Computing Ideal Number of Test Subjects
Sensorial Map Parametrization

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Abstract: A sensory analysis was carried using a special Napping® table on two different set of products in order to investigate on texture perception of material, the tests were done using a human panel. The data collected were analyzed through multiple factor analysis (MFA) which is a particular case of principal component analysis (PCA). The aim of this study is to know the minimum number of subjects in the human panel that can guarantee a meaningful statistical analysis of data, and so far allows a better understanding of the sensory results. We built a particular function that measures the similarity between two representations (two matrices) which are computed using the output of Napping® table. Based on this function and using the whole datasets an algorithm able to measure the robustness is implemented. We found on the two datasets that a minimum number of subjects between 10 and 12 seems to insure a stable and robust statistical analysis of the sensory results.

1 INTRODUCTION

Projective mapping was introduced in 1994 (Risvik et al., 1994) as a method in the field of sensory science, in the aim to collect similarities or dissimilarities between products of the same type. The monography (Varela and Ares, 2014) is a complete about the subject. This procedure of projective mapping is validated for food, beverage and fragrance product (Kennedy and Heymann, 2009; Pagès, 2003)

Napping®procedure, that is particular case of projective mapping, was proposed by (Pagès, 2003) and R libraries `FactoMiner` (Lê et al., 2008) and `SensoMineR` (Lê and Husson, 2008) were implemented. The idea is to ask to some subject to place in a space various sample of a generical product. The number of samples is quite low, between 8 et 20 depending of the type of the product and because it is an human who manipulates these in a physical bounded space. The number of subjects or assesors used in all these experience is variable from 8 to more of 50. In (Kennedy and Heymann, 2009; Dehlholm et al., 2012) clear synthesis of projective mapping were done.

Based on (Faucheu et al., 2015) we are studying the use of this procedure for the evaluation of materials (Dacleu Ndengue et al., 2016), especially the texture of those materials required some investigation, in order to validate the method for this type of product. Because almost all the information about the perception of the product space relies on this, one of the essential points refers to the number of subject that is necessary to achieve a stable analysis. As said before, Napping has previously been used for food, beverage and fragrance product; for those studies, different number of subject were use, from 8 (Risvik et al., 1997) to 83 (Barcenas et al., 2004). The main reason of the difference in number of subject was that it depend on the nature of the product space. Until now, no research has concluded on a minimum number of subjects that can provide a stable representation of product space. For this reason, it appear very important to investigate on that minimum number, in particular because the use of napping for material evaluation is not very common.

The work presented in this paper focused on two main aspects. First of all, a strategy that investigates on the influence of a subject on the global representation of the product space display on the mean representation of sample. Secondly, a strategy that investigates on the minimum number of subject necessary to achieve a stable mean representation of the product space.

In the second section we will describe our data, the

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Figure 1: Image of one sample WC and one sample of replica R.

Figure 2: Image of two sample of smartphone cover case and their materials.

section 3 will explain the details about experiments, collected dataset, statistical analysis, RV-coefficient which is important for our approach and the algorithms we proposed. The results of evaluation are given in section 4. In the last section some conclusions are presented.

2 DATASETS

Two product spaces were use in this study. Those samples were used in a sensory study aims at investigating on texture perception of materials.

2.1 First Product Space: Wood Countertype and Their Replica

We take into account 9 samples for the Wood Countertype (WC) and 9 samples for the replica (R), see Figure 1. 18 untrained subjects participated to a sensory analysis aimed at determining if familiarity affects visual, tactile and visio-tactile perception of the texture. This first product space generated 6 datasets.

2.2 Second Product Space: Smartphone Cover Case and Materials

12 Smartphone cover case for which texture was studied in order to determine how does the texture perception change according to the sample presentation. 23 untrained subjects took part to the experiment. The samples were tested inform of material and in form of object. So, two datasets are generated.

Finally, 8 datasets were obtained from these product spaces and were analyzed in the study.

