Affective Dynamics: Principal Motion Analysis of Temporal Dominance of Sensations and Emotions Data

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Abstract—Temporal dominance (TD) methods can be used to record temporal changes in multiple sensory and affective responses. TD methods have found wide applications in the analysis of eating experiences of humans. However, extant analyses performed on TD data do not fully utilize the time-series properties of such data. The present study validates the prospect of principal motion analysis (PMA) of TD data. PMA is an extension of principal component analysis, and can be used to resolve multivariate motion data into base principal motions. In this study, panelists were asked to evaluate the tastes of ten types of pickled plums using the temporal dominance of sensations (TDS) and emotions (TDE) methods. Additionally, the panelists were asked to rate the plums using the semantic differential method. Results obtained using both methods were observed to demonstrate good agreement with each other in terms of the structures of reduced variable spaces. As realized in this study, implementation of the combined TD–PMA approach can potentially facilitate statistical discrimination of all food products, whereas conventional methods, such as principal component analysis of data provided via use of the semantic differential method, can at best discriminate only 67% of product pairs. PMA can, therefore, be considered as a suitable technique to reveal the characteristics of TD data.

Index Terms—Principal motion analysis, Temporal dominance, Semantic differential method

1 Introduction

There exist many evaluation techniques that facilitate investigation of the sensory and affective aspects of eating experiences. Some of the most common and successfully employed approaches in this regard are scoring methods that employ descriptive norms. These include the semantic differential (SD) method, quantitative descriptive analysis, and sensory profiling. During application of these methods, panelists evaluate foods after tasting them or after a period of contemplation. In contrast, the trace [1], time-intensity [2], and temporal dominance of sensations/emotions (TDS/TDE) methods [3], [4], [5] can be employed to capture temporal changes in the gustatory, osmatic, textural, and affective experiences that occur during the time interval between the commencement and end of tasting. In this paper, the acronym "TD" refers to both TDS and TDE. Recently, the TD method has attracted increased attention on account of its inherent advantages with regard to effective collection of multiple response types, whereas the trace and time-intensity methods can only be used to record a single, or at best two, response types using descriptive norms [6], [7]. Thus far, the TD method has been used for evaluating such food products as cheese [3], [8], wine [9], [10], chocolate [4], strawberries [11], fruit juices [12], and pickles [13].

As described in section 2, TD methods record the temporal evolution of dominantly experienced sensory and affective statuses of individuals during eating. That said, TD methods are still relatively new, and a generalized method for analysis of temporal changes in measured data is yet to be established. Extant studies concerning the TD method have mainly focused on the investigation of properties of data obtained using the TD approach [3], [14], [15], comparison of the TD approach against other sensory evaluation methods [3], [9], [12], [16], [17], [18], pursuit of experimental protocols [12], [19], [20], [21], [22], and availability for various types of edible products. To facilitate analyses of TD data, extant studies [9], [13], [15], [18], [23], [24] have employed techniques involving visual inspection of time profiles or statistical analyses of characteristic values computed from them. A typical example of one such time-profile characteristic value is referred to as the dominance duration during which a certain sensory or affective attribute is reported as being dominant [9], [13], [24], [25], [26]. Other examples include the maximum value of each attribute type within the time profile. These characteristic values do not capture the dynamic or time-evolutionary aspects of TD data; to address this issue, Lepage et al. [20] split the entire eating duration into three phases, and subsequently computed characteristic values for each phase. Further, Franczak et al. [27] and Lecuelle et al. [28] modeled temporal and stochastic transitions concerning the most salient eating experiences using the Markov model. Nonetheless, these approaches do not fully utilize the temporal evolution of TD data.

This study aims at investigating the ability of the principal motion analysis (PMA) technique [29], [30] to resolve multivariate-motion TD data into base principal motions. As described in section 3, PMA has primarily been used for analysis of human motions, and has thus far not been

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applied to TDS data. Although PMA does not yield a unique solution, it is considered suitable for use in this study owing to its ability to analyze multivariate time-series data using only a small number of base functions called principal motions. PMA is, therefore, generally compatible with most statistical testing methods (such as analysis of variance) while maintaining time-series profiles of sensory and affective attributes. To collect test data, TD tasks were performed in combination with static sensory evaluation tasks (e.g., the semantic differential (SD) method) for ten types of plum pickles. Subsequently, results obtained using the two approaches were compared to statistically discriminate the food products. Furthermore, the semantic validity of results obtained using PMA was compared against that of results obtained using the SD approach. Part of the experimental data recorded and subsequent analyses performed in this study were presented in [13] during a comparison of results obtained via principal component analysis of SD and TDS data.

2 Temporal Dominance (TD) Method

This section provides an introduction to the temporal dominance method in order to facilitate easy understanding of the remainder of this paper. For further details, readers are referred to [31], [32]. As already stated, the TD method effectively records evolutionary changes in multiple types of subjective experiences that occur during eating, drinking, and smelling [3]. Sensory evaluation methods, such as the SD method and sensory profiling, statically capture multiple types of verbally described attributes. Trace and time-intensity methods capture dynamic changes within single attributes. Intuitively, it can be realized that TD methods somewhat correspond to a combination of these two conventional approaches. Thus far, TD methods have mostly been used for evaluation of eating experiences; however, they can potentially be used for evaluation of other nonvisual attentive experiences as well.

TD tasks employ graphical user interfaces (GUI) on a computer screen, as depicted in Fig. 1 (a), and instants at which panelists make a selection by tapping on the screen are recorded. Options visible on the screen are marked by words describing the gustatory, osmatic, textural, or affective experiences. In the case of eating tasks, panelists select the "start" option immediately after placing the food in their mouths, at which instant the task is initiated. At arbitrary time instants, panelists are asked to select an option with a description that best corresponds to their eating experience at that instant. As depicted in Fig. 1 (b), panelists subsequently make other selections corresponding to changes in their experience. The system is designed such that once a selection is made, it would automatically apply to all subsequent experiences until another selection has been made. At each instant, only one selection can be made. The same selection can be made multiple times during a single operation, whereas certain options may remain unselected throughout. This operation continues until panelists swallow the food specimen, and the "stop" option is selected. With regard to option selection criteria, instructions provided to panelists may influence their selection behavior [14]. In our experiments, in accordance with the studies

