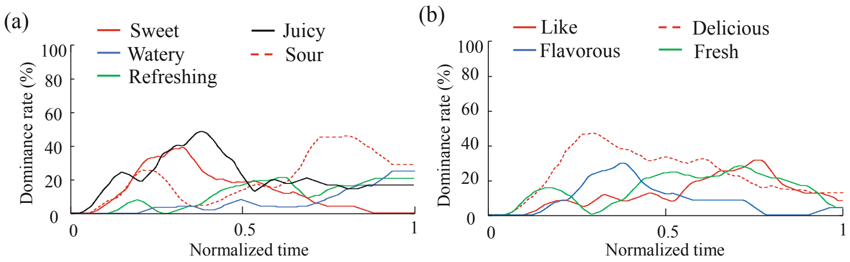

Fig. 3. Temporal dominance (TD) curves for (a) sensory and (b) affective/evaluative responses to strawberries. Modified from [4, 5].

3 State-Space Modeling of Temporal Dominance Curves

3.1 State and Observation Equations

The state and observation equations used in this study are

$$\boldsymbol{m}_{t+\Delta t} = \boldsymbol{A}\boldsymbol{m}_t + \boldsymbol{B}\boldsymbol{u}_t \tag{1}$$

$$\boldsymbol{y}_t = \boldsymbol{C}\boldsymbol{m}_t + \boldsymbol{D}\boldsymbol{u}_t + \boldsymbol{e}_t \tag{2}$$

where, $\boldsymbol{y}_t$ and $\boldsymbol{u}_t$ are the output and input vectors at time t, respectively. We established a model that estimates changes in affective responses from those in perceptual responses; hence, the inputs and outputs represent the dominance rates of perceptual and affective responses at time t, respectively. $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$, and $\boldsymbol{D}$ are the coefficient matrices related to the variables. These coefficients indicate the strength of influence among variables. $\boldsymbol{e}_t$ and $\boldsymbol{m}_t$ are the vectors for observation error and state variables at time t, respectively. From (1), the present state variables could be determined using the past state and input vectors; therefore, the present state variables implicitly contain information about the past states of the system. Hence, $\boldsymbol{m}_t$ is called the vector of memory.

3.2 Canonical Variate Analysis (CVA)

To define the state variables $\boldsymbol{m}_t$, we used canonical variate analysis (CVA) for time-dependent inputs and outputs [9]. CVA finds the relationships between input and output variables by computing the canonical variates that are the linear combinations of input and output variables.

The past vector $\boldsymbol{p}_t$ and future vector $\boldsymbol{f}_t$ are defined as follows:

$$\boldsymbol{p}_t = \left[y_{t-\Delta t}^T, \cdots, y_{t-l\Delta t}^T, u_{t-\Delta t}^T, \cdots, u_{t-l\Delta t}^T\right]^T \tag{3}$$

$$\boldsymbol{f}_t = \left[y_t^T, y_{t+\Delta t}^T, \cdots, y_{t+h\Delta t}^T\right]^T \tag{4}$$

where, l and h represent time lags for the past and future, respectively. The time lags determine the temporal orders that should be considered in the model. We determined $l = h = 1$ in the latter computation. Δt is the sampling period used to generate discrete TD curves, with a value of $\Delta t = 0.033$ normalized time, corresponding to approximately 1 s.

We calculate the vector of memory $\boldsymbol{m}_t$ using the past vector $\boldsymbol{p}_t$:

$$\boldsymbol{m}_t = \boldsymbol{W}^T \boldsymbol{\Sigma}_{pp}^{-\frac{1}{2}} \boldsymbol{p}_t \tag{5}$$

where, $\boldsymbol{W}$ is a matrix of the left singular vector obtained by singular value decomposition, as represented in (6). $\boldsymbol{\Sigma}_{pp}\, and\, \boldsymbol{\Sigma}_{ff}$ are the variance matrices of $\boldsymbol{p}_t\, and\, \boldsymbol{f}_t$, respectively, and $\boldsymbol{\Sigma}_{pf}$ is the covariance matrix of $\boldsymbol{p}_t$ and $\boldsymbol{f}_t$:

$$\boldsymbol{\Sigma}_{pp}^{-1/2} \boldsymbol{\Sigma}_{pf} \boldsymbol{\Sigma}_{ff}^{-1/2} = \boldsymbol{W} \boldsymbol{\Sigma} \boldsymbol{V}^T \tag{6}$$

where, $\boldsymbol{\Sigma}$ is a diagonal matrix of the singular values.

