

Affective Dynamics: Causality Modeling of Temporally Evolving Perceptual and Affective Responses

Takumu Okada, Shogo Okamoto, *Member, IEEE*, and Yoji Yamada, *Member, IEEE*

Abstract—Human perceptual and affective responses change dynamically when stimuli are experienced. In this study, we developed a method for modeling the causal structures of affective dynamics using time-series data. Using the temporal dominance of sensations method, perceptual and affective data were collected from individuals eating strawberries, and the resulting time-series data were mathematically represented using a vector auto-regression model. Multihierarchical and multidimensional causality structures that explain the temporal evolution of perceptual and affective responses were then established based on Granger causality and the information criterion. The established model suggests how affective and preferential responses are triggered following exposure to stimuli. We also assessed the quantitative and semantic validity of the model.

Index Terms—Causality modeling, temporal dominance of sensations, VAR model, Granger causality.

1 INTRODUCTION

Human affective response, or emotional response to a situation or stimulus, has gained increasing attention as a tool for adding value to industrial products or services. To translate abstract consumers' affective responses into physical quantities that can be accessed and controlled by designers, the relationships between consumers' perceptual and affective responses toward products should be clarified. To date, a number of methods for constructing causal models to visually express the causalities between human perceptual and affective responses have been proposed [1], [2], [3], [4], [5], [6], [7]. Under the perceptual and affective causal model, adjectives¹ used in sensory evaluation as evaluation criteria are given as causalities from the lowest to the uppermost layers, as shown in Fig. 1. In this model, sensory adjectives representing the physical characteristics of stimuli are located at the bottom layer, while adjectives expressing affective responses toward stimuli and preferential words representing individual preference or evaluative words are located at the middle layer and top layers, respectively. Using this structure, the causalities among the adjectives can be investigated based on the evaluation values assigned to different adjectives in various sensory evaluation experiments such as semantic differential methods and sensory profiling. So far, for computing the structures, correlation coefficient-based methods using computed evaluation values [1], covariance selection [3], and structural equation modeling [4] have been suggested. In a different approach, panelists have been asked to directly identify the semantic

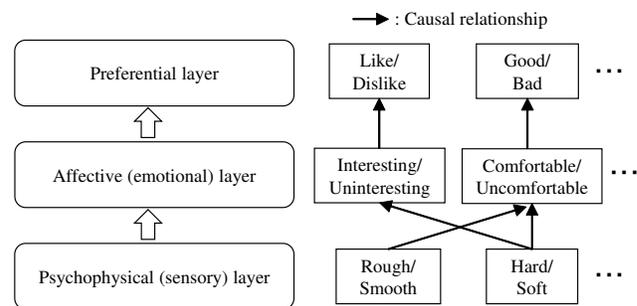


Fig. 1. Example of causal adjective structure established from sensory evaluation. Adapted from [2].

causalities among adjectives [2], [5]. Under either approach, panelists are subjected to stimuli and asked to provide scores for individual or paired adjectives. However, panelists are generally not given specific instruction on how quickly to respond or whether to do so during or after experiencing the stimuli. As a result, such experiments do not consider the time spent on the response and, therefore, the resulting causal models do not consider the dynamic aspects of perceptual/affective responses.

Human affective experiences change temporally from the moment that stimuli are perceived via the senses. For example, the perceived sensory information regarding the taste and flavor characteristics of food are perceived synthetically to create evaluations such as “satisfaction” or “like.” Such series of perceptual and affective responses represent dynamic events expressed along the temporal axis. Researchers have already made attempts to record the pattern of temporal change of sensation or affect. The time intensity or the trace method, for example, has been used to record the temporal change of intensity of single or two types of sensations/affects [8], [9], [10], [11]. These methods

• T. Okada, S. Okamoto and Y. Yamada are with the Department of Mechanical Systems Engineering, Nagoya University. This research was approved by the internal review board of the School of Engineering, Nagoya University (#15-12).

Manuscript received April xx, 2019; revised August xx, 2019.

1. The descriptive norms are not limited to adjectives, but adjectives are mostly used.

involve the use of a slider or joystick to continuously express the magnitude of subjective experiences. The temporal dominance of sensations (TDS) method has been applied to the measurement of simultaneous change in multiple sensations/affects over a number of trials and subjects [12], [13], [14]. The details of the TDS method are described in Sec. 2.1. Whereas the methods described above apply sensory evaluation, physiological quanta can also be used to predict the temporal change of responses. For instance, electroencephalographic data from the scalp [15], [16] and facial expression readings [17] are both considered to reflect temporally varying human subjective experiences. Research involving such physiological quanta has centered on the consistency between such quanta and subjective experience. However, regardless of whether a subjective or physiological quanta approach is adopted, time series of perceptual/affective response are typically discussed qualitatively or analyzed by focusing on changes in a single sensation, while the temporal causalities between perception and affect are neglected.

In this study, a method of causality modeling using perceptual and affective information that dynamically changes from the moment that a stimulus is experienced was developed. The approach is implemented by first recording temporal changes in perceptual and affective responses as modeling targets through the use of TDS methods. By mathematically representing the resulting multivariate time series in the form of a vector auto-regression model, the causalities among the time series can be investigated in terms of their Granger causalities. The Granger causality, explained in Sec. 2.3, is recognized when one variable plays a significant role in predicting another. Finally, the resulting Granger causality model is contracted through the application of an information criterion. The causal models established through this approach express how affects or preferences temporally vary and can aid in the affective design of products and the prediction of consumer affective response.

In this study, food was used as the source of stimulus and perceptual and affective responses were measured from the moment of consumption of the food. In the present context, "perception" encompasses multimodal sensations including taste, flavor (smell), and texture (touch). The primary reason for using food as stimuli was that the protocol of the TDS method was developed in the field of food products and has been applied in a large number of foods. Nonetheless, the methods were also adapted to visual and auditory stimuli [18], [19]. However, they may require further research in order to establish general protocols. Finally, the experimental data of the present study was also used in [20] to investigate the availability of vector auto-regressive (VAR) model; however, the causal modeling was not discussed there.

2 METHODS FOR CAUSALITY MODELING

2.1 Measurement of Perceptual/Affective Responses: Temporal Dominance of Sensations Method

Of the many approaches that have been developed by researchers to capture temporal change in the sensations and affects, we selected the TDS method developed by [12],

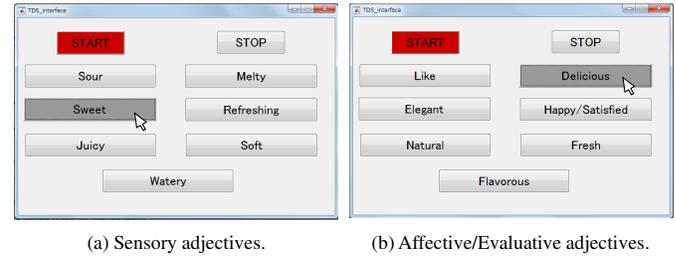


Fig. 2. Graphical user interfaces used in TDS experiments for recording (a) sensory and (b) affective/evaluative adjectives.

