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NOTE

Structural Modeling of Temporal Dominance Responses Using Covariances of Contemporary Changes in Subjective Qualities

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Abstract: The establishment of methods for recording and analyzing the dynamic changes in the human affective responses is important for understanding and utilizing affective dynamics. This study analyzes the structure of sensory and affective responses recorded through the temporal dominance (TD) method, which is an effective dynamic sensory appraisal approach. Temporal evolution is modeled by state-space local-level equations, and the structure of the responses is estimated based on the covariance matrix of the disturbances of the state variables. This approach is applied to the TD responses for strawberries recorded in a previous study, and its validity is examined.

Keywords: *State-space modeling, Partial correlation coefficient, Affective dynamics*

1. INTRODUCTION

The temporal dominance (TD) method [1] has attracted attention as a sensory appraisal method for measuring the temporal changes in multiple types of perceptual and affective qualities using food stimuli. However, few studies have developed a corresponding mathematical model to understand the dynamic relationships among the qualities. Understanding the dynamics provides product developers with new scientific insights. Previously, Markov chain models were developed to represent the random transition of subjectively dominant feelings [2]. Okada et al. developed a method for modeling the causality among the subjective qualities reported in the TD method [3]. Furthermore, Okamoto et al. extracted the principal motions in the time series of TD responses to determine their dimensionality [4]. However, despite these recent studies, in most studies that used TD methods, the TD responses were analyzed based on their static characteristics. Therefore, general methods for understanding the dynamics of affective responses are required.

The aim of this study is to establish the relationship between the subjective qualities in the TD responses based on the covariances among the contemporary changes in the qualities. To the best of the author's knowledge, this approach has yet to be attempted for TD responses. This approach may result in a conclusion similar to that of a study by the author and his colleagues [3] because the present study and [3] seek the relationships among the sensory and affective qualities. Nonetheless, in [3], the time series of TD responses were modeled by autoregressive methods, which use time-lagged data. In contrast, the present method utilizes the contemporary changes in subjective qualities. Therefore, it is insightful to compare the results between the present study and [3] to understand the characteristics of these methods. To perform this comparison, in this study, the experimental data obtained in [3] are analyzed.

2. TEMPORAL DOMINANCE METHOD

The TD method is a popular approach in the field of food sciences [1]. It allows the collection of the temporal changes for multiple types of subjective qualities, whereas previous trace or time-intensity methods were limited to one or two types of qualities.

In this section, the method used in this study is outlined. The TD method utilizes a graphical user interface, as shown in Fig. 1(a), with several buttons with descriptors. An assessor presses the start button immediately after putting a piece of food into his/her mouth. The assessor then sequentially presses the buttons corresponding to the descriptors that best suit his/her dominant feelings. This operation continues until the food is swallowed and the stop button is pressed by the assessor. The same buttons can be pressed multiple times, and some buttons can remain unselected. Once a button is pressed, the selection remains in effect until another button is pressed. One assessor may test the same food several times.

As a result of the abovementioned task, for each button, a binary (i.e., selected or non-selected) time series is recorded, as shown in Fig. 1(b). Each time series is normalized by the period between the start and stop. For each descriptor, among all the participants and trials, the binary series are aggregated and the proportion at which the corresponding button is selected is computed at each time instance. This value is called the *dominance rate* (*proportion*) and ranges between 0 and 1. The