3.3 Bootstrap Resampling

For CVA calculation, the sample size needs to be substantially greater than the number of variables to be analyzed. Usually, TD tasks produce a single set of TD curves from multiple assessors. Hence, CVA cannot be directly applied to TD curves. Therefore, we increased the number of TD curves by bootstrap resampling [10]. The new sample set was generated by sampling the originally observed data with replacements, as described in [8]. The number of assessors for forming one set of TD curves was eight, and a total of 40 sets of TD curves were calculated.

4 Result

4.1 Computed State-Space Model

We established a model including three state variables. The number of state variables was determined based on the ease of interpretation of the state variables. Figures 4, 5, 6 and 7 show parts of the model corresponding to each of the three state variables. In these figures, each node represents the dominance rate of each attribute and state variable, and the edges denote the relationships between nodes. Red and blue edges represent the positive and negative influences, respectively. The values next to the edges are the values of the coefficient matrices corresponding to each edge. Here, the edges whose effect is small are not shown for visual clarity. From (1) and (2), the edges ending at the state variables and affective labels represent influences from the past and present values, respectively.

Figure 4 shows the state-space model related to the first state variable. The first state variable is mainly affected by *juicy* and *sweet* and exhibits a great effect on *delicious*. Therefore, the first state represents the memory of the deliciousness of strawberries.

Figure 5 shows the model for the second-state variable. This state variable is affected by all the perceptual responses and exhibits a positive effect on *delicious* and a negative effect on *fresh*. This state, therefore, represents the memory of comprehensive sensation, and is the average property of subjective responses evoked on eating strawberries.

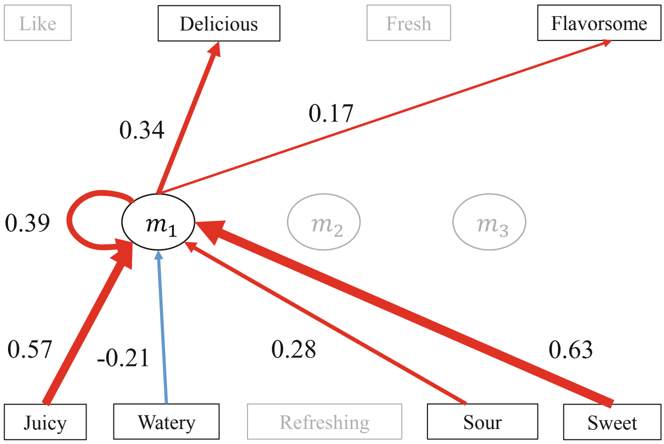

Fig. 4. State-space model related to the first state variable: memory of deliciousness.

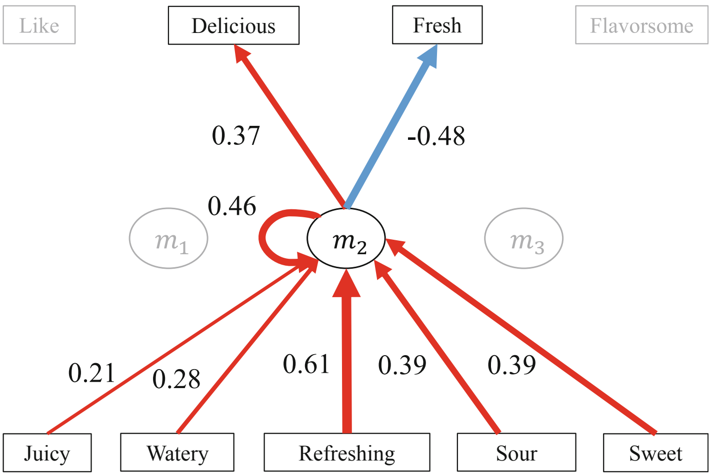

Fig. 5. State-space model related to the second state variable: memory of average experience.

