A DYNAMIC DESIGN OF EXPERIMENTS USING INTELLIGENT TECHNIQUES IN SENSORY EVALUATION

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ABSTRACT

The existing designs of experiments in sensory evaluation are mostly static and offline methods, in which the number of tests is not optimized and the evaluation order of new samples is independent of the current evaluation results. The method we propose in this paper permits to realize a dynamic design of experiments for sensory evaluation. This is an online design of experiments in which new samples are iteratively generated from evaluation results of old samples. Two main ideas of this method are given as follows. 1) For the samples already evaluated, we define a partial order between them according to the similarity degree. For any two samples, the similarity degree is first given by evaluators, which includes not only their order but also the linguistic distance between them. Then, it is adjusted in order to remove the errors of convergence and contrast. With these similarity degrees, all the evaluated samples can be placed on a predefined axis. 2) For a new sample, we look for its right place in the list of already evaluated and ordered samples. This procedure is carried out by estimating its similarity degree with the existing samples. The method of Case Based Reasoning is used for quickly finding the old sample the closest to the new sample. This procedure is repeated, permitting to quickly and iteratively define the order of all the samples with minimal number of tests by maintaining the accuracy of evaluation.

Keywords: ***sensory evaluation, online design of experiments, similarity degree, linguistic distance, Case Based Reasoning***

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1. INTRODUCTION

Sensory evaluation techniques have been widely used in many industrial fields, such as food, cosmetic, automobile and textile. In an enterprise, sensorial evaluation can be mainly used for product quality inspection, development of human oriented product design criteria, normalized communication inside the enterprise and with its partners, and identification of consumer's behavior and market exploitation.

In a sensory evaluation, evaluators determine the quality level of each sample according to the results of comparison between any two samples (tests). In practice, the evaluation order of samples is not optimized and the cost of evaluation, strongly related to the number of tests, is rather high. The existing designs of experiments in sensory evaluation are mostly static and offline methods, in which evaluation orders of new samples can not be adjusted by current evaluation results [1]. For evaluating n samples, we need to perform about n(n-1)/2 tests. Therefore, we need to optimize this evaluation order (design of experiments) by developing a heuristic strategy so that the number of tests can be largely reduced while the evaluation precision is not changed significantly.

The method we propose in this paper permits to realize a dynamic design of experiments for sensory evaluation by using the method of Case Based Reasoning (CBR), i.e. solving new problems based on the solutions of similar past problems [2]. It is an online design of experiments in which new samples are iteratively inserted to their right positions according to the evaluation results of old samples. Two main ideas of this method are given as follows. 1) For the samples already evaluated, we define a partial order between them according to the similarity degree. For any two samples, the similarity degree is first given by evaluators, which includes not only the order between these two samples but also the linguistic distance between them (inferior, similar, superior, ...). Then, it is adjusted in order to remove the errors of convergence and contrast [3]. These similarity degrees permit to form a distribution of all the evaluated samples on a predefined axis. 2) For a new sample, we look for its right place in the list of already evaluated and ordered samples. This procedure is carried out by estimating its similarity degree with existing samples. Considered as one application of CBR, it permits to quickly find the old sample the closest to the new sample. This procedure is repeated, leading to quickly and iteratively generating the order of all the samples with minimal number of tests by maintaining the accuracy of evaluation.

2. SIMILARITY DEGREE BETWEEN TWO SAMPLES

When comparing two samples i and j, we generally have three possibilities, i.e. *similar*, $i \prec j$ (inferior partial order), $i \succ j$ (superior *partial order)*. When integrating a new sample into a set of existing ordered samples, its right place can be determined by comparing it with the old samples. In this way, we need to define an inferior partial order $\prec$ for ranking all evaluated samples according to the related comparison results.

In practice, when comparing two samples, apart from the previous information, evaluators can also perceive distance or intensity of similarity between them. In order to quickly find the right position of a new sample, we need to exploit this information. In this situation, each evaluator not only gives the partial order between two samples but also estimates the distance between them. This distance, generally taking linguistic values such as "quite different", "very similar", "a little different", characterizes the intensity of the difference or the similarity between these two samples.

