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Technical Paper

Trajectory plots that highlight statistically different periods among multiple foods studied using the temporal dominance of sensations method

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The temporal dominance of sensations (TDS) method allows us to record temporal changes in multiple sensations during an experience, such as eating food. A trajectory plot is used to visualize the experimental results of the TDS method and is useful for comprehending multidimensional sensory transitions in a low-dimensional principal component space. Castura *et al.* (2023) proposed an approach to statistically compare multiple food products in such spaces. We rectify the hypothesis-testing method of that approach and modify the visualization method, such that the periods in which the products are statistically different from each other are easily recognized. The developed method helps us understand when and how a food product feels different from others during the eating experience and can contribute to designing new products by focusing on their time-series experience.

Keywords: temporal dominance of sensations (TDS), bootstrap resampling, *t*-squared test, data visualization

Introduction

The temporal dominance of sensations (TDS) method (Pineau *et al.*, 2009; ISO 13299, 2016; Visalli *et al.*, 2023) allows us to record time-evolving changes in multiple sensation types. Popular visualization methods for TDS task results include TDS curves (Pineau *et al.*, 2009) and trajectory plots (Lenfant *et al.*, 2009). The former method exhibits temporal changes in the dominance of individual tastes, flavors, and mouth sensations on a plane in which the horizontal axis is time. Hence, TDS curves are suitable for inspecting changes in individual sensations over time. In contrast, TDS trajectories present no time axis and exhibit transitions of multiple types of sensations in a multidimensional space, which is typically a two-dimensional plane owing to visual clarity. The TDS trajectory method allows for the simultaneous comparison of multiple food products in the same space (Merlo *et al.*, 2019; Nguyen and Wismer, 2022; Delompré *et al.*, 2020).

Nonetheless, until recently, no statistical methods or hypothesis tests were available to compare TDS trajectories among food products. The biggest reason for this is that the uncertainty or potential variability of the trajectories cannot be estimated based on the results of the standard protocols of the TDS method. Castura *et al.* (2023) solved this problem using a bootstrap resampling method. The bootstrap resampling method for the TDS method was introduced by Okamoto *et al.* (2020, 2021) and enables the estimation of population parameters related to uncertainty and data augmentation from a population with limited samples. Using the resampling method, Castura *et al.* (2023) computed the confidence intervals of trajectory plots and contrasted them; then, they used this method to discriminate three types of wines. Their approach allowed a statistical comparison of eating experiences between more than two distinct foods using trajectory plots.

This study modifies the method of Castura *et al.* (2023) in two ways. First, to compare two trajectories in a multidimensional space, t^2-tests involving multiple dimensions were used, whereas, Castura *et al.* (2023) conducted a hypothesis test for each dimension. Second, we

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introduced a visualization method that clarified the periods of a trajectory that were significantly different from others, which allowed us to easily recognize meaningful differences among multiple TDS trajectories. Castura *et al.* (2023) effectively used animations to show the confidence intervals of multiple trajectories at each moment, whereas our method is more suitable for still images. The trajectory plot is an effective method to facilitate the simultaneous comparison of more than two food products. The method of visualizing statistical differences between the trajectories of different products provides analysts with valuable insights into temporal experiences. Owing to the modifications made in this study, TDS trajectories will become a more effective visualization and analysis method. This study is an extension of the research presented by Natsume *et al.* (2023b), where only two food products were compared in a non-statistical manner, whereas, the method of the present study allows for the comparison of two or more products using hypothesis testing.

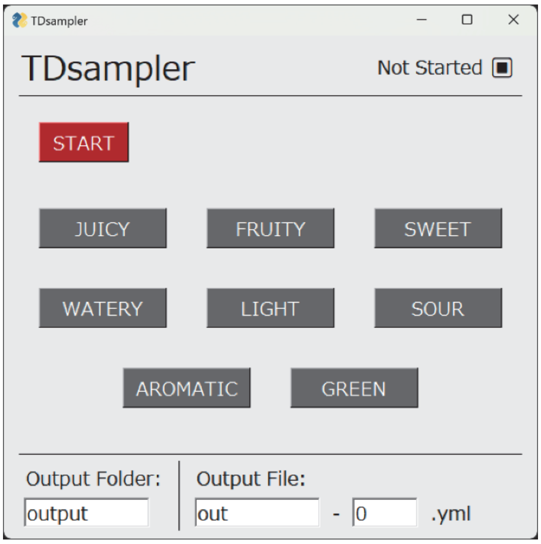

Fig. 1. The graphical interface used in the temporal dominance of sensations (TDS) tasks. Each button represents an attribute word. Adapted from Natsume *et al.* (2023a).

