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PREFERENCE-ORIENTED FORM DESIGN: APPLICATION TO CARS' HEADLIGHTS

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ABSTRACT
The integration of customer preferences is nowadays a challenge in new product development. In this paper, we describe a method which integrates the customer preferences for the design of geometrical forms. We illustrate the approach by the design of a car's headlight. From a product space, the method is based on the definition of a perceptual space, built by multidimensional scaling, and which lead to the definition of interpretable perceptual dimensions. Objective measures of the form, computed from the design variables of the design model, are selected to interpret the perceptual dimensions. These measures are representative of the overall form and of the curvature variations. At this level, the Fourier coefficients of a closed curve are used to represent the information on the curvature variations. Next, from the preferences of a customer, the target values of the selected measures corresponding to a preference optimum are calculated. We show in the paper the interest of this approach for the design of forms. The method is illustrated by the design of a car's headlight, modeled by Bezier curves and integrated in a front-end.

Keywords: customer centered design, perceptual space, multidimensional scaling, preference modeling, form design, Fourier coefficients.

1 INTRODUCTION
The development of new products that satisfy consumers' needs and preferences is a very important issue. The control of the risks in product innovation and the reduction of the innovation cycles require valid and fast customer's preference measurements, for determining new products that maximize preference. In particular, the form of a product is an important factor in the success or the failure of a product [1]. Since several years, in various research fields, many research works for form design are dedicated to preference measurements and preference modeling.
In Japan, Kansei engineering, founded by M. Nagamachi at Hiroshima University about 30 years ago, is a powerful approach to product design involving user's perceptions [3]. Kansei engineering proposes to quantify people's perceptions about the product form and to translate the consumer perceptions into the design elements. The principle is to collect subjective evaluations of users on a set of product, and to analyze and interpret the ratings using multivariate statistical techniques. Various modeling methods can be used to provide useful design rules (linear or non linear model, neural networks, rough set theory) or trend prediction [3].
In engineering, the multiattribute utility theory (MAUT) has become the basic theory to express an objective function in engineering and the basis of Decision-Based Design [4]. It has been shown that consumer form preference can be summarized in a utility function, which can then be used as a constraint for concept design generation [5]. Concerning preference tests, interactive genetic algorithms were proposed for user preference assessment [6], or for designing car silhouettes involving the style designer in the evaluation process [7].
In marketing, the influence of product attributes on the preference is investigated by compositional and decompositional methods. The typical decompositional method, Conjoint Analysis, is subjected to an increasing number of publications since several years [8], in particular for the design of forms. A comparison of choice based and rating based conjoint concerning the design of cars' front-ends is presented in [9]. In [10], a method is proposed to measure customer preference of automobile headlights using Choice Based Conjoint analysis, and an interesting parameterization of the design

variables of the headlights is defined. But the main limitation of conjoint analysis is that it works with qualitative factors, with various modalities (or levels). For the particular case of forms, the number of factors that must be taken into account can be very important, in order to not simplify too much the design problem.
For this reason, we have been interested in methods which consider quantitative factors for the description of the forms. With CAD systems, a given geometrical form can be parameterized in several different ways (Bezier curves, B-splines,…), of different complexity. When the form is complex, several hundreds, indeed several thousands of design variables must be defined. In this case, it is of course totally illusory to try to built directly a model between the preferences and the design variables.
The main idea of this work is that one must take into account a particular information in order to simplify the description of the forms: the user's perceptions. The main assumption under which this work is based on is that the preference is a function of the perceptions, and that the human perceptions of a given set of objects are characterized by interpretable perceptual dimensions. In order to define a parsimonious preference model, we propose to define measures, based on the design variables of the form, and which explain the perceptual dimensions
We present in section 2 the method we developed, based on the generation of a product space and user tests. Section 3 is dedicated to the application to car's headlight design. The tests carried out and the data analysis tools used are described in detail. Section 4 presents an analysis of the results. Conclusions and perspectives are drawn in section 5.