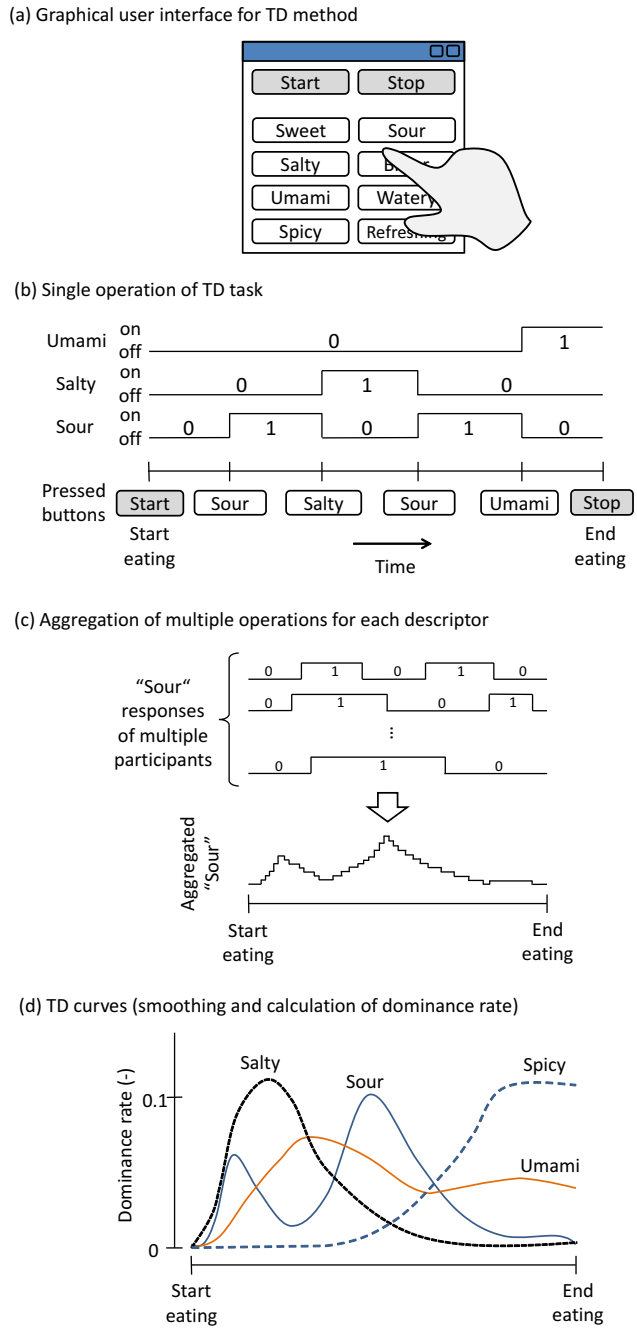

Fig. 1. Temporal dominance (TD) method–(a) Graphical user interface for option selection; (b) Data obtained during single operation; (c) Aggregation of responses recorded from all panelists for each descriptor; (d) TD curves obtained upon completion of smoothing operation. The curve indicates temporal changes in frequencies at which each response was recorded at each instant.

performed by Pineau et al. [3] and other researchers [12], [24], the panelists were instructed to make selections based on those experiences that drew their attention the most.

For each above-described operation, binary functions of time are acquired to demonstrate whether corresponding attributes have or have not been selected at each instant. These binary functions are normalized with respect to the time instant at which the "stop" option is selected by

panelists. Binary functions obtained for each attribute[1] are aggregated among all operations, as depicted in Fig. 1 (c). These aggregated values are then divided by the number of operations to compute selection frequencies, i.e., dominance rates. Finally, smooth dominance rates are obtained via a smoothing operation, as depicted in Fig. 1 (d). A low-pass filter with a 1 Hz cutoff frequency was used in this study, because at most one option was recorded during each second within the period of high-frequency option selection by panelists.

3 Principal motion analysis (PMA) using resampled TD curves

3.1 Resampling of TD curves

Implementation of the TD method requires a sufficient number of panelists to produce smooth dominance-rate profiles. For example, in the experiment performed by Pineau et al. [3], 16 panelists participated in TDS tasks to generate TD curves for each food product. In the study performed by Thomas et al. [24], 68 panelists signed up to facilitate curve generation. Likewise, 20 ($n = 20$) panelists signed up for participation in the experiments performed in this study. A set of p different TD curve types for each product was obtained by integrating the responses obtained from the n panelists. Treating this curve set as one sample, q such samples were collected for q food products. In the present case, $q = 10$. However, PMA in general requires collection of more samples. Thus, to facilitate creation of additional samples, the sampling exercise was repeated n times with successive replacements from the pool of panelists, in accordance with the sampling method reported in [37], [38]. This process was performed n times to acquire n sets of TD curves for each product. An aggregate of $n \times q$ sets of curves was used for the computation of PMA, which is described in the next section.

3.2 Principal motion analysis (PMA)

The principal motion analysis (PMA) technique was introduced by Park et al. [29], [30] as an extension of the principal component analysis technique in the temporal dimension. Thus far, PMA has been used for analyzing redundant systems, such as human motion [33], [34], [35]. The technique essentially computes several representative motions—called principal motions—from a set of multivariate time-series samples. These principal motions are independent from each other[2]. A multivariate motion sample can be represented by a linear combination of principal motions. In general, the number of meaningful principal motions is substantially smaller compared to that of variables included in original samples. All multivariate time-series samples are fit into a space with reduced dimensions.

In terms of the k-th sample, let $x_{ijt}^{(k)}$ denote the dominance rate of the descriptor j at time t for food product i. The column vector $\boldsymbol{x}_{ij}^{(k)}$ contains discrete time values, and can be expressed as

$$\boldsymbol{x}_{ij}^{(k)} = (x_{ij1}^{(k)} \cdots x_{ijt}^{(k)} \cdots x_{ijs}^{(k)})^{\mathrm{T}} \in \mathbb{R}^{s\times 1} \tag{1}$$

wherein temporally continuous dominance rates have been discretized into s values within the normalized time domain with $t = 1, \cdots, s$. The conjunct column vector can be expressed as

$$\boldsymbol{y}_i^{(k)} = (\boldsymbol{x}_{i1}^{(k)\mathrm{T}} \cdots \boldsymbol{x}_{ij}^{(k)\mathrm{T}} \cdots \boldsymbol{x}_{ip}^{(k)\mathrm{T}})^{\mathrm{T}} \in \mathbb{R}^{sp\times 1} \tag{2}$$

using which TD curves for p different types of descriptors corresponding to the k-th sample of product i can be represented by a single vector. Conjunct vectors for all n samples of product i can be consolidated in the following matrix form.

$$\boldsymbol{Z}_i = (\boldsymbol{y}_i^{(1)} \cdots \boldsymbol{y}_i^{(k)} \cdots \boldsymbol{y}_i^{(n)}) \in \mathbb{R}^{sp\times n}. \tag{3}$$

Subsequently, data corresponding to all products can be expressed using an extended matrix as follows.

$$\boldsymbol{W} = (\boldsymbol{Z}_1 \cdots \boldsymbol{Z}_i \cdots \boldsymbol{Z}_q) \in \mathbb{R}^{sp\times nq}. \tag{4}$$

Hence, q is the number of tasted food products.

Usually, $\boldsymbol{W}$ can be expanded using a set of independent vectors acquired by solving an eigenvalue expansion, and vectors with primary eigenvalues can subsequently be regarded as principal motion vectors. However, such vectors may possess negative values, whereas dominance rates are greater than zero in principle. Hence, a non-negative matrix factorization [36] was performed in this study, using which $\boldsymbol{W}$ could be expressed as

$$\boldsymbol{W} \approx \boldsymbol{V}\boldsymbol{H} \tag{5}$$

wherein vectors $\boldsymbol{V} \in \mathbb{R}^{sp\times r}$ and $\boldsymbol{H} \in \mathbb{R}^{r\times nq}$ contained only positive values. Here, r denotes the number of principal motions to be considered, and each column vector of $\boldsymbol{V}$ corresponds to a principal motion vector. The value of r is, in general, small—3 in the case of the present study—compared to the size of the matrix $\boldsymbol{W}$. The vector $\boldsymbol{H}$ contains scores corresponding to principal motion vectors. TD curves of an arbitrary sample $\boldsymbol{y}_i^{(k)}$ can be expressed as a linear combination of r principal motion vectors weighed by scores contained within $\boldsymbol{H}$; i.e.,

$$\boldsymbol{y}_i^{(k)} \approx \boldsymbol{V}\boldsymbol{h}_i^{(k)}. \tag{6}$$

In the above equation, $\boldsymbol{h}_i^{(k)} \in \mathbb{R}^{r\times 1}$ denotes a column vector of $\boldsymbol{H}$. In other words, all samples were made to fit within the r-dimensional space, each dimension of which corresponds to one principal motion. As regards factorization of non-negative matrices, the *nnmf* function within the MATLAB package (ver. 2017b; MathWorks, Inc.) was used in this study.