Materials and Methods

Procedures for the temporal dominance of sensations method Here, general procedures for a TDS task are outlined to help understand this paper. Further details are provided in the literature (ISO, 2016; Pineau *et al.*, 2009; Pineau & Schlich, 2015). The TDS task is performed using a computer. As shown in Fig. 1, the attribute words are displayed on the screen as buttons, including the start and stop buttons. The task begins when the panelist places the food sample in its mouth and presses the start button. Then, the panelist selects an attribute word that describes the dominant sensation. When the dominant sensation changes, the panelist selects another button, and the currently selected button is automatically unselected. In the standard method of ISO 13299, multiple buttons cannot be selected simultaneously (ISO, 2016). Some attribute words are selected multiple times or never selected. When the food sample is swallowed, the panelist presses the stop button to end the task. The panelist repeats the task several times for the same food. More than ten panelists are recommended for each food product (ISO, 2016).

Temporal dominance of sensations curves The result of a TDS task is a set of binary functions of a continuous time t. The function for the i-th attribute of the j-th trial is represented as $f_i^{(j)}(t)$. The parameter t is the time normalized between 0 and 1, which represent the moments when the start and stop buttons are pressed, respectively. At an arbitrary t, $f_i^{(j)}(t) = 1$ if word i is selected, otherwise, $f_i^{(j)}(t) = 0$.

TDS curves (ISO, 2016; Pineau *et al.*, 2009) are typically used to visualize the results. The TDS curve is the mean of all trials at t. Hence, the curve $p_i(t)$ for the i-th attribute is given by:

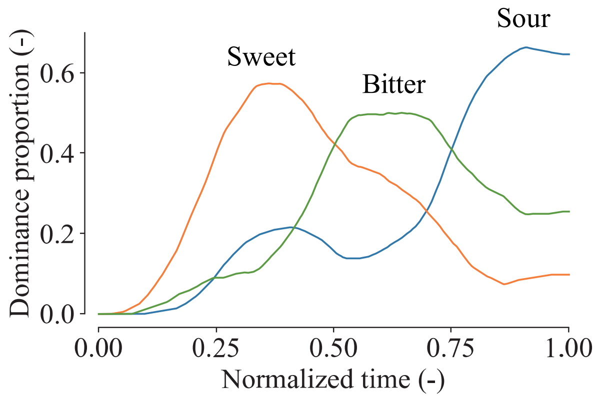

Fig. 2. An example of the TDS curves of three attributes, namely sweet, sour, and bitter.

$$p_i(t) = \frac{1}{n}\sum_{j=1}^{n} f_i^{(j)}(t), \quad \cdots\cdots \text{ Eq. 1}$$

where n is the total number of trials. The TDS curve for each attribute word indicates the dominance proportion, which is the proportion of trials in which the attribute word is selected at time t. Fig. 2 shows an example of the TDS curves. Note that TDS tasks typically involve several attributes; however, for visual clarity, this example includes only three attributes. The sweet and bitter attributes are prominent at approximately $t = 0.3$ and 0.6, respectively. The sour attribute is the most prominent at the end of the task, with a proportion of approximately 0.6, indicating that it is selected in 60 % of all the trials in the last phase.

Trajectory plots of the temporal dominance of sensations *curves in the principal component space* Before computing the trajectory plots, the continuous TDS curves are discretized into arbitrary R intervals in the time domain using Eq. 2. In this study, we computed trajectory plots at 1 000 discretized intervals ($R = 1\,000$).

$$P_i[k] = R \int_{\frac{k}{R}}^{\frac{k+1}{R}} p_i(t)\, dt \qquad \cdots\cdots \text{ Eq. 2}$$

In Eq. 2, $P_i[k]$ is the discretized curve value on the k-th interval ($k = 0, 1, \ldots, R-1$). This conversion uses the average of $p_i(t)$ for each discretized interval.

A trajectory plot (Lenfant *et al.*, 2009) shows the temporal evolution of the dominant proportions of all attributes for a certain food using a single curve. In other words, multiple TDS curves, that is, multidimensional sensory changes, are compressed into a single curve. Trajectory plots of TDS curves are typically drawn by plotting the first and second principal component scores of $P_i[k]$ on a two-dimensional principal component plane. However, they can be determined in a space with higher dimensions using the third and remaining principal components. Scores are obtained by performing a principal component analysis on vectors $(P_1[k], \ldots, P_i[k], \ldots, P_{i'}[k])^{\mathrm{T}}$ with attribute words as variables, where i' is the number of attributes. There are R scores per set of TDS curves. Fig. 3 shows an example of a trajectory plot. The vectors for the attributes are also presented. The horizontal axis represents the score for the first principal component and is mostly aligned with the sour vector, indicating that higher scores along this axis are sourer. Similarly, the vertical axis corresponds to the second principal score and is characterized as sweet and bitter.

