Dynamic State-Space Modeling with Factorial Memories in Temporal Dominance of Sensations, Emotions and Temporal Liking

Kyoichi Tachi and Shogo Okamoto, *Member, IEEE*

Abstract—There are few mathematical models that describe how human perceptual and affective responses evolve with time. We developed a state-space model of the interrelationships based on time-evolving perceptual and affective responses acquired by the temporal dominance (TD) method. We defined and computed the state variables that endow the system with memory using canonical variate analysis. Furthermore, we determined the model parameters on the basis of a cross-validation approach such that the observed and estimated changes in the affective responses are highly correlated. We applied this method to the TD curves of responses to eating strawberries and plum pickles, reported in our previous work. The model describes what happens during food intake in terms of a few state variables that summarize a large number of observable responses reductively, thus helping to make the perceptual and affective dynamics understandable.

Index Terms—Temporal dominance, latent variable, memory, sensation, emotion, canonical variate analysis.

1 Introduction

Human perceptual and affective responses to stimuli are not static, but change dynamically with time. Temporal-dominance (TD) methods [1], [2], [3], [4], [5] are used in food industry to record such multiple subjective experiences in time-series form. This sensory-evaluation technique enables the study of how perceptual (gustatory, osmatic, and textural), affective, and preferential responses evolve during food intake. TD methods have a great potential for new applications or experimental designs. For example, TD methods realize research on dynamic linkage among multiple types of feelings and human physiological data such as skin conductance [4].

However, since TD has been in intensive use for a comparatively short time, only a few mathematical approaches to the data acquired by it have been developed. These include methods based on Granger causality [6], [7], which seek causal relationships between the perceptual and affective responses on the basis of their time-series; Markov models [8], [9], [10], which treats TD data stochastically and compute the expected probabilities that a type of subjective response is observed after another type of subjective response; and principal motion analysis [11], which decomposes time-series TD responses into modal spectra and can be used for discriminating between food products; a graph theoretical model [12] to suggest the frequency of temporal transition from one feeling to another; a covariance selection model established by concurrent changes among multiple types of feelings [13]. Visalli et al. proposed to separate the entire duration of stimulus experience into three phases and separately analyze each phase [14]. Most other studies have computed static or quasi-static indices from the records of TD tasks; standard methods to model the dynamic nature of TD response have yet to be established.

In a typical TD task (described in Section 2), approximately 10 types of responses are assessed. As TD tasks for recording perceptual and affective responses are generally conducted separately, up to 20 types of responses must be explained in a single model. Such a large number of observed variables prevents intuitive understanding of the relationships within the data. A more reductive methodology is required if the interdependences of perceptual and affective responses are to be understood. In fact, reductive methods have been employed by many sensory studies involving static (non-dynamic) sensory appraisal methods [15]; however, in terms of TD methods, most of the methods mentioned earlier [6], [7], [8], [9], [10], [12], [13], [14] do not aim at a reductionistic treatment of the time-series data acquired by TD methods. The technique in [11] is capable of decreasing the model dimensions by using modes computed from the time-series responses recorded by TD tasks, but, although it excels at discriminating between different types of food products, this method does not provide an understanding of the relationships between the sensory and affective responses.

In the present study, by using state-space modeling, we establish relationships between perceptual and affective time-series responses. State-space models include measured variables and unmeasured or latent variables to explain the behavior of typically mechanical and information systems. The latent variables are called states. They are not directly observed in TD experiments, but function as memories of past responses and are helpful in understanding the relationships between observable quantities. Usually, the number of state variables is smaller than the number of perceptual and affective responses evaluated in the TD task; therefore, state variables can provide a reductionist representation of the entire model. Further, the state-

• *K. Tachi is with the Department of Mechanical Systems, Nagoya University, Japan. S. Okamoto is with the Department of Computer Sciences, Tokyo Metropolitan University, Japan.*
E-mail: okamotos@tmu.ac.jp

variable model allows us to estimate the affective responses as outputs when the perceptual responses are provided as inputs. None of the previous approaches [6], [7], [8], [9], [10], [11], [12], [13] can simultaneously offer a reductionist representation and the prediction of affective responses.

The present study is based on [16], in which we introduced the state-space modeling of TD responses to strawberries. In this study, we establish state-space models of TD responses to strawberries from 10 participants [6], [7] and plum pickles from 20 participants [11], [17]. The model parameters are determined by cross-validation approach such that the observation and estimation of TD responses exhibit a high correlation coefficient, which was not performed in [16]. For this purpose, a number of samples are attained by a bootstrap sampling method. We discuss the semantic validity of the model (chiefly in the case of strawberries, as plum pickles are popular in Japan but possibly not popular in much of the world). We note that the method developed here is also applicable to data recorded by temporal check-all-that-apply method [18], a popular modification of a TD method.

2 Temporal-Dominance (TD) Method

In this study, we use a TD method [1], [2], [3] to study the time evolution of perceptual and affective responses. The TD method enables the simultaneous measurement of multiple types of assessors' subjective responses to various stimuli. Thus far, the protocols of TD methods have been established and validated for food and beverage stimuli. TD methods have also been tested with tactile stimuli [19] and audio-visual stimuli [4], [20], [21], but less extensively. In future, the TD method is expected to be a standard one for multiple sensory modalities. Here, we briefly introduce the method; more details can be found in previous reports [1], [2], [3].

In the TD method, a graphical touch-panel interface is used, as shown in Fig. 1 (a). The assessor presses the start button upon the initiation of food intake. Various other buttons on the touch panel may then be pressed, their labels corresponding to possible dominant feelings about (or perceptions of) the food while eating it. Here, the "dominant" sensation is the sensation catching attention at that moment, not necessarily the one with the highest intensity. The assessor selects a corresponding button each time the dominant feeling changes; only one button can be selected at any given moment. The stop button is pressed when the sensations associated with food intake are no longer predominant. A button can be selected more than once, and not every button needs to be selected.

The times at which buttons are selected in each trial are recorded. As a result, we can obtain a binary time-series for each button as shown in Fig. 1 (b). We can calculate TD curves by integration and smoothing the binary time-series from all trials (Fig. 1 (c)). The horizontal axis of a TD curve is the normalized time with zero at the moment of pushing the start button and one at that of pushing the stop button. The vertical axis is the dominance rate, the ratio between how often the button was selected at each time and the total number of trials (i.e., the number of assessors × the number of trials per assessor).

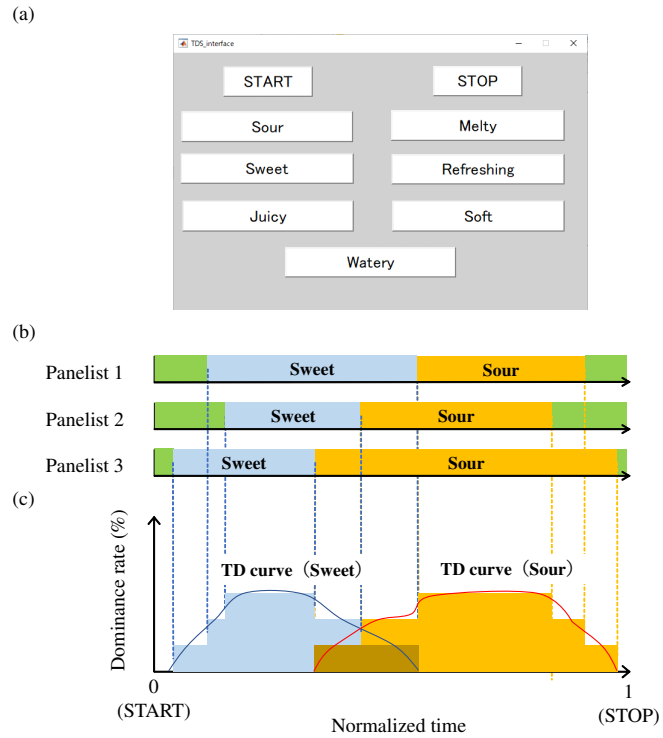


Fig. 1. Overview of temporal-dominance (TD) methods. (a) Example of a graphical user interface used in TD experiments. (b) Binary data obtained by TD method from three assessors (panelists). (c) TD curves calculated by accumulating and smoothing the panelists' binary responses. Adapted from [16].