4 Experiments

4.1 Panelists

Twenty Japanese university students (age: 21–26, 16 male, 4 female, $n = 20$)[3] participated in the TD tasks performed

1. As a variation of TD methods, multiple analog scales are used to produce non-binary functions [12], [21].

2. This depends on the data processing method employed. In the case of the present study, non-negative matrix factorization was performed for matrix expansion, wherein principal motions were approximately orthogonal to each other. If singular-value decomposition had been used, the resulting principal motions would be completely orthogonal.

3. There is no general agreement about the necessary number of panelists for TD methods. Typically, at least more than 10 panelists are invited [31].

in this study as panelists, after providing informed written consent. All panelists were familiar with plum pickles as a common food product.

4.2 Food products

Ten types of commercially available plum pickles, called *umeboshi* in Japanese—(P1–P10, $q = 10$), were used in this study. *Umeboshi* refers to the Japanese plum pickled with salt. They are flavored with Japanese red basil (*shiso*), bonito soup, and so on. In the study, three *umeboshi* were honey-flavored (relatively sweet) and four were basil-flavored (relatively sour), whereas the others were bonito-flavored with moderate umami. During experiments performed in this study, *umeboshi* pulp was torn into small pieces, and one piece was placed on a spoon and provided to a panelist for tasting.

4.3 Selection of descriptors

During TD tasks, not more than ten descriptors must be provided to panelists [19]. For descriptor determination, a list of 163 candidate descriptors was prepared for describing sensory and affective experiences during eating. A team of six members, including the authors, ate the plum pickles and selected possible descriptors from the prepared list in a "check-all-that-apply" manner. Options that were voted for most often by the members were then selected as descriptors, such that their total count would not exceed 10 for each category of sensory and affective experience.

Nine sensory descriptors—*sour*, *sweet*, *umami*, *salty*, *smooth*, *refreshing*, *juicy*, *fruity*, and *watery*—were selected. Among these, *sour*, *sweet*, *umami*, and *salty* are fundamental tastes [39], whereas *watery*, *refreshing*, and *smoothing* are more concerned with texture, i.e., tactile sensations felt in the mouth. *Juicy* can be described as the density of juice extracted when a food sample is squeezed in the mouth. *Fruity* is a comprehensive term, but it mostly relates to the sense of smell. Additionally, eight affective and evaluative descriptors—*like*, *dislike*, *delicious*, *expensive*, *rich*, *deep*, *sharp*, and *arousing*—were selected. *Deep* can be defined as the intensity of multiple umami factors. Additionally, *rich* refers to the variety of tastes experienced by the taster. *Sharp* can be defined as the rapid increase in stimulating tastes and flavors.

Thus, the number of descriptive words equaled $p = 9$ and 8 for the TDS and TDE tasks, respectively. These words were displayed to the panelists in their native language, i.e., Japanese[4] on the graphical user interface described in Fig. 1. Either of the two groups of words—sensory or affective—was presented during a single TD operation. Sensory and affective descriptors were not mixed during the TD task. Further, all descriptors were used during the SD task.

4.4 Sensory evaluation tasks (TD methods and after-tasting scoring method)

In this study, all 20 panelists performed the TD and after-tasting scoring tasks (SD method) in a random manner. Prior to the experiments, all panelists were briefed on the descriptor definitions used in the two types of tasks.

4.4.1 TD tasks

Prior to performing the main tasks, panelists were asked to attend a 5–10-min training session to familiarize themselves with the method and graphical user interface (GUI) setup. During this session, panelists were asked to repeatedly perform TD tasks using a set of sensory and affective descriptors.

During each trial, panelists were asked to close their eyes, pinch their own nose, and place a food specimen in their mouth using a disposable plastic spoon, on which a piece of pulp was placed by the experimenters. This was done to prevent visual and osmatic cues from affecting the experiment. Immediately following food intake, panelists opened their eyes and nose and proceeded with performing the GUI-based option selection task. Once they felt a change in experience, they selected a different option. On average, each task lasted approximately 10 s. Prior to each trial, panelists were asked to rinse their mouths.

Each panelist performed 20 trials (ten food products for each of the TDS and TDE tasks). The order in which the TDS and TDE tasks and products were presented to the panelists was randomized. Note that TDS and TDE tasks were separately conducted, following the methodology of earlier studies such as [4], [22]. Further, the option labels were randomly placed on the GUI panel for each panelist.

4.4.2 After-tasting semantic difference (SD) task

In this study, the panelists performed SD tasks using seven-grade scales for nine sensory and eight affective words written on the same questionnaire sheet. The phrases "strongly agree" and "strongly disagree" represented the two extremes of each scale, while "neutral" represented the center. In the analysis in section 4.5.2, positive and negative values were assigned to "agree" and "disagree" grades, respectively.

Prior to execution of the main tasks, the panelists trained themselves to score the food products as per the descriptive norms provided. During this 5–10-min training session, the panelists were allowed to eat all products used in the latter main task.

In the main SD task, similar to the TD tasks, panelists were asked to eat a piece of pickle placed on a spoon and subsequently provide a response in accordance with their eating experience. Similar to the TD tasks, they could take only one piece of food for a single trial. Furthermore, they closed their eyes and nose before the intake of the food. Once again, all food products were presented in a randomized order. Each panelist took approximately 2 min (on average) to respond to the questionnaire for each product.

4.5 Data analysis

4.5.1 Analysis of TD data

Binary functions corresponding to the nine ($p = 9$) sensory and eight ($p = 8$) affective descriptors obtained during each TD operation were normalized with respect to the time at which the "stop" option was selected by each panelist. Subsequently, resampling was performed to acquire TD

4. The corresponding Japanese sensory words were *suppai*, *amai*, *umai*, *shoppai*, *nameraka*, *sawayaka/sappari/assari*, *zyushi*, *furuthi*, and *mizuppoi* in the order of descriptors listed in the above passage. Likewise, the corresponding affective words were *suki*, *kirai*, *oishi*, *johinna/kokyuna*, *yutakana*, *ajiwai-fukai*, *surudoi*, and *mega-sameru*.

