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A new method is proposed based on construction of perceptual maps using techniques of correspondence analysis and interval algebra that allow specifying the measurement error expected in panel choices in the evaluation form described in unstructured 9-point hedonic scale.

Keywords: Interval algebra, correspondence analysis, panelist

Introduction

Sensory analysis is important in many domains: to improve the quality of products throughout the development process, to describe sensory properties of products, and to compare products to competitor's products (Latreille et al., 2006). Murray, Delahunty & Baxter (2001) treated the importance of descriptive sensory tests, noting that the sensory scientist requires an arsenal of sophisticated tools (Lawless & Heymann, 2010) to be applied to the detection (discrimination) and description of both the qualitative and quantitative sensory components of a consumer product by a trained panels of judges (see also Meilgaard, Civille & Carry, 1999). The qualitative aspects of a product include aroma, appearance, flavor, texture, aftertaste, and sound properties, and distinguish it from others. Sensory judges quantify these product aspects in order to facilitate description of the perceived product attributes.

There are several different methods of descriptive analysis: for instance, quantitative descriptive analysis (Stone & Sidel, 1993). Rossi (2001) suggested

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repeatability and reproducibility measures defined by Mandel (1991). Others proposed more elaborate methodologies based on univariate or multivariate analysis with graphical and tabular representations of results.

Acceptance tests are generally applied to assess how much the consumer likes or dislikes a particular product (Prescott, 2009; Menezes et al., 2012). Different numerical scales are used for this purpose, especially the hedonic scale. Lim (2011), however, stated measurements of sensory or hedonic responses are inherent to effects relating to sensory and cognitive processes.

The stimulus-response model allows the interpretation that the first phase of sensory process, involving input of a stimulus, causes a sensory signal shown by feelings expressing quality and/or intensity. With regard to cognitive process, the initial phase is the decision that involves choice of scale, resulting in a more precise response to a specific sensory attribute, among other factors.

The relationship between sensory perceptions (sensory processing) and hedonic experience (cognitive process) is mentioned in the model as internal representation. Individual responses are certainly featured in a descriptive study summarized in numerical data. (Lim & Fujimaru, 2010). As to interference of the contextual effect in stimulus-response model, consider a situation where sensory perception comes from a trained panel with the ability to detect small differences between samples. Based on this panel’s observations, and also considering the homogeneity of results obtained by a trained panel, results will certainly be more accurate than those of an untrained panel, which may show fatigue and unwillingness to perform all the tests, as well as heterogeneity in their skills and sensory perceptions. These are all important factors contributing to inaccurate responses.

Another factor that contributes to inaccuracy of answers is that responses from this range in practice are treated as continuous points. This suggests that parametric statistics such as analysis of variance may return incoherent results (Peryam & Pilgrim, 1957), because the assumptions are generally violated. See Gay & Mead (1992), Giovanni & Pangborn (1983), Lim, Wood & Green (2009), Lim & Fujimaru (2010), O'Mahony (1982), and Villanueva, Petenate and Silva (2000).

To find consumers who have similar liking patterns, clustering techniques have often been used (Yenket et al., 2011a; Liggett et al., 2008; Carlucci et al., 2009; Ares et al., 2010; Neely et al., 2010; Schmidt et al., 2010; Sinesio et al., 2010). Furthermore, to avoid the shortcomings inherent in the points system, new descriptive methodologies, such as the Quantitative Descriptive Analysis (QDA) have been developed (Stone & Sidel, 1993).

The advantages of QDA over other methods of evaluation are: (1) confidence in judgment of 10-12 trained panelists, instead of a few experts, (2) development of objective description closer to consumer language, and (3) consensual development of descriptive terminology, which implies higher concordance in judgments among panelists.

Amorim et al. (2010) indicated a good sensory panel should provide results that are accurate, discriminating, and precise. Thus, in a successful analysis, it is key to have a set of robust tools for monitoring individual assessor's performances as well as the performance of the panel as a whole. The success of using a sensory panel depends on its performance, i.e., its ability to identify small differences between products in certain attributes with statistical significance (Kermit & Lengard, 2005).