TD methods are used for recording perceptual responses (TD of sensations) and affective and preferential responses (TD of emotions). In general, perceptual and affective responses are measured separately in repeated trials, not in a single trial; the data collection for the present study was also conducted in this standard way.

3 State-Space Modeling of Temporal-Dominance Curves

3.1 State and observation equations

In this study, we construct a model that estimates changes in affective response from changes in perceptual response. The output and input vectors for the model are the discrete differential series of affective and perceptual dominance rates:

$$\boldsymbol{y}_t = [y_{1t}, \ldots, y_{it}, \ldots, y_{pt}]^{\mathrm{T}}, \tag{1}$$

$$\boldsymbol{u}_t = [u_{1t}, \ldots, u_{jt}, \ldots, u_{qt}]^{\mathrm{T}}, \tag{2}$$

where y_{it} and u_{jt} are the differential values between two successive instants t and $t + \Delta t$ of responses to the i-th affective and j-th perceptual descriptor, respectively. Note that i runs from 1 to p and j from 1 to q.

The state equation and observation equation are

$$\boldsymbol{m}_{t+\Delta t} = \boldsymbol{A}\boldsymbol{m}_t + \boldsymbol{B}\boldsymbol{u}_t, \tag{3}$$

$$\boldsymbol{y}_t = \boldsymbol{C}\boldsymbol{m}_t + \boldsymbol{D}\boldsymbol{u}_t + \boldsymbol{e}_t, \tag{4}$$

where $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}$ and $\boldsymbol{D}$ are coefficient matrices for each variable; $\boldsymbol{e}_t \in \mathbb{R}^{p\times 1}$ is the observation error vector, with

mean $\mathbf{0}$; and $\boldsymbol{m}_t \in \mathbb{R}^{d\times 1}$ is the vector of state variables at time t. d is the number of state variables and can be arbitrarily determined. From (3), the present state variables can be determined using the past state and input vectors; the present state variables implicitly contain information about the past states of the system. Hence, $\boldsymbol{m}_t$ is called the vector of memory. We show a concrete method of calculating it in Section 3.2.

3.2 Canonical variate analysis

To determine the values of the state (memory) variables $\boldsymbol{m}_t$ at instant t, we use canonical variate analysis for time-evolving inputs and outputs [22]. The past vector $\boldsymbol{p}_t \in \mathbb{R}^{p'\times 1}$ and future vector $\boldsymbol{f}_t \in \mathbb{R}^{f'\times 1}$ are defined as

$$\boldsymbol{p}_t = [\boldsymbol{y}_{t-\Delta t}^{\mathrm{T}}, \ldots, \boldsymbol{y}_{t-l\Delta t}^{\mathrm{T}}, \boldsymbol{u}_{t-\Delta t}^{\mathrm{T}}, \ldots, \boldsymbol{u}_{t-l\Delta t}^{\mathrm{T}}]^{\mathrm{T}} \tag{5}$$

$$\boldsymbol{f}_t = [\boldsymbol{y}_t^{\mathrm{T}}, \boldsymbol{y}_{t+\Delta t}^{\mathrm{T}}, \ldots, \boldsymbol{y}_{t+h\Delta t}^{\mathrm{T}}]^{\mathrm{T}}, \tag{6}$$

where $l \in \{1, 2, ...\}$ and $h \in \{0, 1, 2, ...\}$ represent time lags (or forward steps) for the past and future, respectively. The sizes of the vectors are $p' = l(p+q)$ and $f' = p(h+1)$. $\boldsymbol{p}_t$ includes the system's past inputs and outputs at t, whereas $\boldsymbol{f}_t$ includes the current and future outputs at t.

The values of the vector of state variables $\boldsymbol{m}_t$ at t are computed using the past vector $\boldsymbol{p}_t$:

$$\boldsymbol{m}_t = \boldsymbol{W}^{\mathrm{T}} \boldsymbol{\Sigma}_{pp}^{-\frac{1}{2}} \boldsymbol{p}_t, \tag{7}$$

where $\boldsymbol{W} \in \mathbb{R}^{p'\times d}$ is a matrix of the left singular vector obtained by singular value decomposition, as in (8) below; and $\boldsymbol{\Sigma}_{pp} \in \mathbb{R}^{p'\times p'}$ is the variance matrix of $\boldsymbol{p}_t$. We also define $\boldsymbol{\Sigma}_{ff} \in \mathbb{R}^{f'\times f'}$ as the variance matrix of $\boldsymbol{f}_t$, and $\boldsymbol{\Sigma}_{pf} \in \mathbb{R}^{p'\times f'}$ as the covariance matrix of $\boldsymbol{p}_t$ and $\boldsymbol{f}_t$:

$$\boldsymbol{\Sigma}_{pp}^{-\frac{1}{2}} \boldsymbol{\Sigma}_{pf} \boldsymbol{\Sigma}_{ff}^{-\frac{1}{2}} = \boldsymbol{W} \boldsymbol{\Sigma} \boldsymbol{V}^{\mathrm{T}}. \tag{8}$$

Here, $\boldsymbol{\Sigma} \in \mathbb{R}^{d\times d}$ and $\boldsymbol{V} \in \mathbb{R}^{f'\times d}$ are a diagonal matrix of the singular values and the matrix of the right singular vector, respectively.

3.3 Bootstrap resampling

In canonical variate analysis, overfitting occurs unless the sample size, i.e., the number of curve sets, is sufficiently large compared to the number of variates to be analyzed. In the TD method, a single set of TD curves is acquired by superimposing the responses of all assessors (Fig. 1 (c)). Hence, canonical variate analysis cannot be directly applied. To circumvent this problem, we increase the number of TD curves by bootstrap resampling [23], i.e., forming a new sample set by sampling the original observational data with replacement [11]. In this study, we generated a single set of TD curves by sampling n times at random from a pool of n participants. By repeating this process 40 times, we produced 40 sets of TD curves, to which canonical variate analysis was applied.

3.4 Selection of model parameters

To construct a state-space model, we need to choose the past (l) and future (h) time lags and the number of state variables (d). In earlier studies [24], [25], the time lags were determined such that the correlation coefficients between observed and estimated values were maximized. However, that approach led to overfitting when applied to our problems. To determine the number of state variables, Bartlett's test or Akaike's information criterion is typically used. However, Bartlett's test led to overly complicated models for our problems ($d = 9$ in the case of strawberries, for example). On the other hand, Akaike's information criterion led to overly simplified models ($d = 1$ in the case of strawberries) that were not capable of predicting the affective time-series.

Thus, we determined the model parameters by using two-fold cross-validation. We divided the forty sets of TD curves generated by the bootstrap resampling into two groups at random. We then computed the state-space model using the data of one group and obtained the state values ($\boldsymbol{m}_t$) and model coefficients ($\boldsymbol{A}$–$\boldsymbol{D}$) corresponding to them. The correlation coefficients between the observed and estimated values were then computed using the data of the other group. The two groups were switched, and the same process was repeated. The correlation coefficients acquired in this way were averaged. These procedures were conducted exhaustively for all the combination of parameters defined by $l = 1, ..., 5$, $h = 0, ..., 10$, and $d = 1, ..., 6$. (This parameter space was determined through a preliminary search with a small number of bootstrapped samples.) We then employed the parameter sets that achieved the greatest correlation coefficients.

3.5 Edge reduction of the model based on confidence interval

The coefficients $\boldsymbol{A}$–$\boldsymbol{D}$ were computed between all variables, but some of them were not statistically significant. We used the sets of bootstrap samples, from each of which the coefficient values, along with their means and confidence intervals, were computed. If the mean of a certain coefficient differed from zero by at least one confidence interval, then that coefficient was considered significant and retained in the model; insignificant coefficients were dropped. This process of edge reduction greatly facilitates the interpretation of the state-space models.

4 TD RESPONSES FOR STRAWBERRIES AND PLUM PICKLES

4.1 TD curves for strawberries

Fig. 2 shows the TD curves obtained in [6], [7] as the assessors (eight male and two female university students, 22–24 years old: $n = 10$) were eating strawberries. All the assessors conducted TD of both sensations and emotions tasks. The researchers recorded the responses using a set of adjectives chosen in advance. We removed *melty*, *soft*, *happy/satisfied*, *natural*, and *elegant*, which we judged to be statistically meaningless according to the criteria given in [1], and used the remaining nine descriptors (listed in Table 1) in our later analysis. The curves were smoothed

TABLE 1
Descriptors used to represent perceptual and affective/evaluative responses to strawberries [7].