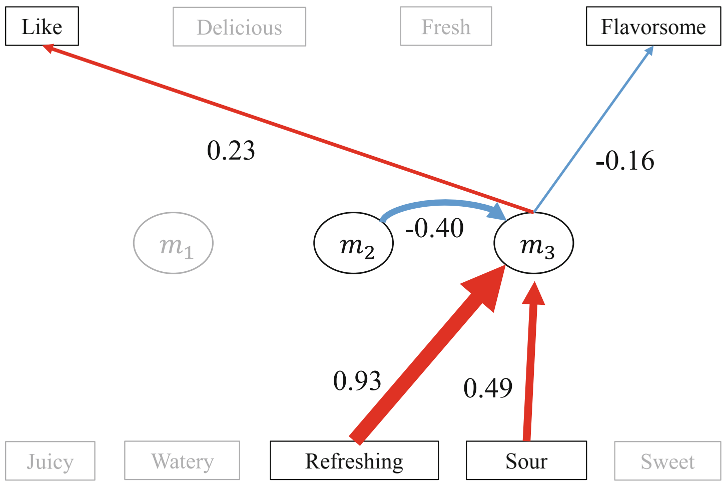

Fig. 6. State-space model related to the third state variable: memory of coolness.

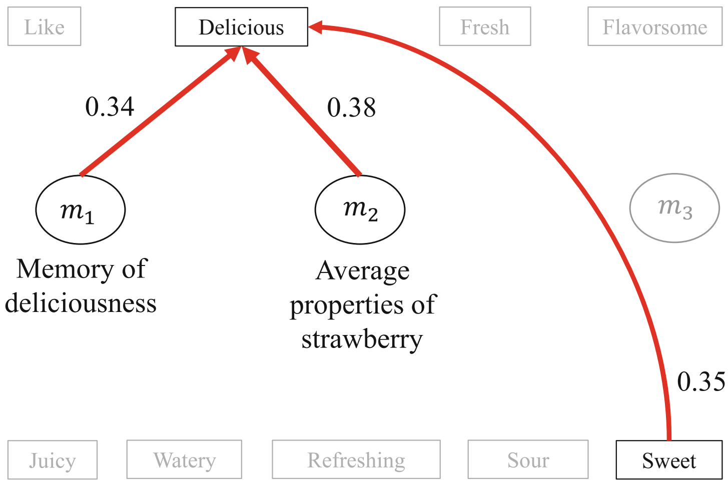

Fig. 7. State-space model related to *delicious*.

Table 2. Correlation coefficients between observed and estimated TD curves.

Responses	Correlation coefficients
Like	0.81
Delicious	0.84
Fresh	0.09
Flavorsome	0.90

As shown in Fig. 6, the third state variable is affected by *refreshing* and *sour*; therefore, it represents the memory of the cool feeling associated with eating strawberries. This state has a positive effect on *like*, whereas it has a negative effect on *flavorsome*.

As an example, we show the edges connected to *delicious* (shown in Fig. 7). *Delicious* is positively affected by *sweet* and the first- and second-state variables.

4.2 Estimation Accuracy

Figure 8 shows the observed and estimated TD curves for the four types of affective responses. The orange and blue lines represent the observed and estimated values, respectively. The correlation coefficients between the observed and estimated values are listed in Table 2.

As shown in Table 2, *like*, *delicious*, and *flavorsome* could be predicted with sufficient accuracy; however, the correlation coefficient of *fresh* was 0.09, indicating that *fresh* was not well-represented by the present model. Furthermore, despite its large correlation coefficient, as shown in Fig. 8(a), the differences between the observed and estimated values of *like* were large. The trends could be predicted accurately; however, the absolute values were not representative of reality.

The optimization of the past and future time lags and the number of states is necessary to increase the estimation accuracy of the model.