In this paper, the similarity degree for two samples takes linguistic values according to the comparison result given by evaluators. According to this idea, we define a fuzzy similarity function between two samples *i* and *j*, denoted as $S_{i/j}$. According to Figure 1, when comparing the i^{th} sample (new sample) and the j^{th} sample (old sample), their relation can be expressed by evaluators using 7 linguistic values L1, L2, L3, S, R3, R2 and R1, representing *very inferior, inferior, a little inferior, similar, a little superior, superior and very superior* respectively. For simplicity, we define for these linguistic values the corresponding numerical values, i.e. 0, 0.17, 0.33, 0.5, 0.67, 0.83, 1. These values uniformly divide the range [0, 1] into 7 segments.

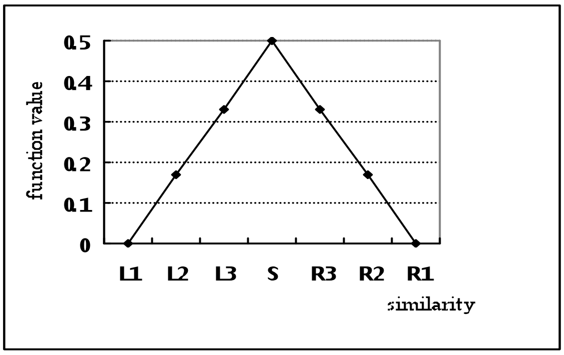

Figure 1: Fuzzy similarity function for two samples

Evidently, if the i^{th} sample is located on the left side of the j^{th} sample, then the j^{th} sample is located on the right side of the i^{th} sample and we have

$$S_{i/j} = 1 - S_{j/i}$$

If $S_{i/j} \in [0,0.5)$, the i^{th} sample is inferior to the j^{th} sample. Closer the value of $S_{i/j}$ is to 0, more the i^{th} sample is distant from the j^{th} sample on its left.

If $S_{i/j} \in (0.5,1]$, the i^{th} sample is superior to the j^{th} sample. Closer the value of $S_{i/j}$ is to 1, more the i^{th} sample is distant from the j^{th} sample on its right.

If $S_{i/j} = 0.5$, the i^{th} sample is considered to be the same as the j^{th} sample.

3. THE PROPOSED PROCEDURE OF EXPERIMENT DESIGN FOR SENSORY EVALUATION

An experiment design for sensory evaluation aims at evaluating all samples with the smallest number of tests. Concretely, we should find for each new sample its right place in the list of already ordered samples. Therefore, the nearest left (inferior) sample and the nearest right (superior) sample should be determined using the similarity function defined in Section 2. One example is shown as Figure 2.

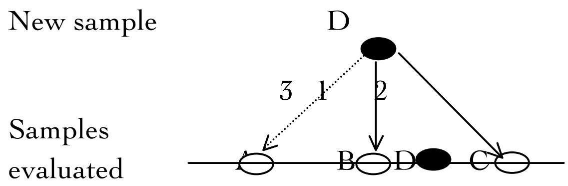

Figure 2: A case of test in sensory evaluation

In Figure 2, the determination of the right place of a new sample D can be considered as a case inference problem. Before inserting D, we have a list of 3 ordered samples, denoted as A, B and C, i.e. $A \prec B \prec C$. If no design experiment is available, we have to compare D with all existing samples. Then, 3 tests are necessary. For ranking a set of n samples, we need to perform n(n-1)/2 tests or comparisons. However, the number of tests can be reduced to $n\log_2 n$ if we use the dichotomy experiment design, which iteratively compares the new sample with the medium of the list of evaluated samples. In the example of Figure 2, if we use the dichotomy method, we first compare D with the median sample B. If D is inferior to B, we compare D with A. If D is superior to B, we compare D with C. If we introduce the similarity function defined in Section 2 to each comparison, we can further reduce the number of tests by directly estimating the position of the new sample D from the similarity between D and the medium B and the distribution of the samples A, B, C. The general principle for calculating similarity degrees of evaluated samples is given as follows.

Step1: Building similarity degrees between evaluated samples.

Assuming that there exist r already evaluated and ordered samples before inserting a new sample x. These ordered samples, denoted as 1, 2, …, r, are distributed in the interval [0, 1] according to the distances or similarity degrees between them. The relative similarity degrees of these r samples related to their right neighboring samples can be obtained from the linguistic values given by evaluators. These relative similarity degrees, denoted as $s_1, s_2, \ldots, s_{r-1}$ do not take into account the effects of the convergence error and the contrast error. In this case, when introducing the new sample x to this ordered list, the relative similarity degrees of the old samples $s_1, s_2, \ldots, s_{r-1}$ maintain unchanged. However, the real similarities taking into account the convergence and contrast errors are generally updated by the insertion of x. In the same time, the right position of x can be found by estimating its real similarity degrees with the old samples. This procedure repeats until all samples are integrated into the ordered list of evaluated samples recurrently.