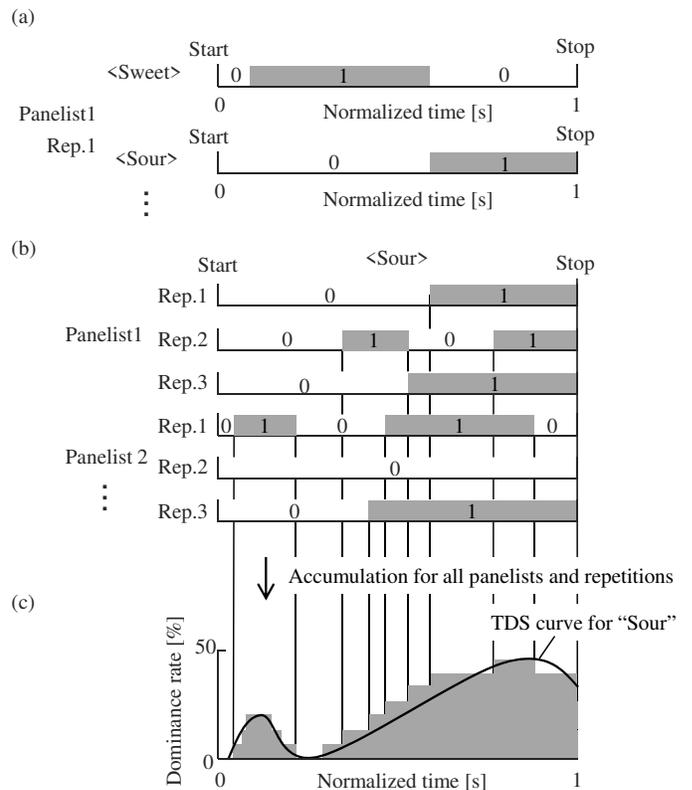


Fig. 3. Generation of TDS curve. (a) Binary data obtained from a single trial. (b) Binary data corresponding to repetition of selection of "sour" by panelists. (c) TDS curve for "sour" generated by smoothing the dominance rate obtained from the binary data in (b).

which can efficiently measure multiple subjective attributes from the moment that food is consumed.

The TDS method can be implemented using graphical user interfaces such as those shown in Fig. 2. A panelist pushes the start button as soon as they have placed the food in their mouth and then pushes the button corresponding to their dominant sensation at that moment. Each time the dominant sensation changes, they push the corresponding button, repeating the process until the food has been completely ingested, at which point they push the stop button. They are allowed to push the same button as many times as they desire.

The TDS method is used to produce a time series for each sensation/emotion called the TDS curve, which shows the dominance of the sensation relative to others. Fig. 3 illustrates the generation of the TDS curve. Fig. 3(a) shows binary data obtained from a single trial representing the

time interval during which each sensation/emotion is selected. The horizontal axis represents the normalized time span from the ingestion (start) to the swallowing of the food (stop). From the data accumulated from all panelists over several trial repetitions, the number of selections of each sensation/emotion at each time is counted (Fig. 3(b)). The dominance rate is then computed by dividing the number of selections for each button by the total number of trials (no. of panelists \times no. of repetitions) (Fig. 3(c)). For instance, the dominance rate during a time interval in which all of the panelists select the same button will be 100%. Finally, a continuous TDS curve is obtained by smoothing the dominance rate results.

2.2 Mathematical Modeling of Multiple Time Series: Vector Auto-regression Model

The data obtained using the TDS method (TDS curve) are multivariate time series representing the relative intensity of perception and affective responses for each evaluative word. These time evolutions can be mathematically expressed using a vector auto-regression (VAR) model. Once the time series are expressed in the form of a VAR model, the causalities among the variables can be statistically investigated by applying the concept of Granger causality, explained in the following section, and which is the main reason for the VAR model being used by the proposed method. The VAR model for n variables with a model order q is expressed as follows:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}^{(1)}\mathbf{y}_{t-\Delta t} + \mathbf{A}^{(2)}\mathbf{y}_{t-2\Delta t} \cdots + \mathbf{A}^{(q)}\mathbf{y}_{t-q\Delta t}. \quad (1)$$

where \mathbf{y}_t is a vector of n variables, $\mathbf{A}^{(j)}$ is the coefficient matrix for the past j lags ($\mathbf{A} \in \mathbb{R}^{n \times n}$), \mathbf{c} is a constant vector, and n is the number of types of recorded sensations and affective responses. At each time t , one of the n variables is expressed as a linear function of the past q time-lagged values of all variables, including itself. Each parameter of the VAR model ($\mathbf{A}^{(j)}$, \mathbf{c}) is estimated using the least-squares method. The model order q is selected based on how the information criterion is to be managed; we adopted the order at which the information criterion becomes minimum over the range $q = 1-10$. As the information criterion, we used the Akaike information criterion (AIC) [21], which is explained in Appendix A. The AIC will be also used in the latter process, as described in Sec. 2.4.3. Because the VAR model uses discrete data, we discretized the continuous TDS curves with a sampling period of Δt .

2.3 Causality between Time Series: Granger Causality

To represent the statistically judged causality between time series produced by the VAR model, the proposed method applies the Granger causality approach [22]. To judge the causality from variables y_2 to y_1 , two VAR models are applied to estimate y_1 —one that includes y_2 and one that does not. If, based on a comparison of errors, the estimation accuracy of y_1 is significantly increased through the inclusion of y_2 , a Granger causality from y_2 to y_1 is accepted. In this study, conditional Granger causality [23], which represents an expansion of the original Granger causality approach from two to multivariate causality, was applied.

Here, we explain how to test for conditional Granger causality from y to x in the presence of three variables

(x, y, z). The VAR (q) model for estimating the value of x at time t using z is expressed as follows:

$$\hat{x}_t = c_1 + \sum_{j=1}^q a_1^{(j)} x_{t-j\Delta t} + \sum_{j=1}^q a_2^{(j)} z_{t-j\Delta t} \quad (2)$$

Similarly, the VAR (q) model for estimating the value of x using y and z is expressed as

$$\hat{x}_t = c_2 + \sum_{j=1}^q b_1^{(j)} x_{t-j\Delta t} + \sum_{j=1}^q b_2^{(j)} y_{t-j\Delta t} + \sum_{j=1}^q b_3^{(j)} z_{t-j\Delta t}. \quad (3)$$

The squared sums of estimation errors obtained by (2) and (3) are R_0 and R_1 , respectively. Then,

$$F_{y \rightarrow x} = \frac{(R_0 - R_1)}{R_1 / (T - nq - 1)} \quad (4)$$

asymptotically follows a $\chi^2(n)$ distribution in which T is the sample number and n is the number of variables. When y directly affects x , $R_0 > R_1$ holds and $F_{y \rightarrow x} > 0$. In our study, the presence of Granger causality from y to x could be admitted when the p value of $F_{y \rightarrow x}$ was equal to or less than 0.10. In the presence of more than three variables, causalities are judged in the same manner.

In the remainder of this paper, this conditional Granger causality will simply be referred to as Granger causality. The MVGC Matlab Toolbox [24] was used to conduct the Granger causality testing. Stationarity of data was assumed in the causality testing process.

2.4 Causality Modeling

In this section, we explain the method used to establish causal models through application of Granger causality and the information criterion. We apply Granger causalities between sensory and affective adjectives in constructing a two-layered model. Following this, we analyze the causalities among the affective adjectives. Finally, the AIC is applied to the Granger causalities detected at each stage to determine whether they will be retained in the final model. As an example of this model construction, in Sec. 4, we establish a model using the sensations and affects generated by eating strawberries.