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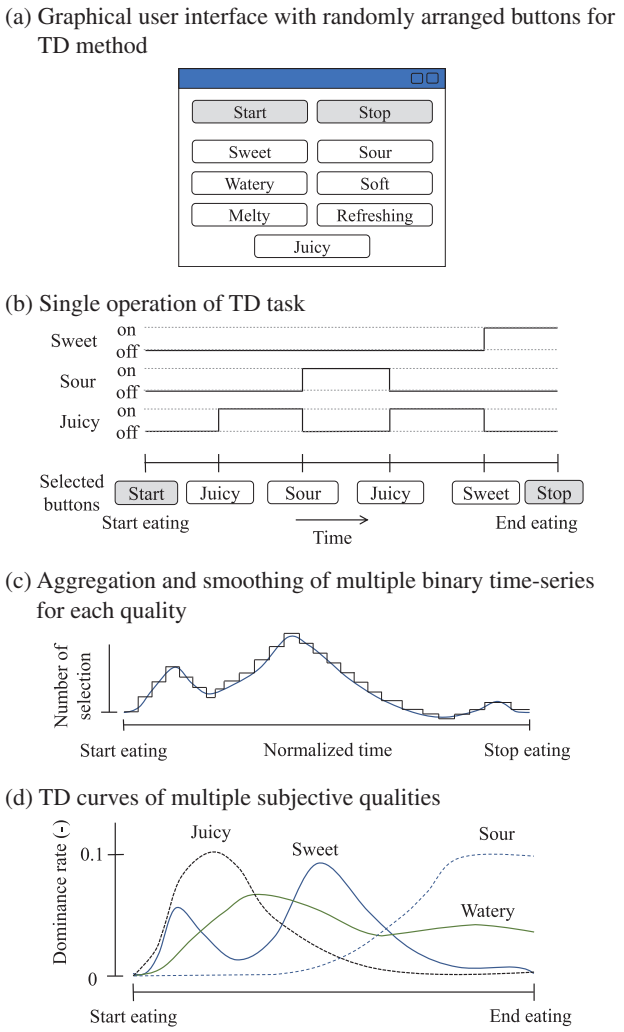

Figure 1: General process of temporal dominance method

(a) Graphical user interface used in a task.
(b) Binary time series of selected buttons in a single task.
(c) Aggregation of binary time series and smoothing of curves among all assessors.
(d) Temporal dominance curves of multiple subjective qualities. Adapted, in part, from [4].

dominance rates are transformed into smooth curves by using a low-pass filter, as shown in Fig. 1(c). Hence, by integrating all the assessors' responses, one set of mean TD curves is acquired, as shown in Fig. 1(d).

3. STRUCTURAL MODELING OF TEMPORAL DOMINANCE RESPONSES

3.1 State-space local-level models and covariance matrix of state disturbances

The multivariate time series of TD responses are modeled by state and observation equations. They enable us to discuss the temporal evolutions of variables while removing the effects of random errors in the observed values. An observed value y_{it} at time t, which is the instantaneous dominance rate of the TD curve for descriptor i, is modeled to be the sum of its state u_{it} and random error ε_{it}. The state is expressed as a first-order autoregressive model. For all p variables $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{pt})^T$, the observation and state equations are defined as follows:

$$\boldsymbol{y}_t = \boldsymbol{u}_t + \boldsymbol{\varepsilon}_t, \tag{1}$$

$$\boldsymbol{u}_{t+1} = \boldsymbol{u}_t + \boldsymbol{\eta}_t. \tag{2}$$

In the above equations, $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\eta}_t$, which are called disturbances, are random variables subjective to the normal distributions of zero means and are defined as follows:

$$\boldsymbol{\varepsilon}_t \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{H}), \tag{3}$$

$$\boldsymbol{H} = [h_{ij}], \quad (i, j = 1, \ldots, p), \tag{4}$$

$$\boldsymbol{\eta}_t \sim \mathrm{N}(\boldsymbol{0}, \boldsymbol{Q}), \tag{5}$$

$$\boldsymbol{Q} = [q_{ij}], \quad (i, j = 1, \ldots, p). \tag{6}$$

In (3)–(6), $\boldsymbol{H}$ and $\boldsymbol{Q}$ are the covariance matrices of the disturbances for the observed and state variables, respectively. These covariances are unknown parameters that are estimated using the maximum likelihood estimation method. Although p types of state variables seem independent of each other in (2), their disturbances can be correlated.

The non-diagonal element q_{ij} in $\boldsymbol{Q}$ is the covariance between the disturbances, i.e., the contemporary changes for the two state variables i and j over the entire period of the task. If q_{ij} is not zero, a relationship between the two variables is suggested; hence, the structure among the state variables can be discussed on the basis of $\boldsymbol{Q}$.

3.2 Significance of partial correlation coefficients among the disturbances of state variables

A covariance matrix can be transformed into a partial correlation matrix that directly suggests the relationship between variables. In general, in order to judge the significance of partial correlation coefficients, t-tests are used. However, in the t-tests, the number of samples n is assumed to be the number of, e.g., participants or objects. For the case of state-space models, n is determined as the number of quantization levels of normalized time. Hence, the validity of the t-test for state-space modeling is uncertain.