When introducing the sample x, using the dichotomy principle, we first compare it with the median sample (m), which divides the r already evaluated samples into two subsets.

For the left subset, we estimate the real similarity degrees of all evaluated samples related to the median sample (m). The main idea of this estimation is to remove or decrease the effects related to the contrast and convergence errors, appearing in relative similarity degrees given by evaluators according to their direct perception. The principle of these errors [3, 4] can be illustrated as follows.

The contrast error is characterized by two samples scored as being very different from each other and the magnitude of the difference being much greater than expected. The convergence error is usually brought about by contrast between two samples masking smaller differences between one of these and other samples in the test. In practice, the existence of one effect most often is accompanied by the other. As shown in Figure 3, when inserting a new sample D into a list of ordered samples A, B, and C, the convergence and the contrast errors occur together. When D is inserted on the left (or right) side of the segment (A, B, C), the distances between the old samples A, B, C will be reduced by the contrast with D and then the similarity degrees between them will be enhanced (convergence error). In this case, we need to decrease these similarity degrees in order to remove the convergence error and identify the real relationship between these samples. When D is inserted into the segment (A, B, C), the distance between the two extremes A and C will be increased by introduction of new middle samples and then the similarity degrees between the old samples A, B, C will be reduced (contrast error). In this case, we need to increase these similarity degrees in order to remove the contrast error and identify the real relationship between these samples.

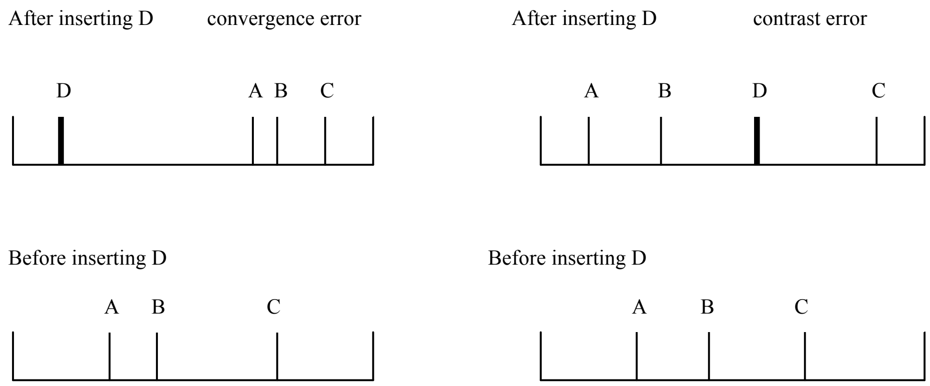

Figure 3: Convergence and contrast errors

Under this principle, when comparing the samples of the left subset with the median sample m, the corresponding real similarity degrees can be calculated as follows.

For three different samples A, B and C, the corresponding real similarity degrees are shown as Figure 4.

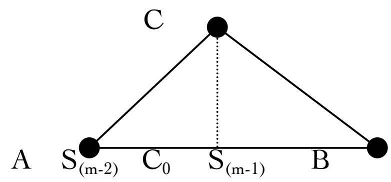

Figure 4: Similarity degrees for three samples

In Figure 4, $S_{(m-2)}$ and $S_{(m-1)}$ represent the relative similarity degrees between A and C and between C and B respectively when the effects of the contrast error and the convergence error are not taken into account. If we consider the effects of the contrast error and convergence error, when C drops in the left subset after comparing it with *(m)*, we have $S_{m-1/m} = S_{(m-1)}\ (1+t_{(m-1)\ k})$, in which $S_{m-1/m}$ is the real similarity degree of the sample (m-1) related to the medium sample m and $t_{(m-1)\ k}$ denotes the evaluator's memory capacity for the k^{th} test [5, 6]. $t_{(m-1)\ k}$ is a random parameter depending on the initial capacity memory of evaluators, denoted as t_0. This memory capacity is calculated using a random function developed according to the principles given in [6]. In the same way, when C drops in the right subset, we have $S_{m+1/m} = S_{(m-1)} (1-t_{(m+1)k})$ with $S_{m+1/m} = 1 - S_{m/m+1}$.