2.4.1 Initial Two-layered Structure of Granger Causality

Many earlier studies employed two-layered models with sensory and affective descriptors being at the lower and upper layers, respectively [6], [7], [25], [26]. In some cases, preferential adjectives will be placed in layers higher than those in which other adjectives are placed [1], [2], [3], [27], [28]. Whereas the causal structure of the upper layer is largely affected by individual differences [27], sensory and affective adjectives can be semantically clearly segregated [26]. Based on these facts, the model can be expanded from a two-layer perception and emotion structure [4]. We initiate the process by locating the sensory and affective adjectives in the lower and upper layers, respectively, as shown in Fig. 4(a), and then using this structure as a basis.

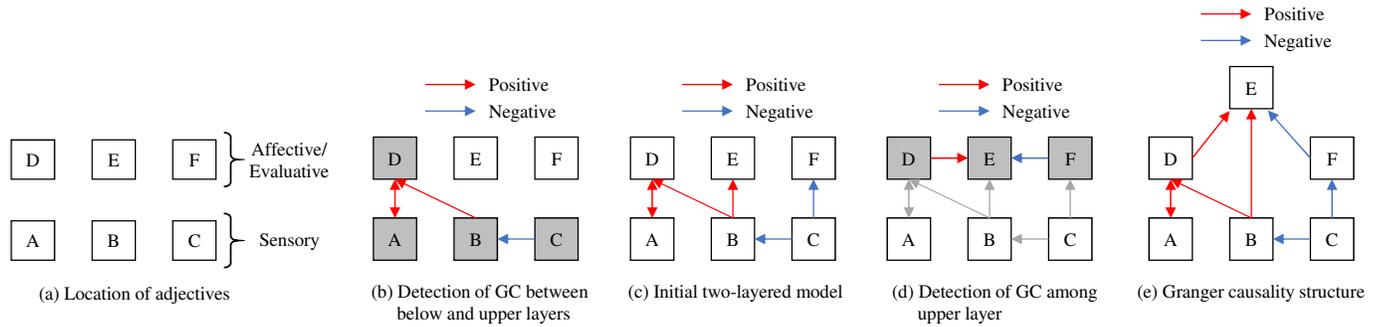


Fig. 4. General flow for constructing the structure of Granger causality (GC); the model is developed from (a) to (e). (a) Sensory adjectives and affective adjectives placed into the bottom and upper layers, respectively. (b) and (c) Initial two-layered model is constructed by investigating Granger causalities between lower and upper layers. (d) Granger causalities among the adjectives in the upper layers. (e) Multi-layered structure is built for visual clarity. Highlighted nodes in (b) and (d) are the target nodes investigated for Granger causality at each step.

As shown in Fig. 4(b), the Granger causalities among all of the variables in the bottom layer (A, B, C) and one variable in the upper layer (D) are exhaustively investigated. In this example, a positive causality from B to C , a bidirectionally positive causality from A to D , and a negative causality from C to B are detected². The positivities and negativities of the respective causalities are determined from the signs of the partial regression coefficients in the VAR model. The arrows of causality in the figure show time directionality; i.e., they represent how a causal variable affects a resultant variable Δt periods later. Performing this operation repeatedly on each of the variables in the upper layer produces a two-layered model containing all the causalities between perception and affect, as shown in Fig. 4(c). In this study, we applied a 10% level of significance in the Granger causality test results as the criterion for the adoption of a causality into the model. The model becomes simpler as this criterion is made more severe, as doing so reduces the number of detected causalities. In the example of following sections, the adoption of 5% or 1% significance levels led to overly simplified models; hence, we adopted 10%. Even if a high significance level is used, redundant causalities are excluded through the procedure described in Sec. 2.4.3. Therefore, in this step of the initial two-layer modeling, it is better to include as many potential causalities as possible. If the model is overly simplified at this stage, the subsequent processes will not revitalize the missing causalities.

Another factor that reduces the number of causalities detected under conditional Granger treatment is increasing the number of variables that are considered simultaneously. This is because increasing the number of explanatory variables in the VAR model reduces the contribution of each variable to the objective variable, making the detection of statistically significant contributors more difficult. Therefore, the proposed method exhaustively investigates the causalities among a subset of the variables to establish a model based on their superimposition, as described above. By restricting the number of variables considered simultaneously in this manner, the model is prevented from becoming too simple (See Appendix B).

2. Because unidirectional causalities between all considered variables are investigated, causality from upper to lower variables ($D \rightarrow A$) or among lower variables ($C \rightarrow B$) can be detected.

2.4.2 Granger Causality in Upper Layers

The two-layered model includes causalities both among sensory variables and between sensory and affective variables. In this subsection, Granger causalities among the variables in the upper layer, which are not considered in the two-layered model, are exhaustively investigated. In the example shown in Fig. 4(d), causalities from D and F to E are detected as a result of the causality investigation. Variables such as E , which are affected by other variables in both the lower and upper layers, are expected to represent more abstract concepts. Thus, by allocating E even at the upper layer, the causal model in Fig. 4(e), which fully considers the bidirectional causalities between all variables, is obtained.

2.4.3 Finalization by Akaike Information Criterion

The causal model obtained thus far was established by superimposing the Granger causalities among subsets of all variables. In the process, the estimation accuracy of the overall model was not considered, and it is possible that some redundant causalities with minimal contributions to the accuracy of the overall model have been included. It is also possible that some indirect causalities have been included in the model. To address these issues, the model is modified based on an information criterion, the AIC. The AIC is an index reflecting both the estimation accuracy and the complexity of the model. We sequentially applied the AIC to exclude redundant causalities to produce a simplified model. For example, if the removal of a causality decreases the AIC, then the corresponding arc is excluded from the model. This operation is repeated until the AIC ceases to diminish upon further causality exclusion, at which point the finalized contracted model is obtained. Note that there is no guarantee that the final causal model produced by this method is the optimal solution.

3 TDS EXPERIMENT USING STRAWBERRY

To test the structure defined in the preceding section, we conducted a TDS experiment using strawberries as a food example. In the following subsections, we describe how a causal model was established based on time series of perceptual and affective responses obtained by eating strawberries.

TABLE 1
Sensory and affective/evaluative adjectives used in strawberry experiment. Japanese words presented to the panelists are shown in *italics*.

Sensory		Affective/Evaluative	
Sweet	<i>amai</i>	Like	<i>suki</i>
Watery	<i>mizuppoi</i>	Flavorous	<i>hozyunna</i>
Refreshing	<i>sawayaka/sappari</i>	Fresh	<i>sinsenna</i>
Juicy	<i>jusina</i>	Happy/Satisfied	<i>kohukuna/manzokuna</i>
Sour	<i>suppai</i>	Delicious	<i>oishii</i>
Soft	<i>yawarakai</i>	Natural	<i>sizenna</i>
Melty	<i>torokeruyona/namerakana</i>	Elegant	<i>johinna</i>

3.1 Selection of Adjectives

Some researchers have pointed out that displaying too many words on the interface overloads the panelists of TDS methods. As a suggested limit, the number of words should not exceed ten [29]. We selected the adjectives to be used through a preliminary survey in which a check-typed questionnaire generated by the authors was administered.

