Outlier analysis in time-evolving sensory evaluation tasks

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***Abstract*—The temporal dominance of sensations (TDS) method measures the time-evolving changes in subjectively reported sensations. This method has been used to obtain average experiences among panels, and there has been no method to analyze individual differences in such dynamic experiences. Therefore, we proposed a dissimilarity index to quantitatively judge how two TDS tasks deviate and then successfully screened an outlier among 51 TDS tasks for strawberries. The task judged as an outlier was semantically different from the average task.**

***Index Terms*—Sensory evaluation, Temporal dominance of sensations**

I. Introduction

The temporal dominance of sensations (TDS) method [1] is a time-evolving sensory evaluation method that records changes in multiple sensations over time while eating foods and enjoying audiovisual contents. However, this method aims to quantify the average experience among all panels (i.e., assessors) and is believed to be unsuitable for analyzing individual differences. There have been few studies on individual differences in TDS methods. The only example is the grouping of panels using a semi-Markov chain model [2]. There has been no method to statistically analyze outliers from multiple panels or TDS tasks. Therefore, we propose a method of analyzing individual differences and outliers in TDS task results.

II. TDS tasks and curves for strawberries

During the tasks of the TDS method, a graphic user interface with multiple buttons on a computer screen is used. Each button has a label describing sensations. The panel exposed to sensory stimuli presses the button of an attribute that is closest to the sensation that they consider the most dominant. Another button is then selected when the dominant sensation changes. This operation lasts until the food in the mouth disappears or the stimulus is no longer felt. A percentage of the panel that consider a certain sensation to be dominant at a given time, out of the total panel, is called the dominance proportion of the sensation. The time series of the dominance proportion is called the TDS curve, representing the average behavior of the entire panel.

We measured the taste, smell, and texture changes while eating strawberries using the TDS method. Eight types of attributes were used. These included taste, osmatic, and textural attributes. We collected TDS curves from 17 university students while eating strawberries. One strawberry was eaten in a single TDS method task. Each participant conducted three trials, and 51 (17×3) samples were collected. The experiment was approved by the Institutional Review Board of the School of Engineering, Nagoya University (#20-20).

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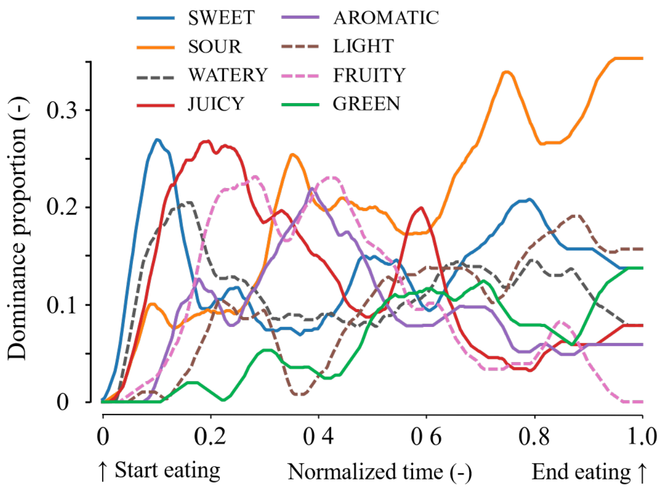

Fig. 1: TDS curve while eating strawberries

Fig. 1 shows the obtained TDS curves. The horizontal axis is the normalized time, which takes the value of zero when the strawberry is put into the mouth, and one when the strawberry is swallowed. Typically, sweet and juicy sensations dominated in the early stage while eating strawberries. The experience of fruitiness then became prominent. In the last phase, the sourness was dominantly felt by the panels.

III. Dissimilarity index for individual TDS tasks

The result of trial A of the TDS task is defined by a set of binary functions of the normalized time $A_i(t)$ for attribute $i = 1, 2, \ldots, q$. q denotes the number of attributes used in the TDS task. This function takes the value of either 0 (not selected) or 1 (selected). The sum of $A_i(t)$ at a certain time t is 1 because multiple attributes can never be selected simultaneously in the TDS method. To ensure that the sum of $A_i(t)$ is 1, even when no attribute is selected, we defined $A_0(t)$, whose value is 1 only when no attribute is selected.

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This allows us to compare the similarity between the two trials, for which the times elapsed until the first attribute selected is different. t is a discrete value because it is calculated by a computer. The width of the discretization is expressed as Δt.