Bootstrap resampling of the temporal dominance of sensations data In the TDS method, a food product produces a set of TDS curves, from which one trajectory curve is drawn. Bootstrap resampling can be used to compute the uncertainty of the TDS curves and trajectory (Okamoto *et al.*, 2020; Okamoto, 2021; Castura *et al.*, 2023). As shown in Fig. 4, using this method, a new sample set is established by sampling

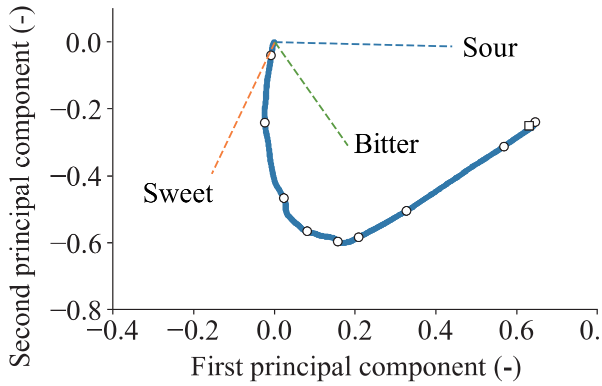

Fig. 3. An example of a trajectory plot, which corresponds to the trajectory of the TDS curves in Fig. 2. Straight lines starting from the origin are the vectors of attributes. The blank circles and square at the end of the trajectory split the whole tasting period into ten equal sub-periods at $t = 0.1, 0.2, \ldots, 1.0$. The trajectory transits between the sweet and bitter attributes in the first half of the period and between the bitter and sour attributes in the second half.

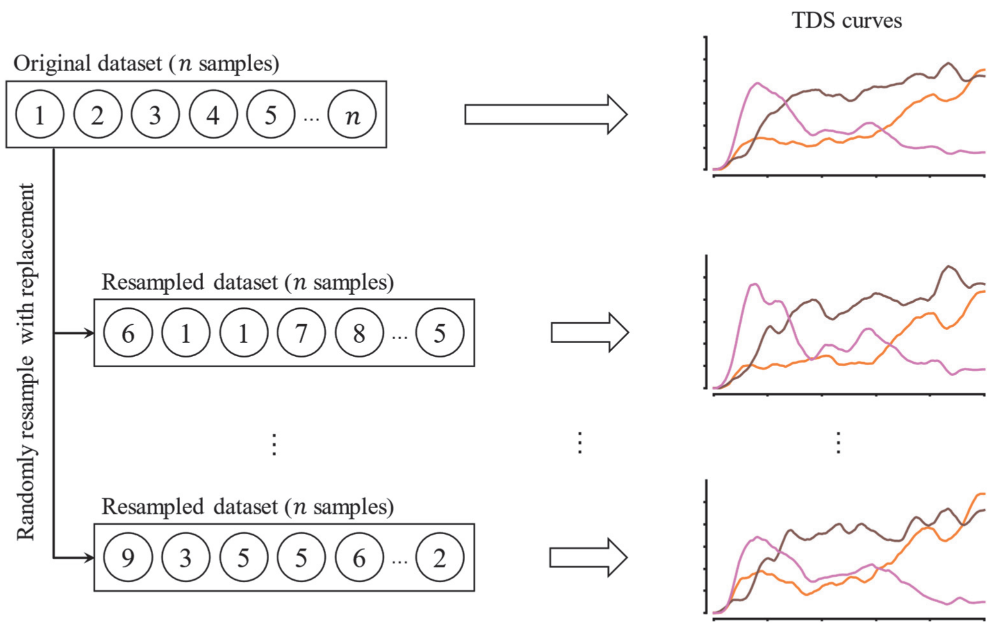

Fig. 4. Bootstrap resampling, in which a dataset, namely a set of TDS trials, of the same size as the original dataset is generated by randomly resampling elements with duplicates from the original dataset. For each resampled dataset, a trajectory curve is calculated. This operation is repeated many times to acquire the distribution of trajectory curves.