A good panel performance is achieved when each panelist discriminates between products (large product variability), repeats the assessments (small within-assessor variability) and agrees with all other panelists on the sensory sensation that is described by a particular attribute with certain strength (small between-assessor variability) (Derndorfer et al., 2005). Sample size estimation has been discussed (Gacula & Singh, 1984; Moskowitz, 1997; Lawless & Heymann, 2010; Gacula & Rutenbeck, 2006) over the last twenty years. It can be concluded that sample size calculation is generally an approximation because the formula contains elements based on assumptions such as the variance in the data and amount to be detected. Sensory scales vary in length; as a result, the variance and amount to be detected become a problem.

The sample or base size used in consumer acceptance tests has varied in practice, mostly based on experienced for a particular product. Thus, the proposed methodology is to construct perceptual maps with techniques of correspondence analysis (Blasius et al., 2009) that allow specification of the measurement error expected in relation to consumer/panelist choices in the evaluation form, described in an unstructured 9cm-point hedonic scale through interval algebra (Gioia & Lauro, 2005, 2006).

To illustrate this methodology, a case study is presented on sensory acceptance, considering different numbers of panelists in the evaluation of three genotypes of soybeans [Glycine max (L.) Merrill] called Black (MGBR07-7141), Brown (BRSMG-800A) and Yellow Soybeans (BRSMG-790A).

The statistical methodology proposed is applied to sensory acceptance tests, and has the advantages of quantitative descriptive analysis (QDA). The accuracy of the response interval is inferred by panelists, considering the expected measurement error in relation to consumer/panelist choices in the evaluation form (described in unstructured hedonic terms). Usually, unstructured line scales are constructed, and a sample set is used to train panelists to reliably score the intensity of the chosen attributes.

Description of procedure for performing sensory tests applied to three soybean genotypes

Genotypes of soybeans [Glycine max (L.) Merrill] fit for human consumption in many seed coat colors came from the breeding program of the Embrapa/Epamig /Triângulo Foundation partnership, and sensory tests were performed at the Sensory Analysis Laboratory, Federal Institute IFTM-Triângulo Mineiro - Campus Uberaba, Brazil. The three genotypes were named according to the seed coat colors: Black (MGBR07-7141), Brown (BRSMG-800A), and Yellow Soybeans (BRSMG-790A).

Soybean genotypes were first soaked for 10 hours and then cooked with twice their volume of water. Cooking time was about 45 minutes in a pressure cooker, where each breed was cooked separately until they reached softness. Then the beans were cooled to approximately 25°C and served without spices. Acceptance test was conducted with 50 potential consumers of soybeans among students, teachers and administrative staff at IFTM, aged between 15-50 years, both genders.

The analysis was performed in individual white-lighted booths and samples were served in white plastic cups with a three-digit code. Six grains were served in each container and water was supplied to cleanse the palate between samples. Grains were presented in monadic sequential scheme (one at a time) in unstructured 9cm-hedonic scale from 1 (dislike extremely) to 9 (like extremely) to assess appearance, texture, and overall acceptance.

Incorporation of fundamentals of interval algebra in correspondence analysis and construction of perceptual maps

Based on the panelist scores obtained, the concepts of interval algebra were incorporated into sensory analysis considering each score and giving a measurement error $\xi = \pm 0.2$ cm and $\xi = \pm 1.0$ cm, which was determined by a priori knowledge of the researchers.

In agreement with the statistical methodology and given the unstructured 9-point hedonic scale, imposition of measurement error ξ to be made by the panelists in marking the acceptance form was made by considering two conjectures. First, the panelists showed some similar sensory abilities, i.e., there is a slight error in marking, arbitrarily set at $\xi = \pm\, 0.2$ cm, to be considered in measuring results. Second, the panelists show some heterogeneous sensory abilities, i.e., there was an error of considerable extent, arbitrarily set at $\xi = \pm\, 1.0$ cm, to be considered in measuring results.

