Principal Component Analysis of Time Series Taste Data to Classify Processed Ham

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Abstract: Temporal dominance of sensations (TDS) is a sensory evaluation method that measures changes in several types of sensations over time during food sample tasting. Previous analytical methods for TDS do not classify different foods using the dynamic sensory information of the TDS method results. We developed a new approach to classify products by principal component analysis computation of the time-series information of sensory responses. This method could classify five different hams in a two-dimensional principal component space. The time-series information possessed by each dimension was interpretable, which suggests that the developed method is helpful for analyzing the temporal properties captured by TDS methods.
Keywords: *Temporal dominance of sensations, Principal component analysis, Ham*

1. INTRODUCTION

Temporal dominance of sensations (TDS) is a type of dynamic sensory evaluation [1]. It enables recording of time-series changes in multiple types of sensations while a human is experiencing a stimulus. This revolutionary method has been widely used over the last decade in the field of food science. Researchers in other fields, including affective engineering, have recognized it as an effective approach for capturing sensory dynamics [2, 3].

The most significant feature of the TDS method is the recording of the time evolution of sensory responses. However, major analysis methods do not make use of such dynamic properties. For example, ISO 13299 [1] standardized methods for visualizing the results of TDS methods, but no statistical analyses were based on the dynamic data acquired using the TDS method. Dynamic analyses were developed in some studies [4–6], where causality analysis [4], short-memory model [5], and semi-Markov model [6] of TDS data were introduced. These earlier studies mathematically modelled the time-series sensory responses of humans. In contrast, the present study developed a method to segregate different food products using the time-series data.

We classified several brands of a food product in a principal component space, which is suitable for product classification, because food samples are localized with little effect of accidental or noisy variation in the responses of sensory evaluation tasks. However, earlier approaches computed space based on non-time-series information calculated from the results of TDS tasks [7, 8]. For example, the maximum response value during the entire task period was used in one study [7]. The present approach computes the principal component space based on the discrete time-series results of the TDS tasks. We then applied this method to separate the results of the TDS method for five different brands of processed ham.

This study was approved by the Institutional Review Board of the Faculty of Engineering, Nagoya University (#20-20).

2. METHODS

2.1 TDS tasks on five types of processed ham

In TDS tasks, a graphical user interface is used, as shown in Figure 1. Several buttons labeled with gustatory, olfactory, and textural attributes are arranged. A panelist places a food piece in his/her mouth and presses a button that best explains the sensation that is dominantly felt. This button selection was repeated until the panelist swallowed food. At any instant, only one button can be selected and the button is selected until the next button is pressed. Eleven types of attributes were used: juicy, tender, smoky, umami, salty, fatty, sweet, elastic, dry, fibrous, and fragile.

We used five types of processed ham sold at supermarkets in Japan. Each ham was cut into 3-cm squares and presented to the panelists. Food samples were stored at room temperature (approximately 20°C). Each panelist tested each type of ham five times in random order. Prior to each tasting task, the panelist rinsed his/her mouth with water.

2.2 Panelists

Eleven university students in their 20s participated in the tasks after providing informed consent.

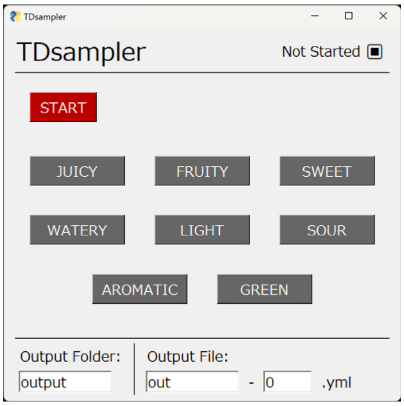

Figure 1 Button panel used for TDS task [9]

