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Mapping aesthetic properties to 3D free form shapes through the use of a machine learning based framework

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Abstract.

Current production is moving from the mass production concept to the product customization and personalization. Customers are not anymore only buyers. Not only they are becoming actors within the Product Development Process (PDP) but, thanks to new production technologies like 3D printers, they can be both designers and producers. In this scenario, the development of user-friendly design tools is crucial. Declarative approaches are suitable and can address such requirements. They exploit generally understood and shared concepts closer to the way people perceive shapes than to the way shapes are modeled with complex geometric models. To this aim, this paper presents a generic framework for understanding the shape characteristics associated to perceptual/aesthetic properties of 3D free form shapes. This framework is used to investigate whether there is a common judgment to characterize the flatness of surfaces and which are the surface shape characteristics affecting the flatness perception? From the experiments, it results that the size and transition of the surrounding influence the perception of the flatness of a given surface strengthening the classification consistency.

Keywords: *Free form surfaces, Geometric Modeling, Declarative Modeling, Machine Learning Application, Aesthetic Properties, Industrial Design*.

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Introduction

Today, there exists a large variety of products with many shape variants. In such a situation, the aesthetic appearance of the product and its emotional affection are key factors often driving the customer choice. Thus, designing appealing objects plays a key role in the commercial success of a product, and being able to design attractive shapes while controlling the evoked positive emotions can help to better address customers' desires.

Understanding such affective influence of the product shape in the early design phases of the Product Development Process (PDP) requires the use of appropriate methods that can extract and transform subjective impressions about a product into concrete design parameters and characteristics. This methodology refers to as Affective Engineering (AE). Integrated in the PDP, AE provides a platform where emotional features are incorporated into design of appealing products (Nagamachi, 2011). AE deals with perception of shapes, which refers to very complex emotional-intuitive mechanisms that capture, organize, identify and interpret the sensory information in the nervous system. The perception is sometimes described as a process of constructing mental representations of the sensory information, shaped by knowledge, memory, expectation and attention. It is therefore linked not only to shape elements but also to many other product and customer characteristics, such textures, material, cultural and fashion values. The final and long-term objective of the AE is to define a direct mapping between the product characteristics and the emotions it evokes. Giannini et al. (Giannini & Monti, 2010) provide an overview of the most common AE methodologies used to investigate the relationships between shape features and emotions from various disciplinary perspectives, including psychology and computer science. Among the discussed methods, the one proposed by the FIORESII project team involves the engineering in reverse approach which considers the aesthetic properties of the final shape as a mean for linking the shape characteristics to the emotional impression and as modelling tools for attaining it (Giannini, Monti & Podehl, 2006).

The aesthetic properties identified by the FIORES II project play a key role in the perceptual impression of shapes and correspond to terms normally used by designers when modifying a shape. The development of geometric modelling systems allowing the users to employ previously defined words to construct the desired shape is called Declarative Modelling (Lucas, Martin, Philippe, & Plémenos, 1990). Its main advantage is the ability to allow the creation of objects by providing only a set of abstract words, generally based on geometric, topological or physical properties widely known. This methodology could be very useful for defining user-friendly tools easy to use also by nonprofessional designers. Actually, taking into consideration the fact that customers are valued more than before, they are currently more and more included within the product definition cycle. Now, with the availability of new materials and the development of new manufacturing technologies such as low cost 3D printing (Hod, 2014) and five-axis CNC machines, the question is not anymore which shape can be produced, but which shape should be produced to best fit the customers' requirements? Thus, not only designers have more 'freedom' to design what they like but also users can play the role of both designers and producers. As a consequence, CAD systems need to be more intuitive and to offer user-oriented design tools and parameters integrating an interaction language closer also to non-professional designers. This interactive language presents a qualitative judgment of the shape from a perceptual and appearance point of view and often considers more abstract and general notions (e.g. words) to describe the shape. These words can be used to define high-level manipulation tools if the relationships between the abstract word meaning and the corresponding underlying geometric characteristic of the shape are identified. When people classify shapes, with respect to some properties, they unconsciously follow certain rules linked to various elements, including the changes of the surface shapes. Sometimes, these rules can be explicitly explained but more often they are implicit and difficult for the persons to be expressed in terms of geometric properties of the shape. This is even much more difficult when the aim is to map emotions to a geometric model. This is due to the fact that describing a shape is a very difficult and ambiguous task which relies on personal knowledge, experience, culture, judgment as well as on different languages (Wiegers, Wang, & Vergeest, 2009). Despite this complexity, various efforts have been done to describe verbally shapes according to overall characteristics (Kassimi & Beqqali, 2011; Lian, Rosin, & Sun, 2010). However, they have mainly focused on retrieval issues thus they are not enough precise to specify which areas should be more affected by the modifications.