2 BRIEF OVERVIEW OF THE METHOD

The proposed method for the interpretation of preferences for product design is described in Figure 1. It is based on the following stages:

1. **Generation of a *product space*** made of different products, which roughly all meet the same usage functions, but differ according to their performances, style, aesthetics, … The chosen products must be neither too similar nor too different,
2. **User-test "dissimilarity assessment"**. The task of the subjects is to assess the perceptual dissimilarity between all pairs of products of the *product space* on a scale from "0" (perfect similarity) to "1" (perfect dissimilarity). The output of this stage is a dissimilarity matrix of generic term δ_{ij}
3. **Multidimensional scaling (MDS)**. MDS uses dissimilarity assessments to create a geometrical representation of the products in a perceptual space of low dimensionality [11]. The principle of MDS is to find a set of points in a k-dimensional space such that the distances among them correspond as closely as possible to the dissimilarity δ_{ij} (or a function of it) given in the input matrix. This is done by minimizing a criterion function called *stress,* which represents the 'badness of fit' of the dissimilarities on the distances. The output of this stage is a representation of the products in a k-dimensional space, the *perceptual space*.
4. **Definition of measures**. This stage consists in considering various objective physical characteristics (measures) of the product, suspected to play a role in the perceptions. These measures are proposed next to explain the perceptual dimensions of the perceptual space.
5. **Selection of measures**. The measures that are in relation (generally linear) with the position in the perceptual space are selected [12]. They are assumed to explain the perceptual dimensions.
6. **Preference test**. The test provides an assessment of the customer preferences for each product of the product space.
7. **Preference modeling**. A model is proposed to explain the preference by the perceptual dimensions (fitting of the preference on the perceptual space). This technique, called external preference mapping (PREFMAP), has different phases according to the model used (vector model, circular, elliptic, quadratic) [13]. One objective of this stage is to find, if it exists, an ideal point corresponding to an optimum of preference. With this model, the perceptual coordinates of this optimum are computed.
8. **Characterization of the optimum of preference**. The values of the selected measures corresponding to the ideal product are interpolated, on the basis of the relations defined at stage 5. These values characterize the ideal product and give useful constraint to the designer, constraints which take into account customer preferences.
9. **Design of the product**. This last stage consists in designing a product satisfying the target

value of the measures of the ideal product.

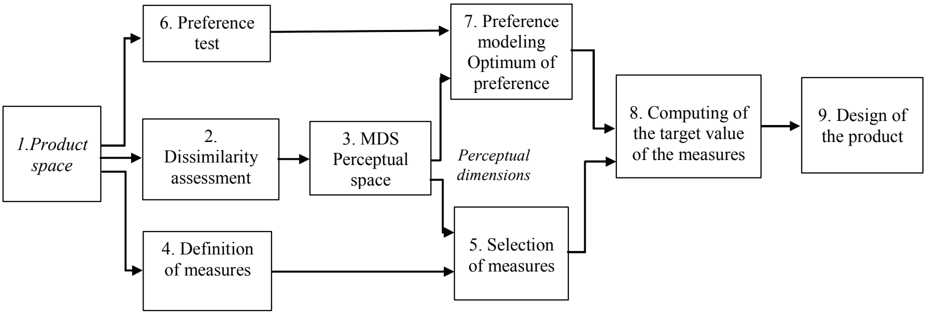

Figure 1: synoptic of the method

We propose to describe each stage of the method on a particular example, a car's headlight.

3 CASE STUDY: DESIGN OF A CAR'S HEADLIGHT

3.1 Introduction

We considered the following design problem: given the silhouette of a car's front-end (Figure 1), how to change the design of the headlight by taking into account the users' preferences? This problem corresponds for example to the "restyling" of vehicles, which consists in slight changes in the design of a vehicle at the middle of its life, in order to stimulate the sales and to give it a second youth.
We are of course aware that the application of our methodology to this particular problem is not yet for tomorrow: this part of the vehicle remains an exclusive domain of the designers because it plays a very important role in the identity of the car. Nevertheless, this example has to be considered as an illustration to show how the method works.
Similarly to a previous study [10], the shape of the headlight was modeled with two 4-control points Bezier curves (P0, P1, P2, P) for the upper contour and (P, P3, P4, P0) for the lower (Figure 2).

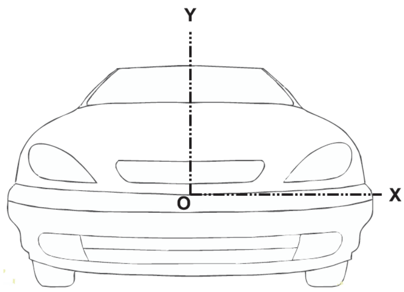

Figure 1: Silhouette of the car's front-end used for the tests

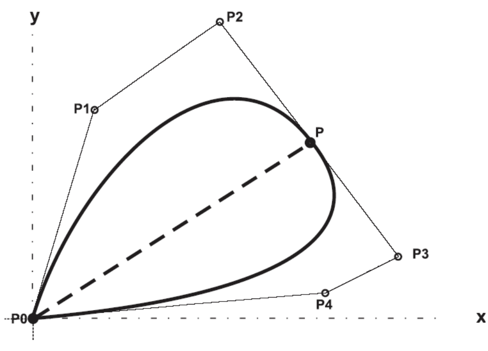

Figure 2: parameterization of the shape with two Bezier curves

The headlight shape is finally defined by 12 independent design variables (the coordinates in the plane (x, y) of the points P0, P1, P2, P, P3, P4). This parameterization will be the basis for the definition of the product space.