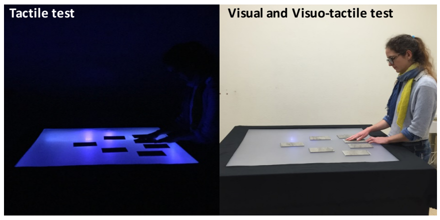

Figure 3: NappOmatic set-up for tactile, visual and visuo-tactile perception of surface textures.

3 METHODS

3.1 Sensory Analysis and Data Collection

We used a NappOmatic table (Faucheu et al., 2015). We present briefly this setup and we explain also the procedure for the subjects /assessors.

NappOmatic Setup

The sensory experiments in this study aims at collecting insights on the tactile, visual and visuo-tactile perception of the two sets of samples. The procedure used here was adapted from Napping® (Pagès, 2003) which is a descriptive method deriving from the projective mapping (Risvik et al., 1994) originally developed for food and beverages.

In projective mapping, panelists are asked to position on a large sheet of paper the products according to the products' similarities and dissimilarities. Projective mapping serves as a simple and quick technique to obtain product inter-distances. We developed a custom-made setup NappOmatic to perform projective mapping with samples of materials and textures under visual, tactile and visual-tactile conditions (D'Olivo et al., 2013; Faucheu et al., 2015) .

The NappOmatic experimental set-up is displayed on Figure 3. The mapping area was defined as a square of $93cm \times 93cm$. In visual and visuo-tactile tests, the room lights are on. For tactile tests, the room is dark and the table is equipped with UV back lights that enable to see the sample holder silhouette and position, without seeing the texture and details of the sample surface.

In this setup, the assessor can easily perform a tactile exploration of the sample surface and position the sample on the table (Figure 4). The number of samples should be limited in order to avoid any sensory tiredness. The tabletop is made of a translucent material and a camera installed under the table takes a picture of the mapping surface at the end of each test. The back of the samples are tagged with QR

Figure 4: QR codes on the map.

code printed on fluorescent paper to increase the contrast under UV light in order to enable the automatic extraction of the sample positions using a software specifically developed for this task.

For each assessor j, the data collected are the coordinates (X_{ij}, Y_{ij}) of each sample i and descriptors associated to the samples by the assessors during the experiment.

These data are processed through a Multiple Factor Analysis (MFA) implemented in the SensoMineR software (Lê et al., 2008; Lê and Husson, 2008). MFA is based on a Principal Component Analysis (PCA) and have the advantage to allow the structuration of the data in group to balance the influence of the assessors in the analysis. From the MFA analysis, for a given sensory modality, a mean representation of the samples among the panel is extracted. In addition, the descriptors cited by the assessors give indications on how the samples were perceived and these descriptors also give insights on the meaning of the axes deriving from MFA.

Test Instructions

The assessors were instructed to arrange the samples on the table, according to their perceived similarities and differences. Samples that are perceived similar should be close together, and those which are different should be far from each other. After positioning the samples, the assessors were asked to give attributes, words that qualify their own perception of the texture of each sample or group of samples. They were not allowed to lift the sample from the table, but the exploration gestures were free.

3.2 Statistical Analysis with through Mean Representation

For a given sample, for each assessor j, the data collected have the coordinates (X_{ij}, Y_{ij}) of each sample i and words associated to the samples by the subject.

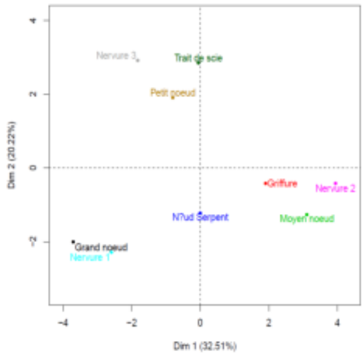

Figure 5: A mean representation, it was obtained for WC sample in visuo-tactile.