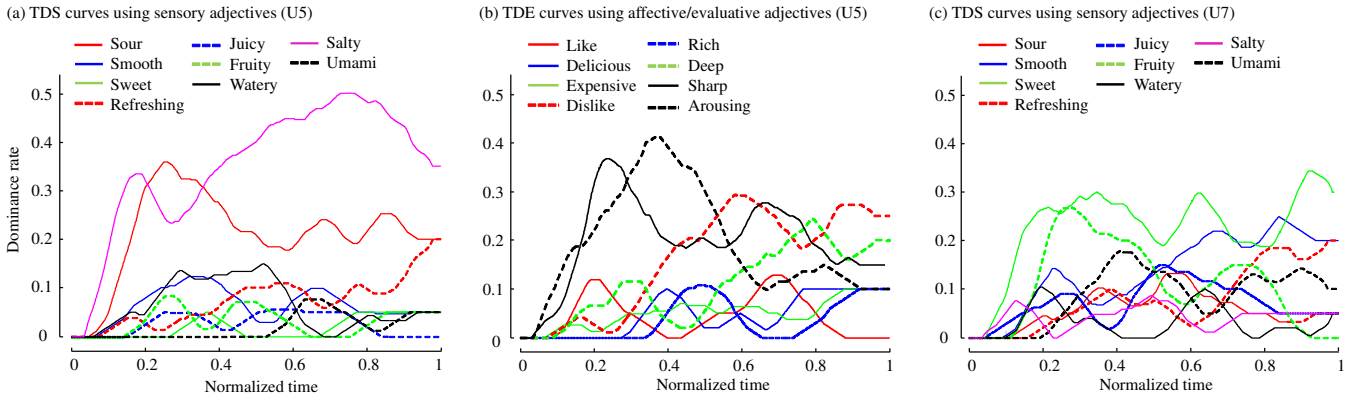

Fig. 2. Example of TD curves obtained for food specimens U5 and U7—(a) TDS curves for sensory descriptors for specimen U5; (b) TDE curves using affective/evaluative descriptors for specimen U5; (c) TDS curves using sensory descriptors for specimen U7. Normalized times 0 and 1 respectively indicate the commencement and end of an operation.

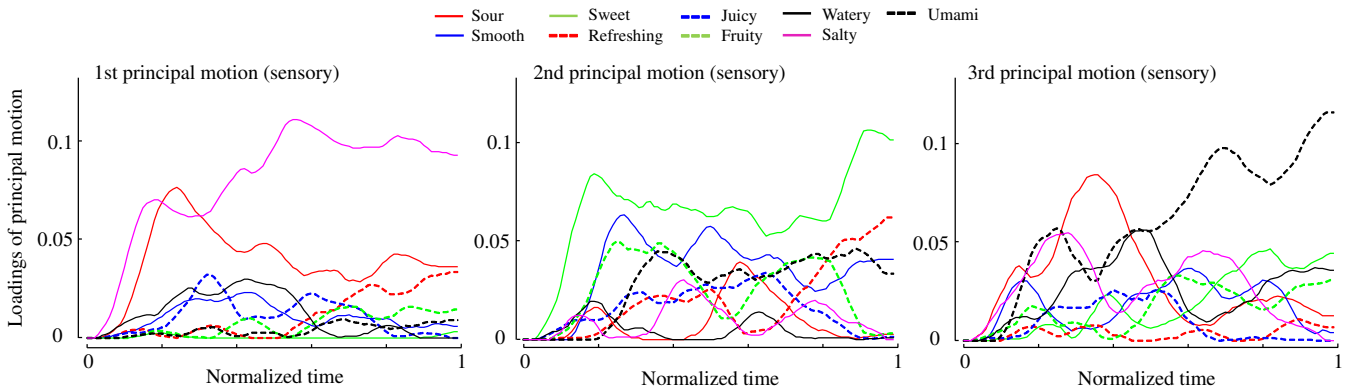

Fig. 3. First three principal motions of sensory responses obtained using TDS data.

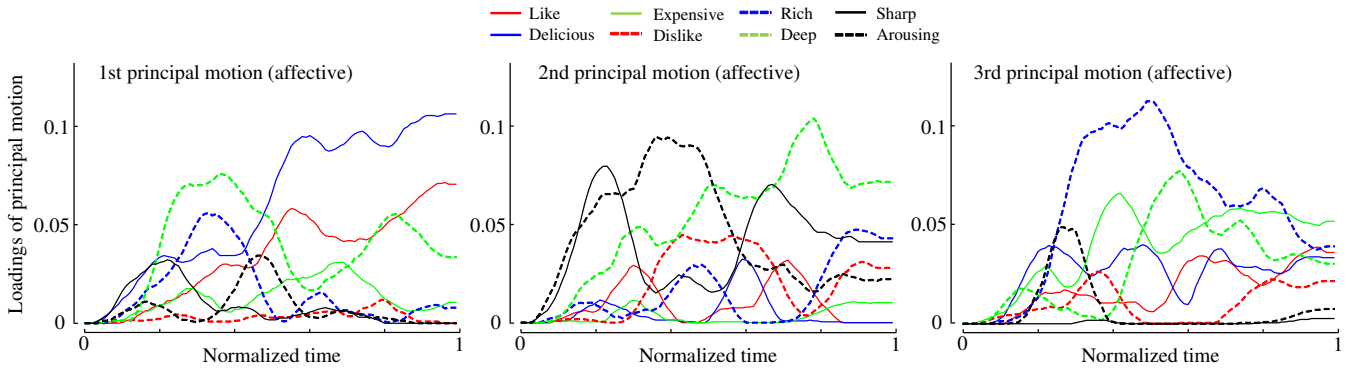

Fig. 4. First three principal motions of affective responses obtained using TDE data.

curves. Each continuous curve was split into 100 discrete points ($s = 100$). Finally, matrices with orders of 900 ($p = 9 \times s = 100$) $\times$ 200 ($n = 20 \times q = 10$) and 800 ($p = 8 \times s = 100$) $\times$ 200 corresponding to the sensory- and affective-descriptor sets, respectively, were separately used for PMA computation.

To compare PMA with representative analysis methods employed in extant studies, so-called dominance durations were also calculated using the original sample set. The dominance duration of a descriptor corresponds to the period for which the descriptor remains selected. Each sample was characterized by a set of nine (TDS task) and eight (TDE task) dominance durations. Principal component analysis (PCA) was then performed on 200 (10 products $\times$ 20 panelists) samples for each of the TDS and TDE tasks.

4.5.2 *Analysis of after-tasting SD task*

Responses obtained from each panelist were transformed into z-scores for each descriptor. Thus, one sample obtained from one panelist for one food product could be represented as a vector comprising nine or eight normalized variables,

and 200 (10 products $\times$ 20 panelists) such vectors were used to perform PCA.

In addition to the above-mentioned PCA computation using normalized raw sample data, PCA was also performed after resampling to facilitate comparison against PMA results. For each product, 20 vectors were sampled from the pool of the 20 panelists' responses, with successive replacements as described previously; subsequently, they were averaged to acquire a new sample vector. This process was repeated to prepare 20 new samples corresponding to each of the ten products. The 200 samples, thus prepared, were used to perform PCA computations.

4.5.3 Multivariate analysis of variance (MANOVA) for discriminating products

Food products considered in this study were discriminated by comparing their principal motion and principal component scores acquired, respectively, from the TD and aftertasting scoring tasks. To this end, multivariate analysis of variance (MANOVA) was used to compare two arbitrary products, each of which was characterized using multiple variables. Two major principal motions and components were employed because two is the number often adopted to represent samples on a planar sheet, and all the product pairs were discriminated by using only two principal motions computed from the TD results. Hence, each product was represented by two principal scores for either of the two tasks, meaning that the number of multivariate for MANOVA was two. One MANOVA test compared two products, each of which consisted of twenty samples. This was true for TD and SD tasks, and the numbers of samples used in the test were the same for all the combinations of tasks and descriptive word sets. This test was performed on all pairs prepared using the 10 products—45 pairs (${}_{10}\mathrm{P}_2$) in total. When the p-value of the test for a pair was observed to be less than 0.05, that pair was judged to be discriminated. The p-value was not corrected for multiple tests.

