Hierarchical Clustering Analysis of Temporal Dominance of Sensations Tasks

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Abstract: Temporal dominance of sensation (TDS) is used to obtain the time-series of multiple types of sensory responses during food consumption. Results of existing analysis methods for TDS are the averages of all panels. Individual differences and their time-series similarity have seldom been studied. We defined a dissimilarity index to compare individual TDS trials and performed hierarchical clustering on TDS data of strawberries using the index. Fifty-one trials were classified into four clusters with different characteristics. The method will be useful for individual analyses of time-series sensory evaluation data.
Keywords: *Dissimilarity, Hierarchical clustering, Strawberry*

1. INTRODUCTION

The temporal dominance of sensations (TDS) method [1] is a time-series sensory evaluation method for measuring sensory changes over time while eating or watching a movie. This method has been widely used since the mid-2010s, mainly in the field of food science, because it allows the efficient collection of the temporal evolution of multiple types of sensations.

Most of the TDS analysis methods developed so far have dealt with average responses among all panels [1-4]. Only a few methods are available for multi-layer or individual analyses. An example is the study by Cardot et al., which focused on groups of panels with similar responses in TDS tasks [5]. The authors used a semi-Markov chain model to classify panels into several groups. Lepage et al. proposed a method to compare the ability of multiple panels to discriminate foods [6]. However, no method has been developed to classify or compare individual TDS trials based on their time-series similarity.

We defined a dissimilarity index for comparing TDS trials based on their time-series similarities. The purpose of this study is to perform a hierarchical clustering of TDS trials using this index and to examine its validity. We applied the clustering method on open data of TDS for strawberries [7].

2. TDS TASKS AND CURVES

As shown in Figure 1, the TDS method is performed using a computer application with a graphical user interface. The computer screen displays buttons with short adjectives (attribute words) that describe sensations such as “sweet” and “sour.” Start/stop buttons are also displayed to control the start and end of the task. In the case of eating food, the subject (panel) puts a piece of food in their mouth and presses the start button to begin the task. Thereafter, at any time during tasting, the panel presses the button with the attribute word suitable to express the most dominant sensation they feel. It is not possible to select more than one attribute at the same time. Once a button is pressed, it remains selected until the next button is pressed. There may be attributes that are never selected throughout the task, and there may be attributes that are selected multiple times. When the food is swallowed, the panel terminates the task by pressing the stop button.

TDS curves are typically used to visualize the

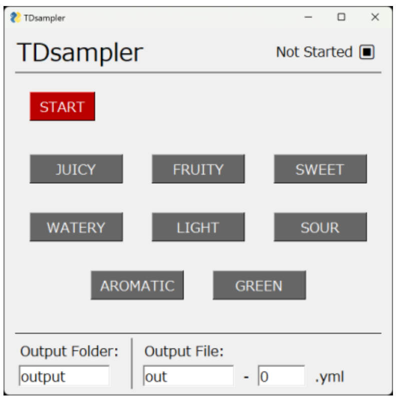

Figure 1: Graphical user interface used for TDS tasks

experimental results [1]. The TDS curve is the average of the time-series responses over all trials and shows the proportion of trials in which each attribute is considered dominant at any given time.

3. CLUSTERING ANALYSIS

3.1 Formulation of TDS trials

The time-series response obtained in the TDS task is represented by the function of time $f_i^j(t)$, where j ($j = 1, 2, \dots, n$) and i ($i = 1, 2, \dots, q$) are the serial numbers of trials and attribute words, respectively. t is a continuous value that is normalized from 0 to 1 for the time from start to end of the TDS task. The function has two values; 1 when the attribute is selected, and 0 when the attribute is not selected.

The summation of $f_i^j(t)$ is 1 among all j, due to the nature of TDS that multiple attributes cannot be selected at the same time. However, it is 0 from the start of the task until the first attribute is selected. The length of this period (delay) varies from trial to trial. We defined a time-series with $i = 0$, i.e., $f_0^j(t)$, to compare trials considering the length of the delay period. $f_0^j(t)$ takes the value 1 during the delay period and 0 from the time the first attribute is selected until task completion. Consequently, i takes values from 0 to q ($i = 0, 1, \dots, q$).