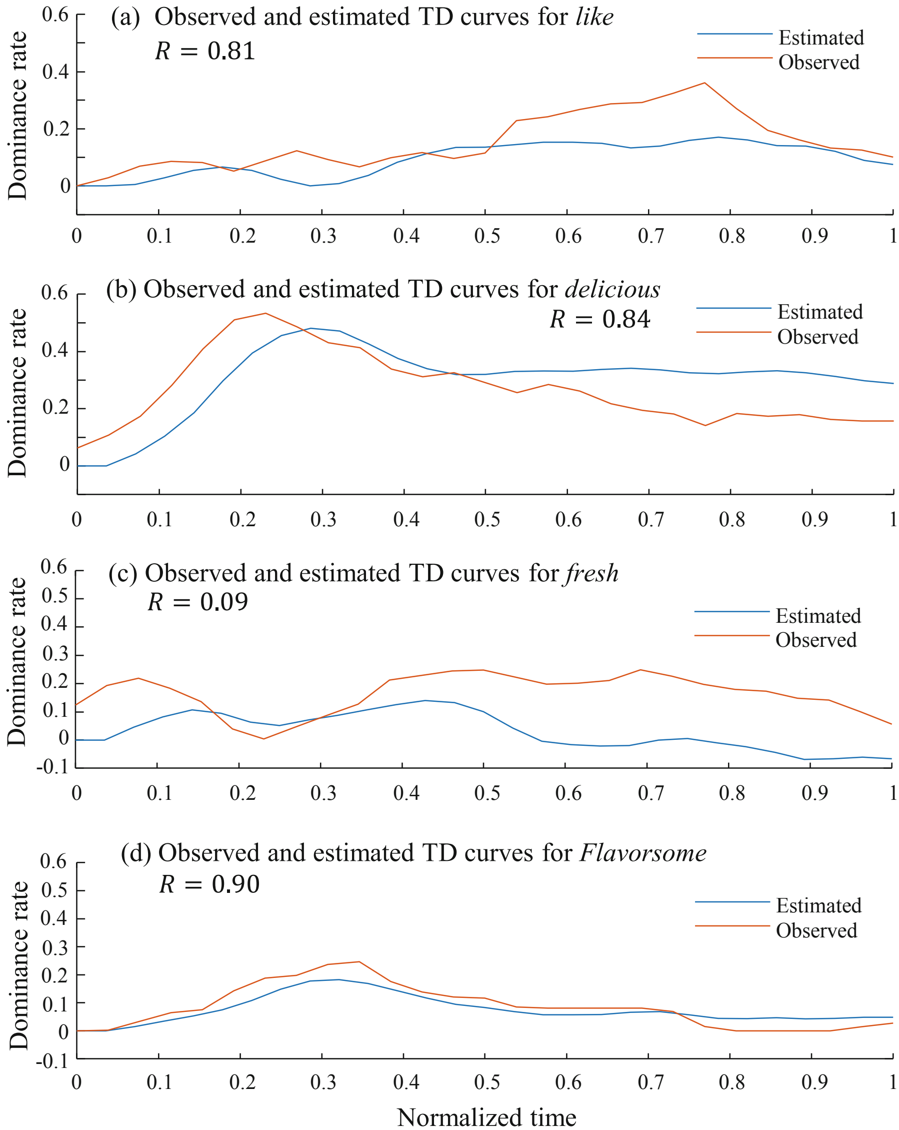

Fig. 8. Observed and estimated TD curves for (a) *like*, (b) *delicious*, (c) *fresh*, and (d) *flavorsome.*

5 Conclusion

In this study, we applied a state-space modeling method to the data acquired by the TD method. To this end, we employed canonical variate analysis of past and future data on resampled TD curves generated for the intake of strawberries. Using state-space modeling, it was possible to represent the temporal evolutions of affective responses, and the three state variables could sufficiently express the relationship among the nine subjective responses. In the model established here, some attributes could not be estimated with sufficient accuracy. This problem could be solved by optimizing the model. We also need to confirm the generality of this method by applying it to TD responses to other foods. Furthermore, the semantic validity of the model calculated by this method remains to be studied.

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