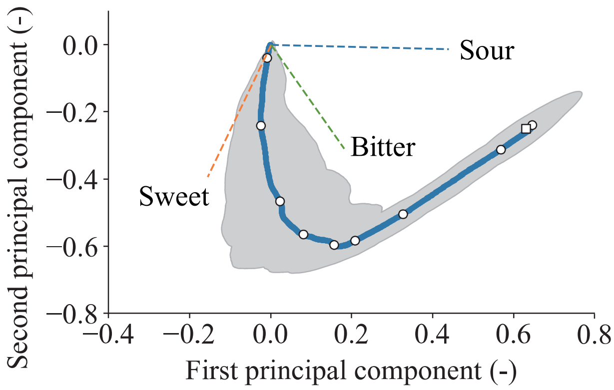

Fig. 5. The trajectory plot of Fig. 3 with overlaid 95 % confidence ellipsoids.

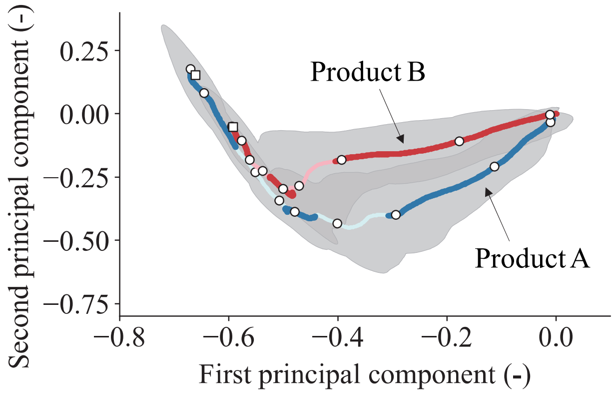

Fig. 6. An example of the visualization of statistically different periods. During the periods represented by bold lines, the two products are significantly different from each other on the principal component space.

with replacement. When an experiment originally includes n trials for a food product, a new sample set includes n trials drawn from the original sample set with a replacement. The TDS curves and corresponding trajectories are computed for the new sample set. This process is repeated hundreds of times to compute the uncertainty, that is, the confidence interval of the trajectory. In our study, the number of repetitions for each food product was 200.

Confidence intervals for the trajectory plots The uncertainty of the locus of each discrete point in the trajectory plot can be estimated using a dataset generated by the bootstrap resampling method (Castura *et al.*, 2023). Here, as an index of uncertainty, we used a 95 % confidence interval (Okamoto *et al.*, 2021; Castura *et al.*, 2023). For each time point, based on the distribution of the samples, the 95 % confidence interval ellipsoid is given by:

$$(\boldsymbol{x}-\bar{\boldsymbol{x}})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\bar{\boldsymbol{x}}) = \chi^2_{q,0.05}\,, \qquad \cdots\cdots \text{ Eq. 3}$$

where $\boldsymbol{x} = (x_1, \dots, x_q)^{\mathrm{T}}$ is the coordinate on the q-dimensional space, and $\bar{\boldsymbol{x}}$ and $\boldsymbol{\Sigma} \in \mathbb{R}^{q\times q}$ are the centroid vector and variance-covariance matrix for the resampled points, respectively. The parameter $\chi^2_{q,0.05}$ is the chi-squared value of the degree of freedom q at a significance probability of 0.05. In the case of the two-dimensional principal component plane, $q = 2$ and $\chi^2_{q,0.05} = 5.99$. Fig. 5 shows the trajectory plot of Fig. 3 with 95 % confidence intervals. The gray areas represent the overlaid confidence ellipses for all discrete time points.

Judgment of the significant differences between multiple trajectory plots First, we describe a method for comparing two food products, namely A and B, where $\bar{\boldsymbol{x}}_A[k] = \left(\bar{x}_A^{(1)}[k], \dots, \bar{x}_A^{(q)}[k]\right)^{\mathrm{T}}$ and $\bar{\boldsymbol{x}}_B[k] = \left(\bar{x}_B^{(1)}[k], \dots, \bar{x}_B^{(q)}[k]\right)^{\mathrm{T}}$, respectively, are the mean coordinate vectors of the resampled trajectories of A and B in a q-dimensional principal component space at a particular time k $(k = 0, 1, \dots, R-1)$.

To compare the trajectories of A and B, a hypothesis test was used to determine the significant differences in the principal component space at each discretized moment. We used the t^2-test to determine whether the centroids of the two groups differed significantly. As described in the *Introduction*, Castura *et al.* (2023) judged the difference between two products by performing a t-test on each dimension of the principal component space. However, in a multidimensional space, the judgment should be based on the distance between the centroids of the two groups, considering the covariance structure among multiple variables.