5 Results

5.1 TD-curve examples

Fig. 2 depicts TD curves computed using results obtained from panelist responses for two products—U5: basil-flavored and U7: honey-flavored—considered as examples. As regards product U5, *sour* and *salty* tastes were salient, and selection of these responses was observed to rapidly increase immediately after intake of product U5 (Fig. 2 (a)). Subsequently, responses corresponding to the *sour* experience became moderate, whereas those corresponding to intense *salty* experiences lasted until the end of the operation. Along with these two salient sensations, high values were recorded for *arousing* and *sharp*, both of which are stimulating experiences (Fig. 2 (b)). During the second half of the operation, responses corresponding to experiences *dislike* and *deep* gradually increased in number. In contrast, taste responses observed for the honey-flavored food specimen (U7) were *sweet* for the most part (Fig. 2 (c)). In particular, during the early phase, the sensory experience was rated to be *fruity* by most panelists. During the last phase, corresponding responses for U7 were observed to change to *sweet*, *smooth*, and *refreshing*. Thus, temporal sensory and affective responses concerning the two products demonstrated substantial change.

It is to be noted that during the very early phase of an operation, the sum of all response curves did not equal 1.0 because panelists were still indecisive about their dominant experiences, and thus, no options were selected during such phases. This phenomenon can be explained in terms of the delay in gustatory detection and identification [40].

5.2 Principal motions and scores

Figs. 3 and 4 depict examples of principal motions represented as TDS and TDE curves. Although only the first and second principal motions were considered during the product discrimination described in section 5.4, motions 1–3 have been depicted in these figures. Note that unlike PCA, the computation of contribution ratios does not hold for non-negative matrix factorization.

Primary motions concerning sensory descriptors are depicted in Fig. 3. As can be observed, the first motion was clearly featured by *sour* and *salty* responses. The *sour* response was observed to be more dominant during the early phase, whereas the *salty* response remained dominant until the end of the operation. The second motion was featured by responses *sweet* and *juicy*. During the last phase, the *refreshing* response was observed to gradually become dominant. The third principal motion can be described by the *sour* response during the early phase, and this was observed to change to *umami* during the second half of the operation.

Additionally, principal motions of affective responses are depicted in Fig. 4. The first motion mainly comprised positive experiences such as *like* and *delicious*. These responses seem to be strongly correlated. During the early phase, *deep* and *rich* responses were observed to be moderately dominant. The second motion was featured by the *sharp* and *arousing* responses during the early phase. Subsequently, the *deep* response was observed to gradually increase until the end of the operation. The third motion was featured by the *rich*, *deep*, and *expensive* responses, which correspond to positive feelings. However, interestingly, the third motion did not include dominant *like* and *delicious* responses.

Fig. 5 depicts distribution examples concerning the ten types of plum pickles on principal motion planes. For each product, the centroid and standard deviation of 20 samples prepared using the resampling method have been depicted. On the plane of sensory descriptors, basil-flavored pickles, such as samples U3, U5, and U10, exhibited high scores corresponding to the first principal motion featuring *sour* and *salty* responses. In contrast, honey-flavored pickles exhibited large scores corresponding to the second principal motion featuring *sweet* and *juicy* responses. Bonito-flavored pickles exhibited small first- and second-principal motion scores; however, large scores corresponding to the third principal motion were observed in this case, as described by the central plot in Fig. 5. The third motion demonstrated intense *umami* responses.

On the plane of affective descriptors, two honey-flavored pickles (U4 and U8) and one basil-flavored pickle (U9) were observed to demonstrate large scores corresponding to the

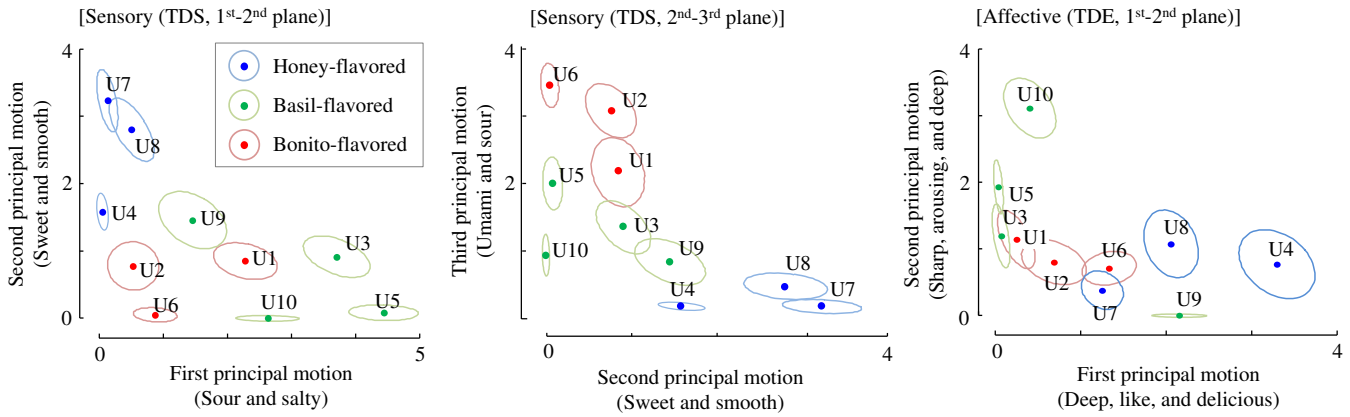

Fig. 5. Distribution of food samples on principal motion planes (TDS data). Dots denote centroids of samples, whereas the spread of ellipses denotes the region of influence of standard deviations.

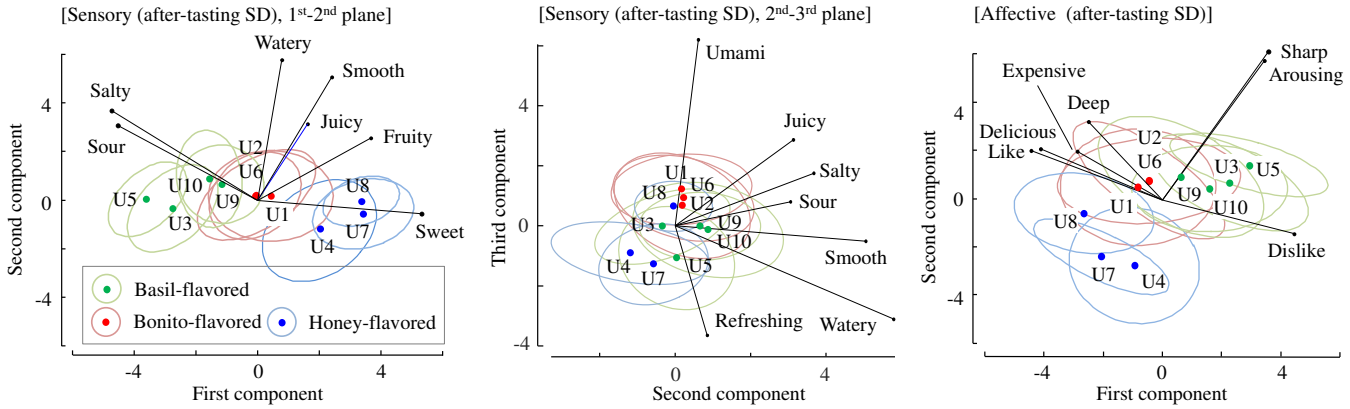

Fig. 6. Distribution of food samples on principal component planes computed by using ratings from SD tasks. Dots denote centroids of samples, whereas the spread of ellipses denotes the region of influence of standard deviations. Note that only those descriptors with large loadings have been considered for inclusion in this figure. Centroids of specimens U2 and U6 can be observed to be largely overlapped in the leftmost plot.