Some attempts to try to identify aesthetic properties and to link them to geometric characteristic have been undertaken (Giannini, Monti, & Podehl, Aesthetic-driven tools for industrial design, 2006). However, those approaches only refer to free form curves and are not yet formalized for free form surfaces. Actually, this is due to the fact that trying to define the aesthetic properties of 3D shapes and map them to free form surface characteristics using classical observation techniques is practically impossible. Those mechanisms are very complex and involve many factors. Therefore, finding the direct relationships between aesthetic properties and the free form surface geometric characteristics requires implementing more sophisticated methods. Having capitalized such knowledge, new industrial applications can be foreseen in which the customer is an important actor alongside with the other experts in analyzing and defining the product.

The objectives of this paper is to propose and to test a generic framework for collecting and processing the judgments of multiple users subjected to the visualization of free form shapes which have to be classified with respect to aesthetic properties. Those free-form shapes are characterized by intrinsic geometric characteristics that can be extracted in a pre-processing step. The key element of the proposed framework is the application of Machine Learning Techniques (MLTs), and more precisely supervised learning techniques, in detecting the classification rules between the user-specified aesthetic properties and the automatically-extracted geometric characteristics of the free form shapes presented to the users. Effectively, supervised learning techniques are good at finding relationships and rules between numerical values and classes of numerous instances.

Based on a preliminary validation on free form curves classified with respect to the straightness property (Petrov A. , Pernot, Véron, Giannini, & Falcidieno, 2014), this framework is extended to free form surfaces. Here, the idea is to evaluate whether there exists a common judgment to characterize the flatness of a free form surface. The extraction of the aesthetic classification rules is based on considering the perception of the aesthetic property of non-professional designers (potential customers) by conducting interviews. In addition, the proposed framework is exploited to investigate if and how the size of the surrounding and the transition towards the surrounding affect the perception of the flatness of a given surface area. Finally, this approach helps identifying the set of geometric characteristics involved in the classification rules.

In the remainder of this paper, section 1 introduces the different elements constituting the generic framework. Section 2 details the elements of the framework and notably the generation of the instances, the extraction of the geometric characteristics of those instances as well as the adopted classification method. Then, section 3 introduces the experiments and methods which have been set up to answer to four main questions : 1) Is there a common perception of the flatness, 2) Is the amount of surrounding influencing the perception of flatness ?, 3) Is the type of surrounding influencing the perception of flatness ?, 4) What are the most relevant attributes to characterize the flatness ? The final section concludes this paper.

1 Overall framework specification

Machine Learning Techniques (MLTs) and supervised learning algorithms exploit statistical mechanisms for discovering classification rules from already categorized data to make prediction on new occurrences. Therefore, it requires the definition of a huge structured dataset (the base of the temple in Figure 1.1Figure 1.1) on which classifiers will be trained. The specification of such a training set is very crucial since it affects the relevance of the extracted classification rules. Not only the number but also the choice of the selected shapes is very important. The general validity of the identified classification rules is not guaranteed if the variability of the shapes is limited and does not cover the possibilities of shape arrangements that may affect the perception of a given aesthetic property. Thus, specific methods for the creation of those instances have been devised through the modification of instance replications and are further described in next section. The way the training and testing sets are defined is explained in the section 2.2. Furthermore, the approach followed for associating the classification to the single instance can be different and may affect the organization and number of the instances in the dataset. For instance, if the classification results from interviews, repetition of instances can be useful to verify the consistency in cataloguing.