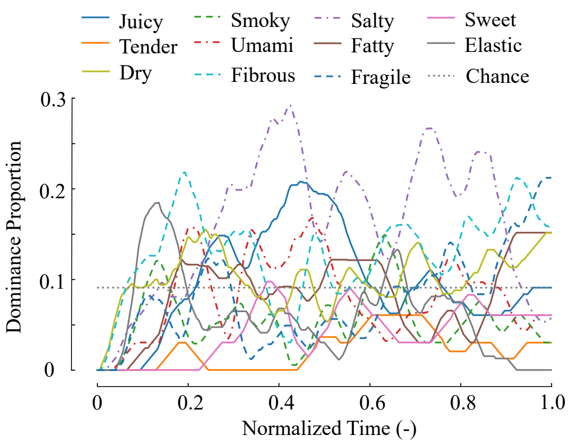

Figure 2 TDS curves of Ham C. Temporal evolution of proportions at which each attribute is dominantly perceived. Chance level is 0.09.

2.3 Bootstrap resampling of TDS tasks and TDS curve

By performing the TDS tasks described in Section 2.1, we obtained 55 results (11 panels × 5 replications) for each product. The results of the TDS task included a set of continuous time functions. Each time function indicates whether an attribute has been selected at any time.

In the TDS method, the TDS curves shown in Figure 2 were computed by combining the results of all panels. The TDS curve shows the proportion of trials in which an attribute was selected at any given time. To calculate this proportion, the duration of each TDS task was normalized from zero (start of the task) to one (end of the task).

Only a set of TDS curves is obtained from all panelists. Hence, many curve sets are generated by bootstrap resampling [10, 11] to apply statistical analysis to the TDS curves. Following these methods [10, 11], TDS curves were generated by randomly selecting 55 samples from the results of 55 tasks with replacement. For each type of ham, bootstrap resampling was performed 200 times to generate 200 TDS curve sets. Hence, 1000 (200 × 5) sets of TDS curves were calculated.

2.4 Principal component analysis of TDS curves

We performed principal component analysis on 1000 sets of TDS curves that were obtained by bootstrap resampling. The interval from the start to the end of the task was divided into ten equal parts, and the last value of the TDS curve in each part was used for the analysis. Hence, each TDS curve set consisted of 110 variables (11 types of attributes × 10 discrete points).

3. RESULTS

Figure 3 shows scatter plots of the resampled TDS curves for the first and second principal components. Each mark represents a different ham product. Different types of ham formed different clusters in the principal component space and five types of ham were distinguished. The first principal component alone did not classify hams C, D, or E. However, the second principal component clearly distinguished them.

The principal component coefficients of the attributes are shown in Figure 4 (a) and (b). Here, only prominent positive and negative attributes are shown. In these figures, dots for the same attributes are connected by lines. A positive coefficient for an attribute at a given time point means that its dominance proportion was higher than its average among all hams. A negative coefficient indicates that it is less dominant than average. Attributes not drawn in the figures are nearly the average of all hams.

4. DISCUSSION

As shown in the scatter plots in Figure 3, the five types of ham were classified using only two principal components. Rodrigues et al. attempted to classify three types of chocolate using principal component analysis based on the results of TDS tasks [7]. They did not use the time-series information of the TDS curves but only three parameters for each attribute, including the maximum value of the curve, for their principal component analysis. The three types of chocolate were not classified in a two-principal component plane. Although we cannot simply compare this study with [7], our results suggest the usefulness of a classification method that utilizes the time-series information of the TDS curves.

Here, the meanings of the two principal components were interpreted. In the first principal component shown in Figure 4 (a), the dominance proportions of *dry* and *fibrous* were positive, whereas those of *sweet* and *tender* were negative during the first half period. Furthermore, *salty* was less dominant during the latter half of the task. The findings indicate that the first principal component exhibits the characteristics of ham with substantial dry and