The questionnaire presented a total of 137 adjectives expressing characteristics of strawberries that are perceived via taste/smell/texture and characteristics representing the affective/evaluative aspects of strawberry consumption. The sensory adjectives included words expressing basic taste factors such as “sweet” and “sour” and words pertaining to flavor and texture such as “fruity” or “refreshing” to represent a cooling sensation in the mouth. For affective/evaluative adjectives, we added some words to the list of adjectives identified by King et al. [30].

Seven panelists participated the preliminary experiment by checking all adjectives that applied to their perceived sensations or affects while eating strawberries. Based on the total number of selections, we identified seven sensory and affective/evaluative adjectives apiece. Table 1 lists the fourteen selected adjectives by type. We avoided the use of compositive words and attempted to use words that represented multiple synonyms. We also attempted to select multidimensional sensations without redundancy and omission. Prior to the actual experiment, we presented definitions of each word to the panelists to standardize their interpretations.

3.2 Panelists

The panelists were ten Japanese university students (eight male and two female, age: 22–24), all of whom provided written informed consent before the experiment. They were not studying affective sciences or engineering. None of the panelists routinely smoked, and consumed taste-altering substances such as coffee one hour before experiment.

3.3 Tasks

The TDS experiments were conducted using a touch panel. Before the experiments began, the panelists were allowed to operate the interface to get used to the task of pushing buttons and the use of the touch panel.

One strawberry was used per one trial. After drinking water to rinse their mouth at the beginning of each trial, each panelist took the strawberry behind a partition, pinched their nose and, with the other hand, placed the

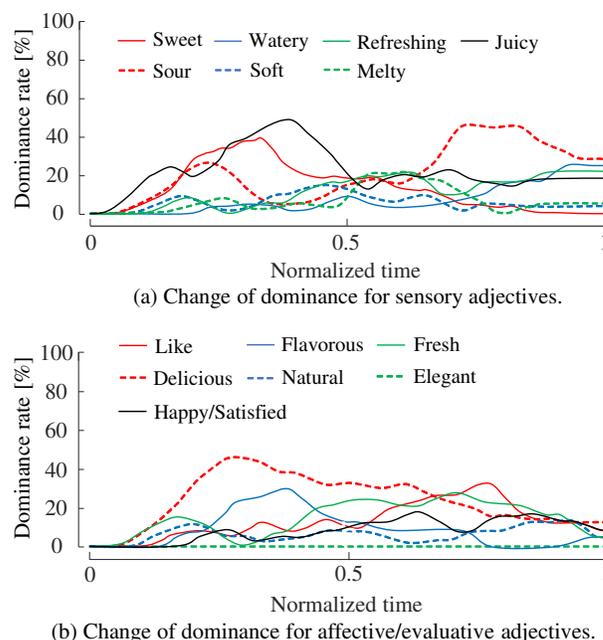


Fig. 5. Temporal change in perceptual and affective/evaluative responses. TDS curves for (a) sensory adjectives and (b) affective/evaluative adjectives.

strawberry into their mouth with their eyes closed. This procedure was used to cut off sight and smell stimuli prior to eating. Immediately after putting the strawberry into their mouth in one bite, each subject opened their eyes, released their hands from their nose, and began the task of pushing buttons. This task continued until the food diminished in the participants’ mouth and the stop button was pressed.

Testing involved alternately displaying selections of each type of adjective on the interface, as shown in Fig. 2, from which the panelist made a selection. The order in which two types of adjectives were presented, as well as the location of the adjectives on the interface, were randomized for each panelist. Each panelist conducted this task three times for each type of adjective group, completing six trials in total. Each trial took approximately 30 s, although the duration of the task was not set. Also, for any of the TDS procedures, the panelist could press the buttons as frequently as s/he wanted. A break of a few minutes was given between trials.

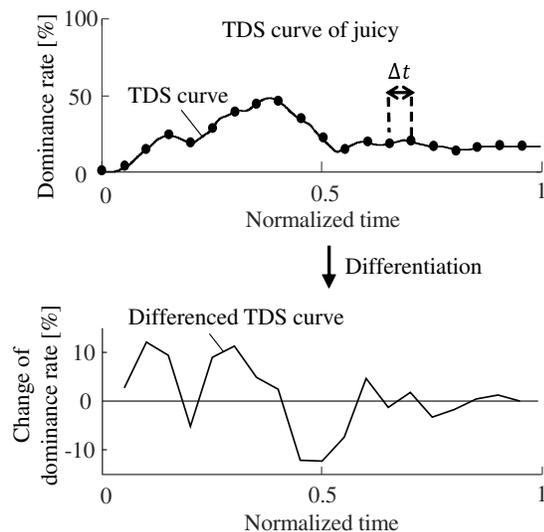


Fig. 6. Example of differentiation of TDS curve. Each curve is differentiated using the sampling period Δt .

3.4 Results

The graphs in Fig. 5 show the perceptual and affective responses obtained by the experiment. The horizontal axis represents the normalized time span from the intake of the strawberry until the completion of each perception trial (average: approximately 30 s). A moving average filter with a range of 1.5 s was used to smooth the dominance rate³. The sensory adjectives “juicy” and “sweet” were most common in the first halves of the trials, while “sour” was prominent in the second halves. The affective/evaluative adjective “delicious” was dominant overall, although “flavorous” was prominent in the first halves and “like” and “fresh” were prominent in the second halves. By contrast, the adjectives “soft,” “melty,” “elegant,” “happy/satisfied,” and “natural” were infrequently selected throughout the experiment. As these sensations were not considered to be dominant based on the criterion in [12], that is, whether the responses are significantly greater than the chance, they were excluded in the subsequent construction of the causal model.

4 CONSTRUCTION OF CAUSAL STRUCTURE WHILE EATING STRAWBERRY

We constructed a causal model of perceptual and affective responses for strawberries by applying the method explained in Sec. 2.4.

4.1 Data Processing

The sampling period of the VAR model, Δt , defines the minimum response speed considered under the model. During our experiments, the time from the selection of a button to the selection of another button was approximately 1 s at minimum; accordingly, we used a sampling period

3. Although the range of the filter did not significantly affect the model that was ultimately obtained, the estimation accuracy of the model increased at longer ranges because doing so suppressed difficult-to-predict high frequency content.

of 1 s to describe the continuous data obtained from the experiment.

As the Granger causality test assumes data stationarity, we investigated the stationarity of the time series obtained from the experiment by conducting an Augmented Dickey-Fuller (ADF) test [31] as a unit root test, from which it was determined that the possibility of non-stationarity could not be denied for some of the variables. We therefore de-trended the TDS curves by translating them to difference series using a sampling period of Δt . Fig. 6 shows an example of the translation. Subsequent ADF testing on the resulting difference series denied the non-stationarity of the data at a significance level of 5% for all variables. This difference time series was therefore used to establish the causal model. The translation of causality from time to difference series ensured that changes in a causal variable would result in changes in its resultant variables.

Finally, we adopted $q = 1$ as the order of the VAR model following the criterion described in Sec. 2.2.