Importantly, the accuracy of each measurement depended on the skills of panelists. No matter how careful the measurement and how precise the scoring in the evaluation form, there was always an uncertainty due to panel heterogeneity. However, as scoring uncertainty is considered when using interval algebra for constructing perceptual maps, both inaccuracy and accuracy of scores become predictable. Therefore, it is consistent to use a smaller sample size in acceptance testing. Thus, considering 50 panelists for each sensory attribute, each interval observation was represented by $\left[\underline{f}_{ij}; \overline{f}_{ij}\right]$ for the i^{th} taster ($i = 1, ..., I = 50$) and j^{th} cultivate ($j = 1, ..., J = 3$), the lower limit $\underline{f}_{ij}$ being calculated by the score $ij - \xi$ and the upper limit $\overline{f}_{ij}$ represented by the score $ij + \xi$.

Thus, interval sensory data were organized in a contingency table of interval frequency for constructing perceptual maps (Table 1) in a way similar to correspondence analysis (Guedes et al., 1999).

Table 1. Contingency table of interval frequency used for constructing perceptual maps

Panelist n(i)	Genotypes of Soybeans: Black (MGBR07-7141)	Yellow (BRSMG-790A)	Brown (BRSMG-800A)	Total
n_1	$\left[\underline{f}_{11}; \overline{f}_{11}\right]$	$\left[\underline{f}_{12}; \overline{f}_{12}\right]$	$\left[\underline{f}_{13}; \overline{f}_{13}\right]$	$\left[\sum_{j=1}^{J}\underline{f}_{1j}; \sum_{j=1}^{J}\overline{f}_{1j}\right]$
n_2	$\left[\underline{f}_{21}; \overline{f}_{21}\right]$	$\left[\underline{f}_{22}; \overline{f}_{22}\right]$	$\left[\underline{f}_{23}; \overline{f}_{23}\right]$	$\vdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n_I	$\left[\underline{f}_{I1}; \overline{f}_{I1}\right]$	$\left[\underline{f}_{I2}; \overline{f}_{I2}\right]$	$\left[\underline{f}_{I3}; \overline{f}_{I3}\right]$	$\vdots$
Total	$\left[\sum_{i=1}^{I}\underline{f}_{i1}; \sum_{i=1}^{I}\overline{f}_{i1}\right]$	…	…	$\left[\sum_{i=1}^{I}\sum_{j=1}^{J}\underline{f}_{ij}; \sum_{i=1}^{I}\sum_{j=1}^{J}\overline{f}_{ij}\right]$

Following the structure of the interval data shown in Table 1, we obtained the correlation matrix considering interval data (1).

$$[Q]=\begin{bmatrix} [\underline{q}_{11};\overline{q}_{11}] & [\underline{q}_{12};\overline{q}_{12}] & [\underline{q}_{13};\overline{q}_{13}] \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ [\underline{q}_{I1};\overline{q}_{I1}] & [\underline{q}_{I2};\overline{q}_{I2}] & [\underline{q}_{IJ};\overline{q}_{IJ}] \end{bmatrix} \tag{1}$$

where each element was calculated by the expression (2) following specific mathematical operations for interval division (Gioia & Lauro, 2005).

$$[\underline{q}_{ij};\overline{q}_{ij}]=\frac{[\underline{f}_{ij};\overline{f}_{ij}]}{\left[\sum_{i=1}^{I}\sum_{j=1}^{J}\underline{f}_{ij};\sum_{i=1}^{I}\sum_{j=1}^{J}\overline{f}_{ij}\right]} \text{ for } i=1,\ldots,I;\ j=1,\ldots,J \tag{2}$$

After obtaining the correlation matrix considering data interval, use the chi-square correction which resulted in the matrix **[*D*]**, each element being obtained by (3).