We ignore the words and we treated only the numerical data. These data are processed through MFA implemented in the `SensoMineR` and `FactomineR`, (Lê et al., 2008; Lê and Husson, 2008) packages of the R software. From the MFA analysis, for a given sensory modality, a mean representation of the samples among the panel is extracted as in Figure 5.

A mean representation can be also represented as a matrix of final coordinate of the sample. Various other techniques could be applied on this mean representation like K-means or K-medoids or hierarchical clustering.

3.3 RV-coeficient

In (Robert and Escoufier, 1976) Robert and Escoffier introduced the RV-Coefficient in the aim to compare two representations U and V in the same space. In (Abdi, 2007) a deep analysis is done and we will take the following formula :

$$RV = \frac{trace(U^tV)}{\sqrt{trace(U^tU) \times trace(V^tV)}}$$

RV-coefficient is a measure of similarity of two representations, like cosine in interval [0,1]. A value near of 1 means very close representations, a small value means different representations.

3.4 Algorithms

The common idea of both algorithms was to compute the RV-coefficient between the main representation of the whole dataset (All) and the representation of a part of dataset ($Part$). We note this function as RV, for example, $RV(All, Part)$. We remember that All is formed by the contributions U_j of all the assessor j, $1 \leq j \leq N$, where N is the number of assessors.

Contribution of an Assessor. The idea is to compute $RV(All, All \setminus \{U_j\})$, for all j. So, the algorithm 1 which computes these values RV is quite simple:

Data: dataset All with the coordinates of the samples indicated by each assessors
$N \leftarrow size(All)$;
forall the $j \in 1 : N$ **do**
  $coef \leftarrow RV(All, All \setminus \{U_j\})$
end
Examine $coef_j$, $j = 1, N$

Algorithm 1: Algorithm to compute and the decide about the importance of an assessor.

If we can see that all the assessor has an equivalent importance, the natural question is how to find a minimum number of assessors. In this aim, the following algorithm 2 offers the possibility to decide which is this minimum number. The algorithm generates for every possible size k, $k < N$, a given number N' of parts of All with cardinality k and for each part, we compute its value of RV function, than we will take into account only the min, the max and the average of these values. The decision of the minimum number of assessor will be taken examining the table of min, max, average.

Data: dataset All with the coordinates of the samples indicated by each assessors
$N \leftarrow size(All)$;
$N' \leftarrow N - 1$;
forall the $k \in 2 : N - 1$ **do**
  forall the $j \in 1 : N'$ **do**
    $P \leftarrow RandomPart(All, k)$;
    $rv_j \leftarrow RV(All, All \setminus \{U_j\})$
  end
  $min_k \leftarrow \min(rv_j)$;
  $max_k \leftarrow \max(rv_j)$;
  $avg_k \leftarrow average(rv_j)$;
end
Examine min_j, max_j, avg_j, $j = 2, N - 1$

Algorithm 2: Algorithm to compute and the decide about the minimum number of assessors.

$RandomPart(A, k)$ generates a random subset of A having the cardinal k.

4 RESULTS

As said before, the RV coefficient was calculated between different configurations, in order to analyze the similarity and at the end, work out with the determination of the minimum number of subject that will guarantee a stable and statistically valid mean representation that is related to the perception.

Table 1: The table of the assessors influence on the mean representation for the smartphone cover case sample with 23 assessors.

Map without assessor	RV coef	p-value
1	0.9969245	9.647078e-06
2	0.9968665	7.686154e-06
3	0.9993329	7.652130e-06
4	0.9992873	7.316040e-06
5	0.9995793	7.969934e-06
6	0.9932582	1.222052e-05
7	0.9994813	8.492618e-06
8	0.9987969	8.993405e-06
9	0.9953651	6.763334e-06
10	0.9989282	6.687446e-06
11	0.9977334	8.360140e-06
12	0.9994534	7.552652e-06
13	0.9985761	7.457676e-06
14	0.9990266	6.415641e-06
15	0.9987920	7.058059e-06
16	0.9984504	7.141431e-06
17	0.9989072	6.864290e-06
18	0.9988803	8.242877e-06
19	0.9979545	6.610175e-06
20	0.9939960	1.494437e-05
21	0.9995917	8.265173e-06
22	0.9990081	8.223297e-06
23	0.9981801	9.765529e-06