3.2 Generation of the product space

25 headlights were generated by making vary the design variables of the model. The shapes of the headlights designed, inserted in the same silhouette, are given in Figure 3. The product space was generated by trying to design different models of headlights, with respect to the feasibility and the

reliability of the forms. At this level, the difficulty is to try to cover "at best" the design space. An empirical solution was proposed, but techniques like Latin Hypercube Sampling could be used to provide a sounder design [14].

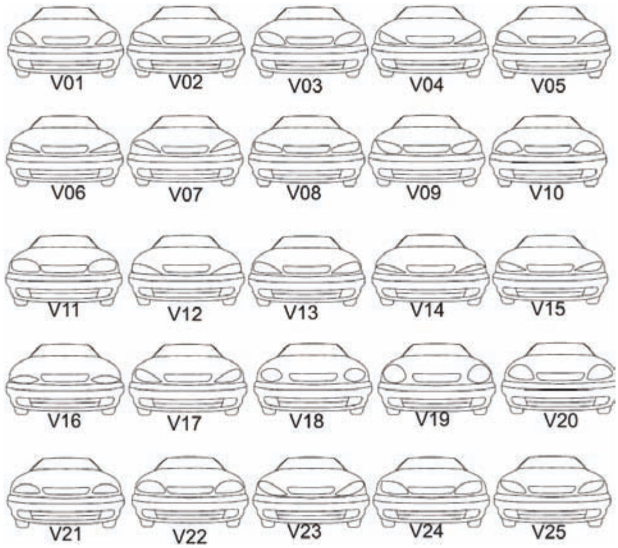

Figure 3: picture of the 25 headlights of the product space

A specific interface was used for the definition of the different models (Figure 4).

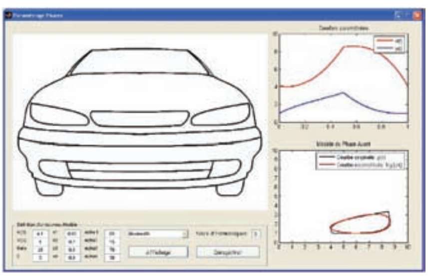

Figure 4 : interface for the definition of the headlights

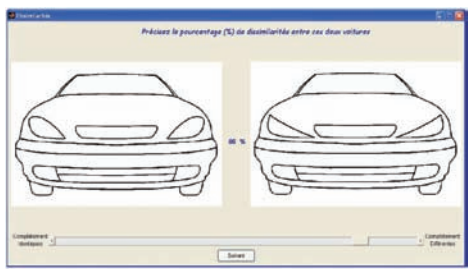

Figure 5 : interface for the pairwise dissimilarity test

3.3 Pairwise dissimilarity test – Multidimensional scaling

3.3.1 Test

A perceptive dissimilarity test was carried out on the product space of $N = 25$ products. The number of dissimilarities to assess was $N.(N\text{-}1)/2 = 300$. For each pair of products, the task asked to the subject was to assess the dissimilarity between the two front ends on a scale from 0% (products completely similar) to 100% (product completely dissimilar) (Figure 5). Only one subject made the test, what we consider as sufficient to illustrate the method. However, given that the assessment of the dissimilarity is subjected to assessments' errors, we are of course aware that several subjects should be used in order to scatter the effect of these errors and to improve the reliability of the data.

3.3.2 Perceptual space

The dissimilarity matrix was next processed with a multidimensional scaling algorithm in order to define the perceptual space [15]. A non-metric algorithm was used, which fits as closely as possible the rank order of the distances in the perceptual space on the rank order of the dissimilarities. A twodimensional configuration was retained for the representation; the positions of the different front-ends are given in Figure 6.