$$d_{ij}=\frac{[\underline{q}_{ij};\overline{q}_{ij}]-[\underline{q}_{i.};\overline{q}_{i.}][\underline{q}_{.j};\overline{q}_{.j}]}{\sqrt{[\underline{q}_{i.};\overline{q}_{i.}][\underline{q}_{.j};\overline{q}_{.j}]}} \tag{3}$$

where marginal probabilities were respectively defined for lines and columns of the correlation matrix considering data interval, according to expressions (4) and (5).

$$\left[\underline{q}_{i.};\overline{q}_{i.}\right]=\begin{bmatrix}\left[\sum_{j=1}^{J}\underline{q}_{1j};\sum_{j=1}^{J}\overline{q}_{1j}\right]\\ \left[\sum_{j=1}^{J}\underline{q}_{2j};\sum_{j=1}^{J}\overline{q}_{2j}\right]\\ \vdots\\ \left[\sum_{j=1}^{J}\underline{q}_{Ij};\sum_{j=1}^{J}\overline{q}_{Ij}\right]\end{bmatrix} \tag{4}$$

$$\left[\underline{q}_{.j};\overline{q}_{.j}\right]=\left[\left[\sum_{i=1}^{I}\underline{q}_{i1};\sum_{i=1}^{I}\overline{q}_{i1}\right]\ \left[\sum_{i=1}^{I}\underline{q}_{i2};\sum_{i=1}^{I}\overline{q}_{i2}\right]\ \cdots\ \left[\sum_{i=1}^{I}\underline{q}_{iJ};\sum_{i=1}^{I}\overline{q}_{iJ}\right]\right] \tag{5}$$

Interval mathematical operations used for calculating probabilities were performed as described by Gioia & Lauro (2005). Thus, regarding the correlation matrix considering data interval **[*D*]**, whose dimension is *I* lines by *J* columns, corrected by the chi-squared distance, covariance matrices associated with profiles 'line' and 'column' keeping interval data were respectively determined by (6) and (7).

$$[\Sigma_L]=[D]^T[D] \tag{6}$$

$$[\Sigma_C]=[D][D]^T \tag{7}$$

The normalization procedures used for profiles 'line' and 'column' were performed with singular value decomposition (Gioia & Lauro, 2006; Deif & Rohn, 1994; Seif, Hashem & Deif, 1992) considering the matrices $[\mathbf{\Sigma}_L]$ and $[\mathbf{\Sigma}_C]$ whose dimension is *I* lines by *J* columns. The position of each profile 'line' in relation to profiles 'column' were obtained in (8) and (9).

$$[L]=[D_L]^{-\frac{1}{2}}[U] \tag{8}$$

where $[\mathbf{D}_L]^{-½}$ is the square root of the diagonal matrix of the marginal probabilities 'line' of **[*Q*]** and **[*U*]** is the matrix of normalized eigenvectors of $[\mathbf{\Sigma}_L]$. Similarly, the position of each profile 'column' in relation to profiles 'line' was determined by

$$[C]=[D_C]^{-\frac{1}{2}}[V] \qquad (9)$$

where $[V]$ is the matrix of eigenvectors normalized of $[\Sigma_C]$, and $[D_C]^{-½}$ is the square root of the diagonal matrix of marginal probabilities 'column' of $[Q]$.

Based on the interval matrices $[L]$ and $[C]$ the coordinates related to profiles 'line' were been given by $[\tilde{L}] = [D_L]^{-1}[Q]^T[C]$ and the coordinates related to profiles 'column' were obtained by $[\tilde{C}] = [D_C]^{-1}[Q]^T[L]$.

A total inertia of the cloud of points is illustrated in Figure 1.