4.1 Individual Assessor

For the first algorithm, for every dataset, the influence of an assessor on the mean representation given by RV-coefficient was very close to 1, confirmed by the p-value, see table 1. This results confirms that the influence of each assessor is balanced in the mean representation, and also every assessor has the same importance in the experiments. This results confirms the reality : all the assessor had the same level of expertise.

4.2 Minimum Assessors Number

For the R and WC datasets the results were analyzed in every sensory modality: tactile, visual and visuo-tactile. From various groups two to seventeen assessors, the RV coefficient was calculated between those configurations and the one with the entire panel (18 subjects). As the procedure was performed 17 times (for statistical validity), the mean value as well as minimum, maximum were calculated. In addition, the P-value of those RV coefficient were also examine to make sure the results are statistically significant. Table 2 display the results of the WC and R samples in tactile, visual and visuo-tactile conditions.

Table 2: The tables of RV values computed for WC datasets and for R datasets (up and middle) and for the datasets of smartphones : cover case and material.

Tactile				Visual				Visuo-tactile			
nb. assessors	min	moy	max	nb. assessors	min	moy	max	nb. assessors	min	moy	max
2	0.46	0.62	0.76	2	0.57	0.76	0.9	2	0.55	0.67	0.8
3	0.62	0.73	0.81	3	0.59	0.8	0.86	3	0.62	0.75	0.83
4	0.62	0.79	0.89	4	0.7	0.85	0.92	4	0.7	0.78	0.84
5	0.77	0.83	0.91	5	0.74	0.88	0.94	5	0.68	0.82	0.89
6	0.72	0.85	0.92	6	0.86	0.91	0.95	6	0.75	0.84	0.91
7	0.84	0.89	0.94	7	0.87	0.93	0.96	7	0.82	0.89	0.93
8	0.83	0.9	0.94	8	0.85	0.94	0.98	8	0.83	0.91	0.95
9	0.88	0.92	0.96	9	0.89	0.94	0.98	9	0.86	0.91	0.96
10	0.87	0.93	0.97	10	0.93	0.96	0.97	10	0.89	0.93	0.96
11	**0.92**	**0.95**	**0.97**	**11**	**0.94**	**0.96**	**0.98**	**11**	**0.91**	**0.94**	**0.96**
12	0.92	0.96	0.98	12	0.94	0.97	0.98	12	0.92	0.95	0.98
13	0.94	0.96	0.99	13	0.95	0.97	0.99	13	0.91	0.96	0.98
14	0.95	0.97	0.98	14	0.97	0.98	0.99	14	0.95	0.97	0.98
15	0.95	0.98	0.98	15	0.98	0.98	0.99	15	0.93	0.98	0.99
16	0.98	0.99	0.99	16	0.98	0.99	0.99	16	0.97	0.98	0.99
17	0.98	0.99	0.99	17	0.99	0.99	0.99	17	0.98	0.99	0.99