Perceptual	Affective/Evaluative
Sweet	*Like*
Sour	*Delicious*
Watery	*Fresh*
Refreshing	*Flavorsome*
Juicy	

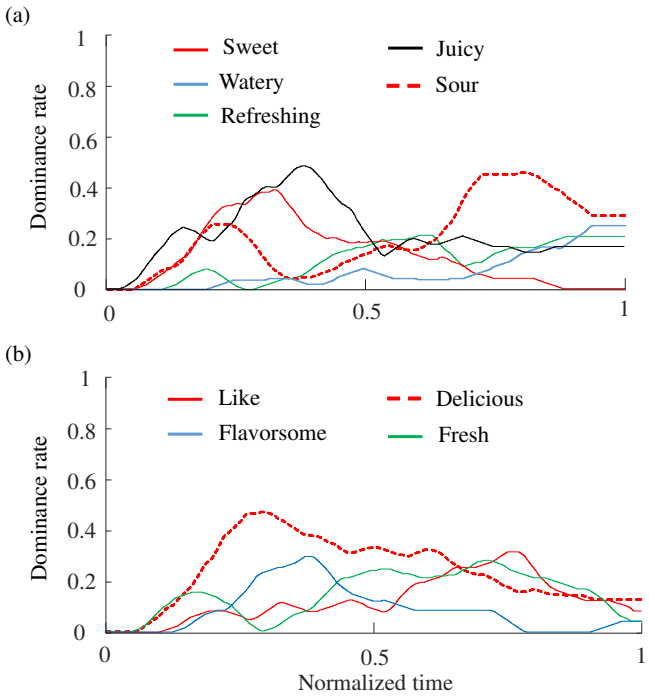


Fig. 2. Temporal-dominance (TD) curves for (a) sensory adjectives and (b) affective/evaluative adjectives for strawberries (modified from [7]).

by a low pass filter with a cutoff frequency of $1/\Delta t$, where Δt was 1/30 the normalized time, or approximately 1 s. Continuous TD curves were discretized into 31 points with a sampling interval of Δt.

4.2 TD curves for plum pickles

Another published study [11], involving twenty university student assessors (16 males and four females, 21–26 years old: $n = 20$), contains TD curves for ten types of plum pickles. Similar to the case of strawberries, all the assessors conducted TD of both sensations and emotions tasks. We used the curves for the bonito-flavored plum pickle, shown in Fig. 3, eliminating the adjectives *expensive*, *refreshing*, and *fruity* because of their small dominance rates; the 14 adjectives we retained are listed in Table 2. The smoothing and discretization methods employed with the plum-pickle data were the same as those with the strawberry data.

5 Results

5.1 Strawberries

5.1.1 Selected model parameters

For strawberries, the selected model parameters l (past lags), h (future lags), and d (number of state variables) are listed in

TABLE 2
Descriptors used to represent perceptual and affective/evaluative responses to plum pickles [11].

Perceptual	Affective/Evaluative
Sour	*Like*
Sweet	*Dislike*
Umami	*Delicious*
Salty	*Flavorsome*
Smooth	*Rich /Deep*
Juicy	*Sharp*
Watery	*Arousing*

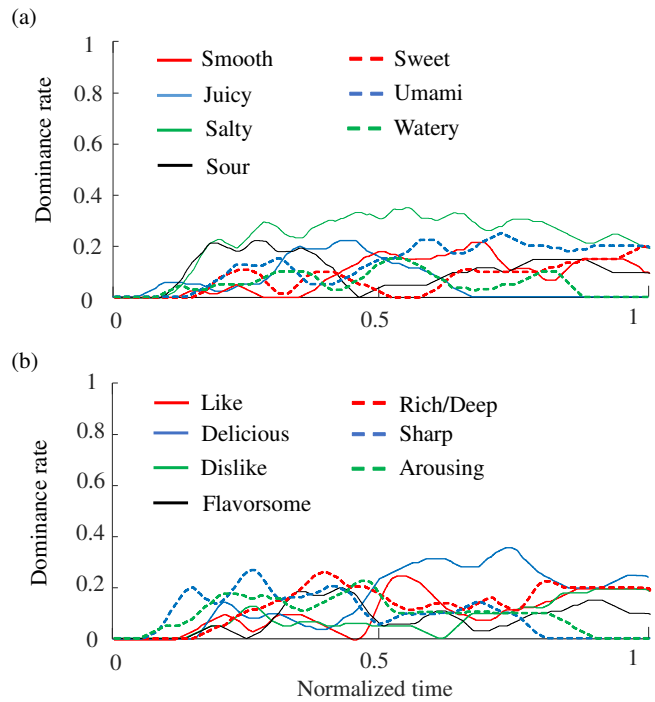


Fig. 3. Temporal-dominance (TD) curves for (a) sensory adjectives and (b) affective/evaluative adjectives for plum pickles (modified from [11].)

Table 3. The values of l and d vary among affective descriptors, whereas $h = 1$ is selected for all of them. The parameter values that maximize the mean estimation accuracy for all types of descriptors are $(l, h, d) = (2, 1, 3)$; we used this parameter set to construct the model for strawberries.

5.1.2 State-space model for strawberries

The state-space model for strawberries constructed using the above parameters is shown in Fig. 4. The model is shown in a decomposed manner because it includes many edges.

TABLE 3
Parameters to maximize the estimation accuracy of individual affective descriptors for strawberries. l: time lag for the past, h: time lag (or forward step) for the future, d: number of state variables. The parameters in the bottom row are used for the final model.

	l	h	d
Like	3	1	5
Delicious	1	1	2
Fresh	5	1	3
Flavorsome	2	1	5
Whole model	2	1	3

In these figures, the nodes indicate perceptual responses, affective responses, or state variables. The edges indicate significant influence between nodes. The values next to the edges are the coefficients corresponding to each edge. Dotted edges are statistically significant; however, their effects are comparatively weak, with the absolute values of the coefficients less than one third that of the largest influence on each node. Red and blue edges indicate positive and negative influences, respectively. As defined in (3) and (4), edges connected to state variables are the effects of past values, and edges connected to affective adjectives are the effects of current values.

Fig. 4 (a) shows that the first state variable (m_1) is mainly affected by *juicy* and *sweet* and exerts a powerful effect on *delicious*. Therefore, it represents the memory of the deliciousness of strawberries.

Fig. 4 (b) shows that the second state variable (m_2) is strongly affected by *watery*; influences from the other perceptual responses are small. This state variable represents the memory of wateriness of strawberries; it exhibits negative effects on *like* and *fresh* and positive effects on *delicious* and *flavorsome*.

The third state variable (m_3), shown in Fig. 4 (c), is negatively affected by *watery* and positively affected by *refreshing* and *sour*. This state variable may represent the memory of the coolness or unripeness of strawberries. This state exhibits a positive effect on *like* and a negative effect on *flavorsome*.

Figs. 4 (d)–(g) show the parts of the model pertaining to each affective word. The node *like* is influenced by the memories of wateriness (m_2) and coolness (m_3) and by the perceptual variables *watery*, *refreshing*, and *sour*. The node *delicious* is mainly influenced by *refreshing* and by the memories of deliciousness (m_1) and wateriness (m_2). The node *fresh* is weakly influenced by several perceptual responses and memories; therefore, it must be considered a comprehensive subjective response. The node *flavorsome* is mainly influenced by *refreshing* and m_1 (memory of deliciousness), but is also moderately affected by the other two types of memories, i.e., wateriness (m_2) and coolness (m_3). The semantic validity of these connections will be discussed in Section 6.1.

5.1.3 Estimation accuracy for strawberries

Fig. 5 shows the observed and estimated TD curves for affective descriptors (in orange and blue, respectively). These curves are the means of resampled TD curves. Note that the curves are not shown at very small normalized times because the past values for the perceptual descriptors and states are not defined for $t < 0$ and the estimate for $t < l\Delta t$ is also not defined. The correlation coefficients between the observed and estimated values are listed in Table 4. These were computed from the 29 discrete points in Fig. 5, excluding the first two undefined points. The correlation coefficients for *delicious* and for *flavorsome* are approximately 0.90, and thus they are predicted with sufficient accuracy. By contrast, *like* and *fresh* are only moderately correlated. In terms of *fresh*, despite its moderate correlation coefficient, i.e., 0.49, the estimated and observed curves are substantially different, suggesting a difficulty in estimating *fresh* using the sensory responses (see also Section 6.1).