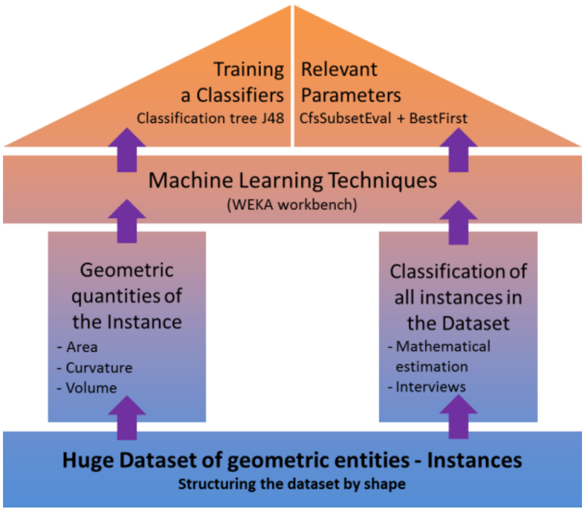

Figure 1.1: The overall framework

The second element of the framework is the other pillar of the temple (left pillar of the temple in Figure 1.1). It gathers the geometric quantities characterizing the instances, i.e. free form surfaces in this paper, which are potentially meaningful for the identification of the classification rules. Here, the key issue is to define which geometric quantities are relevant regarding a given aesthetic property. A very important point to consider is to tune the geometric characteristics (e.g. area, curvature, length, volume) in order to obtain shape descriptors independent of the size, position and orientation of the considered shapes. The choice of the geometric quantities is crucial since the instances will be characterized and described by those values from which MLTs will try to extract the classification rules. Thus, if the quantities to be analyzed are not well chosen, the identified rules may be not representative. The different quantities which have chosen are detailed in section 2.3 together with the method used to extract them.

The third element of the framework is the pillar representing the classification of all the instances of the dataset (right pillar of the temple in Figure 1.1). It firstly requires the specification of the set of classes to consider, then their assignment to each instance of the dataset. In this paper, the assignment results from the analysis of interviews over a group of participants. When dealing with participants, several issues inherent to the reliability of the classification have to be solved. For example, an efficient and intuitive way for conducting the interviews over a sufficiently representative sample (e.g. number, scientific and cultural backgrounds) has to be found. The method used to let the participants classifying a huge number of instances in a reasonable time is detailed in section 2.4.

The fourth element is the beam of the temple that corresponds to the adopted MLTs and associated control parameters. This part represents the actual application of the MLT with the selection of the most suitable learning algorithms for this kind of application, i.e. link between geometric quantities and aesthetic properties using supervised learning techniques. Here, the main challenge relies on the identification of the best couple of classifier and associated control parameters, i.e. the couple that would maximize the rate of well-classified instances. If the instances are classified with more than one label (multiple labeling) then, before applying the basic single label learning algorithms, dedicated problem transformation methods have to be applied. Actually, such methods transform a multi-labeled classification into a single-labeled classification while preserving the relation between all labels (Read, 2010). In the implemented version of the approach, five of the most widely used learning algorithms have been tested and tuned: C4.5 Decision Tree (Quinlan, 1993), Naïve Bayes (George & Langley, 1995), k-Nearest Neighbor (Tan, Steinbach, & Kumar, 2006), Support Vector Machine (Vladimir, 1995) and Classification Rules (Cohen, 1995). The method used to identify the best learning algorithm is introduced in section 3.1.

The final element of the framework is the roof that represents the experiments and results. Here, two methods have been designed to answer four questions: 1) Is there a common perception of the flatness, 2) Is the amount of surrounding influencing the perception of flatness ?, 3) Is the type of surrounding influencing the perception of flatness ?, 4) What are the most relevant attributes to characterize the flatness ? The first method transforms the multi-label in a single-label problem so as to perform comparison with a more general classification, whereas the second method performs several mutual comparisons between the classifications of several participants. The two methods are introduced in section 3.3. Then, the analyses and tests performed to answer the four questions are presented in sections 3.4 to 3.7.

2 Setting up the framework for free form surfaces

Differently from what has been possible for free form curves classified with respect to the straightness property (Petrov A. , Pernot, Véron, Giannini, & Falcidieno, 2014), for free form surfaces, there exists no known relationship between the aesthetic properties and the geometric quantities of free form surfaces. Therefore, several issues have to be faced. First, the type of aesthetic property has to be identified (section 2.1). Then, to be able to apply Machine Learning Techniques, a huge dataset has to be generated (section 2.2). The geometric quantities characterizing the free form surfaces also have to be identified and extracted from all the instances of the database (section 2.3). Finally, before training the classifiers, all the surfaces/instances have to be classified using a dedicated approach (section 2.4).