4.2 Initial Two-layered Model

Fig. 7(a) shows the initial two-layered model constructed using the method explained in Sec. 2.4. The Granger causality was tested for among the five sensory adjectives in the bottom layer and one of the four affective/evaluative variables in the upper layer. The following causalities between sensory and affective/evaluative adjectives were identified: strawberry *sweetness* causes *flavorous*; bidirectional causality was detected between “sweet” and “delicious”; as *watery* strawberries are perceived as having a little taste, negative causalities between this sensory adjective and “fresh” and “like” were observed. Among the sensory adjectives, bidirectional causalities were detected among “sweet,” “juicy,” and “refreshing.” Each node of the graph contains the correlation coefficients between the values observed on the TDS curves and the values estimated by the VAR models. The VAR model for each adjective includes the adjective and all adjectives that are linked to it through Granger causality as explanatory variables. For example, in Fig. 7(a), the VAR model for “like” includes “watery” and “like” itself as explanatory variables. If an adjective was linked to no other adjective through Granger causality, its value was estimated using only its past information (AR model).

4.3 Model with Full Granger Causalities

Fig. 7(b) shows the modified causal model showing causalities among the affective/evaluative adjectives. Here, positive causalities from “delicious” to “flavorous” and from “fresh” and “flavorous” to “like” have been newly detected. Ultimately, only the adjective “like” was found not to cause other sensations and was therefore placed in the top layer. The resulting model shows the temporal process in which the taste or texture of strawberry causes an affect and then a preferential judgment. For instance, both “sweet” and “delicious” lead to “like” via “flavorous.” Although this causal structure of perception-emotion-preference has been reported in previous studies [1], [2], [3], [4], [5], [27], [28], our model suggests that these previously obtained causal structures can be observed as actual dynamic events starting from the moment of experiencing a stimulus.

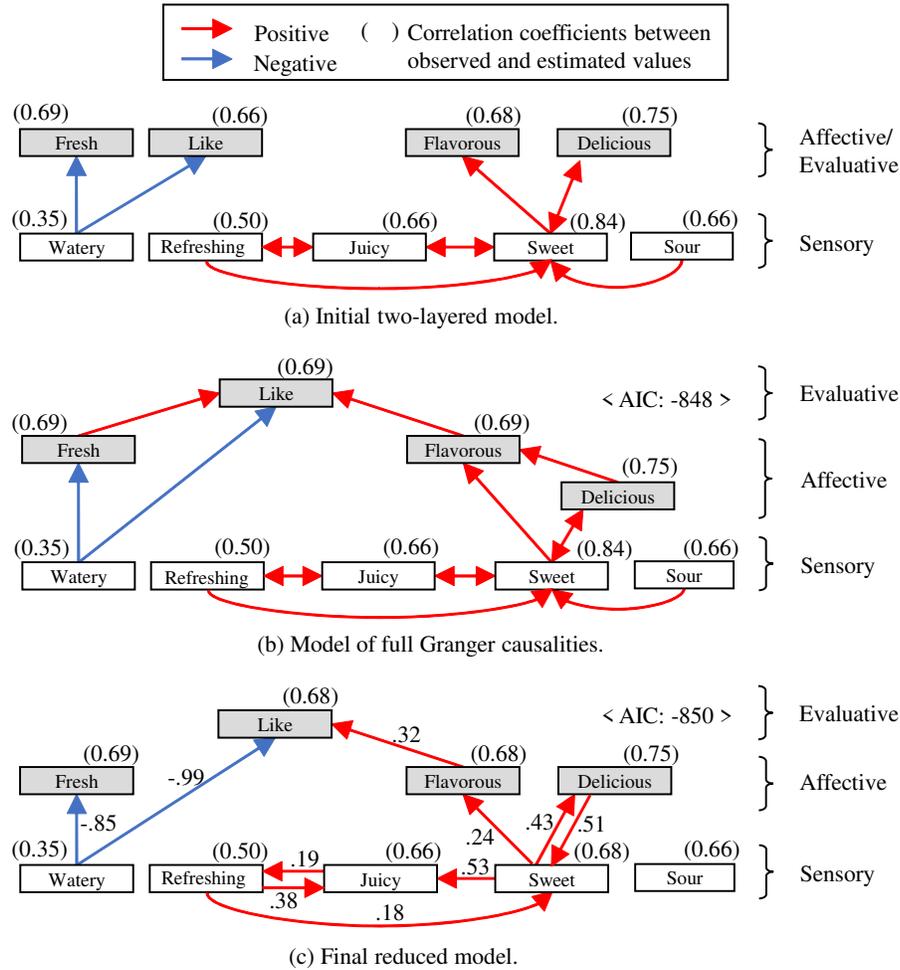


Fig. 7. Structure of Granger causality of adjectives for strawberry. (a) Initial two-layered structure comprising sensory and affective/evaluative layers. (b) Model of full Granger causalities. (c) Final reduced model. Values aside arcs are the coefficients of influence.

4.4 Final Reduced Model

Fig. 7(c) shows the final AIC-based reduced model, in which four causalities have been excluded from the model shown in Fig. 7(b). The excluded causalities are those from “delicious” to “flavorous,” from “juicy” to “sweet,” from “sour” to “sweet,” and from “fresh” to “like.” As a result of the contraction process, the AIC of the model decreases from -848 to -850. Under the reduced model, the causal relationships among the adjectives in the lower layer are simplified and “sour” is decoupled from other adjectives; nevertheless, the estimation accuracy of the original model is retained. For example, an examination of the correlation coefficients between the observed and estimated values reveals that “like” and “flavorous” can be estimated efficiently using fewer variables while maintaining accuracy, as the correlation coefficients representing the estimation accuracy of these variables are reduced by an insignificant amount under simplification even though there is one less causal (explanatory) variable. This demonstrates how simplification through application of the AIC to trim the set of explanatory variables produced by the VAR model enables a more efficient expression of the model.

TABLE 2
Results of cross validation using sample groups A and B. Correlation coefficients R between observed and estimated values are listed.

Adjectives	Cross validation (test data, training data)			Original model based on all samples
	(A, B)	(B, A)	Average	
Like	0.35	0.52	0.44	0.68
Delicious	0.43	0.68	0.56	0.75
Fresh	0.61	0.56	0.59	0.69
Flavorous	0.67	0.30	0.49	0.68

5 VALIDATION OF CAUSAL MODEL

We then investigated the quantitative and semantic validity of the proposed method of causal modeling by performing cross validation to assess the generalization ability of the estimation model for affective responses constructed based on the causal model. We further investigated the semantic validity of our causal model obtained via a comparison experiment using fake models.

5.1 Quantitative Validity

A two-fold cross validation approach was used to validate the established model. The performance of the estimation model was assessed by dividing the total sample set into two groups, which were used as sources of test and training data, respectively. The estimation operation was then applied to the two sample groups alternatively to test the generalization ability of the model. TDS curves were generated from each sample group (groups A and B, each representing the results obtained by five panelists over three trials). Causal models were then established by applying Granger causality and the AIC, with VAR models constructed for each sample group to estimate their respective affective/evaluative variables. Estimates were constructed for one of the sample groups using the estimation equations obtained from the other group and, finally, correlation coefficients between the observed and estimated values were calculated.

Table 2 shows the results of the cross validation. The largest and smallest mean correlation coefficients were obtained for “fresh” (0.59) and “like” (0.44). The mean correlation coefficient among all of the variables was 0.52. Relative to the original model established from all of the samples, the correlation coefficients decreased by 0.18 on average, a result that may be partially attributable to individual differences among the panelists.