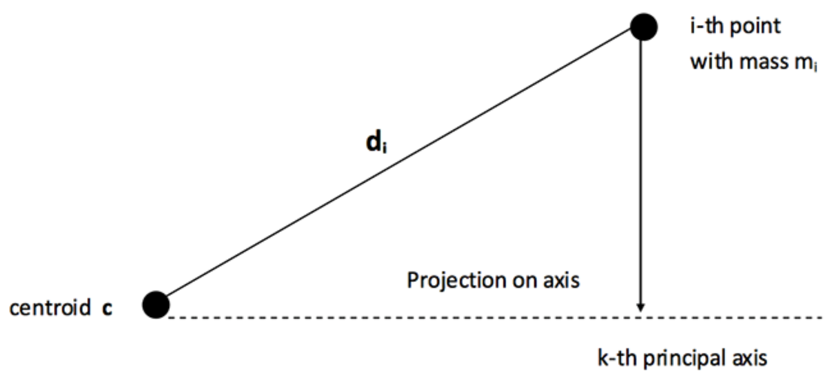

Figure 1. Inertia of decomposition in correspondence analysis

The coordinates obtained enabled the construction of interval perceptual maps, using a routine in R (R Core Team, 2013), and similar to technique preference maps as follows: coordinate values, variance explained on the first two components, consumer space, descriptive space, descriptive attributes that promote liking as recommended Yenket, et al. (2011b).

Results

Considering acceptance data in interval scale in relation to the attribute appearance, the results compiled in Figure 2 correspond to perceptual maps constructed respectively to $\xi = \pm 0.2$ cm (A) and $\xi = \pm 1.0$ cm (B). Percentage of sample variation explained for axes F1 and F2 is shown in Table 2.

Table 2. Decomposition of sample variability for the attribute appearance

	Axis	Inertia	Proportion	Cumulative (%)
(A) $\xi = \pm$ 0.2 cm	F1	[1.6918; 2.2516]	[0.8420; 0.8629]	[84.20; 86.29]
	F2	[0.2687; 0.4225]	[0.1370; 0.1579]	[97.90; 102.8]
	Total	[1.9605; 2.6741]		
(B) $\xi = \pm$ 1 cm	F1	[1.9584; 4.0786]	[0.5950; 1.742]	[59.50; 174.2]
	F2	[1.3326; 2.3408]	[0.3646; 0.4049]	[95.96; 214.69]
	Total	[3.2910; 6.4194]		

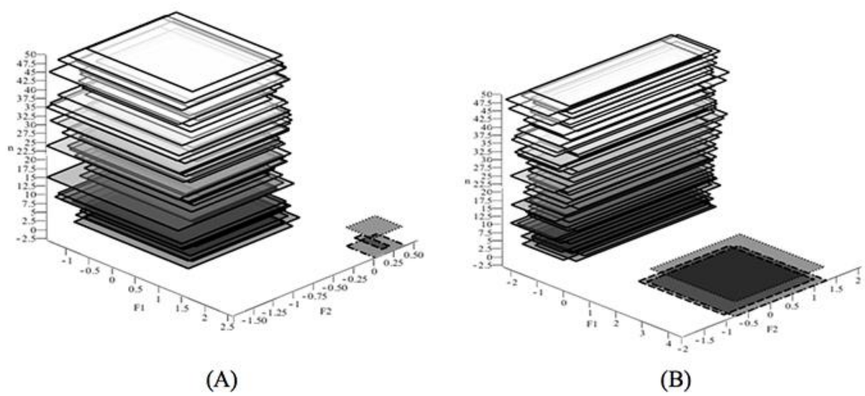

Figure 2. Perceptual map using interval scale for the attribute 'appearance'. Grayscale shows the 50 panelists, dotted line displays cultivar MGBR07-7141 (Black Soybeans), dash line for cultivar BRSMG-790A (Yellow Soybeans), and dashed-dotted line for cultivar BRSMG-800A (Brown Soybeans).

Results in Figure 2(A) indicated when considering a small measurement error $\xi = \pm$ 0.2 cm there is statistical evidence to state that the panel responses were homogeneous with respect to the attribute appearance, however, there was no evidence of preference for any particular soybean cultivar. Nevertheless, by increasing the measurement error to $\xi = \pm$ 1.0 cm, results in Figure 2(B) showed panel scores with a certain degree of similar homogeneity and no preference to cultivate, since a simple inspection of the rectangles indicated they had similar areas.