We defined the dissimilarity index between two TDS tasks A and A' as follows:

$$d(A, A^{'}) = \frac{1}{\sqrt{2}R} \sum_{k=0}^{R} \sqrt{\sum_{i=0}^{q} \left(A_i(k\Delta t) - A_i^{'}(k\Delta t)\right)^2} \quad (1)$$

where R and q are the number of discretized points of the normalized time ($R = 1000$) and attributes used in the TDS tasks ($q = 8$), respectively. This formula averages the geometric distances (Euclidean distances) of the two trials, along the normalized time, when trials A and $A^{'}$ are viewed as coordinates $(A_0(t), A_1(t), \ldots, A_q(t))$ and $(A_0^{'}(t), A_1^{'}(t), \ldots, A_q^{'}(t))$ in the $q+1$ dimensional space. As mentioned above, the sum of $A_i(t)$ at a certain time t is 1. Therefore, the maximum Euclidean distance is $\sqrt{2}$. Dividing the entire value by $\sqrt{2}$ makes the maximum value of d equal to 1. Consequently , the d value ranges from 0 to 1, with 0 being the perfect match between the two TDS tasks, and 1 is the complete mismatch.

IV. Outlier Analysis of TDS Tasks Using Dissimilarity Index

When the results of the n trials for attribute i are expressed as $A_i^1(t), A_i^2(t), \ldots, A_i^n(t)$, their average is the dominance proportion:

$$P_i(t) = \frac{1}{n} \sum_{j=1}^{n} A_i^j(t) \quad (2)$$

where n is the number of TDS trials ($n = 51$). We then computed the dissimilarity between trial k and the average dominance proportions, that is, $d(A^k, P)$. Although $P_i(t)$ is not a binary function, we can compute the dissimilarity between A^k and the average by applying (1) because the Euclidean distance can be defined for non-binary and continuous $P_i(t)$ values.

Here, we used the experimental data of strawberries to identify potential outliers among the set of dissimilarities from the average. The set of dissimilarities for all the TDS tasks is $C = \{x | x = d(A^k, P), k = 1, 2, \ldots, n\}$. We applied the Kolmogorov-Smirnov test on C and found $p = 0.38 > 0.05$. The assumption of normality was not rejected. Fig. 2 shows the distribution of d values.

We judged samples that do not fall within 95% of the distribution, that is, $[-\infty, 1.64\sigma]$ as an outlier, where σ is the standard deviation. Based on this criterion, one sample, shown as orange in Fig. 2 was judged to be an outlier. Fig. 3(a) shows $A_i(t)$ of this trial. Fig. 3(b) shows the second farthest trial from the average, although it was not categorized as an outlier.

The panel in Fig. 3(a) selected *juicy, fruity* and *aromatic* in the first half period. These results are consistent with the average behavior shown in Fig. 1. However, this panel selected *aromatic* in the second half period, which is not prominent in the average curves. In addition, this panel selected *green*, which exhibited a low dominance proportion on average. Hence, this trial deviates from the average trend, especially in the second half of the period.

The panel shown in Fig. 3(b) first selected *watery*, and then *sweet* in the middle phase, consistent with the average trend. However, the other selections, including *juicy* in the last phase, do not match the average trend. Therefore, this panel also deviates largely from the average curve shown in Fig. 1.

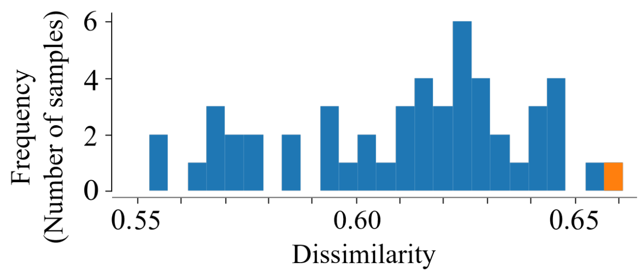

Fig. 2: Distribution of d values. The right-most sample is outside 95% of the distribution.

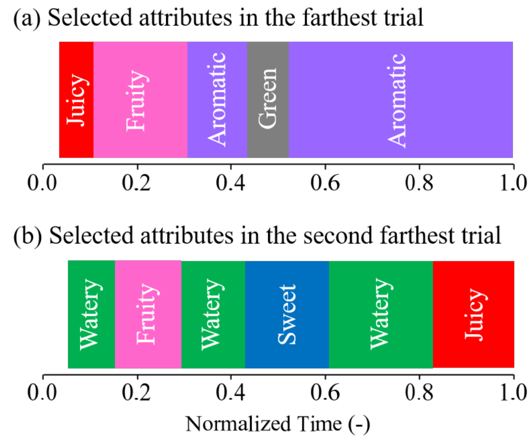

Fig. 3: Selected attributes in the trials most and second farthest from the average

V. Conclusion

We proposed a dissimilarity index for TDS tasks. Thus far, such individual analysis methods have yet to be developed for TDS methods. We applied the proposed dissimilarity index on the 51 TDS tasks for strawberries and found one potential outlier. This outlier is semantically different from the average temporal dominance curves of the 51 tasks. The validity of this index remains to be studied in the future.

References

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