TABLE 4
Correlation coefficients between observed and estimated temporal-dominance curves for strawberries

Adjective	Correlation coefficient
Like	0.54
Delicious	0.88
Fresh	0.49
Flavorsome	0.94

TABLE 5
Parameters to maximize estimation accuracy of individual affective descriptors for plum pickles. l: time lag for the past, h: time lag (or forward step) for the future, d: number of state variables. The parameters in the bottom row are used for the final model.

	l	h	d
Like	1	5	3
Delicious	4	5	1
Dislike	4	5	1
Flavorsome	4	3	1
Rich and deep	1	1	4
Sharp	2	1	2
Arousing	2	5	1
Whole	2	4	2

5.2 Plum pickles

5.2.1 Selected model parameters

The selected model parameters for plum pickles are listed in Table 5. Like those for strawberries, they vary among affective descriptors. The parameter set $(l, h, d) = (2, 4, 2)$ is best in terms of the average correlation coefficients among all types of affective descriptors, and we used it for the analysis of plum-pickle data.

5.2.2 Computed state-space models for plum pickles

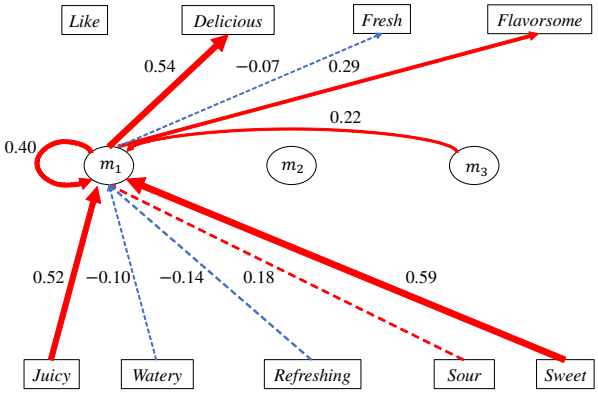
The state-space models related to state variables for plum pickles are shown in Fig. 6. The models specific to affective adjectives are shown in the Appendix.

Fig. 6 (a) is the model related to the first state variable. This state is positively affected by the second state variable and by all perceptual responses except *sweet*. It is especially affected by *salty*, *sour*, and *umami*, which are the general tastes of bonito-flavored plum pickles [11]. Also, the first state variable exhibits strong effects on *like* and *delicious*. This state may correspond to the overall reaction to plums, or the valence.

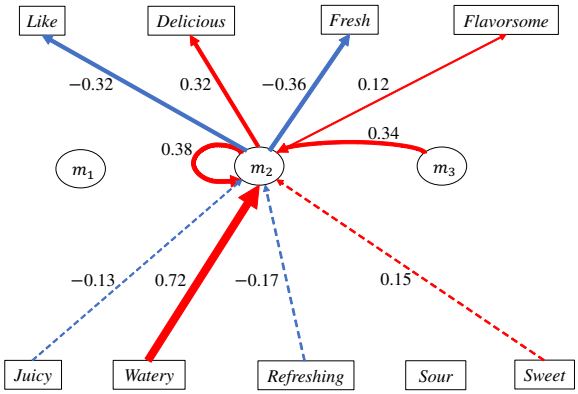
Fig. 6 (b) is the model related to the second state variable. This state is strongly affected by *sweet* and *juicy*, from which we infer that it may represent the memory of the sweetness of fruit.

5.2.3 Estimation accuracy for plum pickles

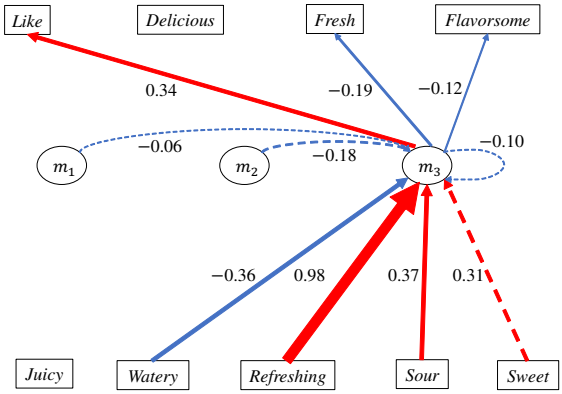
Fig. 7 shows the observed and estimated TD curves for plum pickles. Their correlation coefficients, summarized in Table 6 were computed using the 29 discrete points, excluding the first two points. The correlation coefficients for *delicious*, *dislike* and *rich and deep* are equal to or greater than 0.8, suggesting that the model represents them accurately. By contrast, the correlation coefficients for the other attributes are moderate or low, with that for *sharp* being the smallest at 0.36.



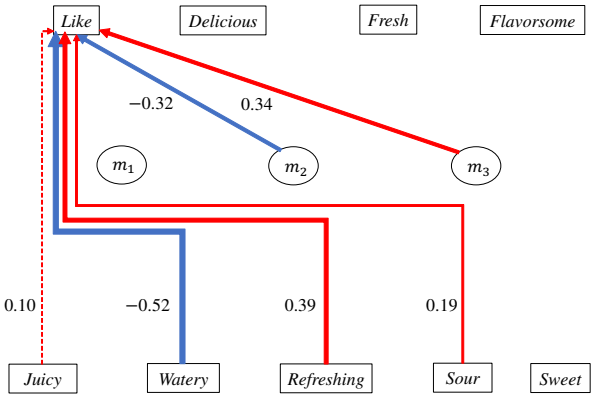
(a) State-space model related to the first state variable: memory of deliciousness.



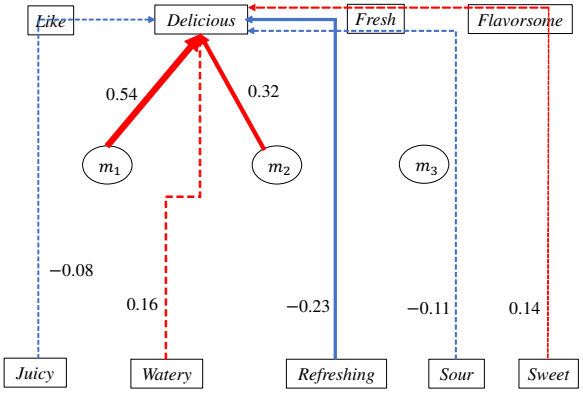
(b) State-space model related to the second state variable: memory of wateriness.



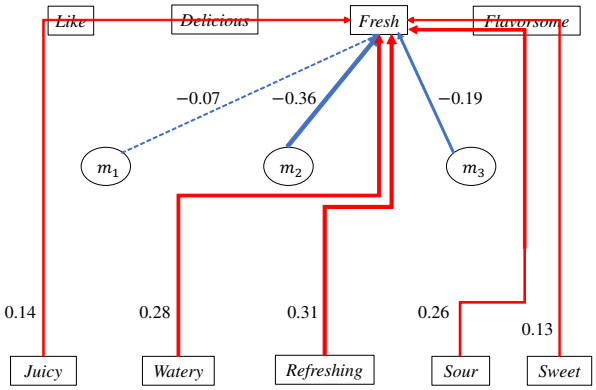
(c) State-space model related to the third state variable: memory of coolness or unripeness.



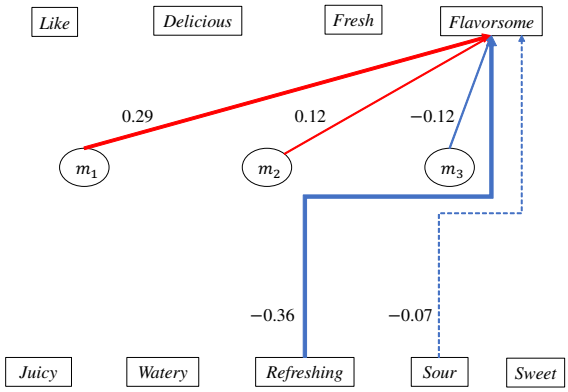
(d) State-space model related to *Like*.



(e) State-space model related to *Delicious*.