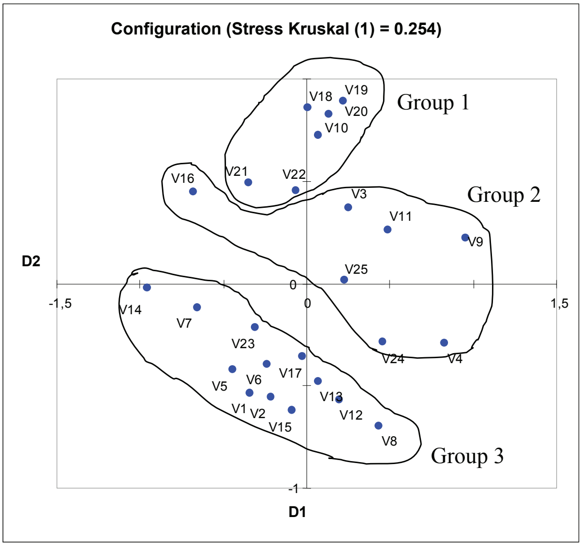

Figure 6: position of the front-ends in the perceptual space (solution of the MDS) and definition of the groups of the HAC

3.3.3 Interpretation of the perceptual dimensions D1 D2

In order to help the interpretation of the MDS dimensions, a hierarchical ascendant classification (HAC) was made on the perceptual dissimilarity matrix (given by the subject). The principle of HAC is to build a hierarchical tree (dendrogram, figure 7), which shows the level of each aggregation according to the dissimilarity between the products. The method used the Euclidian distance for the computation of the dissimilarities and the Ward's method as the linkage rule (rule for the computation of dissimilarities between groups of products). A partition of three groups of cars can be defined (highest jump in the dendrogram).

Group 1 is made up of the cars V18, V19, V21, V22, V10, V20.

Group 2 is made up of the cars V14, V7, V5, V23, V15, V1, V17, V8, V6, V12, V13.

Group 3 is made up of the cars V4, V9, V11, V24, V16, V3, V25.

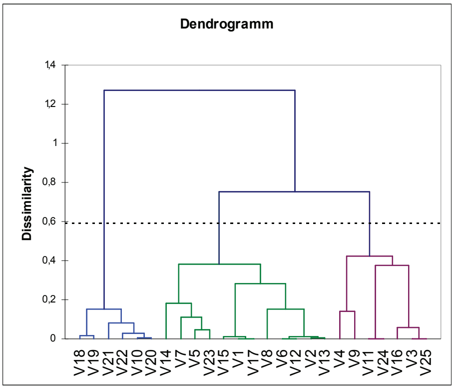

Figure 7: partition of the product space using HAC

The composition of the groups is also given on the perceptual space (figure 6). With the partition of the cars, a prototype of each group can be defined (the product that is the closest to the centre of gravity of the group). A morphological analysis of the groups gives the typical attributes of a group. This information is given in table 1.

Table 1: characterization of each group and definition of the prototype

	Group 1	Group 2	Group 3
Typical Attributes	- rounded, little elongated headlight - great surface - two angular points - principal inertia axis little inclined	- elongated headlight - two angular points - great surface area	- very elongated headlight - one angular points (interior) - little surface area
Prototype			

This first analysis indicates that the surface area is a variable that seems to explain the second dimension of the perceptual space: on the top of Figure 6 are located the headlights with a great surface area (group1), on the bottom the ones with a little surface area. Next, the angular points and the elongation of the form seem to play a role in the perceptual positioning. But their influence is not clear at this level of the study: it is necessary to define several measures to quantify this influence. The HAC gives nevertheless interesting information on the forms concerning the positioning.

3.4 Definition of measures

The "measures" are objective measurements of the headlight shape, defined from the design variables of the model. In the light of the HAC and the MDS, several candidate measures were proposed to explain the perceptual positioning.

3.4.1 Measures related to the overall shape and the overall position of the headlight

The following measures were computed (Figure 8):

- S: surface area of the shape,
- I_1, I_2: quadratic moment of the section S compared to the first (resp. second) principal axis of inertia,
- L_1, L_2: length of the shape along the first (resp. second) principal axis of inertia,
- ψ: angle of the first principal axis of inertia w.r.t the horizontal axis.

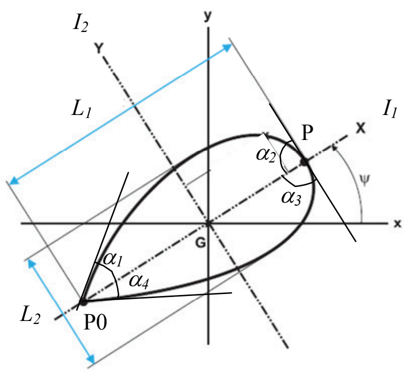

Figure 8: representation of the different measures

3.4.2 Measures related to the curvature of the shape

The previous measures give indication on the overall form of the shape. It is also necessary to define measures which represent locally or globally the curvature variations of the shape. Locally, we focused on the two angular points P0 and P and we proposed the four following measures:

- $\alpha_1, \alpha_2, \alpha_3, \alpha_4$: angles between the tangent to the shape and the first principal axis of inertia at points P0 (α_1,α_4) and P (α_2,α_3) (Figure 8).