Tactile				Visual				Visuo-tactile			
nb. assessors	min	moy	max	nb. assessors	min	moy	max	nb. assessors	min	moy	max
2	0.4	0.62	0.78	2	0.46	0.6	0.72	2	0.4	0.62	0.78
3	0.56	0.7	0.79	3	0.57	0.7	0.76	3	0.56	0.7	0.79
4	0.56	0.79	0.87	4	0.68	0.76	0.84	4	0.56	0.79	0.87
5	0.66	0.79	0.89	5	0.61	0.78	0.86	5	0.66	0.79	0.89
6	0.68	0.84	0.9	6	0.74	0.83	0.89	6	0.68	0.84	0.9
7	0.74	0.85	0.92	7	0.82	0.88	0.92	7	0.74	0.85	0.92
8	0.81	0.9	0.94	8	0.84	0.88	0.92	8	0.81	0.9	0.94
9	0.82	0.91	0.94	9	0.86	0.91	0.95	9	0.82	0.91	0.94
10	0.89	0.92	0.95	10	0.87	0.92	0.95	10	0.89	0.92	0.95
11	0.88	0.93	0.97	11	0.89	0.92	0.95	11	0.88	0.93	0.97
12	**0.92**	**0.95**	**0.98**	**12**	**0.93**	**0.94**	**0.97**	**12**	**0.92**	**0.95**	**0.98**
13	0.93	0.96	0.97	13	0.93	0.96	0.98	13	0.93	0.96	0.97
14	0.94	0.97	0.98	14	0.94	0.96	0.98	14	0.94	0.97	0.98
15	0.96	0.98	0.99	15	0.94	0.97	0.98	15	0.96	0.98	0.99
16	0.98	0.98	0.99	16	0.97	0.98	0.99	16	0.98	0.98	0.99
17	0.99	0.99	0.99	17	0.98	0.99	0.99	17	0.99	0.99	0.99

Smartphone cover case				Sample material			
nb. assessors	min	moy	max	nb. assessors	min	moy	max
2	0.5	0.76	0.88	2	0.5	0.73	0.84
3	0.63	0.81	0.93	3	0.66	0.8	0.9
4	0.67	0.85	0.93	4	0.64	0.82	0.91
5	0.8	0.88	0.94	5	0.69	0.87	0.92
6	0.79	0.9	0.96	6	0.82	0.9	0.95
7	0.85	0.92	0.95	7	0.84	0.91	0.96
8	0.89	0.93	0.96	8	0.87	0.92	0.96
9	0.88	0.94	0.96	9	0.88	0.94	0.96
10	**0.92**	**0.95**	**0.97**	**10**	**0.89**	**0.94**	**0.97**
11	0.94	0.96	0.98	11	0.93	0.96	0.98
12	0.94	0.96	0.98	12	0.94	0.96	0.98
13	0.95	0.97	0.98	13	0.94	0.96	0.99
14	0.95	0.97	0.98	14	0.94	0.97	0.99
15	0.96	0.98	0.99	15	0.95	0.97	0.98
16	0.96	0.98	0.99	16	0.96	0.98	0.99
17	0.97	0.98	0.99	17	0.97	0.98	0.99
18	0.98	0.99	0.99	18	0.97	0.98	0.99
19	0.98	0.99	0.99	19	0.97	0.99	0.99
20	0.98	0.99	0.99	20	0.97	0.99	0.99
21	0.99	0.99	0.99	21	0.99	0.99	0.99
22	0.99	0.99	0.99	22	0.99	0.99	0.99

The minimum value of RV coefficient was considered for better precision. On the view of those results, it was observed that, for WC samples the similarity with the global mean representation reaches 0.92 with 11 subjects; while for the R samples, it reaches 0.92 for 12 samples.

For the smartphone datasets, as for the WC and R samples, the minimum RV coefficient values were analyzed. Those values expressing the similarity between the global mean representation of 23 assessors and maps obtained with a number of assessors comprises between 2 and 22.

In the table 2 it can be observed that with 10 subjects, the RV coefficient reaches 0.92, so 10 is a minimum number of assessors.

5 CONCLUSIONS

In this paper we have used datasets collected for sensorial analysis of materials. The questions solved are:

- how many subjects are necessary to realize a significant experience
- how could we prove that this minimal number is correct

A methodology based on the use of a synthetic value, in our case, the RV value, was described and implemented. The method was applied on various datasets and the obtained results proved the correctness of our approach.

This methodology can be applied in other experiences in the aim to optimize the sensorial map.

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