(f) State-space model related to *Fresh*.



(g) State-space model related to *Flavorsome*.

Fig. 4. State-space models for strawberries related to (a) the first state variable (memory of deliciousness), (b) the second state variable (memory of wateriness), (c) the third state variable (memory of coolness or unripeness), (d) *like*, (e) *delicious*, (f) *fresh*, and (g) *flavorsome*.

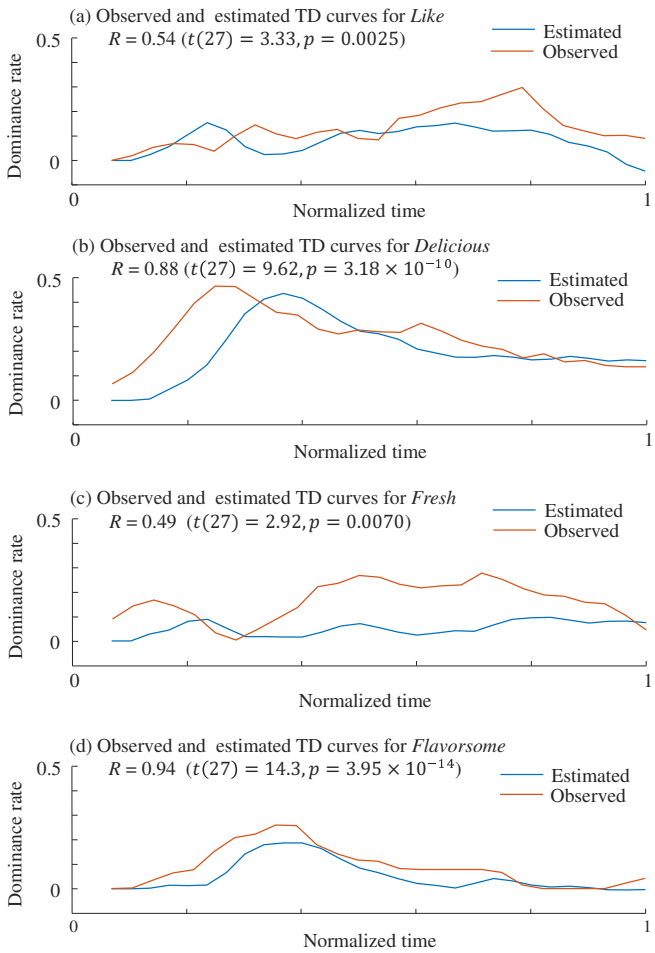


Fig. 5. Observed and estimated temporal-dominance (TD) curves for strawberries: (a) *like*, (b) *delicious*, (c) *fresh*, and (d) *flavorsome*. R is the correlation coefficient between the observed and estimated values in the curves. Results of the significance tests of correlation are also shown.

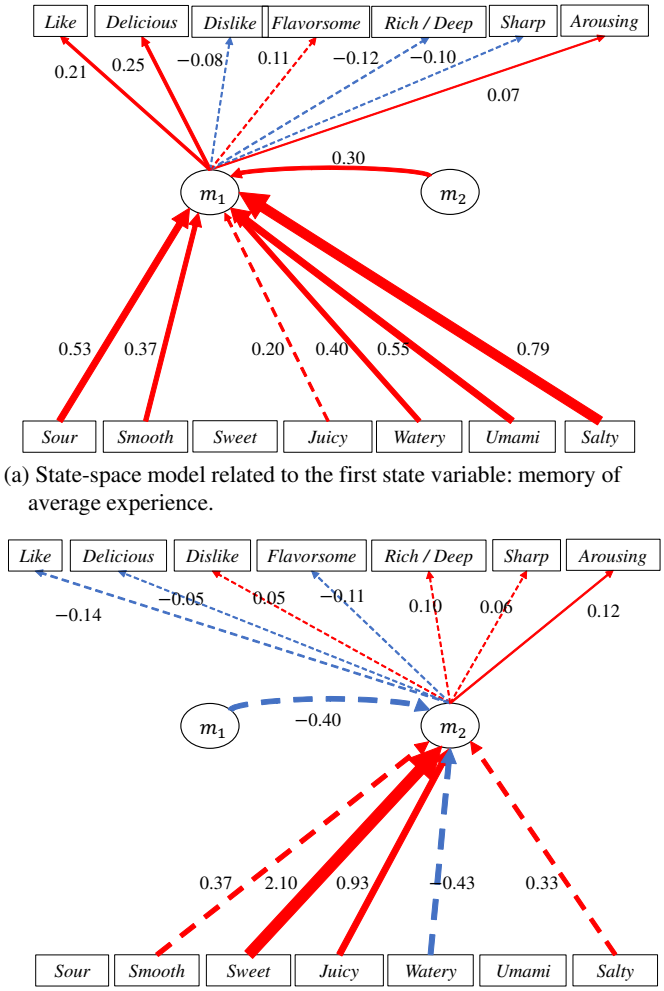
TABLE 6
Correlation coefficients between observed and estimated temporal-dominance curves for plum pickles

Adjective	Correlation coefficients
Like	0.51
Delicious	0.96
Dislike	0.85
Flavorsome	0.44
Rich and deep	0.80
Sharp	0.36
Arousing	0.48

6 Discussion

6.1 Semantic validity of the model for strawberries

Like that of previous studies [7], [9], [10], [11], [12], [13], the modeling method in this one is meant to provide insight into the dynamics of perceptual and affective responses. It is therefore important to consider whether the interpretation put on the model is semantically valid. We discuss this only in the case of strawberries by citing some literature, because, as mentioned previously, plum pickles are eaten in very limited regions of the world or in certain cultures, and the validity of the model may not be evident to readers



(a) State-space model related to the first state variable: memory of average experience.

(b) State-space model related to the second state variable: memory of sweetness of fruit.

Fig. 6. State-space models for plum pickles related to (a) the first state variable: memory of overall reaction; and (b) the second state variable: memory of sweetness of fruit.

unfamiliar with this food.

The three types of states that could be considered as predominant memories were found in the strawberry model. These memories correspond well to the principal components found by Oliver et al. [26] in their study where several types of strawberries were classified on the basis of a rating task using normative descriptors, i.e., quantitative descriptive analysis. According to [26], the positive extreme of the first principal component was characterized by the sweet and floral flavor and fruity aroma. These characteristics are close to those of the first memory (memory of deliciousness) in our model. The negative extreme of the first principal component was characterized by the under-ripeness such as green flavor and aroma, sourness, and citrus flavor and aroma. These characteristics are close to those of the third memory (memory of coolness and unripeness) in our model. The second principal component in [26] was mostly related to the appearances of strawberries, which were not investigated in the present study. The third principal component in [26] was characterized by the quantity of fluid in strawberries, which corresponds to the substances of our second