The t^2 statistic is computed as

$$t^2 = \frac{n_A n_B}{n_A + n_B}(\bar{\boldsymbol{x}}_A - \bar{\boldsymbol{x}}_B)^{\mathrm{T}}\boldsymbol{S}^{-1}(\bar{\boldsymbol{x}}_A - \bar{\boldsymbol{x}}_B), \qquad \cdots\cdots \text{ Eq. 4}$$

where n_A and n_B are the sizes of the resampled datasets for products A and B, respectively. In addition, $\boldsymbol{S} \in \mathbb{R}^{q\times q}$ is the pooled variance-covariance matrix for the two products. The t^2 value approximately follows an F distribution:

$$F = \frac{n_A + n_B - q - 1}{(n_A + n_B - 2)q}t^2 \sim F(q, n_A + n_B - 1 - q). \qquad \cdots\cdots \text{ Eq. 5}$$

If the F value is greater than the critical value of $F(q, n_A + n_B - 1 - q)$ at a significant probability α, then the trajectory points of products A and B are considered significantly different.

In the interval immediately after the start button is pressed, the two products are not compared because the $\boldsymbol{S}^{-1}$ cannot be computed. In such an interval, we treat the coordinates of the trajectory as fixed at the origin, and the mean coordinate vector of one product in Eq. 4 is set to $\mathbf{0}$, that is, $\bar{\boldsymbol{x}}_B = \mathbf{0}$, and t^2 is computed using Eq. 6.

$$t^2 = n_A(\bar{\boldsymbol{x}}_A - \mathbf{0})^{\mathrm{T}}\boldsymbol{S}^{-1}(\bar{\boldsymbol{x}}_A - \mathbf{0}). \qquad \cdots\cdots \text{ Eq. 6}$$

Table 1. Definitions of eleven attributes used for TDS tasks.

Attributes	Description
Umami	One of the basic tastes. No definition was provided.
Juicy	Lots of juice extracted in the mouth.
Fragile	Easily broken down into pieces.
Sweet	One of the basic tastes. No definition was provided.
Elastic	After being bitten, the ham is likely to return to its original shape.
Salty	One of the basic tastes. No definition was provided.
Dry	Ham includes little juice.
Fatty	The ham includes fat that melts in the mouth.
Soft	Small biting force is required.
Smoky	Taste and smell of smoked food.
Fibrous	Ham includes lots of fibers.

The trajectory of product B is fixed to the origin, and the $\boldsymbol{S}$ is computed using only product A. The corresponding F statistic is determined as follows:

$$F = \frac{n_A - q}{(n_A - 1)q} t^2 \sim F(q, n_A - q). \quad \cdots\cdots \text{ Eq. 7}$$

Note that such intervals exist near the origin in the principal component space.

When more than two products are compared, the t^2-test is performed multiple times. The Bonferroni correction of the critical probability is applied when comparing m $(m > 2)$ products (Castura et al., 2023). For example, when we want to know whether a product is different from others, we repeat the t^2-tests to make comparisons between the products. Hence, the hypothesis tests are repeated $m - 1$ times for each time point. For each test, the significant probability α is adjusted by a factor of $m - 1$.

Visualization of multiple trajectories with significantly different periods We draw trajectory plots of multiple products for comparison in the same principal component space. Fig. 6 shows an example of the trajectories for two products. The intervals in which the two products are significantly different are represented by bold lines, and the intervals with no significant differences are represented by thin lines. This helps us visually understand when these products are experienced distinctly during eating. When three or more products are being addressed simultaneously, regarding a certain product, bold lines are drawn along periods when that product is significantly different from any of the others.

Example using Five Processed Hams

Temporal dominance of sensations data for processed hams We used data collected by Hariu *et al*. (2023), in which TDS tasks were performed on commercially available processed hams. We used the data for five types of ham priced at approximately 30–50 JPY per slice. The five products were labeled as Hams 1, 2, 3, 4, and 5. For each product, 55 trials were conducted, that is, two to four trials were conducted for individual assessors. Eighteen university students in their twenties (15 males and 3 females) joined as assessors and ate a piece of ham cut into 3 × 5 cm pieces, which were kept at room temperature.

The attributes used in the assessment were umami, juicy, fragile, sweet, elastic, salty, dry, fatty, soft, smoky, and fibrous. These attributes were selected from the pool of 85 attribute words established in the literature, such as Lorido *et al*. (2016). For the selection, six panelists including the authors and their colleagues rated all the attributes applicable to express the tastes of ham in a check-all-that-apply manner. Fifteen highly voted for attributes were then examined via preliminary TDS trials, in which four attributes were rarely used by the panels. Table 1 lists the definitions of 11 attributes provided to the panelists.