Given the two differential conjectures by different margins of error to be considered in response marking, and also keeping in mind the statement of Cohen (1990) related to beliefs and opinions of consumers about a product, such results would most likely help companies develop packaging, labels, and advertising campaigns to inform consumers about characteristics and properties of products in order to raise consumer expectations and encourage purchase. Thus, constructing perceptual maps via interval scaling definitely minimizes uncertainties regarding product acceptability as far as publicity is concerned.

Perceptual maps for evaluation of the attribute overall acceptance are described in Figure 3, while percentage of sample variation explained for axes F1 and F2 is shown in Table 3.

Table 3. Decomposition of sample variability for the attribute overall acceptance

	Axis	Inertia	Proportion	Cumulative (%)
(A) $\xi = \pm$ 0.2 cm	F1	[1.4175; 2.8151]	[0.7120; 0.8189]	[71.20; 81.89]
	F2	[0.3133; 1.1386]	[0.1810; 0.2879]	[89.3; 110.68]
	Total	[1.7308; 3.9537]		
(B) $\xi = \pm$ 1 cm	F1	[1.0985; 2.6511]	[0.4706; 0.5616]	[47.06; 56.16]
	F2	[0.8572; 2.9814]	[0.4383; 0.5293]	[90.89; 109.09]
	Total	[1.9557; 5.6325]		

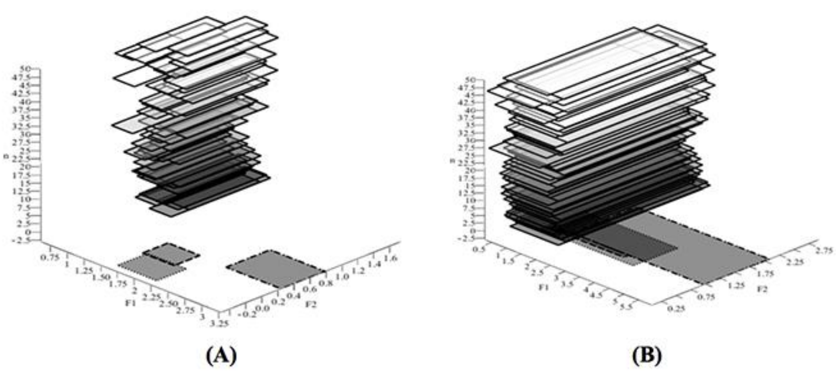

Figure 3. Perceptual map using interval scale for the attribute ‘overall acceptance’. Grayscale shows the 50 panelists, dotted line displays cultivar MGBR07-7141 (Black Soybeans), dash line for cultivar BRSMG-790A (Yellow Soybeans), and dash-dotted line for cultivar BRSMG-800A (Brown Soybeans).

Considering the situation of a small and essential error in response marking represented by $\xi = \pm\ 0.2$ cm (Figure 3(A)), a greater heterogeneity is seen between panelists. However, cultivar preference is inconclusive with regard to the attribute overall acceptance, as rectangle areas look similar. When considering the conjecture in which scale variability is greater, results in Figure 3(B) indicated homogeneous panel scores, although showing no specific preference for any particular soybean cultivar, as the rectangles do not overlap. Yenket et al. (2011a) mentioned this may be based on the frequency of a particular product being most or least liked by individual consumers and is not based on mean liking scores for a group of consumers.

Using perceptual maps reinforces the hypothesis that incorporating measurement error in data analysis is recommended provided there is a priori knowledge of the critical values for the margin of error. However, not all errors have to be measured. Behrens & Silva (2004) stated that the score given to the attribute ‘overall acceptance’ is merely determined by a simple inspection. Also, the response is related to the panelist attitude influenced by individual learning and experience on the object of our study: soybean genotypes, degree of individual acceptance/preference, and motivational component associated with action tendency. Perceptual maps for evaluation of the attribute ‘texture’ are shown in Figure 4, while percentage of sample variation explained for axes F1 and F2 is shown in Table 4.