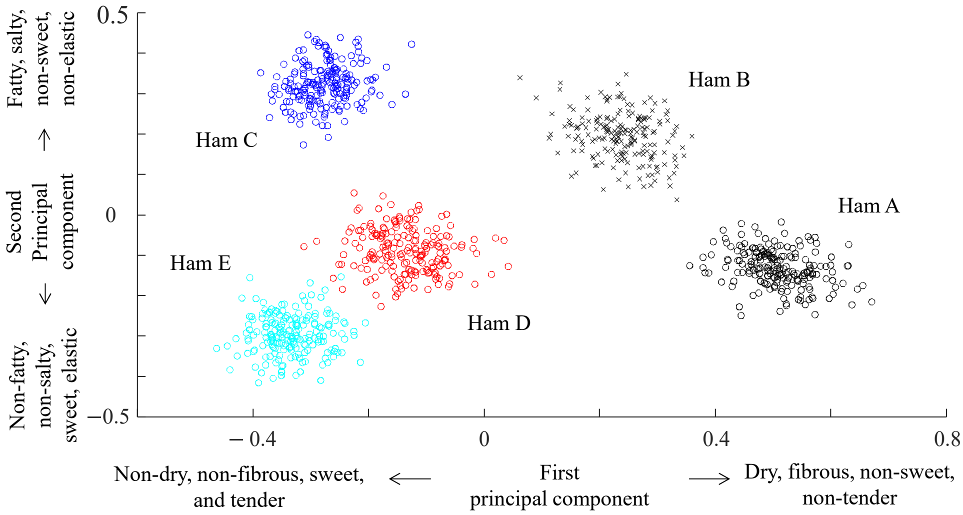

Figure 3 Loci of 1,000 TDS curves on the principal component plane

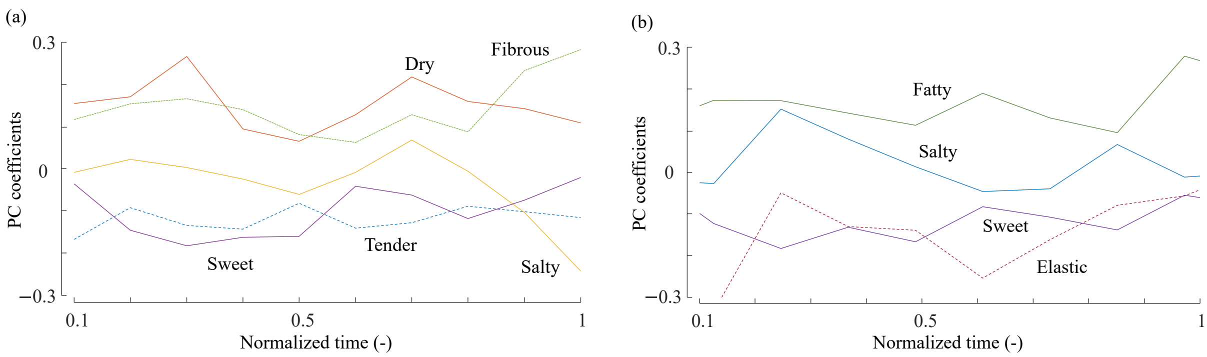

Figure 4 Prominent coefficients of the (a) first and (b) second principal components

fibrous textures, but little sweetener. Hams A and B exhibit the aforementioned characteristics.

In the second principal component, shown in Figure 4 (b), *fatty* was more dominant than the other attributes throughout the entire task period. *Salty* was also prominent in the first half. By contrast, *sweet* and *elastic* were less dominant. These characteristics indicate that the second principal component was fatty and salty ham. Note that being less elastic means that the ham was not resilient. Hams B and C are located in the positive region of the second principal component.

Ham D was located approximately at the origin of the plane and was close to the average characteristic of the five types of hams.

5. CONCLUSION

The present study distinguished food products based on a time-series sensory analysis, namely, the TDS method. We computed a principal component space, each of which was established using the temporal changes in dominance proportions of gustatory, olfactory, and textural attributes. Unlike earlier studies that used non-temporal parameters, our study utilized time-series information from TDS methods. We demonstrate that the proposed method can separate five types of hams on a two-dimensional principal component plane. After testing it with other food products, the general effect of the proposed method will be validated.

ACKNOWLEDGMENT

This study was supported in part by The Tojuro Iijima Foundation for Food Science and Technology.

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