Fig. 7 shows the TDS curves for the five products. For Ham 1, the elastic and salty attributes are prominent in the early and later phases, respectively. For Ham 2, the soft, elastic, and sweet attributes are dominant in the early phase, whereas the fragile attribute is prominent in the last phase. For Ham 3, the elastic and salty attributes are dominant in the early and remaining periods, respectively. For Ham 4, the dry and elastic attributes are prominent in the early phase, whereas the salty, fragile, and fibrous attributes are prominent in a later phase. For Ham 5, the elastic, fatty, and umami attributes are prominent in the early phase, and the salty attribute is prominent in a later phase.

Trajectory plots with confidence intervals and significantly different periods For each ham product, we obtained 200 sets of resampled TDS curves with $n = 55$ and $n_{\mathrm{A}} = n_B = 200$ to compute the 95 % confidence intervals. The overall significance level for the multiple comparison was

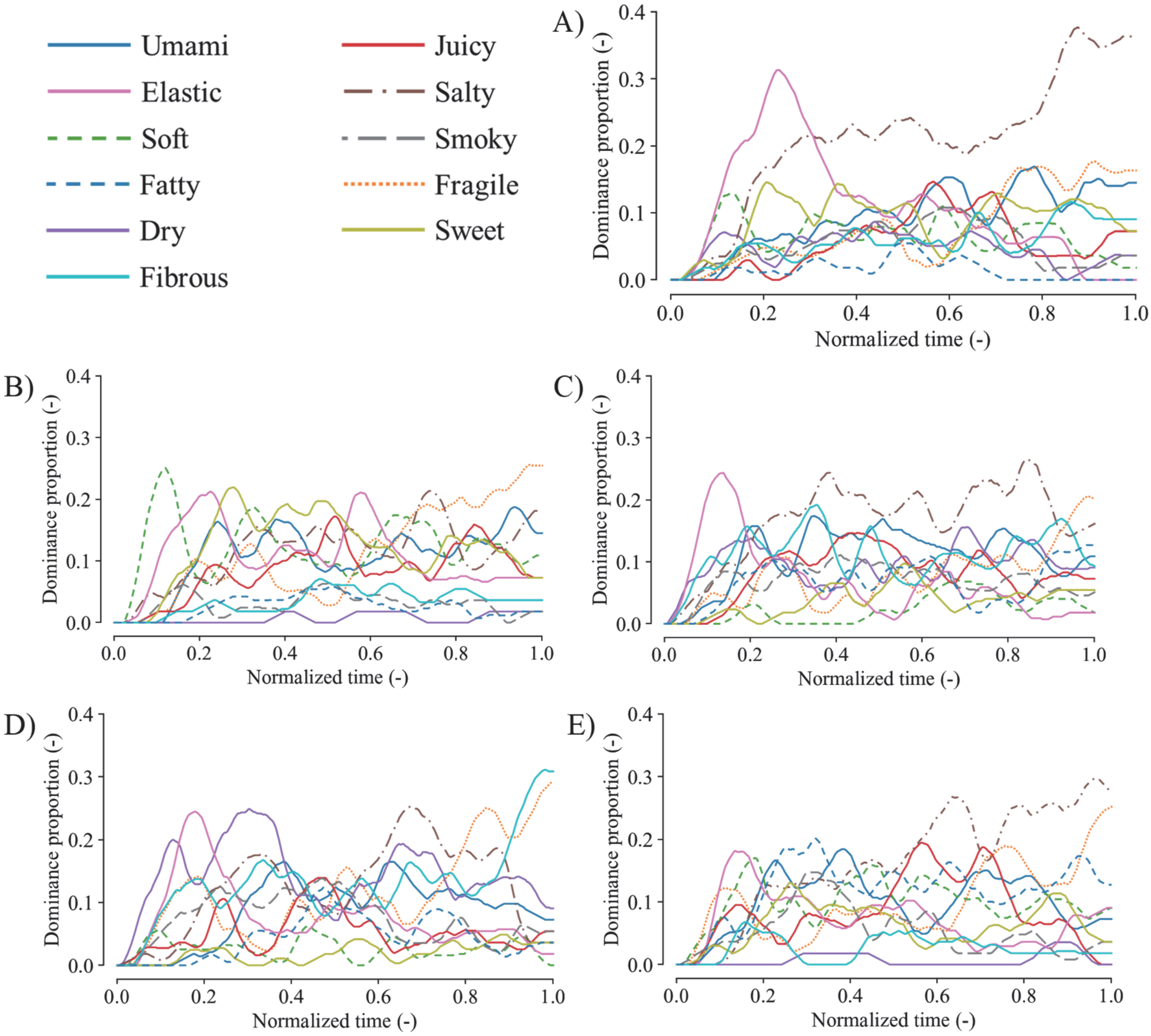

Fig. 7. TDS curves of five ham products. TDS curves of Hams (A) 1, (B) 2, (C) 3, (D) 4, and (E) 5.