To characterize the overall variation of the curvature, we considered the Fourier coefficients of the contour. This technique is used in image processing to represent a closed curve in the frequency domain [16]. A closed curve in the plane (x, y) can be considered as a periodic signal, given by the parametric equations $x(t)$ and $y(t)$. In our application, we considered a discretization of the curve with N_s points: these N_s points of the contour are represented by the discrete functions $x[n]$ and $y[n]$, their coordinates in the plane (O, x, y). The discrete Fourier transform of these two functions allows the definition of the Fourier coefficients $tfx[k]$ and $tfy[k]$ (equation 1):

$$tfx[k] = \frac{1}{N_s}\sum_{n=0}^{N_s-1} x[n]e^{-j2\Pi\frac{kn}{N_s}} \qquad tfy[k] = \frac{1}{N_s}\sum_{n=0}^{N_s-1} y[n]e^{-j2\Pi\frac{kn}{N_s}} \tag{1}$$

$tfx[0]$ and $tfy[0]$ represent simply the centroid of the points, $tfx[k]$ and $tfy[k]$ represent the magnitude of the kth harmonic. We implemented the fast Fourier transform in *matlab* (function *fft*), and the inverse fast Fourier transform (*ifft*) to reconstruct curves from their Fourier coefficients. Because the sizes of the individual harmonics decrease rapidly, a good approximation to the original curve is obtained from a partial sum with very few terms in it [17]. From a perceptual point of view, we noticed that a curve reconstructed from the first coefficients was very similar to the original. For this reason, we considered only the $K=4$ first Fourier coefficients of the curves.

In a similar way of measures used in psychoacoustics to explain the timbre of musical sounds [18], we defined the spectral centroid from the Fourier coefficients (first moment of the spectrum) (equation 2):

$$SC_x = \sum_{k=1}^{K} \frac{k.tfx[k]}{tfx[k]} \qquad SC_y = \sum_{k=1}^{K} \frac{k.tfy[k]}{tfy[k]} \tag{2}$$

The spectral centroid is an indicator of the magnitude of the overall curvature variation: it is minimum and equal to 1 for a shape corresponding to an ellipse, which has only one harmonic. It increases with the magnitude of the curvature variation: greater the SC, greater the curvature variations. For example, the front-ends of the product space with extreme values of SC_x are represented in figure 9 (V18: weak value of SC_x, V12: great value of SC_x).

$SC_x = 1.14$ $SC_x = 1.34$

Figure 9: illustration of headlight's curve with different values of the SC_x

3.4.3 Correlation of the measures with the perceptual space

The following measures were considered to explain the perceptual positioning: S, I_1, I_2, L_1, L_2, I_1/I_2, L_1/L_2, ψ, $\alpha_1+\alpha_4$, $\alpha_2+\alpha_3$ SC_x, SC_y. At this level, "explain the perceptual positioning" signifies to notice a relation (statistically significant) between the value of the measure and the perceptual positioning. We limit our study to linear relations. From a mathematical point of view, the strength of the correlation between the perceptual positioning on the dimensions D_1 and D_2 and the different measures m_i is represented by a linear model (linear regression - equation 3):

$$\hat{m}_i = a_i.D_1 + b_i.D_2 + c_i \tag{3}$$

Three indicators were used to estimate the quality of the linear adjustment:

- The determination coefficient of the regression $R^2(m_i,D_{1,2})$. It represents the percentage of variance taken into account by the linear model,
- The *p-value* of the Fisher's test (variance analysis – significance of the model),
- The Mean Absolute Percentage Error (*MAPE*). It represents the forecast accuracy of the model (equation 4): smaller the *MAPE*, better the forecast accuracy.

$$MAPE = 100\sum_{i=1}^{N}\frac{|\hat{m}_i - m_i|}{m_i} \quad (4)$$

The values of these indicators for each measure are given in Table 2.