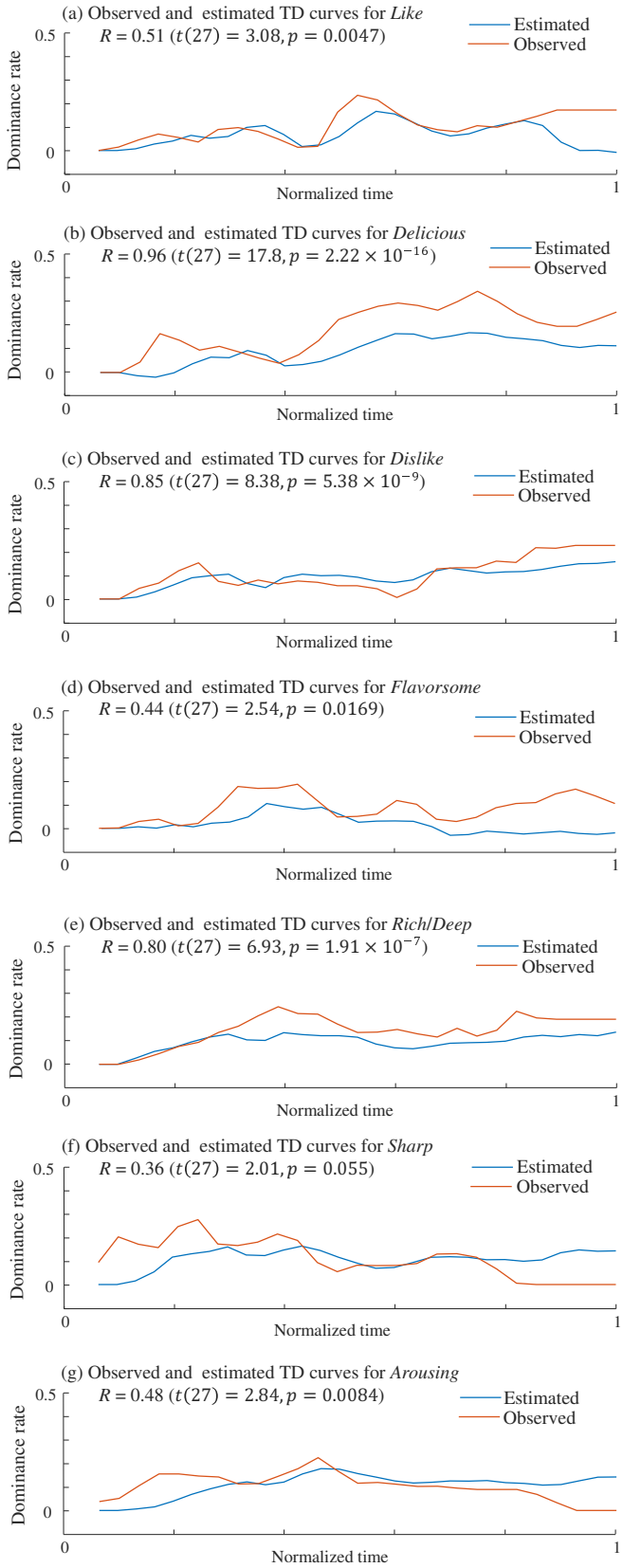


Fig. 7. Observed and estimated temporal-dominance (TD) curves for plum pickles: (a) *like*, (b) *delicious*, (c) *dislike*, (d) *flavorsome*, (e) *rich and deep*, (f) *sharp*, and (g) *arousing*. Results of the significance tests of correlation are also shown.

memory (memory of wateriness). The study by Oliver et al. [26] did not investigate the dynamic sensory appraisal; however, some common features can be found in [26] and our dynamic sensory appraisal.

As shown in Fig. 4 (e), *delicious* was positively influenced by the memories of deliciousness (m_1) and wateriness (m_2). The memory of deliciousness is an accumulation of past *juicy* and *sweet*. Hence, this part of the model is interpreted as stating that sweeter, juicier, and waterier strawberries are judged more delicious. This appears plausible for strawberries.

As shown in Fig. 4 (d), *like* was negatively affected by *watery* and the memory of wateriness (m_2). It is difficult to say whether or not this connection is reasonable; however, in a sensory study of strawberries [27], the amount of liquid in strawberries was neutral or negative against the consumer preferences, which is consistent with our results. By contrast, *refreshing* and *sour* positively influenced *like*, as did the memory of coolness or unripeness (m_3). Thus, strawberries that felt cool, refreshing, and sour were preferred. For most fruits, sweetness is a positive factor [27], [28], [29], [30]; however, in our data, *sweet* hardly affected *like*. Instead, as mentioned above, *sweet* pertained to *delicious*. In most of the earlier studies, either *like* or *delicious* was used in ratings, but not both; the meanings of these two descriptors might have been mixed. One might expect that the responses to *delicious* and *like* would be similar; however, in our data, they were influenced differently by *watery* and *refreshing*. This dissociation between deliciousness and liking was seen in our past analysis using the same data [7]. Ares et al. also reported that deliciousness and liking responses were different in their study using milk desserts [31], but that deliciousness can be a driver of liking.

In terms of *fresh*, our model may be inadequate, given the low correlation coefficient (0.49) between observation and estimation. As shown in Fig. 4 (f), *fresh* received positive effects from all the perceptual responses, and negative effects from the memories of wateriness (m_2) and coolness (m_3). Although the direct effects of *watery*, *refreshing*, and *sour* on *fresh* were positive, the indirect effects through m_2 and m_3 were negative. It is difficult to explain these connections semantically. We speculate that the perceptual descriptors used in our data did not cover the information necessary to judge the freshness of strawberries. According to Péneau et al. [32], although the subjective judgment of freshness in strawberries and apples is influenced by many factors, including odor and texture, visible aspects such as bruises and surface glossiness are the most important. These were not addressed in the questionnaire that we used.

Flavorsome represents the good odor. It was positively affected by the memories of deliciousness (m_1) and wateriness (m_2). It is reasonable that the memory of deliciousness would positively influence *flavorsome*, because this memory is composed of the time-lagged descriptors *juicy* and *sweet*. As shown in Fig. 4 (e) and (g), *flavorsome* and *delicious* have similar structures. This seems fair, because taste preference for strawberries is strongly related to their aroma [30], [33], [34].

In general, our model of strawberries seems to be semantically acceptable. At the very least, it does not include apparently incorrect connections between the descriptors.

Nonetheless, this point should be further studied involving various type of foods and stimuli in future.

Here, the strawberry model of the present study and that of our past report [16] are compared. In [16], the model parameters were arbitrarily determined ($(l, h, d) = (1, 1, 3)$) whereas in the present study, they were determined such that the mean prediction performance was maximized ($(l, h, d) = (2, 1, 3)$) as in Section 3.4. In terms of *delicious* and *flavorsome*, the correlation coefficients between the observation and estimation are similar between the present model and that in [16]. The correlation coefficient for *like* in the present model decreased to 0.54 from 0.81 in [16]. In contrast, the coefficient for *fresh* increased to 0.49 from 0.09. The mean correlation coefficient of the present model is 0.71, which is slightly greater than 0.66 in [16]. This is understandable because the parameters in the present model were selected to maximize the mean correlation coefficient. Nonetheless, a criterion for parameter selection should be adjusted according to the objective of the model establishment.

6.2 Limitations of the method and study

We constructed models to estimate the changes in affective responses from those in perceptual responses. In reality, affective and perceptual responses may exert a mutual influence, and their effects may not be unilateral. Further, affective responses are known to influence each other [35], [36], [37]. Our method does not incorporate such factors, perhaps limiting the realism of the model. Perceptual and affective responses can influence each other in the model presented in [7]: a model, however, that does not allow the introduction of latent memory variables. Multi-layered modeling methods [37], [38], [39], on the other hand, may mitigate the response-interaction problem more effectively: such models consider multiple layers of affective responses whereas the present model has only a flat output layer.

As may be seen from Tables 3 and 5, time-lag parameters differ among the descriptors. This is interesting and should be studied in future. However, our method uses the same time lag for all descriptors chosen so that the average ability of the model is maximized. In future, model parameter flexibly determined by descriptors should be substituted for the present model's unique time-lag values.

One concern about the present study is that the bootstrap resampling method for TD data has not been validated. Thus far, the same or similar approaches have rarely been employed and its adverse effects such as the biases of dominance rates are unknown. However, samples made by the resampling method do not include impossible values, such as negative dominance rates and sums of rates exceeding 100% at any instances.

There is no established requirement in the food industry or among researchers for the minimum estimation-accuracy of TD curves. Okada et al. [7] estimated the TD curves of strawberries using the same data as the present study and vector auto-regression modeling. Compared to their cross-validation results, our model appears better: the correlation coefficients between the observed and estimated TD curves of the present model are higher than those in [7] by 0.1–0.45 points. However, this difference may simply be due to the higher number of connections among variables and the greater complexity of the present model. The criteria of model selection differ between modeling methods, and a single performance value is an inadequate basis for comparison. In future, methods for performance comparison should be developed.

7 Conclusion

We proposed a state-space modeling method for temporal-dominance responses and tested it on TD data for strawberries and plum pickles. We computed the state variables using canonical correlation analysis, which was possible once we had prepared a large set of samples by bootstrap resampling. We determined the model parameters by cross-validation. The model included memory variables that summarized the directly observed variables reductively. For example, for strawberries, the dynamic changes of nine types of TD curves were connected by three types of factorial memories: memories of deliciousness, coolness, and wateriness. These results suggest that these three memories play prominent roles in the time-dependent subjective experience of eating strawberries. The semantic validity of the model was assessed and found to be acceptable. The model partly predicted the TD curves of affective responses; however, some aspects, including the flexible determination of model parameters, should be explored further to improve the model's utility.