In this study, the significance of partial correlation coefficients is judged based on the confidence intervals estimated by bootstrap samples. Bootstrap resampling for TD responses was introduced in [4], where observations were randomly sampled with replacement m times. Based on these m samples, a set of TD curves is computed. A partial correlation matrix of the disturbances of state variables is then computed from the set of curves. This process of resampling and computation of matrices is repeated 1000 times, and the distribution of partial correlation

coefficients is estimated. The significance of the coefficients is then judged on the basis of their confidence intervals.

4. EXAMPLE OF STRAWBERRIES

As previously mentioned, in this study, the TD responses to strawberries recorded in [3] are analyzed. In the analysis, five types of sensory responses (*juicy*, *watery*, *sweet*, *sour*, and *refreshing*) and four types of affective responses (*fresh*, *delicious*, *flavorsome*, and *like*) are used. Figure 2 shows the TD curves computed by eight participants (m = 8) in [3]. For the computation of these curves, a low-pass filter with a cutoff frequency of 1 Hz was applied, as stated in Section 2.

The mean period between the start and stop buttons was approximately 30 s. In terms of the sensory responses in Fig. 2(a), in the first half phase, *sweet* and *juicy* responses were salient. In the second half phase, *sour* became gradually strong. In terms of the affective and hedonic responses shown in Fig. 2(b), *delicious* and *flavorsome* responses were salient in the early phase, whereas *like* and *fresh* responses were salient in the last phase.

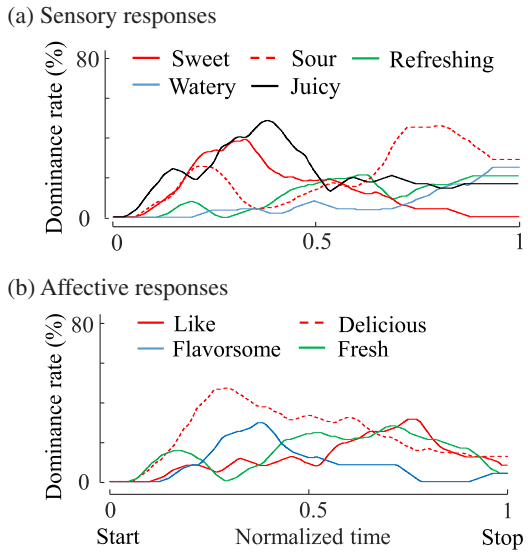

Figure 2: Temporal dominance responses to strawberries

(a) Sensory responses.
(b) Affective and hedonic responses. Adapted from [3].

The continuous TD curves were discretized into 30 temporal points, as in [3]. The discrete TD curves were then modeled using state-space equations, as described in Section 3.1. For the computation of these equations, the KFAS package (ver. 1.3.7, J. Helske) for the R programming language was used.

Table 1 lists the means and standard deviations of the partial correlation coefficients among the disturbances for the states. The significance of each coefficient is judged on the basis of its confidence interval. Figure 3(a) shows the suggested link between the sensory and affective responses obtained from the results reported in Table 1. The solid and dotted edges indicate the partial correlation coefficients at the significance levels of 5% and 10%, respectively. Values aside the edges are the mean partial correlation coefficients listed in Table 1. Figure 3(b) is the causal model built in [3] using the same TD responses.

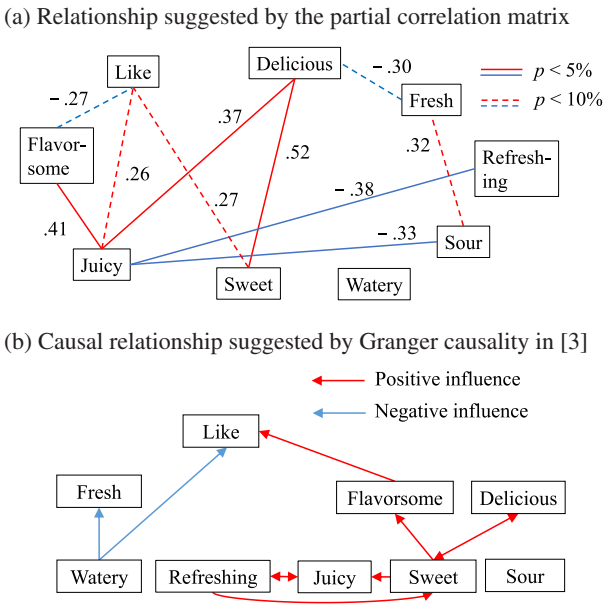

Figure 3: Suggested structure among sensory and affective responses

(a) Relationships suggested by the partial correlations in the present study.
(b) Granger-causality model investigated in [3]. Adapted from [3]. Red and blue arrows indicate positive and negative influences, respectively.