set at $\alpha = 0.01$. The TDS trajectories were then drawn on a two-dimensional principal component plane, that is, $q = 2$. Figs. 8(B)–(D) show examples of the comparisons between two of the five ham products. Fig. 8(B) compares Hams 2 and 5. There exists a short period in $0.1 < t < 0.2$ where the trajectories are not significantly different. During the other periods, the two hams exhibited different tastes and textures. Similarly, Fig. 8(C) compares Hams 3 and 4, whose trajectories were not significantly different, particularly in the early phase ($t < 0.1$). Fig. 8(D) shows the trajectories for Hams 1 and 4, which were largely distinct over the entire period. Fig. 8(E) shows the trajectories for the five hams in the same plane at intervals where all the trajectories differ from each other. The tastes of all hams differed at certain moments of the eating experience. In this case, the Bonferroni correction factor was 10 (${}_5C_2$).

A statistical comparison of the trajectories provides the analyst with greater insights into the examined products. For example, the trajectories for all the hams (Fig. 8(E)) show that the products can be apparently divided into two groups: Hams 3 and 4 comprise a group of fibrous hams with low moisture content, whereas Hams 1, 2, and 5 belongs to a group of soft and sweet hams. The meaningfulness of the differences between these two groups cannot be asserted without a cloud of uncertainty. It is also unclear if there are differences between hams within the same group. Hams 2 and 5 appear to be similar, but as shown in Fig. 8(B), they provide significantly different experiences for most of the periods. Thus, the trajectory plots provide a visual representation of the similarity of multiple products, and the uncertainty-based tests provide a statistical basis for judging their resemblances.

Discussion

Castura *et al.* (2023) computed the uncertainties of the trajectory of TDS curves by using the bootstrap resampling method to statistically compare multiple trajectories; in this