2.1 From the straightness of curves to the flatness of surfaces

As a starting point in the definition of aesthetic properties of free-form surfaces, the flatness has been taken into consideration as the extension of the straightness for curves. It is a qualitative descriptive term, which can be well understood even by non-professional designers, thus it is a good candidate for the development of declarative modelling capabilities for both professionals and non-experts. We assume that surfaces can be considered flat only if it is perceived very similar to a planar surface. From an engineering point of view, a flat surface corresponds to a surface that belongs to a given interval of tolerance defined by two parallel planes. The distance between the two planes is called the interval of tolerance. From a perceptional point of view, a flat surface is not only a plane but also a surface where the curvature in both directions does not greatly vary from zero. The curvature is not the only indicator of flatness because there are many shapes that are “dominantly” flat but they cannot be considered as flat from the perceptional point of view. Similarly to curves, where the bounding rectangle gives strong indications on the curve straightness, the bounding box dimensions of the surface might be related to the surface flatness. However, it is evident that a direct extension of the curve straightness equation to surface flatness is not possible because the geometry for surfaces is more complex than for curves. Thus, in the context of surfaces, we have designed a specific approach for the classification of surfaces with respect to the flatness property.

2.2 Generation of the instances dataset

The input to Machine Learning Techniques is a set of classified instances (the base of the temple in Figure 1.1). Each instance is an individual and independent example of the concept/rule to be learned and it is characterized by the values of a set of predefined attributes. Therefore, the choice of the instances is very important: the dataset should contain shapes that are representative of the possible surfaces appearing on industrial products and suitable for the flatness evaluation while presenting meaningful variations on the key shape characteristics/attributes. Additionally, since we are interested in understanding the rules which drive the perception of flatness of surfaces belonging to complex objects, it becomes crucial to understand if and how such a perception is changing depending on the type of the product as well as on the surrounding, i.e. the shape context embedding the analyzed surface. Thus, we decided to consider surfaces belonging to two very common industrial products: a coffee machine and a car (Figure 2.1).

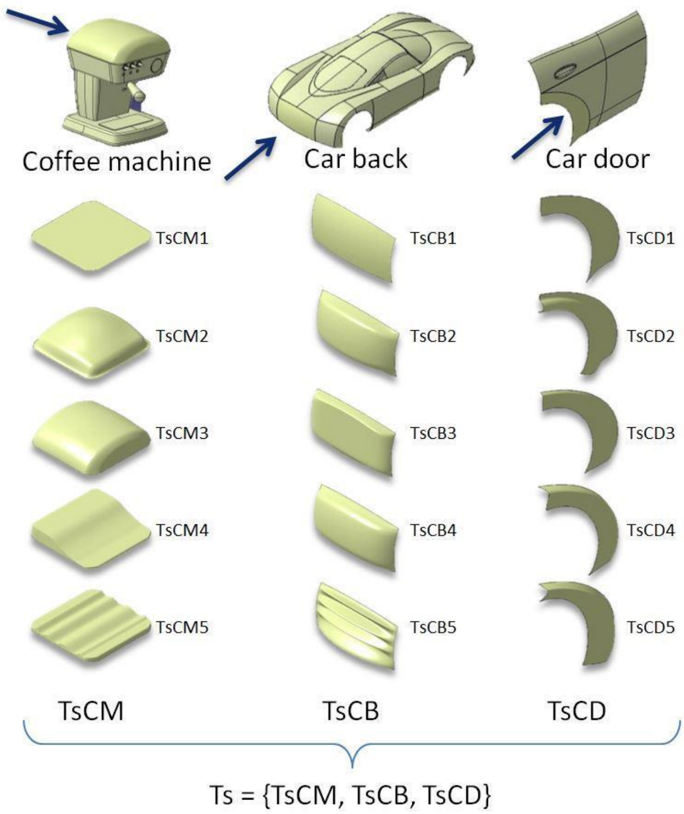

Figure 2.1: Target Surfaces of 3 different objects

Moreover, since the objective is also to pave the basis not only for classification capabilities but also for modification tools, it becomes important to consider surfaces obtainable through continuous variation. Starting from the assumption that the flattest surface is the planar one, to generate the Initial Dataset (IDS) we have performed a continuous deformation of a single planar patch to reach the so-called Target Surfaces (TS) belonging to three object areas : coffee machine (CM), car back (CB) and car door (CD). During the deformation, each surface shape originates an IDS instance. Various target surfaces have been considered to satisfy the need of making a direct relationship between geometric properties and aesthetics, e.g. to determine the influence of the geometric properties such as symmetry (rotational or planar), asymmetry or the undulation to the perception of flatness. For the analysis of the impact of a specific property, a surface can be more suitable than others. For instance, the target shapes of a coffee machine or a car back can be considered as more "regular" shapes than the one of the car door since: the former shapes can be easily used to represent symmetric shapes whereas the latter is not suitable for this purpose. The full set of the adopted target shapes is shown in Figure 2.1.