5.2 Semantic Validity

In addition to quantitative consistency, we assessed the semantic reasonableness of the results produced by our method. The model shown in Fig. 7(c) expresses the process through which the taste and the texture of a strawberry influences affect and preference. It is seen that “sweet” evokes “delicious” and “flavorous” sensations and that “flavorous” sensation leads to a judgment of “like.” Perception of “watery” reduced the sensation of “fresh” and “like.” Although all of these sensations appear to be semantically reasonable, the semantic validity of a model requires support by the judgments of multiple individuals.

Accordingly, we presented the four distinct causal models shown in Fig. 8 to a set of panelists and instructed them to rank the models from the viewpoint of semantic validity. The model in Fig. 8(a) is identical to the one in Fig. 7(c). We generated three comparative models by adding slight modifications from the model (Fig. 8(b)–(d)). Even though we had no comparative models as immediate references, to avoid presenting completely random models we generated the three comparative models by excluding one causality each from the model in Fig. 7(c) and then adding a new causality. In the model in Fig. 8(b), we have excluded the causality from “watery” to “like” and added one from “sour” to “like.” Similarly, for models (c) and (d) we have changed the cause of “flavorous” from “sweet” to “juicy” and the cause of “like” from “flavorous” to “fresh,” respectively.

Sixteen university students participated in this experiment (fourteen males and two females, age: 22–25). The panelists compared the validity of the causalities included in each model and ranked the models while eating strawberries.

TABLE 3

Ranking of four causal models. The total ranks at the bottom were determined by summing the ranks awarded by all participants for each model.

Panelists	Rank			
	(a) Original	(b) M I	(c) M II	(d) M III
A	2	4	1	3
B	2	3	1	4
C	1	2	3	4
D	3	2	4	1
E	2	3	1	4
F	2	1	3	4
G	4	1	2	3
H	1	3	2	4
I	2	1	4	3
J	1	2	3	4
K	2	4	3	1
L	3	2	1	4
M	2	3	1	4
N	4	3	1	2
O	3	1	2	4
P	2	1	3	4
Rank sum	36	36	34	53
Total	2	2	1	4

The semantic validity of the model obtained using the proposed method would be considered to be validated if the rank given to the model in Fig. 8(a) was not below those given to the three similarly structured comparison models.

Table 3 lists the results of the ranking for each panelist. The bottom total rank (rank sum) is calculated as the sum of the ranks given by all panelists for each model. The rank sum of modified model (d) is largest, while those of (a), (b), and (c) are of similar magnitude. The results of Friedman testing suggest a significant difference among these ranks of $\chi^2(3) = 8.47$. Similarly, the results of post-hoc Wilcoxon’s rank sum testing reveal that there is a significant difference at a level of 1% between model (d) and the other three models. In other words, the semantic validity of (d) is lower than those of (a), (b), and (c) but there is no significant difference among the latter three models. However, the semantic validity of the causal model obtained using the proposed method is not lower than those of the other causal models to any significant degree.

6 DISCUSSION

The results described in the preceding section support the quantitative and semantic validity of the causal model established by our method. In terms of quantitative validity, the average correlation coefficient between the observed affective response values and those estimated from the model was approximately 0.7. However, this value was decreased to 0.52 in the cross validation. The semantic validity of a causal model is generally determined by panelists; based on a vote of the sixteen public panelists in the semantic validation exercise, the established model was judged to be semantically valid, and no marked semantic contradictions are apparent in the model shown in Fig. 7(c).

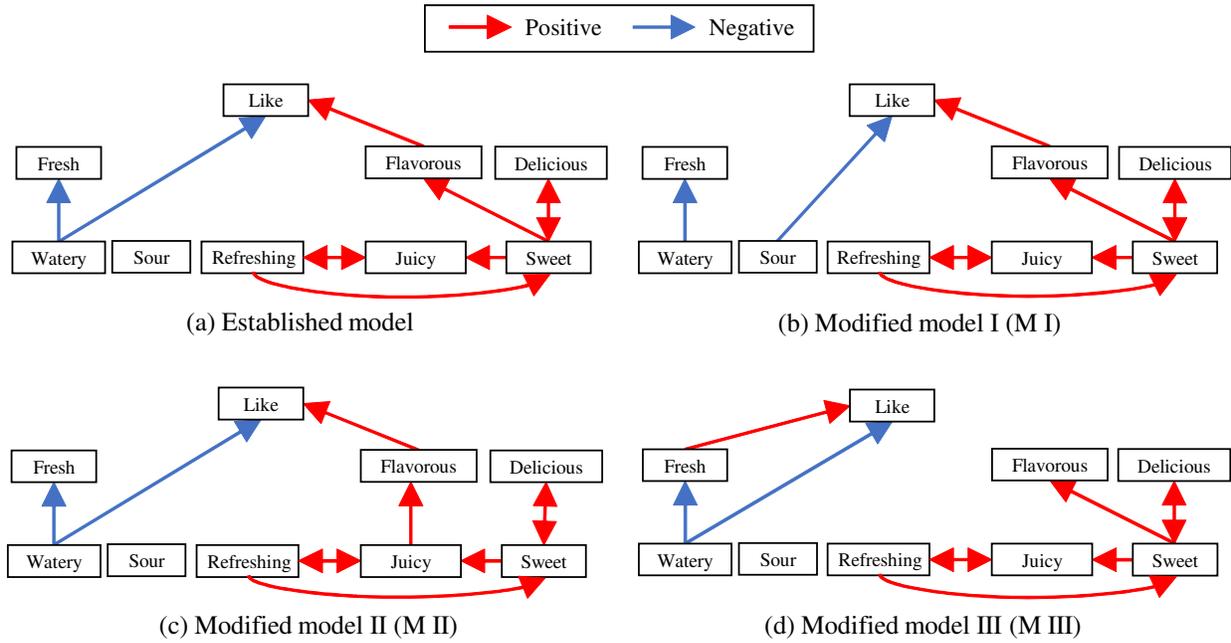


Fig. 8. Comparison of four models to assess semantic validity. (a) Model obtained using proposed method. (b)–(d) Models in which one arc is removed from (a) and one arc is added.

It is interesting to note that a bidirectional causality was detected between “delicious” and “sweet” in the established model. There are two potential interpretations of this relationship. First, it might be the case that “sweet” and “delicious” are semantically similar. Our model indicated that sweet strawberries are delicious, i.e., that the terms are semantically close. Another interpretation is that there is a recurrent process between perceptual and affective response. When an individual judges a sweet strawberry to be delicious, he/she may be judging a delicious strawberry to be sweet at the same time. Although the causalities from perceptions to affects are intuitive, inverse causalities can also occur. For example, it is well known that dual relationships hold between emotion and pain [32], [33]. In our model, the sensation of sweetness at a certain moment causes a feeling of deliciousness Δt periods later. In a similar manner, a sensation of deliciousness causes an experience of sweetness Δt periods later.

One promising use of the newly established model is the prediction of temporal changes in affective responses. For instance, it allows us to estimate the propagation of a transient change in one gustatory feeling. If the sweetness experienced from strawberries is more intense at any one instant, then Fig. 7(c) indicates that the “flavorous” response increases Δt later, and the “like” response also does so after another Δt . “Sweet” also influences its own intensity in the next several periods of Δt . In this way, the change in one response leads to changes in multiple other responses during finite intervals. These subsequent changes, caused by a change in one variable, are analyzed based on the impulse responses for the VAR models. This kind of analysis is more effective for processed foods and cuisines than for fruits, in that it supports the design or manipulation of the affective experiences produced by tastes, flavors, and textures.