Table 2: characterization of the linear model for each measure

	S	L_1	L_2	ψ	I_1	I_2	SC_x	SC_y	L_1/L_2	I_1 / I_2	$\alpha_1 + \alpha_4$	$\alpha_2 + \alpha_3$
$R^2(m_i,D_{1,2})$	0.42	0.42	0.58	0.02	0.56	0.24	0.70	0.16	0.48	0.54	0.65	0.19
p-value (F-test)	0.2%	0.2%	<0.01%	82%	<0.01%	5%	<0.01%	15%	0.1%	<0.01%	<0.01%	9%
MAPE(%)	16.31	5.40	13.90	99.99	34.33	12.57	2.00	5.44	16.48	45.03	26.17	27.59

Different cases appear in Table 2:

- Measures for which the linear model is not significant (p-value>5%). This is the case for the measures ψ, $\alpha_2 + \alpha_3$, SC_y. The percentage of variance taken into account by the model ($R^2(m_i,D_{1,2})$) is also very weak. We conclude that these measures do not explain the perceptual positioning,
- Measures for which the linear model is significant (p-value<5%) but the predictive power is weak (*MAPE*>10%). This is the case for the measures S, L_2, I_1, I_2, L_1/L_2, L_1, I_1/I_2, $\alpha_1 + \alpha_4$. In this case, the linear model is significant but the predictive power is too weak to make accurate predictions,
- Measures for which the linear model is significant (p-value<5%) and the predictive power is good (*MAPE*<6%). This corresponds to the measures L_1, SC_x.

With these results, we come to the decision that the linear model between the measures and the perceptual positioning is valid with a good reliability level for the two measures L_1 and SC_x. For this reason, we selected L_1, SC_x to explain the perceptual positioning. We will use this information in order to find the target value of these measures for a perceptual positioning corresponding to an optimum of preference.

3.5 Preference data

Preference measurements are generally made on a huge panel of customers, in order to take into account inter-individual differences and to define typical categories of customers. In this study, focused mainly on the description of the method, we decided to simulate the preference of a "virtual" customer with an adjustable and parametric model. Of course, a complete validation of our method will necessitate tests with a panel of real users. This issue will be a perspective of this work.
A quadratic preference model (paraboloid) with an ideal point was defined. This model is built on the perceptual dimensions D_1 and D_2 of the MDS. The model defining the customer preference is given by equation 5:

$$P(D_1, D_2) = d.D_1 + e.D_2 + f.(D_1^2 + D_2^2) \quad (5)$$

This model corresponds to a paraboloid (circular model) with an optimal point of coordinates $D_{1-opt} = \frac{-d}{2f}$ and $D_{2-opt} = \frac{-e}{2f}$. If $f > 0$: the optimum corresponds to a nadir point (anti-ideal). If $f < 0$: the optimum corresponds to an ideal point. We only consider this case in the following of the paper. Figure 10 shows an example of the preference surface for the 25 vehicles V1 to V25, built on the perceptual space.

3.6 Characterization of the optimum of preference

A classical way to exploit preference data is to try to explain the preference scores by objective measures of the products (preference mapping) [13]. Unfortunately, with the data of our example (preference – section 3.5 and measures – section 3.4), the methods based on preference mapping failed to predict correctly the preference (the quality of the adjustment was very poor and not usable for design). For this reason, we concentrate on the optimum of preference, located in the perceptual space at the point V_{opt} (D_{1-opt} , D_{2-opt}). The problem is to characterize the products corresponding to this optimum according to objective measures, i.e. to calculate values of the measures L_1 and SC_x corresponding to this positioning [19]. The proposed method consists in a linear interpolation between the values of the measures for the three closest products of the optimal product (Figure 11).

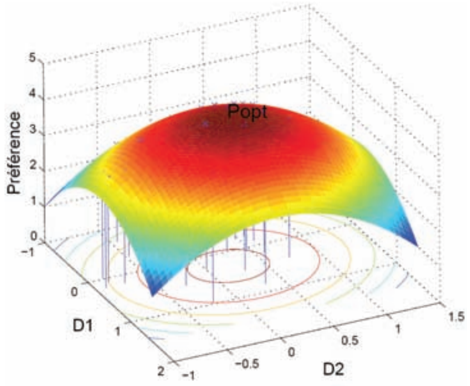

Figure 10: paraboloid of the simulated preferences and definition of the optimum of preference

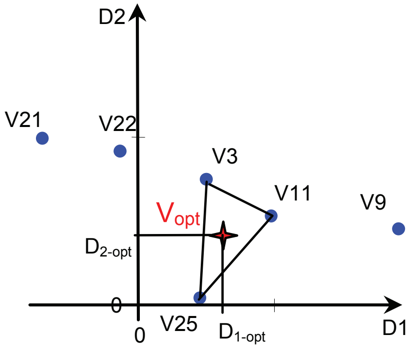

Figure 11: definition of the optimum of preference V_{opt} in the perceptual space