Table 4. Decomposition of sample variability for the attribute texture

	Axis	Inertia	Proportion	Cumulative (%)
(A) $\xi = \pm\ 0.2$ cm	F1	[1.3216; 1.6500]	[0.7698; 0.9402]	[76.98; 94.02]
	F2	[0.3950; 0.1048]	[0.0597; 0.2301]	[82.95; 117.03]
	Total	[1.7166; 1.7548]		
(B) $\xi = \pm\ 1$ cm	F1	[1.1440; 4.4134]	[0.6067; 0.6319]	[60.67; 63.19]
	F2	[0.7414; 2.5701]	[0.3680; 0.3932]	[97.47; 102.51]
	Total	[1.8854; 6.9835]		

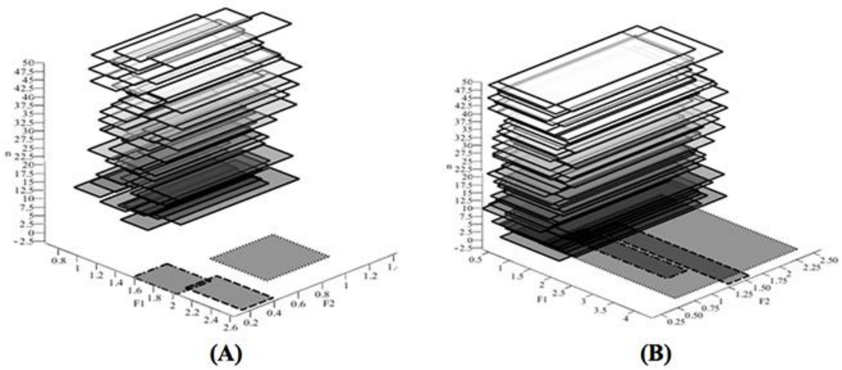

Figure 4. Perceptual map using interval scale for the attribute ‘texture’. Grayscale shows the 50 panelists, dotted line displays cultivar MGBR07-7141 (Black Soybeans), dash line for cultivar BRSMG-790A (Yellow Soybeans), and dashed-dotted line for cultivar BRSMG-800A (Brown Soybeans).

Results plotted in Figure 4(A) showed that scores for the attribute texture were very different, considering that the panelists could have made a mistake of $\xi = \pm\ 0.2$ cm when marking answers. Thus, there is no evidence of preference for any particular soybean cultivar, as rectangles do not overlap. In the situation with the greatest measurement error, arbitrarily set at $\xi = \pm\ 1.0$ cm, the results in Figure 4(B) indicated more homogeneous scores, which showed evidence of similarity among the genotypes BRSMG-790A (Yellow Soybeans) and BRSMG-800A (Brown Soybeans). This was evidenced by overlapping in most areas of cultivar-specific rectangles. Score differentiation regarding the genotype MGBR07-7141 (Black Soybeans) could possibly be influenced by physiological aspects, as seed coat is very important for regulating water absorption.

McDonald Jr. et al. (1988) stated that water intake affects a few morphological characteristics of seed coats that may influence water penetration time. Thus, it is reasonable to assume that physicochemical properties of genotypes with different seed coat colors are differentiated. This fact could possibly imply a genotype appearance more or less pleasing to the panelists, either in appearance or texture, so that responses of sensory evaluations presumably could be influenced by stimulation effect (Lim, 2011). Such effect is impossible to detect by incorporating measurement error, as the contextual interference effect suggested by Lim, Wood, and Green (2009) was recognized as a source of error and bias in evaluation testing.

Conclusion

Different scale variability in the case study showed that using interval algebra in correspondence analysis applied to descriptive tests provided additional information on the accuracy of panelist responses. Concerning the selection of soybean genotypes, incorporating measurement error in data analysis allowed for identification of groups with similar genotypes due to subjective analysis of profile location and overlapping in the quadrants.

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