Appendix A
Figures of the state-space model for plum pickles

Fig. 8 shows the state-space model for plum pickles. Each of Fig. 8 (a)–(g) features the influences on an individual affective descriptor.

Acknowledgments

This study was in part supported by MEXT Kakenhi (15H05923).

References

[1] N. Pineau, P. Schlich, S. Cordelle, C. Mathonnière, S. Issanchou, A. Imbert, M. Rogeaux, P. Etiévant, and E. Köster, "Temporal dominance of sensations: Construction of the TDS curves and comparison with time–intensity," *Food Quality and Preference*, vol. 20, no. 6, pp. 450–455, 2009.

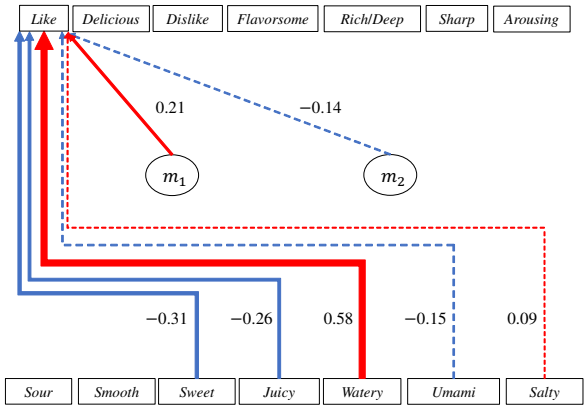
[2] R. Di Monaco, C. Su, P. Masi, and S. Cavella, "Temporal dominance of sensations: A review," *Trends in Food Science & Technology*, vol. 38, no. 2, pp. 104–112, 2014.

[3] P. Schlich, "Temporal dominance of sensations (TDS): a new deal for temporal sensory analysis," *Current Opinion in Food Science*, vol. 15, pp. 38–42, 2017.

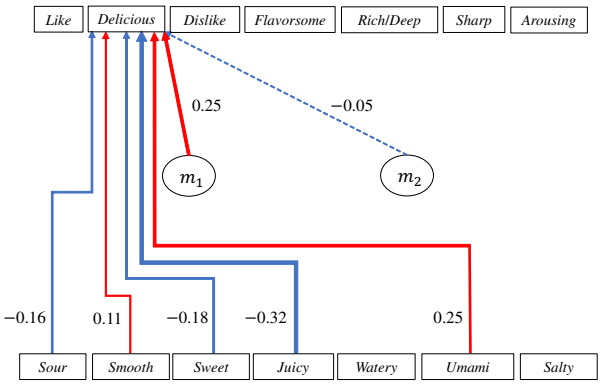
[4] K. Kantono, N. Hamid, D. Shepherd, Y. H. T. Lin, S. Skiredj, and B. T. Carrd, "Emotional and electrophysiological measures correlate to flavour perception in the presence of music," *Physiology & Behavior*, vol. 199, pp. 154–164, 2019.

[5] D. Labbe, P. Schlich, N. Pineau, F. Gilbert, and N. Martin, "Temporal dominance of sensations and sensory profiling: A comparative study," *Food Quality and Preference*, vol. 20, no. 3, pp. 216–221, 2009.

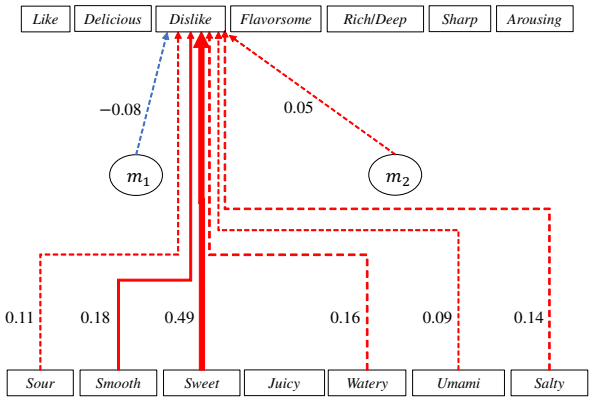
[6] T. Okada, S. Okamoto, Y. Yamada, and T. Ishikawa, "Vector auto-regression model of temporal perceptual and affective responses towards food," in *Proceedings in IEEE Global Conference on Life Sciences and Technologies*, 2019, pp. 43–45.



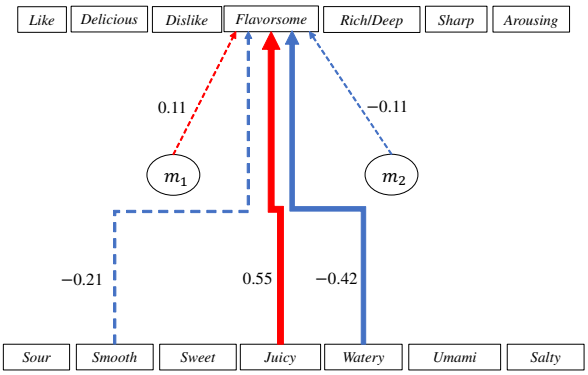
(a) State-space model related to *Like*.



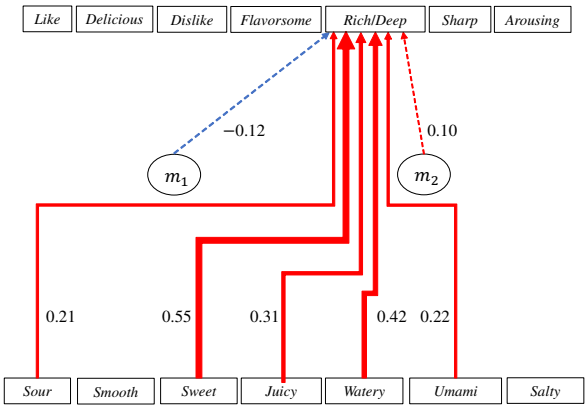
(b) State-space model related to *Delicious*.



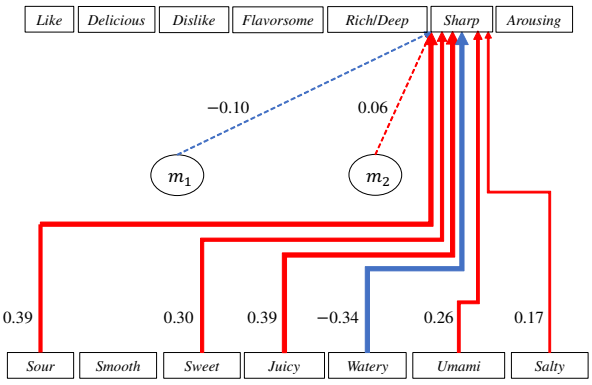
(c) State-space model related to *Dislike*.



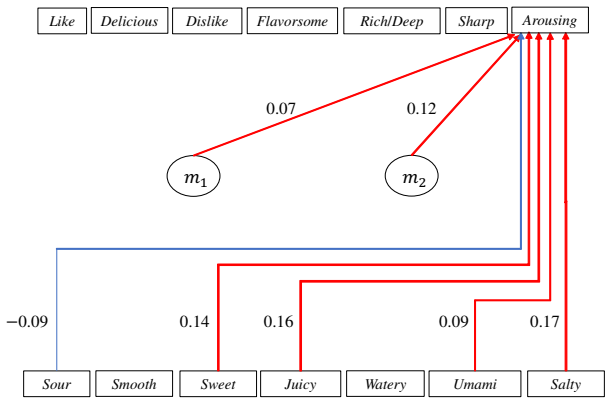
(d) State-space model related to *Flavorsome*.



(e) State-space model related to *Rich/deep*.



(f) State-space model related to *Sharp*.



(g) State-space model related to *Arousing*.

Fig. 8. State-space models for plum pickles related to (a) *like*, (b) *delicious*, (c) *dislike*, (d) *flavorsome*, (e) *rich and deep*, (f) *sharp*, and (f) *arousing*.

[7] T. Okada, S. Okamoto, and Y. Yamada, "Affective dynamics: Causality modeling of temporally evolving perceptual and affective responses," *IEEE Transactions on Affective Computing*, 2019, DOI: 10.1109/TAFFC.2019.2942931.

[8] B. Franczak, R. Browne, P. McNicholas, J. Castura, and C. Findlay, "A Markov model for temporal dominance of sensations (TDS) data," in *Proceedings of 11th Pangborn Sensory Science Symposium*, 2015.