In general, for the left subset, we obtain the real similarity degree of the sample j related to the median sample m as follows:

$$S_{j/m} = (S_{(j+1)} + t_{(m+1)k} S_{(m+1)}) + (S_j + t_{jk} S_j) \text{ for j=m-2, ..., 1}$$

This definition is explained as follows. The real similarity degree of the sample j related to m is calculated from those chose to m iteratively, i.e. $S_{j/m}$ is determined from $S_{j+1/m}$ for j=m-2, ..., 1. As one sample (j+1) exists between j and m, then the real similarity degree between j and m is decreased by the contrast error. Moreover, the contrast error between the sample (j+1) and the medium m should also be taken into account.

t_{jk} denotes the memory capacity of the k[th] evaluation for the j^{th} sample.

The same idea can be applied to the right subset. We obtain

$$S_{j/m} = (S_{(j-1)} - t_{(j-1)k} S_{(j-1)}) + (S_j - t_{jk} S_j);\ j = m+2, m+3, ..., r.$$

The real similarity degree of the sample j related to the medium m is calculated from those close to m iteratively.

<u>Step 2</u>: Modification of similarity degrees of all evaluated samples when comparing a new sample x with the median sample m.

For the left subset, we have

If $S_{x/m} = S_{j/m}$, then $S_{j/x} = S_{j/m}$

If $S_{x/m} \prec S_{j/m}$, then $S_{j/x} = S_{j/m} + t_{xk}(S_{j/m} - S_{x/m})$

As the sample x is added to the left of the sample j, the contrast error can decrease the distance between j and m and then push the position $S_{j/x}$ to the right (towards 1). The intensity of this modification is related to the distance between j and x.

If $S_{x/m} \succ S_{j/m}$, then $S_{j/x} = S_{j/m} - t_{xk}(S_{x/m} - S_{j/m})$

As the sample x is added to a position between the sample j and the sample m, we can observe the convergence error. This error can increase the distance between j and m and then push the position $S_{j/x}$ to the left (towards 0). The intensity of this modification is also related to the distance between j and x.

We can obtain similar results for the right subset. These results are symmetric to those obtained for the left subset.

If $S_{x/m} = S_{j/m}$, then $S_{j/x} = S_{j/m}$

If $S_{x/m} \prec S_{j/m}$, then $S_{j/x} = S_{j/m} - t_{xk}(S_{j/m} - S_{x/m})$

If $S_{x/m} \succ S_{j/m}$, then $S_{j/x} = S_{j/m} + t_{xk}(S_{x/m} - S_{j/m})$

Let $M = \max_j \{S_{j/x}\}$ and $L = \min_j \{S_{j/x}\}$, we define the similarity degrees between the new sample x and evaluated samples as follows.

$$S_j(x) = \begin{cases} 0 & , \text{ if } \quad S_{j/x} = L = 0 \\ 0.5 * \dfrac{S_{j/x}}{S_{x/m}} & , \text{ if } \quad 0 < L \le S_{j/x} < S_{x/m} \\ 0.5 & , \text{ if } \quad S_{j/x} = S_{x/m} \\ 0.5 + \dfrac{S_{j/x}}{M} & , \text{ if } S_{xm} < S_{j/x} \le M < 1 \\ 1 & , \text{ if } \quad S_{j/x} = M = 1 \end{cases}$$

Let Δ_L, Δ_R and Δ be the minimal distances of the left subset, the right subset and the whole set of similarity degrees respectively. We calculate

$\Delta_L = \min_j \{0.5 - S_j(x)\}$, for any $S_j(x) < 0.5$

In this case, the sample x should be inserted to the right neighbor of the sample k meeting $0.5 - S_k(x) = \Delta_L$.

$\Delta_M = 0$, if there exists a sample k so that $S_k(x) = 0.5$

In this case, the sample x should be inserted to the same position of the sample k.

$\Delta_R = \min_j \{S_j(x) - 0.5\}$, for any $S_j(x) > 0.5$

In this case, the sample x should be inserted to the left neighbor of the sample k meeting $S_k(x) - 0.5 = \Delta_R$.