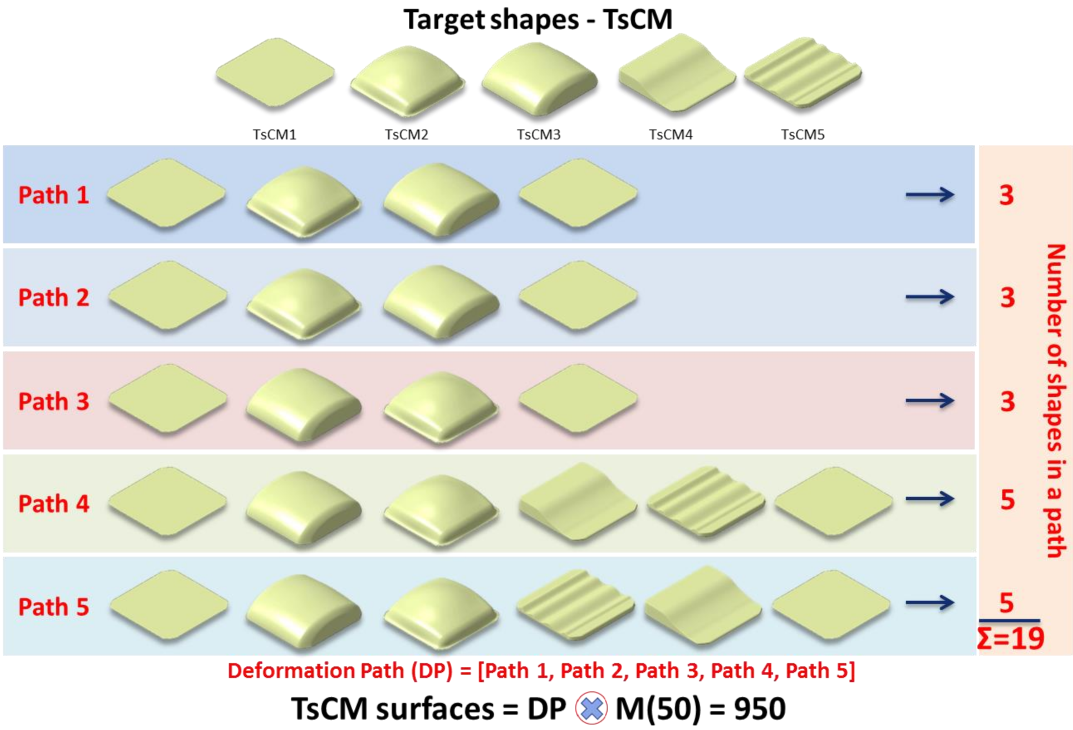

Figure 2.2: Target Surfaces (TS) used to automatically compute the IDS for the consumer appliance (i.e. Coffee Machine) context

2.2.1 Deformation paths and morphing process for shape instances generation

Being the shape classification obtained through interviews (section 2.4), the sequence of presentation of the shapes is rather important since it might affect the perception. Thus, each step of modification of the initial surface is performed in such a manner that during the modification it follows a so-called Deformation Path (DP) defined by the sequence of Target Surfaces (TS). This sequence is then followed by a Morphing (M) operator which generates many instances between the TS. Thus, many instances can be generated and ordered in an easy way which also helps tracking and understanding the changes of flatness classes. The objective of each deformation path is to obtain a wide range of possible shapes changing as much as possible their geometric properties in order to understand how they affect the perception of flatness. The idea is to have shapes with different properties but belonging to the same class of flatness as well as shapes with similar properties but belonging to a different class. The aim is to understand how a shape can be modified within the same class and how it can be modified to change the class. One path can be composed of few or all TS ordered in a different sequence. The final DP of ordered shapes is the collection of all paths together. For example, considering the Coffee Machine, the final DP gathers together all the 5 paths of shapes having TsCM1 as a starting and ending Target Surface. Considering all the paths, 19 TS has been obtained. Based on this, 50 morphed surfaces have been generated between them. Thus, for the Coffee Machine, the IDS is made of 950 surfaces : DP (19) x M(50) = 950 instances. Clearly, the morphing has been limited to 50 instances between two TS. This parameter has been tuned empirically so that the differences between two successive surfaces is very small. Figure 2.2 shows the TS used to automatically compute the IDS for the consumer appliance. Similarly, DPs have been used for the other two spaces of shapes (TsCB and TsCD) for the Car Back and Car Dor, and the corresponding IDS have been generated.