Although in this study, perceptual and affective re-

sponses were estimated using the VAR model, which is linear and time-invariant, in the future it should be possible to apply nonlinear models or modeling that includes temporal change in causal structures. The human perceptual and affective responses are nonlinear [34] and our linear method therefore only approximates them. The concept of Granger causality can also be applied to nonlinear models [35]. As suggested by the profile of TDS curves obtained from our experimental results, the causal structure of perception and affect is perhaps time-varying. For instance, sensations such as “watery” were mostly observed at the end of the eating process and were not selected beforehand. Thus, if the proposed method is applied to portions of the overall TDS curve (e.g., the first or second half only), the resulting causal models might differ from those we obtained. This follows Lepage et al. [36] where the entire period was split into a few phases and analyzed. Capturing the temporal change in the causal structure itself can therefore uncover affective dynamics.

The results of the cross-validation exercise suggest that the generalization ability of the proposed model for predicting affective responses is somewhat lower than that of an independent sample group. One of the main reasons for this lies in individual differences in terms of perceptual and affective response. In cases in which such individual differences are important, it can be effective to classify panelists using cluster analysis [27]. By doing so, causal models can be produced for each classified group and the model suitable to the characteristics of the target consumers can be selected. It has also been reported that individual differences in eating manner affect the dynamic change of sensed texture [37]. To reflect and account for individual differences in eating manner, panelists can be screened by time spent on eating or bite/swallowing timing [17], [38].

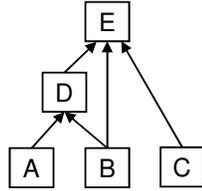


Fig. 9. Example of the structure of Granger causality.

7 CONCLUSION

The objective of this study was to develop a method for the causality modeling of perception and emotion using dynamic perceptual and affective information. We recorded perceptual and affective responses starting from the beginning of the process of consuming food and expressed the resulting time series using VAR models. We then investigated the Granger causalities among the subjective responses to establish a causal model of perception and affect. This model was further simplified through the application of an information criterion (AIC) to construct a final simple and accurate model. Testing of the constructed causal model via the sensations obtained in the process of consuming a strawberry as an example revealed a coherent perception-emotion-preference causal structure. The model was further assessed through cross validation and comparison with modified models. The results revealed that, although the generalization abilities of the proposed model in estimating affective response were somewhat low, the model was semantically reasonable. The proposed method should be useful in the affective design of products and in the prediction of consumers' affective responses and should be of use in analysis of affective dynamics. In future research, the validity of the method in application to a variety of foods should be further assessed.

APPENDIX A

AKAIKE INFORMATION CRITERION

We evaluated the validity of the overall causal model in terms of the typical information criterion AIC [21], which is expressed as follows:

$$\text{AIC} = -2L(\theta) + 2k \quad (5)$$

where the θ are the parameters estimated by the model, $L(\theta)$ is the log likelihood function obtained by estimating the parameters using the maximum likelihood estimation method, and k is the number of estimated parameters. The first term on the right-hand side of the formula is the reward term for goodness of fit of the model, which becomes smaller under more accurate models. The second term represents the penalty term for the number of estimated parameters, k , and increases under more complex models. Smaller AICs correspond to better models that balance accuracy and complexity well.

We illustrate how to compute the AIC of a causal model by using the example shown in Fig. 9, which indicates the causalities among five variables (A–E) using arrows. First, the log likelihood function is computed by using the values estimated using the VAR model for each variable.

The VAR models use all variables that are associated with others through Granger causality, along with the variables themselves, as explanatory variables. For example, the VAR model to estimate the values of D (y_D) is expressed in terms of the explanatory variables y_A , y_B , and y_D as follows:

$$\hat{y}_{D,t} = c + \sum_{j=1}^q a_{AD}^{(j)} y_{A,t-j\Delta t} + \sum_{j=1}^q a_{BD}^{(j)} y_{B,t-j\Delta t} + \sum_{j=1}^q a_{DD}^{(j)} y_{D,t-j\Delta t}. \quad (6)$$

The variables with no associated causal variables, such as y_A , y_B , and y_C , are considered to be exogenous variables and are not taken into account in the computation of the AIC. Then, assuming that the errors ($\epsilon_i = [\epsilon_{D,i}, \epsilon_{E,i}]^T$) between the i th observed values of time series discretized into m samples ($\mathbf{y}_i = [y_{D,i}, y_{E,i}]^T$) and estimated values by VAR models ($\hat{\mathbf{y}}_i = [\hat{y}_{D,i}, \hat{y}_{E,i}]^T$) follow normal distributions, the joint probability of the errors is expressed as follows:

$$f(\epsilon_i) = \frac{1}{\sqrt{2\pi}^n \sqrt{|\Sigma|}} \exp\left(-\frac{1}{2} \epsilon_i^T \Sigma^{-1} \epsilon_i\right), \quad (7)$$

where Σ is the covariance matrix of the errors and n is the number of estimated parameters, which is two in this case. The log likelihood function can then be obtained by multiplying (7) over the entire interval as follows:

$$L(\theta) = \log \prod_{i=1}^m f(\epsilon_i). \quad (8)$$

Next, the number of estimated parameters, k , is obtained as the sum of the number of parameters included in the estimation equations for each variable. For the example shown in Fig. 9, the number of estimated parameters for D is, from (6), $1 + 3q$, while the number for E is $1 + 4q$. Therefore, $k = 2 + 7q$.

APPENDIX B

OVERLY SIMPLIFIED MODEL ESTABLISHED BY CONDITIONAL GRANGER CAUSALITIES AMONG ALL VARIABLES

The model shown in Fig. 7(b) was established by superimposing fourteen causalities among the subsets of the variables. If, instead, the conditional Granger causality were obtained by investigating all of variables simultaneously, the causal model shown in Fig. 10 would be obtained. This model includes only five causalities, and “refreshing,” “flavorous,” and “delicious” have become isolated adjectives. In the presence of a large number of variables, as occurs in this case, conditional Granger causality cannot detect causalities very well, resulting in overly simple models.

ACKNOWLEDGMENTS

This study was in part supported by JSPS Kakenhi (17K20002).

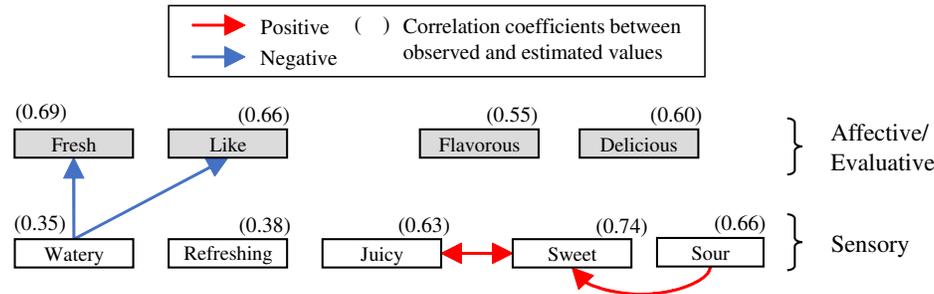


Fig. 10. Overly simplified structure of Granger causality constructed by investigating conditional Granger causality among all adjectives at once.