[9] G. Lecuelle, M. Visalli, H. Cardot, and P. Schlich, "Modeling temporal dominance of sensations with semi-Markov chains," *Food Quality and Preference*, vol. 67, pp. 59–66, 2018.

[10] H. Cardot, G. Lecuelle, P. Schlich, and M. Visalli, "Estimating finite mixtures of semi-markov chains: an application to the segmentation of temporal sensory data," *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, vol. 68, no. 5, pp. 1281–1303, 2019.

[11] S. Okamoto, Y. Ehara, T. Okada, and Y. Yamada, "Affective dynamics: Principal motion analysis of temporal dominance of sensations and emotions data," *IEEE Transactions on Affective Computing*, 2020, DOI: 10.1109/TAFFC.2020.2971700.

[12] J. C. Castura, "Investigating temporal sensory data via a graph theoretic approach," *Food Quality and Preference*, vol. 79, p. 103787, 2020.

[13] S. Okamoto, "Structural modeling of temporal dominance responses using covariances of contemporary changes in subjective qualities," *International Journal of Affective Enginering*, vol. 20, no. 3, pp. 126–129, 2021.

[14] M. Visalli, B. Mahieu, A. Thomas, and P. Schlich, "Concurrent vs. retrospective temporal data collection: Attack-evolution-finish as a simplification of temporal dominance of sensations?" *Food Quality and Preference*, vol. 85, p. 103956, 2020.

[15] C. Peltier, M. Visalli, and P. Schlich, "Comparison of canonical variate analysis and principal component analysis on 422 descriptive sensory studies," *Food Quality and Preference*, vol. 40, pp. 326–333, 2015.

[16] K. Tachi, S. Okamoto, Y. Akiyama, and Y. Yamada, "State-space modeling of temporal dominance data: A case study using strawberry," in *Proceedings of the 8th International Conference on Kansei Engineering and Emotion Research*, vol. 1256, 2020, pp. 139–148.

[17] Y. Ehara, S. Okamoto, T. Okada, and Y. Yamada, "Comparison of the method of temporal dominance of sensations and after-tasting sensory evaluation," in *IEEE Global Conference on Life Sciences and Technologies*, 2019, pp. 210–211.

[18] J. C. Castura, L. Antúnez, A. Giménez, and G. Ares, "Temporal check-all-that-apply (tcata): A novel dynamic method for characterizing products," *Food Quality and Preference*, vol. 47, pp. 79–90, 2016.

[19] L. Boinbaser, M. E. Parente, J. C. Castura, and G. Ares, "Dynamic sensory characterization of cosmetic creams during application using temporal check-all-that-apply (TCATA) questions," *Food Quality and Preference*, vol. 45, pp. 33–40, 2015.

[20] C. Peltier, M. Visalli, and A. Thomas, "Using temporal dominance of emotions at home. impact of coffee advertisements on consumers' behavior and methodological perspectives," *Food Quality and Preference*, vol. 71, pp. 311–319, 2019.

[21] T. C. Merlo, I. Soletti, E. S. na, B. S. Menegali, M. M. Martins, A. C. B. Teixeira, S. dos Santos Harada-Padermo, M. D. Dargelio, and C. J. Contreras-Castillo, "Measuring dynamics of emotions evoked by the packaging colour of hamburgers using temporal dominance of emotions (TDE)," *Food Research International*, vol. 124, pp. 147–155, 2019.

[22] W. E. Larimore, "Canonical variate analysis in control and signal processing," in *Statistical methods in control and signal processing*, T. Katayama and S. Sugimoto, Eds. Marcel Dekker, 1997, pp. 83–120.

[23] B. Efron and R. J. Tibshirani, *An introduction to the bootstrap*. CRC press, 1994.

[24] W. E. Larimore, "Canonical variate analysis in identification, filtering, and adaptive control," in *29th IEEE Conference on Decision and control*. IEEE, 1990, pp. 596–604.

[25] A. Furukawa, J. Kiyono, and H. Otsuka, "Structural matrix identification using microtremor measurements based on canonical variate analysis," *Journal of Applied Mechanics*, vol. 8, pp. 85–93, 2005.

[26] P. Oliver, S. Cicerale, E. Pang, and R. Keast, "Developing a strawberry lexicon to describe cultivars at two maturation stages," *Journal of Sensory Studies*, vol. 33, no. 1, p. e12312, 2018.

[27] ——, "Check-all-that-applies as an alternative for descriptive analysis to establish flavors driving liking in strawberries," *Journal of Sensory Studies*, vol. 33, no. 2, p. e12316, 2018.

[28] X. Huang and F.-H. Hsieh, "Physical properties, sensory attributes, and consumer preference of pear fruit leather," *Journal of Food Science*, vol. 70, no. 3, pp. E177–E186, 2005.

[29] A. K. Thybo, B. F. Kühn, and H. Martens, "Explaining Danish children's preferences for apples using instrumental, sensory and demographic/behavioural data," *Food Quality & Preference*, vol. 15, no. 1, pp. 53–63, 2004.

[30] R. Bhat, J. Geppert, E. Funken, and R. Stamminger, "Consumers perceptions and preference for strawberries-a case study from germany," *International Journal of Fruit Science*, vol. 15, no. 4, pp. 405–424, 2015.

[31] G. Ares, A. Giménez, C. Barreiro, and A. Gámbaro, "Use of an open-ended question to identify drivers of liking of milk desserts. comparison with preference mapping techniques," *Food Quality and Preference*, vol. 21, no. 3, pp. 286–294, 2010.

[32] S. Péneau, P. B. Brockhoff, F. Escher, and J. Nuessli, "A comprehensive approach to evaluate the freshness of strawberries and carrots," *Postharvest Biology and Technology*, vol. 45, no. 1, pp. 20–29, 2007.

[33] J. T. V. de Resende, L. K. Camargo, E. J. Argandoña, A. Marchese, and C. K. Camargo, "Sensory analysis and chemical characterization of strawberry fruits," *Horticultura Brasileira*, vol. 26, no. 3, pp. 371–374, 2008.

[34] C. Jouquand, C. Chandler, A. Plotto, and K. Goodner, "A sensory and chemical analysis of fresh strawberries over harvest dates and seasons reveals factors that affect eating quality," *Journal of the American Society for Horticultural Science*, vol. 133, no. 6, pp. 859–867, 2008.

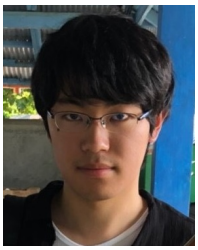
[35] X. Chen, C. J. Barnes, T. H. C. Childs, B. Henson, and F. Shao, "Materials' tactile testing and characterization for consumer products' affective packaging design," *Materials and Design*, vol. 30, pp. 4299–4310, 2009.

[36] S. Okamoto, H. Kojima, A. Yamagishi, K. Kato, and A. Tamada, "Layered-modeling of affective and sensory experiences using structural equation modeling: Touch experiences of plastic surfaces as an example," *IEEE Transactions on Affective Computing*, vol. 12, no. 2, pp. 429–438, 2021.

[37] S. Okamoto, H. Nagano, K. Kidoma, and Y. Yamada, "Specification of individuality in causal relationships among texture-related attributes, emotions, and preferences," *International Journal of Affective Engineering*, vol. 15, no. 1, pp. 11–19, 2016.

[38] I. H. M. Hashim, S. Kumamoto, K. Takemura, T. Maeno, S. Okuda, and Y. Mori, "Tactile evaluation feedback system for multi-layered structure inspired by human tactile perception mechanism," *Sensors*, vol. 17, p. 2601, 2017.

[39] K. Kidoma, S. Okamoto, H. Nagano, and Y. Yamada, "Graphical modeling method of texture-related affective and perceptual responses," *International Journal of Affective Engineering*, vol. 16, no. 1, pp. 27–36, 2017.



Kyoichi Tachi is a mechanical engineer who received a BS in engineering from Nagoya University in 2020. His research interests include affective engineering and biomechanics.

Shogo Okamoto received his PhD in Information Sciences from Tohoku University in 2010. He had been with Nagoya University since 2010; currently, he is an associate professor at Department of Computer Sciences, Tokyo Metropolitan University. His research interests include haptics, assistive robotics, and affective engineering.