The optimal product V_{opt} is considered as the barycenter of three vehicles of the product space (V3, V11, V25 on Figure 11) with the weights α, β and γ respectively. With an additional relation between the coefficients, α, β and γ are solutions of the following system (equation 6).

$$\begin{cases} D_{1-opt} = \alpha.D_{1-V3} + \beta.D_{1-V11} + \gamma.D_{1-V25} \\ D_{2-opt} = \alpha.D_{2-V3} + \beta.D_{2-V11} + \gamma.D_{2-V25} \\ 1 = \alpha + \beta + \gamma \end{cases} \quad (6)$$

Then, the values of the measures for the optimal product V_{opt} are also interpolated with the same coefficients (equation 7):

$$\begin{cases} L_{1-opt} = \alpha.L_{1-V3} + \beta.L_{1-V11} + \gamma.L_{1-V25} \\ SC_{x-opt} = \alpha.SC_{x-V3} + \beta.SC_{x-V11} + \gamma.SC_{x-V25} \end{cases} \quad (7)$$

4 RESULTS - DISCUSSION

4.1 Validation of the interpolation method

Before using the method for the design of a new headlight, we studied the validity of the method by computing the prediction error for the values of the measures L_1 and SC_x for vehicles included in the initial product space. A leave-one-out-cross-validation test was implemented. For each vehicle Vi of the product space, the values of the measures L_1 and SC_x were interpolated using the three closest front-ends in the perceptual space (equation (7)). For each front-end Vi, and each measure L_1 and SC_x, the relative error is given by:

$$\left(E_{L_1}\right)_{V_i} = \left(\frac{\left|L_1 - L_{1-opt}\right|}{L_1}\right)_{V_i} \qquad \left(E_{SC_x}\right)_{V_i} = \left(\frac{\left|SC_x - SC_{x-opt}\right|}{SC_x}\right)_{V_i} \quad (8)$$

These relative errors are plotted in figure 12. The average value of the relative prediction error is 2.7% for SC_x and 9.1% for L_1. This result is in accordance with the results of table 2: the forecast accuracy is better for SC_x than for L_1. The second point is that vehicles at the border of the product space on the perceptual space (like V1, V8, V15, V18) are subjected to an important value of the prediction error. This confirms that the model must be used inside the observations and that predictions at the border could be suspicious.

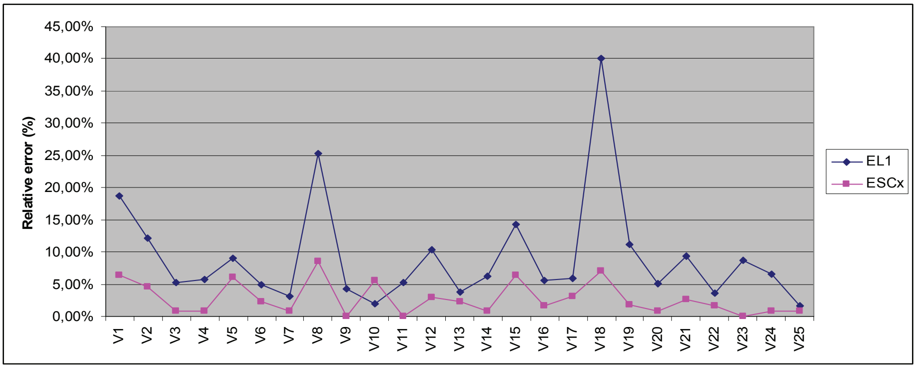

Figure 12: relative prediction error for the two measures L_1 and SC_x

The third point is that the prediction error is relatively small (2.7% for SC_x and 9.1% for L_1) and that it makes sense to specify, for the design, values of the measures with an error with that magnitude. In other words, if the prediction error on vehicles of the product space would be for instance 50%, it will be completely unrealistic to use it for product design.

4.2 Application to a new design

4.2.1 Characterization of the optimum

To illustrate the method for the design of a new headlight, we supposed that the preference data of our "virtual subject" led to an optimum located at the point V_{opt} ($D_{1\text{-}opt}$ =0.3, $D_{2\text{-}opt}$=0.2) (Figure 11). The values of the weights α, β and γ are calculated with equation (6). The values of the measures L_1 and SC_x corresponding to this optimum, calculated with equation (7), are given in table 3. These values are quite consistent and correspond to credible values for a headlight.