The two first paths, i.e. Path 1 and Path 2, are voluntarily the same. Such a repetition at the beginning of each subset is relevant to address the “learning phase” of the interview. It helps the participant to learn the use of the tool and to improve his/her classification consistency. After completing the interview with all participants, the instances corresponding to Path 1 are removed from the dataset IDS before applying MLTs. To investigate the classification consistency and the effect of surface presentation ordering in the classification, the same sequence of instances is repeated and inverted several times. Path 3 contains the same intermediate TS as Path 2 but differs for the exchanged positions of TsCM2 and TsCM3. Path 4 is an extension of Path 3 for which two TS have been added between the third and fourth positions in Path 3. While designing this ordering path, the interviewees are perturbed during the classification process so as to to test their classification rules on a new set of surfaces. Finally, similarly to Path 2 and 3, Path 5 replicates Path 4 with two TS which are swapped.

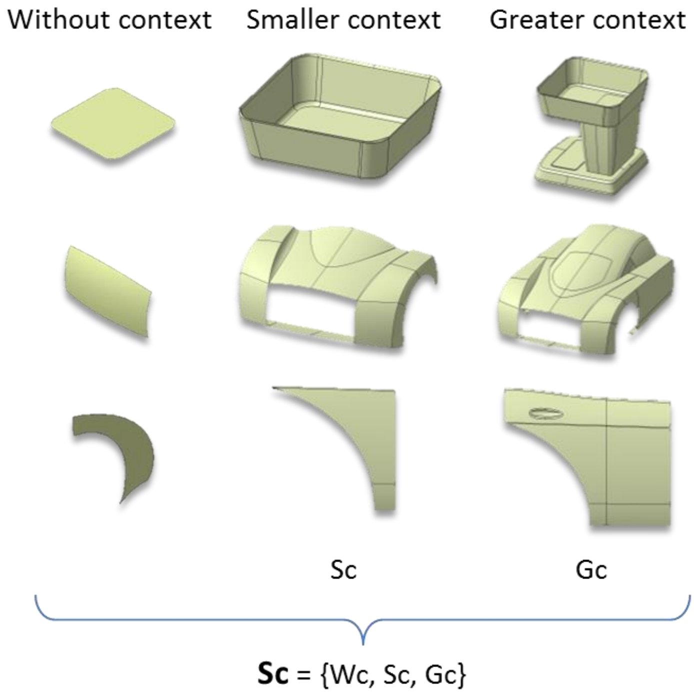

Figure 2.3: Surroundings for the three spaces of shapes

2.2.2 Definition of the surface surrounding

Beside the investigation of the existence of a common judgment for the flatness, we are also interested in understanding if those statements and rules are valid in absolute terms, or if they can be affected by the neighboring conditions in which the shape is considered. Intuitively, looking at some shape areas, trying to judge or describe it, the eye focuses on the surface but (often subconsciously) it also moves the focus towards the nearest surroundings and returns back. This phenomenon confirms the consideration that the perception of flatness for a given area might be affected by the surrounding. Another example is, for instance, when we take in our hand a computer mouse, the perception of the shape differs from the perception if the mouse is placed on a table or other wide plane. In order to investigate the influence of the surrounding to the perception of flatness, we have decided to include in the IDS also instances corresponding to the previous 950 surfaces inserted in different contexts. In particular, we consider two different surroundings: smaller and greater contexts depending on the extension of the neighbor shapes (Figure 2.3).