REFERENCES

- [1] X. Chen *et al.*, "Materials' tactile testing and characterisation for consumer products' affective packaging design," *Materials & Design*, vol. 30, no. 10, pp. 4299–4310, 2009.
- [2] H. Nagano, S. Okamoto, and Y. Yamada, "Modeling semantically multilayered affective and psychophysical responses toward tactile textures," *IEEE Transactions on Haptics*, 2018.
- [3] K. Kidoma *et al.*, "Graphical modeling method of texture-related affective and perceptual responses," *International Journal of Affective Engineering*, vol. 16, no. 1, pp. 27–36, 2017.
- [4] S. Okamoto *et al.*, "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. 14, no. 8, 2018.
- [5] H. Nagano, S. Okamoto, and Y. Yamada, "Semantically layered structure of tactile textures," *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*, pp. 3–9. Springer, 2014.
- [6] K. Drewing *et al.*, "Systematic relations between affective and sensory material dimensions in touch," *IEEE Transactions on Haptics*, vol. 11, no. 4, pp. 611–612, 2018.
- [7] W. Fujisaki, M. Tokita, and K. Kariya, "Perception of the material properties of wood based on vision, audition, and touch," *Vision research*, vol. 109, pp. 185–200, 2015.
- [8] W. E. Lee and M. Pangborn, "Time-intensity: The temporal aspects of sensory perception," *Food Technology*, pp. 71–78, 1986.
- [9] L. Duizer, E. Gullett, and C. Findlay, "Time-intensity methodology for beef tenderness perception," *Journal of Food Science*, vol. 58, no. 5, pp. 943–947, 1993.
- [10] D. E. Taylor and R. M. Pangborn, "Temporal aspects of hedonic responses 1," *Journal of Sensory Studies*, vol. 4, no. 4, pp. 241–247, 1990.
- [11] E. Schubert, "Real time cognitive response recording," *Proceedings of the Inaugural International Conference on Music Communication Science*, pp. 139–142, 2007.
- [12] N. Pineau *et al.*, "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.
- [13] G. Jager *et al.*, "Temporal dominance of emotions: Measuring dynamics of food-related emotions during consumption," *Food Quality and Preference*, vol. 37, pp. 87–99, 2014.
- [14] 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.
- [15] R. Jenke, A. Peer, and M. Buss, "Feature extraction and selection for emotion recognition from EEG," *IEEE Transactions on Affective Computing*, vol. 5, no. 3, pp. 327–339, 2014.
- [16] S. Koelstra *et al.*, "DEAP: A database for emotion analysis; using physiological signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, 2012.
- [17] D. Rocha-Parra *et al.*, "Application of hedonic dynamics using multiple-sip temporal-liking and facial expression for evaluation of a new beverage," *Food Quality and Preference*, vol. 52, pp. 153–159, 2016.
- [18] 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.
- [19] T. C. Merlo *et al.*, "Measuring dynamics of emotions evoked by the packaging colour of hamburgers using temporal dominance of emotions (TDE)," *Food Research International*, 2018. [Online]. Available: <https://doi.org/10.1016/j.foodres.2018.08.007>
- [20] T. Okada *et al.*, "Vector auto-regression model of temporal perceptual and affective responses towards food," *Proceedings of IEEE Global Conference on Life Sciences and Technologies*, pp. 43–45, 2019.
- [21] H. Akaike, "Information theory and an extension of the maximum likelihood principle," *Selected papers of hirotugu akaike*, pp. 199–213, 1998.
- [22] C. W. Granger, "Testing for causality: a personal viewpoint," *Journal of Economic Dynamics and control*, vol. 2, pp. 329–352, 1980.
- [23] J. Geweke, "Measures of conditional linear dependence and feedback between time series," *Journal of the American Statistical Association*, vol. 79, no. 388, pp. 907–915, 1984.
- [24] L. Barnett and A. K. Seth, "The MVGC multivariate granger causality toolbox: A new approach to granger-causal inference," *Journal of Neuroscience Methods*, vol. 223, pp. 50–68, 2014.
- [25] T. Matsuoka *et al.*, "Predicting texture image of covering fabric for car seat by physical properties," *Journal of Textile Engineering*, vol. 54, no. 3, pp. 63–74, 2008.
- [26] S. Guest *et al.*, "The development and validation of sensory and emotional scales of touch perception," *Attention, Perception, & Psychophysics*, vol. 73, no. 2, pp. 531–550, 2011.
- [27] S. Okamoto *et al.*, "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.
- [28] I. H. M. Hashim *et al.*, "Tactile evaluation feedback system for multi-layered structure inspired by human tactile perception mechanism," *Sensors*, vol. 17, p. 2601, 2017.
- [29] N. Pineau *et al.*, "Temporal dominance of sensations: What is a good attribute list?" *Food Quality and Preference*, vol. 26, no. 2, pp. 159–165, 2012.
- [30] S. C. King and H. L. Meiselman, "Development of a method to measure consumer emotions associated with foods," *Food Quality and Preference*, vol. 21, no. 2, pp. 168–177, 2010.
- [31] S. E. Said and D. A. Dickey, "Testing for unit roots in autoregressive-moving average models of unknown order," *Biometrika*, vol. 71, no. 3, pp. 599–607, 1984.
- [32] R. A. Martin, "Is laughter the best medicine? Humor, laughter, and physical health," *Current Directions in Psychological Science*, vol. 11, no. 6, pp. 216–220, 2002.
- [33] S. Bruehl, C. R. Carlson, and J. A. McCubbin, "Two brief interventions for acute pain," *Pain*, vol. 54, no. 1, pp. 29–36, 1993.
- [34] F. Camargo and B. Henson, "Aligning affective responses with fabric features of vehicle seat: An approach using the Rasch measurement model," *International Journal of Affective Engineering*, vol. 14, no. 3, pp. 193–202, 2015.
- [35] E. Baek and W. Brock, "A general test for nonlinear granger causality: Bivariate model," *Iowa State University and University of Wisconsin at Madison Working Paper*, 1992.
- [36] M. Lepage *et al.*, "Panel performance for temporal dominance of sensations," *Food Quality and Preference*, vol. 38, pp. 24–29, 2014. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0950329314000780>
- [37] M. D. de Lavergne *et al.*, "Eating behaviour explains differences between individuals in dynamic texture perception of sausages," *Food Quality and Preference*, vol. 41, pp. 189–200, 2015.

- [38] S. Pecore, C. Rathjen-Nowak, and T. Tamminen, "Temporal order of sensations," *Proceedings of 9th Pangborn Sensory Science Symposium*, pp. 4–8, 2011.



Takumu Okada is a mechanical engineer who received BS and MS degrees in engineering from Nagoya University in 2017 and 2019, respectively. His research interests include affective engineering and haptics.



Shogo Okamoto received MS and PhD degrees in information sciences in 2007 and 2010, respectively, from the Graduate School of Information Sciences, Tohoku University. Since 2010, he has been with the Graduate School of Engineering, Nagoya University. His research interest includes haptics, assistive technology, and affective engineering.



Yoji Yamada received a PhD degree from the Tokyo Institute of Technology in 1990. In 2008, he moved to Nagoya University, as a professor after being an associate professor at the Toyota Technological Institute and a group leader at AIST. His expertise include robotics and safety of machinery.