Table 3: value of the measures L_1 and SC_x for the optimal vehicle V_{opt}

	V3 (α = 0.35)	V11 (β = 0.24)	V25 (γ = 0.41)	V_{opt}
L_1	4.99	4.72	4.92	4.90
SC_x	1.25	1.28	1.26	1.26

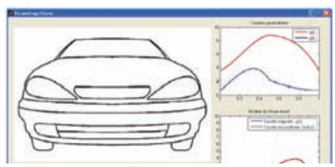

Figure 13

4.2.2 Application to the design of a headlight form

We must then design a headlight shape satisfying two constraints: L_1 =4.90 and SC_x =1.26. There is of course an infinity of solutions to this problem. To define solutions, several methods can be considered: exhaustive exploration of a discretized design space, constraint programming, optimization, … Even if this stage is out of the scope of this paper, for illustration, we propose a possible solution of the design (obtained by optimization) (Figure 13).

Obviously, it is illusory to hope to be able to design totally the headlight shape only from the preference assessments of one subject on 25 products. The ratio between the amount of input information (25 preferences assessments) and the amount of output information (value of the 12 design variables of the model) would be unrealistic in a statistical approach. The key point of the method is that it provides constraints to the designer, constraints based on the processing of customer preference.

4.3 Discussion

4.3.1 Use of the method in industrial design

The objective of the method is of course not to replace the designer: the principle is to give constraints to the designer relatively to the design variables of products, constraints based on a reasoned processing of the preference. The method can be applied to different products, concerning the form, texture, color, or sounds. It can be easily generalized to n-dimensions perceptual spaces. For the

definition of the perceptual space, the MDS solution could indeed needs 3 or 4 dimensions to fit accurately on the dissimilarities. In this case, the linear regression (equation 3) must take into account *n* dimensions to select the measures. Instead of a triangle, a *n*-simplex must be considered to compute the linear interpolation (figure 11).
The method is based on the definition of a product space. Concerning the study of forms, virtual products and CAD systems can be used to generate a great variety of products and to explore different forms. To provide relevant information, the method needs to consider many products in the product space. This can be time consuming for the dissimilarity tests and the preference assessments. There is intuitively a balance between the information in input (the assessments) and the information in output (the constraints given to the designer). If one needs meaningful constraints for the design, it is likely that several products must be assessed and that the product space must be huge.

4.3.2 Limit of the method

The proposed illustration is based on simulated preference, with a "friendly" shape relatively to the perceptions (quadratic, with an optimum corresponding to an ideal point, located "inside" the products of the product space). With preference corresponding to a real panel of subjects, several limitations could appear:

- The preference of the subjects could not be adjusted correctly on the perceptual space with a quadratic model. In this case, it would not be possible to define an ideal point. In a general manner, if the variation of preference according to the perceptual dimension (gradient) is important, it will not be possible to fit a model. It has to be noticed that this case will be in fact not very consistent: it would signify that very similar products according to the perceptions are assessed as very different according to the preferences. This in not in agreement with classical assumptions relatively to the preference [20],
- The optimum of preference could be an anti-ideal point (a minimum of preference). In this case, only the characteristics of the less attractive product can be provided,
- The ideal point could be located outside the area of the product space. In this case, a linear interpolation outside the observations can lead to an important prediction error. Of course, the initial product space has an influence on the results of the method. This issue will be studied in future works.

5 CONCLUSIONS AND PERSPECTIVES

We presented in this paper a method which integrates the customer preferences for the design of forms. The key points of the method are based on the definition of a perceptual space with multidimensional scaling, on the definition and the selection of measures to explain the perceptual dimensions, and on the interpolation of the selected measures corresponding to the optimum of preference. This method was illustrated with a pedagogical example concerning the design of car's headlight shape. Concerning the analysis of forms, we have proposed the use of Fourier coefficients for the description of closed curves, and of the spectral centroid for the representation of the curvature variations. We have seen that the spectral centroid seems to play a role for the interpretation of the perceptions. This has to be confirmed with additional works. Concerning the application of the method in design, we have shown that the results provided led to realistic and consistent designs constraints. An estimation of the prediction error of the selected measures showed that it is weak enough to envisage the use of these predictions as target values for the design. The objective of the method is not to replace the designer, but to constraint the design, on the basis of customer preferences.
Several perspectives can be drawn concerning this work. First, we are going to work on the definition of the product space, which has of course an influence on the results. Second, we will also work on the research of relevant measures concerning the forms, relevant with respect to the perceptions. Third, a validation of the method with a panel of real users must be made, as an estimation of the incertitude concerning the target value of the measures. Finally, the method must be validated on a real case, to show its effectiveness in industrial environment.

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