first principal motion. As depicted in Fig. 4, this motion was featured by a large number of *deep*, *like*, and *delicious* responses. One basil-flavored product (P10) exhibited large scores in terms of the second principal motion, including *sharp* and *arousing* responses. Food specimens, such as U1 and U2, demonstrating small scores for both the first- and second-principal motions exhibited large scores corresponding to the third-principal motion that featured *rich* and *deep* responses.

5.3 Principal component scores corresponding to after-tasting SD tasks

Fig. 6 depicts product distributions on principal component planes computed based on the responses obtained during the after-tasting SD task. Within the sensory descriptor space, contribution ratios for the first three principal components were observed to be 0.40, 0.17, and 0.11, respectively. The first component comprised three responses—*sweet*, *sour*, and *salty*. Honey-flavored pickles that were relatively sweet were placed within the positive region of the first component. In contrast, basil-flavored pickles with intense sourness were placed within the negative region. The second component that reflected the quality of plum pulps featured *watery* and *smooth* responses. The third component comprised *umami* responses, as described by the central plot in Fig. 6. Bonito-flavored products were placed within the positive region of the third component.

Contribution ratios concerning major principal components of affective responses obtained during the SD task equaled 0.48, 0.30, and 0.08. The first component was clearly represented by hedonic aspects, such as *like*, *delicious*, and *dislike*. *Deep* and *expensive* responses were also observed to align with the first component. The second component strongly featured the *sharp* and *arousing* responses. These affective responses were observed in combination with the *sour* and *salty* sensory responses. It can therefore be inferred that experiences of sharpness and arousal can be caused by *salty* and *sour* tastes.

When the resampling method was used during PCA, corresponding results were observed to be largely similar to those obtained using raw samples. No substantial differences were observed in dimensional structures, product allocation within spaces, or contribution ratios corresponding to major components.

TABLE 1
Number of product pairs discriminated by MANOVA. Forty-five pairs made of the 10 products were tested. For the methods using resampling, the values are means of 10 repetitions.

	After-tasting SD task		TD tasks	
	Normal PCA	Resampled PCA	PCA of dominance durations	PMA
Sensory	30	32.2	28	45.0
Affective	24	26.7	22	44.4

5.4 Statistical discrimination of products

Table 1 lists the number of statistically discriminated pairs prepared from among the ten products using the principal component and motion scores exclusively. Products were discriminated based on the planes of first-second principal components or motions. During implementation of the resampling method, sample sets were randomly produced. In such cases, therefore, resampling and test procedures were repeated ten times each, and corresponding mean values have been listed in Table 1. The differences between resampled pools were observed to demonstrate little impact on the discriminative performance. The number of discriminated pairs varied at most by 1 during the ten repetitions.

PMA results were observed to demonstrate the highest discrimination performance. In particular, when using TDS curves, discrimination of all products could be realized. Principal motion scores concerning affective responses were also highly discriminable. As depicted in Fig. 5, standard-deviation ellipsoids of products barely overlapped one another, and these can, therefore, be easily discriminated.

Interestingly, discriminative performances observed via normal PCA of data obtained during after-tasting SD tasks were found comparable to those observed via PCA of TD curves' dominance durations. Nonetheless, the number of discriminable pairs were of the order of 28–30 (62–67% of all pairs) and 22–24 (49–53%), corresponding to the sensory and affective descriptors, respectively. These numbers are very small compared to PMA, wherein discrimination of nearly all pairs could be realized.

As regards after-tasting SD tasks, use of the resampling technique slightly increased the number of discriminable pairs by two or three. It is to be noted that the number of samples analyzed was not increased by resampling, and that the degrees of freedom of MANOVA were identical under all test conditions.

6 Discussion

6.1 Semantic validity of PMA and PCA

As described in sections 5.2 and 5.3, respectively, on the principal-motion and principal-component planes, the allocations of products were reasonable considering the nominal flavors of products. Further, this section discusses the semantic consistency of results obtained using the TD method and performing after-tasting SD tasks. Some extant research efforts [18], [21], [23] have reported similar conclusions based on comparisons of results obtained via principal component analyses[5] of static sensory evaluation and TD methods [18], [21], [23]. Consequently, agreement between the two methods can be considered to corroborate the validity of experiments and analyses performed in this study.

As regards sensory responses, dimensional structures corresponding to the principal motion and component spaces did not demonstrate a perfect match. In the principal motion space depicted in Fig. 5, dimensions corresponding to the *sour* and *salty* responses (first dimension) were observed to be perpendicular to those corresponding to the *sweet* and *smooth* responses (second dimension). In contrast, in the principal component space depicted in Fig. 6, vectors corresponding to the *sour* and *salty* responses were observed to be directed opposite to the *sweet* response. They were perpendicular to those corresponding to the *smooth* responses. These differences were primarily caused by differences in the polarity of TD and SD tasks. TD tasks deal with fully unipolar properties, because all panelist response options considered in this study demonstrated only two states—selected or unselected, and non-negative matrix factorization produces only positive values. During SD tasks, however, each adjective demonstrated bipolar states—agree, neutral, and disagree. Hence, within the principal component space of SD tasks, the response opposite to *salty* and *sour* can semantically be considered to be *sweet*, which is psychologically correct [42]. Nonetheless, considering the gustatory system, wherein these three taste types are considered fundamental and independent [39], the *sweet* response is independent of the *sour* and *salty* responses. In this regard, the principal motion space is biologically sound.

With regard to affective responses, as depicted in Fig. 5 (right), food specimens U4, U8, and U9 exhibited large first-motion scores, whereas specimens U3, U5, and U10 demonstrated low scores. The first motion was characterized by responses *deep*, *like*, and *delicious*. As a result, food specimens U4, U8, and U9 were preferred over U3, U5, and U10. Likewise, on the right plot depicted in Fig. 6, food specimens U3, U5, and U10 were clearly *disliked*, whereas specimen U8 demonstrated large scores corresponding to the *like* and *delicious* responses. Specimens U4 and U9 were rather neutral in terms of likeability, and were, therefore, placed between vectors corresponding to the *like* and *dislike* responses. Further, as depicted in Fig. 6 (right), vectors corresponding to responses *like*, *delicious*, and *deep* demonstrate similar directions, which implies existence of a correlation between these responses during SD tasks. This demonstrates good agreement with results obtained for the first-principal motion using TDS curves exhibiting existence of a coupling between salient responses.