Table 1: Partial correlation coefficients among the disturbances of states corresponding to sensory and affective responses

	Juicy	*Watery*	*Refreshing*	*Sour*	*Sweet*	*Like*	*Delicious*	*Fresh*	*Flavorsome*
Juicy	-	-.02 ± .21	-.38 ± .19*	-.33 ± .25*	-.29 ± .32	.26 ± .23+	.37 ± .23*	.29 ± .28	.41 ± .20*
Watery		-	.01 ± .22	-.04 ± .19	-.06 ± .23	-.07 ± .25	.09 ± .23	-.07 ± .20	-.18 ± .23
Refreshing			-	-.28 ± .27	-.17 ± .25	.25 ± .22	.25 ± .23	.19 ± .25	.03 ± .24
Sour				-	-.15 ± .28	.24 ± .22	.30 ± .24	.32 ± .24+	.03 ± .21
Sweet					-	.27 ± .24+	.52 ± .22*	.22 ± .27	.20 ± .26
Like						-	-.23 ± .27	-.13 ± .26	-.27 ± .21+
Delicious							-	-.30 ± .27+	.03 ± .23
Fresh								-	-.25 ± .28

Means and standard deviations among 1000 samples. * and + indicate the statistical significance at $p<0.05$ and 0.10, respectively.

5. DISCUSSION

The semantic validity of the structure shown in Fig. 3(a) is discussed and compared with the causal model in Fig. 3(b). A strong relationship between *sweet* and *delicious* is seen in both models. Furthermore, with the partial correlation matrix, the relationships *juicy-flavorsome* and *juicy-delicious* are obtained. The state "juicy" is obtained when there is abundant strawberry juice, and the state "flavorsome" is obtained when there is some type of aroma. These suggested relationships are semantically reasonable and are indirectly obtained in Fig. 3(b).

With the partial correlation matrix, an inverse relationship is obtained between *juicy* and *refreshing*, while a positive relationship is obtained with the causal model. *Refreshing* denotes the sense of coolness, and it is difficult to speculate its relationship with *juicy*.

Unlike Fig. 3(b), Fig. 3(a) suggests a negative relationship between *juicy* and *sour*. This relationship may reflect the decrease in *juicy* and the increase in *sour* in the middle of the eating phase, as shown in Fig. 2(a).

Regarding the dotted edges in Fig. 3(b), *like* is positively correlated with *sweet* and *juicy*, which is semantically reasonable for the taste of strawberries. In contrast, the *like-flavorsome* relationships obtained with the partial correlation matrix and the causal model are different. As shown in Fig. 2, in the middle eating phase, the rate of *flavorsome* instances decreases, while that of *like* instances increases. Hence, they may exhibit a negative correlation coefficient. However, psychophysically, the *like* and *flavorsome* responses exhibit a positive relation [5], as shown in Fig. 3(b).

Regarding *watery* and *sour* sensations, the two models produce very different results. In Fig. 3(a), *watery* is not connected with any other responses, whereas in Fig. 3(b), *sour* does not influence the other responses. For these two types of qualities, both models may be incomplete because the *sour* and *watery* qualities seem to be important factors for the taste of strawberries, and both qualities may be linked with the others.

The above results indicate that the two models derived from the same TD responses to strawberries partly agree with each other. Differences between the two models may be attributed to the differences in their mathematical framework. If one of the models is semantically more realistic than the other, then it is possible to conclude which type of model is more suitable for representing the TD data. However, such a conclusion cannot be made solely by considering the example of strawberries.

The method presented in this study uses the bootstrap samples; however, its negative effects on the TD data have not been investigated. Further, the TD data used in this study were obtained from a relatively small number of participants; hence, the generality of the established model of strawberries is low.

6. CONCLUSION

The structure of several types of subjective qualities in TD curves was investigated. For this purpose, the curves were modeled by state-space equations, and the covariance matrix of the contemporary changes in the states was computed. The suggested structure partly agrees with the model used in a previous study. To establish the validity of the model, the present method will be applied to TD responses for several types of foods in a future study.

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