3.2 Dissimilarity index between two TDS trials

In hierarchical clustering, the distance between two samples is used. Therefore, we defined a measure of dissimilarity, or distance, between two TDS trials. This is an improvement on our previously proposed index [8].

First, discretize $f_i^j(t)$, a function of continuous time, into arbitrary R intervals as follows:

$$F_i^j[k] = \int_{\frac{k}{R}}^{\frac{k+1}{R}} f_i^j(t)\, dt\ . \qquad (1)$$

The dissimilarity index D_R for two TDS trials f^a and f^b in any R is defined as follows:

$$D_R(f^a, f^b) = \frac{1}{\sqrt{2}R} \sum_{k=0}^{R-1} \sqrt{\sum_{i=0}^{q} \left|F_i^a[k] - F_i^b[k]\right|^2}\ . \qquad (2)$$

Here, $F_i^a[k]$ and $F_i^b[k]$ at discrete interval k ($k = 0, 1, \dots, R-1$) are considered as coordinates in $(q+1)$-dimensional space. The Euclidean distance between the two coordinates is then computed. D_R is the average of the distances among all intervals. The overall value is divided by $\sqrt{2}$ in order to fit the dissimilarity values within the interval $[0, 1]$. The index is then 0 when the time-series responses of the two discretized trials are in perfect agreement, and 1 when they are in perfect disagreement.

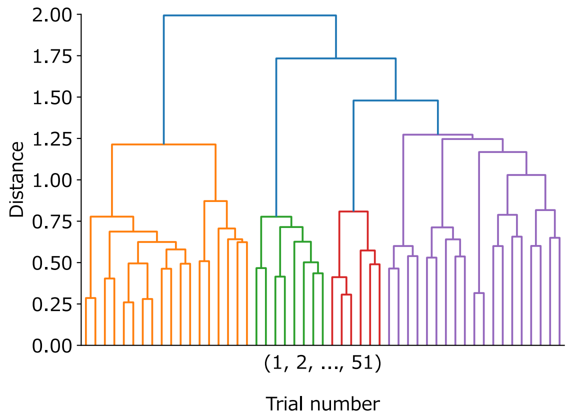

Figure 2: Dendrogram obtained by hierarchical clustering. Trials with the same color belong to the same cluster. There are four clusters.

3.3 Hierarchical clustering

We performed a hierarchical clustering analysis of TDS trials using D_R as the distance measure. D_R was calculated for all pairs of trials, i.e. $\{f^1, f^2, \dots, f^n\}^2$. The pair of trials with the smallest distance constitutes a group. The distances between two groups, or between a group and trial, are calculated in the same way to create a new group. This process is repeated until there is only one group. There are several ways to define the distance between groups, of which Ward's method is the most common and is the method adopted in this study. Empirically, 70% of the maximum distance between groups (the distance between the last two remaining groups) is defined as the criterion for clustering. Pairs of groups with a smaller than the criterion are considered to belong to the same cluster.

3.4 TDS data of strawberries

We used the open data of TDS tasks collected by Shimaoka et al. [7]. The authors performed TDS tasks for strawberries involving 17 university student panels. Individual panels replicated three TDS tasks, in each of which one strawberry was eaten. In total, 51 tasks were performed ($n = 51$). Eight types of attributes ($q = 8$) were selected through another user study. The eight attributes were *sweet, sour, fruity, green, watery, juicy, aromatic*, and *light*.

4. RESULTS

We performed a hierarchical clustering on the 51 strawberry TDS trials as described in Section 3.3. These trials were classified into four clusters. The obtained dendrogram is shown in Figure 2. The leftmost group in