The dimensionality of the two affective spaces demonstrated good agreement with each other. In the TDE space depicted in Fig. 5 (right plot), the first dimension characterized by responses *like* and *delicious* was observed to be orthogonal to the second dimension characterized by responses *sharp* and *arousing*. *Deep* responses were included

5. They used canonical variates analysis (CVA), which is a variation of PCA. PCA and CVA result in similar conclusions with regard to sensory analysis data [41]. Furthermore, PCA tends to discriminate a greater number of product pairs compared to CVA, which is contradictory to intuition [41].

within both dimensions. This was also true within the space calculated using data obtained via SD tasks, as depicted in Fig. 6 (right plot). The *like-dislike* line was observed to be orthogonal to vectors for *sharp* and *arousing*. Further, the vector corresponding to the *deep* response was located between the two dimensions.

Overall, the principal-motion and principal-component spaces computed using the TD- and after-tasting SD-task data, respectively, did not include substantial inconsistencies.

6.2 Advantage of TD-PMA approach over conventional SD method

As described in Table 1, the TD method was observed to discriminate nearly all pairs of the ten food products. In contrast, the after-tasting SD method could discriminate only 30 and 24 product pairs (out of 45) corresponding to the sensory and affective descriptors, respectively. TD data contain information related to the temporal evolution of descriptors, and are richer compared to data acquired using the SD method. Thus, when considering time-series properties, the discrimination performance of food products is highly enhanced. The PMA approach facilitates performance of such statistical analyses of multivariate time-series information. Nonetheless, it must be noted that compared to TD methods, SD methods usually require panelists with more training, and that in this study, only university students were recruited instead of professional panelists.

PCA scores computed using dominance durations as variables were comparable or slightly inferior to those computed using results obtained via SD tasks in terms of product discrimination performance. This does not immediately indicate that the use of dominance durations is not recommended; however, their use also does not offer significant advantages over conventional scoring tasks. This is intuitively reasonable, because dominance durations are based on the most dominant experience being recorded at each instant without involving use of other information. For certain food products considered in this experiment, the dominance duration values of certain descriptors nearly equaled zero. For example, the *watery* response was rarely observed to become dominant throughout the experiment, and the corresponding dominance duration values remained nearly zero. During the scoring task, however, scores corresponding to the *watery* response varied among products, and therefore, could be used for product categorization.

6.3 Limitations of research

We resampled the results of twenty panelists in order to produce smooth TD curves for computing PMA. Without resampling, a large number of panelists would be required, which is costly and impractical for industrial purposes, or each panelist would need to replicate TD tasks multiple times, possibly more than ten, for the same food product to produce smooth TD curves. Such replication was not performed in earlier studies, potentially owing to limitations in availability of edible items. Hence, we consider that PMA and resampling of TD data are inseparable. Nonetheless, it remains unclear whether resampling causes any adverse effects on the conclusions. One concern is that resampling may enhance product discrimination as seen in the case of our PCA plus SD method. A noticeable warning at this point is that we should not conduct resampling based on the small original sample pool.

In addition, affective responses are generally highly individual, and this aspect has been extensively investigated in extant literature [43], [44], [45], [46], [47]. However, TD-based methods are not well compatible with individual analysis. When employing TD methods, responses from individual panelists are aggregated to produce a set of smooth TD curves. Hence, it automatically addresses average properties among panelists. Generation of TD curves for individual panelists requires a large number of repetitions per panelist; however, multiple repetitions of the same stimulus by the same panelist may lead to unknown problems with regard to data analysis. The proposed method is unsuitable with regard to performing individual analysis, owing to the resampling of new sample sets from original ones. In contrast, static sensory evaluation methods, such as the semantic differential technique and sensory profiling, facilitate analysis of individual differences. From this aspect, TD methods may as well be used in conjunction with static methods, as suggested in [21]. Further, they must be complementary in terms of the number of descriptive norms; i.e., the number of descriptors used during a single operation of a TD task must be less than ten [19] to avoid overloading of panelists. In contrast, more descriptors can be used when implementing static methods.

7 Conclusions

This study demonstrates successful validation of principal-motion analysis (PMA) of TD data concerning temporal changes in multiple sensory and affective experiences of recruited panelists for tasting of food products. As observed, PMA linearly decomposes multivariate time-series data into a small number of principal motions that are easily interpretable and common among all samples. Using two scores, each of which corresponded to the first- and second-principal motions, pairs of ten plum pickles were judged to be different with near perfection when pre-prepared sets of sensory or affective descriptors were used during the TD task. In contrast, results obtained through the semantic differential (SD) method—performed as representative of a conventional static method—demonstrated discrimination of only 30 and 24 pairs (out of 45 each) using sensory and affective descriptors, respectively. Results obtained via PCA and PMA using SD and TD data, respectively, were observed to be semantically consistent. It can, therefore, be concluded that PMA is suitable for use in conjunction with the TD method, especially with regard to product discrimination.

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References

[1] R. Cowie, G. McKeown, and E. Douglas-Cowie, "Tracing emotion: an overview," *International Journal of Synthetic Emotions*, vol. 3, no. 1, pp. 1–17, 2012.

[2] W. E. Lee III and M. Pangborn, "Time-intensity: the temporal aspects of sensory perception," *Food technology*, pp. 71–78, 1986.

[3] 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.

[4] G. Jager, P. Schlich, I. Tijssen, J. Yao, M. Visalli, C. De Graaf, and M. Stieger, "Temporal dominance of emotions: Measuring dynamics of food-related emotions during consumption," *Food Quality and Preference*, vol. 37, pp. 87–99, 2014.

[5] N. Pineau and P. Schilch, "Temporal dominance of sensations (TDS) as a sensory profiling technique," in *Rapid Sensory Profiling Techniques*. Elsevier, 2015, pp. 269–306.

[6] L. M. Duizer, K. Bloom, and C. J. Findlay, "Dual-attribute time-intensity measurement of sweetness and peppermint perception of chewing-gum," *Journal of Food Science*, vol. 61, no. 3, pp. 636–638, 1997.

[7] S.-M. Miettinen, L. Hyvönen, R. S. T. Linforth, A. J. Taylor, and H. Tuorila, "Temporal aroma delivery from milk systems containing 0–5% added fat, observed by free choice profiling, time intensity, and atmospheric pressure chemical ionization-mass spectrometry techniques," *Journal of Agricultural and Food Chemistry*, vol. 52, no. 26, pp. 8111–8118, 2004.

[8] D. W. Ningtyas, B. Bhandari, N. Bansal, and S. Prakash, "Sequential aspects of cream cheese texture perception using temporal dominance of sensations (TDS) tool and its relation with flow and lubrication behaviour," *Food Research International*, 2018.

[9] M. Sokolowsky and U. Fischer, "Evaluation of bitterness in white wine applying descriptive analysis, time-intensity analysis, and temporal dominance of sensations analysis," *Analytica Chimica Acta*, vol. 732, pp. 46 – 52, 2012, a selection of papers presented at In Vino Analytica Scientia.

[10] "Case study 6 - a temporal dominance of sensation (tds) analysis of three winesa," in *Sensory and Instrumental Evaluation of Alcoholic Beverages*, H. Heymann and S. E. Ebeler, Eds. San Diego: Academic Press, 2017, pp. 198 – 204.

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

[12] M. Ng, J. Lawlor, S. Chandra, C. Chaya, L. Hewson, and J. Hort, "Using quantitative descriptive analysis and temporal dominance of sensations analysis as complementary methods for profiling commercial blackcurrant squashes," *Food Quality and Preference*, vol. 25, no. 2, pp. 121 – 134, 2012.