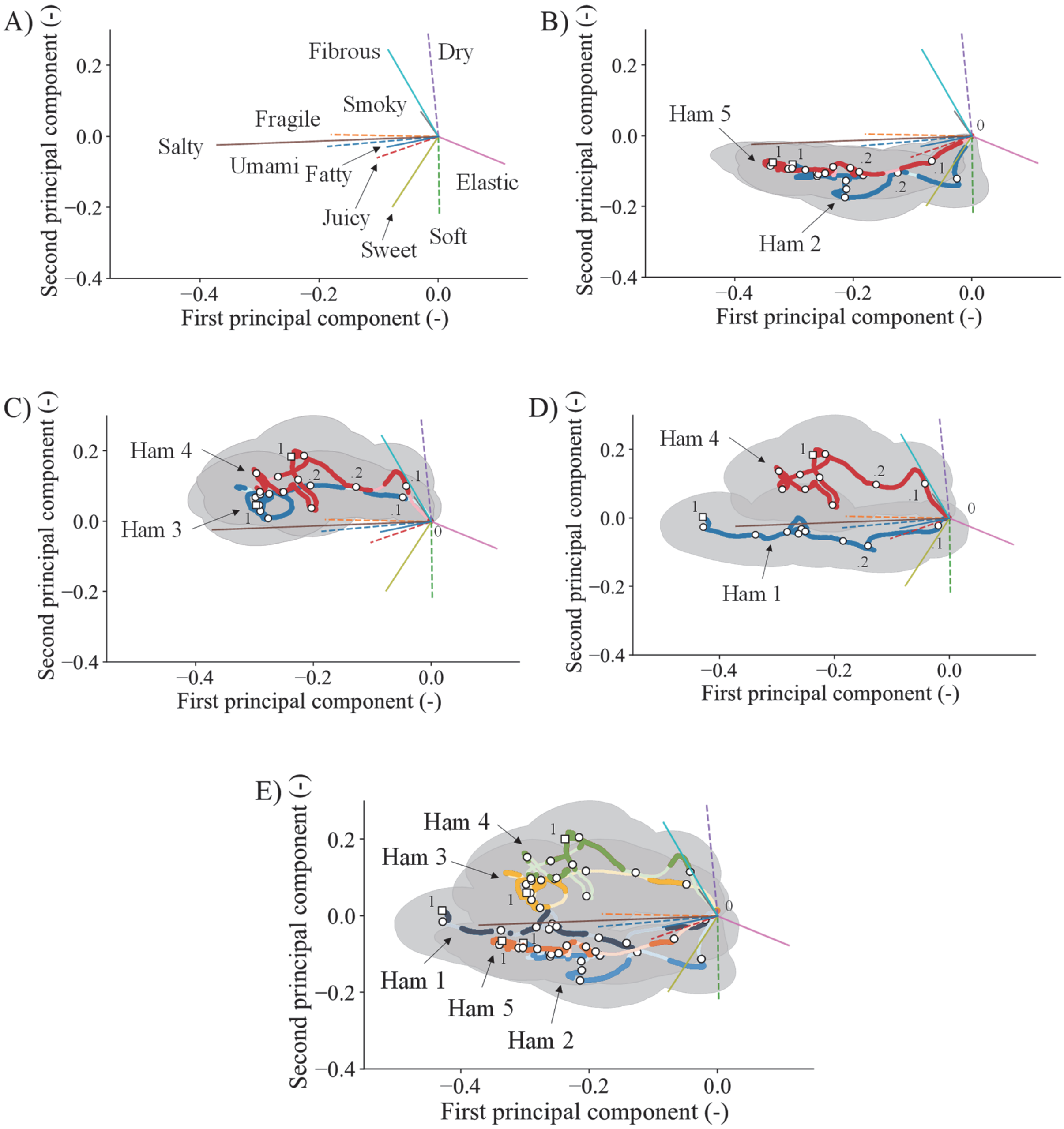

Fig. 8. Trajectory plots of five ham products. Labels near the blank circles indicate t at that time. (A) The legend for all attributes. Comparisons between hams (B) 2 and 5, (C) 3 and 4, and (D) 1 and 4. (E) Trajectory plots of all five hams.

study, the method was modified regarding two aspects. First, we rectified their statistical method. They repeated hypothesis tests along different dimensions in the multidimensional space, which was alternated by the t^2 test. Second, we plotted the uncertainty of the trajectory using a cloud overlaid around the trajectory, whereas Castura *et al*. (2023) visualized the evolution of the uncertainties using animations. Our method is more suitable for still images of trajectories. Finally, we underscored the periods of trajectories that are significantly different from each other. Compared with the method proposed by Castura *et al*. (2023), a clear flaw in our method is that it does not visually provide the confidence intervals for a trajectory at arbitrary moments, since the confidence intervals are overlaid throughout the entire period. Furthermore, when comparing more than two products on the same plane, the temporal evolution of the confidence intervals for each product is not effectively visualized. Animation (Castura *et al*., 2023) can still be effective in solving these problems.

As a problem commonly observed in the analyses of TDS curves and trajectories, many researchers applied hypothesis tests to the data at each instance of the tasks. As a result, several hypothesis tests are repeated for analyzing the same TDS task, which remains a limitation of multiple tests. One approach to avoid such excessive repetitions of hypothesis tests was proposed by Okamoto *et al*. (2020), where all TDS curves for a certain food product were projected into a single point in principal component space. Using that method, TDS curves for two different food products can be compared using only a single hypothesis test. Nonetheless, the test cannot determine the instance during which the TDS curves for the two products differ. Hence, the method proposed in this study and that by Okamoto *et al*. (2020) can be used in a complementary manner. Another concern is the number of products being compared. When the number is large, multiple tests may underestimate the significant differences. Thus, the number of products compared simultaneously should be several at most.

An important future research topic is determining how statistically significant differences in the TDS curves and trajectories relate to the value perceived by consumers. A significant difference does not directly lead to distinctions in the values perceived by consumers. To investigate this, the TDS can be combined with a temporal-liking method (Meyners, 2015; Thomas *et al*., 2015) or a questionnaire on product preferences.

Conclusion

We modified the method of Castura *et al*. (2023) in two aspects: visualization of significantly different periods and confidence intervals for trajectory plots and hypothesis tests in multidimensional spaces. Our visualization method clarified the periods in the trajectories during which the products were significantly different. That is, it is possible to understand how and when products provide different experiences. This method will be used to differentiate strategies in a target market by providing time-series experiences that differ from those for competing products. Furthermore, hypothesis tests using t^2 statistics enabled us to compare multiple curves in a more valid manner. Although we used one type of food product for demonstration, the practical value of the method needs to be confirmed using other types of food in the future.

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