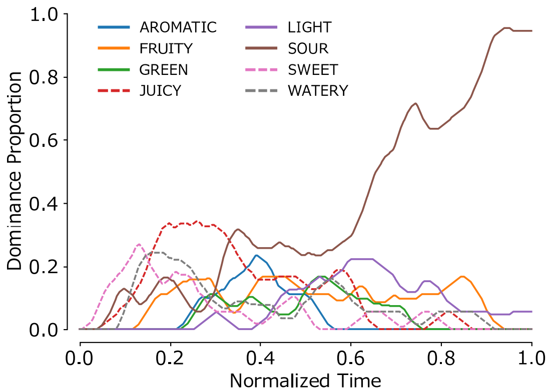

Figure 3-1: TDS curve of cluster 1

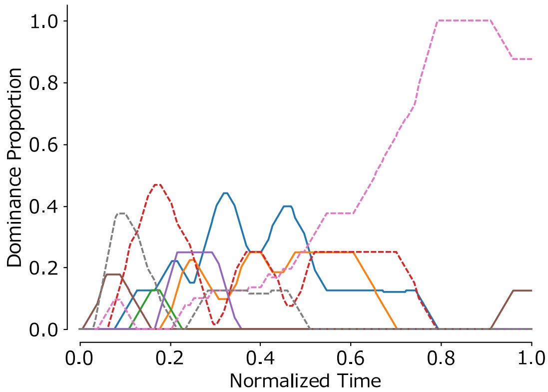

Figure 3-2: TDS curve of cluster 2

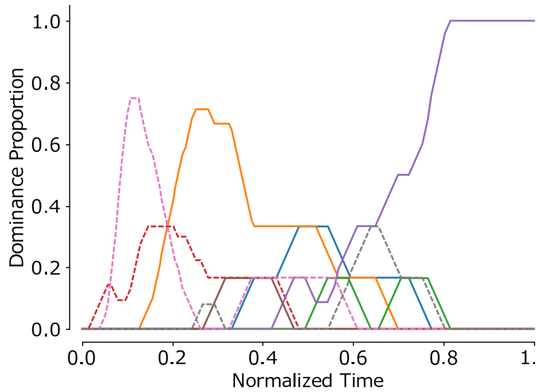

Figure 3-3: TDS curve of cluster 3

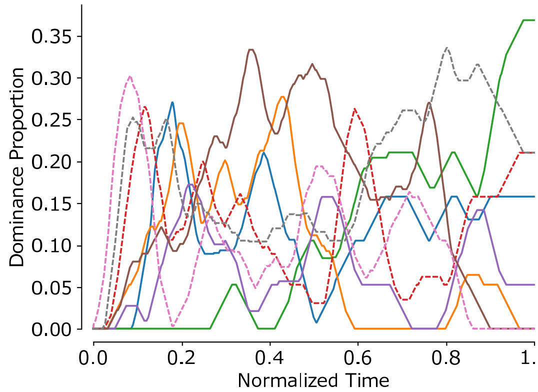

Figure 3-4: TDS curve of cluster 4

the tree was designated as cluster 1, and the clusters were numbered sequentially. The TDS curves for each cluster are shown in Figures 3-1, 3-2, 3-3, and 3-4. The attribute curves follow the legend of Figure 3-1.

5. DISCUSSION

Each cluster has different characteristics. Cluster 1 contains the trials of the panels that perceived *sour* in the second half of the task. This cluster contains 18 trials. Along with cluster 4, it contains more than one-third of all trials.

Cluster 2 is characterized by a higher proportion of *sweet* in the latter half of the task. In the other clusters, *sweet* is selected in the first half. In addition, the proportion of *watery* is high immediately after the start of the task.

In cluster 3, *light* was selected in the latter half of the task. Light was referred as “without remaining sweet taste” [7]. In contrast to cluster 2, this cluster is considered to be a group of panels that perceived the decay of sweetness over time.

Cluster 4 is the largest cluster containing 19 trials. In this cluster, the proportion of *watery* is consistently high. In the latter half of the period, the proportion of *green* is higher. Unlike the other three clusters, no particular attribute becomes more prominent in the latter half of the trial. Since cluster 4 is the largest cluster, it is considered to be a common strawberry eating experience among many panels. In addition, *sour* becomes more prominent in the middle and *green* in the latter half. This suggests that the cluster may have been formed by the presence of unripe individuals in the strawberries used in tasks.

In the strawberry data we used, the food preferences and detailed attributes of panels are unknown. Also, although all the strawberries were of the same brand, the quality of individual strawberries naturally vary. Despite these limitations, the described clustering method will provide profound analysis data when combined with the demographic information of panels and food properties.

6. CONCLUSION

We performed a hierarchical clustering of the TDS tasks for strawberries. Fifty-one trials were divided into four clusters with different time-series characteristics.

When fresh foods such as strawberries are used, the individual differences in the foods affect the results. If the classification is intended to be based on purely individual differences in the panel, it would be better to use a product of constant quality, such as a processed food. Future studies will separate the effects of the individual differences in panels and food products.

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