$\Delta = \min\{\Delta_L, \Delta_M, \Delta_R\}$ corresponds to the already evaluated samples the closest to the new sample x.

We define $U_j = \begin{cases} 1 & \text{if } S_j(x) = 0.5\,(\Delta = \Delta_M) \\ \dfrac{\Delta}{|S_j(x) - 0.5|} & \text{if } \Delta = \Delta_R \text{ and } S_j(x) > 0.5 \text{ or } \Delta = \Delta_L \text{ and } S_j(x) < 0.5 \\ 0 & \text{otherwise} \end{cases}$ and

$$u_j = \frac{U_j}{\sum_{i=1}^{r} U_i}$$

If x drops in the left subset, we have $0 < u_j \le 1$, for $j = 1,2,...,m$, and $u_l = 0$, for $l = m+1, m+2,...,r$.

If x drops in the right subset, we have $0 < u_j \le 1$, $j = m+1, m+2,...,r$, and $u_l = 0$ for $l = 1,2,...,m$.

For r evaluated samples, we obtain the results of $u_1, u_2,...., u_r$ using the previous method and then select the evaluated sample the most similar with the new sample x. The identified evaluated sample corresponds to the biggest value of $u_1, u_2,...., u_r$. If the new sample is inferior to the most left evaluated sample or superior to the most right evaluated sample, this procedure stops and we insert the new sample x to the left or right of all the evaluated samples. Otherwise, this procedure continues by integrating the newest results calculated from the previous equations.

4. EXAMPLES OF EVALUATION

The proposed method has been validated through a number of real applications. One example of fabric hand evaluation is given below to illustrate the effectiveness of this experiment design method and how it can be applied to a practical case.

In this experiment, 100 fabric samples of knitted cotton with different process parameters and different surface treatments have been selected for evaluating their feeling of "softness". It is possible that some samples have the same level of "softness" but the method proposed in Section 3 can also treat them without difficulties. Five evaluators have participated in this evaluation.

The proposed method has been compared with the dichotomy method, which is frequently used in practice for human evaluation. The analysis of the comparison results is given below.

According to the related computation, when the total number of sample is 100, the number of tests for a complete combination is 4950, and that of the dichotomy method is 578, which is in the order of $100 \log_2 100 = 664$. However, using our method, the number of tests varies from 202 to 447 when executing the proposed evaluation procedure for 10 times. The number of tests is randomly distributed and related to the initial memory capacity t_0.

In practice, we obtain the following results: 1) if the memory capacity $t_0 = 0$ (evaluators have complete memory on former tests), when using our method, the minimal number of tests can be $2n$ and all possible numbers of tests are less than $n \log_2 n$. 2) if $t_0 = 1$ (evaluators have no memory on former tests) and $n \le 20$, our method is no more efficient than the dichotomy method. If $n \ge 30$, our method is more efficient than the dichotomy method in any cases because it needs less tests.

Table 1: Comparison of numbers of tests for different evaluation methods

Number of	Number of tests

Samples n	Comparison of all pairs	Dichotomy	The proposed method	
			$t_0 = 0.5$	$t_0 = 1$
10	45	27	26	32
20	190	72	53	77
30	435	122	78	95
50	1225	241	129	190
70	2415	368	177	264
100	4950	578	250	447

From Table 1, we can find that for the comparison of all pairs, the number of tests is in the order of n^2, and for the method of dichotomy, the number of tests is in the order of $n\log_2 n$. The proposed method enables to decrease the number of tests to a linear order of n. Bigger is the number of samples to be evaluated, more the proposed method is efficient. The efficiency of this evaluation method varies with the parameter t_0, which characterizes the capacity of memory of evaluators. The performance of evaluation can be optimized when $t_0=0$ (complete memory).

5. CONCLUSION

This paper proposes an on line experiment design method permitting to effectively decrease the number of tests in sensory evaluation while maintaining high evaluation accuracy. A similarity degree is defined for estimating not only the order of evaluated samples but also the distance between them. These similarity degrees are then modified in order to remove the errors related to convergence and contrast effects. Based on the principle of Case Based Reasoning, we identify the evaluated sample the most similar with the new sample x and then insert x into the neighborhood of this sample. This method has been successfully applied to fabric hand sensory evaluation for determining quality of textile products. It can also be applied to the other human evaluation problems in order to reduce time and cost.

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