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

[14] P. Varela, L. Antúnez, M. Carlehög, F. Alcaire, J. C. Castura, I. Berget, A. Giménez, T. Næs, and G. Ares, "What is dominance? An exploration of the concept in TDS tests with trained assessors and consumers," *Food Quality and Preference*, vol. 64, pp. 72–81, 2018.

[15] J. F. Rodrigues, V. R. de Souza, R. R. Lima, J. ao de Deus Souza Carneiro, C. A. Nunes, and A. C. M. Pinheiro, "Temporal dominance of sensations (TDS) panel behavior: A preliminary study with chocolate," *Food Quality and Preference*, vol. 54, pp. 51 – 57, 2016.

[16] G. Ares, S. R. Jaeger, L. Antúnez, L. Vidal, A. Giménez, B. Coste, A. Picallo, and J. C. Castura, "Comparison of tcata and tds for dynamic sensory characterization of food products," *Food Research International*, vol. 78, pp. 148–158, 2015.

[17] Q. C. Nguyen, T. Næs, and P. Varela, "When the choice of the temporal method does make a difference: TCATA, TDS and TDS by modality for characterizing semi-solid foods," *Food Quality and Preference*, vol. 66, pp. 95–106, 2018.

[18] A. Saint-Eve, I. Déléris, M. Panouillé, F. Dakowski, S. Cordelle, P. Schlich, and I. Souchon, "How texture influences aroma and taste perception over time in candies," *Chemosensory Perception*, vol. 4, no. 1, p. 32, Apr 2011.

[19] N. Pineau, A. G. de Bouillé, M. Lepage, F. Lenfant, P. Schlich, N. Martin, and A. Rytz, "Temporal dominance of sensations: What is a good attribute list?" *Food quality and preference*, vol. 26, no. 2, pp. 159–165, 2012.

[20] M. Lepage, T. Neville, A. Rytz, P. Schlich, N. Martin, and N. Pineau, "Panel performance for temporal dominance of sensations," *Food Quality and Preference*, vol. 38, pp. 24 – 29, 2014.

[21] "Temporal dominance of sensations and sensory profiling: A comparative study," *Food Quality and Preference*, vol. 20, no. 3, pp. 216 – 221, 2009.

[22] R. van Bommel, M. Stieger, P. Schlich, and G. Jager, "Dutch consumers do not hesitate: Capturing implicit 'no dominance' durations using hold-down temporal dominance methodologies for sensations (TDS) and emotions (TDE)," *Food Quality and Preference*, vol. 71, pp. 332 – 342, 2019.

[23] A. Albert, A. Salvador, P. Schlich, and S. Fiszman, "Comparison between temporal dominance of sensations (TDS) and key-attribute sensory profiling for evaluating solid food with contrasting textural layers: Fish sticks," *Food Quality and Preference*, vol. 24, no. 1, pp. 111 – 118, 2012.

[24] A. Thomas, M. Visalli, S. Cordelle, and P. Schlich, "Temporal drivers of liking," *Food Quality and Preference*, vol. 40, pp. 365–375, 2015.

[25] M. Sokolowsky, A. Rosenberger, and U. Fischer, "Sensory impact of skin contact on white wines characterized by descriptive analysis, time-intensity analysis and temporal dominance of sensations analysis," *Food Quality and Preference*, vol. 39, pp. 285–297, 2015.

[26] C. Dinnella, C. Masi, G. Zoboli, and E. Monteleone, "Sensory functionality of extra-virgin olive oil in vegetable foods assessed by temporal dominance of sensations and descriptive analysis," *Food Quality and Preference*, vol. 26, no. 2, pp. 141 – 150, 2012.

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

[28] 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.

[29] F. C. Park and K. Jo, "Movement primitives and principal component analysis," in *On Advances in Robot Kinematics*, J. Lenarčič and C. Galletti, Eds. Dordrecht: Springer Netherlands, 2004, pp. 421–430.

[30] B. Lim, S. Ra, and F. C. Park, "Movement primitives, principal component analysis, and the efficient generation of natural motions," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, 2005, pp. 4630–4635.

[31] R. Di Monaco, "Temporal dominance of sensations: A review," *Trends in Food Science & Technology*, vol. 38, no. 2, pp. 104 – 112, 2014.

[32] 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.

[33] K. Mishima, S. Kanata, H. Nakanishi, Y. Horiguchi, and T. Sawaragi, "Extraction of similarities and differences in human behavior using singular value decomposition," *Proceedings of the Japan Joint Automatic Control Conference*, vol. 52, pp. 39–44, 2009.

[34] J. Aleotti, A. Cionini, L. Fontanili, and S. Caselli, "Arm gesture recognition and humanoid imitation using functional principal component analysis," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2013, pp. 3752–3758.

[35] N. Yamada, S. Okamoto, H. Okumura, Y. Yamada, K. Isogai, and K. Kawakami, "Similarities and differences in manual stretching of physical therapists for equinovarus," *Proceedings of IEEE/SICE International Symposium on System Integration*, pp. 490–495, 2014.

[36] D. D. Lee and H. S. Seung, "Algorithms for non-negative matrix factorization," in *Proceedings of the 13th International Conference on Neural Information Processing Systems*, ser. NIPS'00. MIT Press, 2000, pp. 535–541.

[37] B. Efron, "Bootstrap methods: Another look at the jackknife," *The Annals of Statistics*, vol. 7, no. 1, pp. 1–26, 1979.

[38] B. Efron and R. J. Tibshirani, *An Introduction to the Bootstrap*. Chapman & Hall, 1993.

[39] B. Lindemann, "Taste reception," *Physiological Reviews*, vol. 76, no. 3, pp. 719–766, 1996.

[40] R. Wallroth and K. Ohla, "As soon as you taste it: Evidence for sequential and parallel processing of gustatory information," *eNeuro*, vol. 5, no. 5, pp. e0269–18.2018, 2018.

[41] 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.

[42] S. S. Schiffman and R. P. Erickson, "A psychophysical model for gustatory quality," *Physiology and Behavior*, vol. 7, pp. 617–633, 1971.
[43] 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.
[44] A. Klöcker, C. Arnould, M. Penta, and J.-L. Thonnard, "Rasch-built measure of pleasant touch through active fingertip explorations," *Frontiers in Neurorobotics*, vol. 6, no. 5, 2012.
[45] I. Soufflet, M. Calonnier, and C. Dacremont, "A comparison between industrial experts' and novices' haptic perceptual organization: a tool to identify descriptors of the handle of fabrics," *Food Quality and Preference*, vol. 15, pp. 689–699, 2004.
[46] T. Ishikawa, S. Nakamori, K. Sasaki, K. Miyatake, and M. Ayama, "Investigation of appearance and tactile sensation scales for evaluating clothes in online shopping," *Proceedings of the International Conference on Kansei Engineering and Emotion Research*, pp. 537–543, 2014.
[47] T. Chamorro-Premuzic, C. Burke, A. Hsu, and V. Swami, "Personality predictors of artistic preferences as a function of the emotional valence and perceived complexity of paintings," *Psychology of Aesthetics Creativity and the Arts*, vol. 4, no. 4, pp. 196–204, 2010.

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