2.2.3 Generation of the complete IDS

The same approach described for the coffee machine has been adopted for the car back and car door considering the two sets of TS (TsCB and TsCD) as described on Figure 2.1. Thus, three sets of 950 surfaces can be generated, i.e. a total of 2850 surfaces. Then, placing the three sets in the three previously introduced surroundings (Figure 2.3), the complete IDS has been created (Figure 2.4) containing 8550 instances.

$$\begin{bmatrix} \text{TsCM surfaces} & \text{TsCB surfaces} & \text{TsCD surfaces} \end{bmatrix} \otimes \begin{bmatrix} Wc1 & Sc1 & Gc1 \\ Wc2 & Sc2 & Gc2 \\ Wc3 & Sc3 & Gc3 \end{bmatrix} = \begin{bmatrix} \text{TsCM + Wc1} & \text{TsCM + Sc1} & \text{TsCM + Gc1} \\ \text{TsCB + Wc2} & \text{TsCB + Sc2} & \text{TsCB + Gc2} \\ \text{TsCD + Wc3} & \text{TsCD + Sc3} & \text{TsCD + Gc3} \end{bmatrix}$$

$$\textbf{Ts} \otimes \textbf{Sc = IDS}$$

Figure 2.4: Complete IDS composed by surfaces immersed in different surrounding contexts

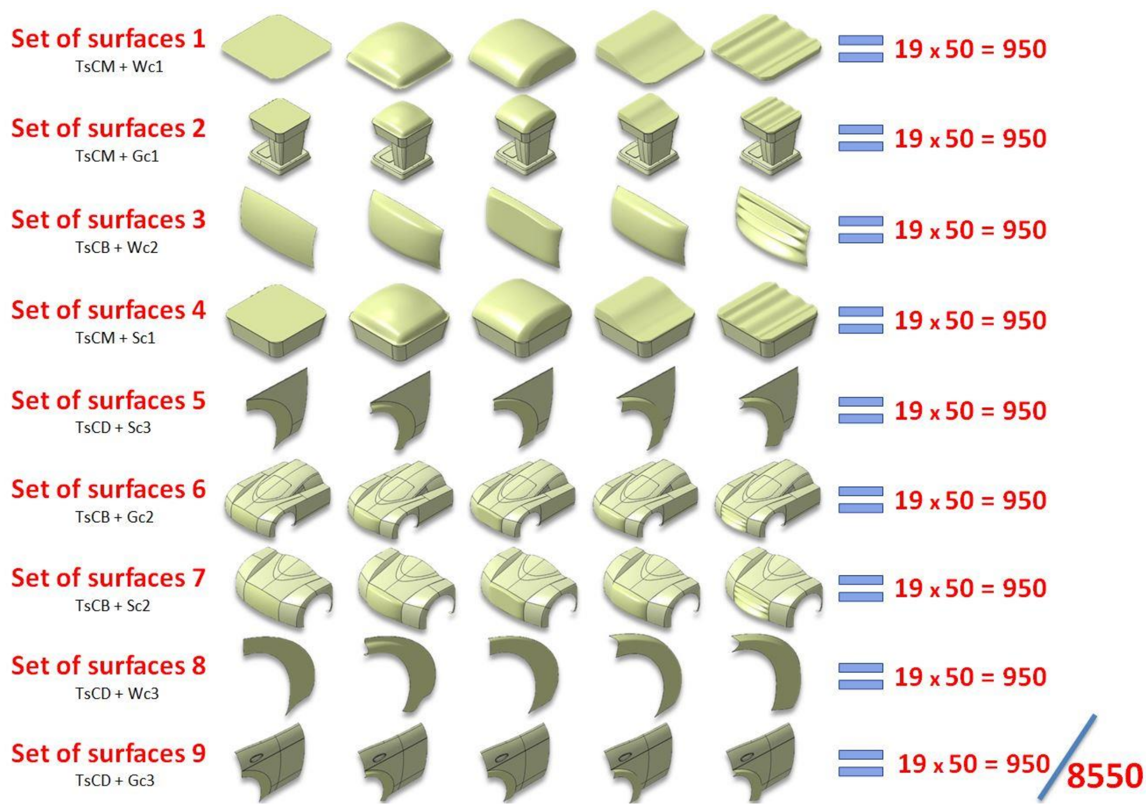

Figure 2.5: Restructuring the IDS to be used for the interviews

However, since it can be difficult to manage such a huge dataset during the classification process, it has been divided it into smaller sets. Therefore, we decided to maintain the division according to the specific paths (Ts) and contexts (Sc) creating (3x3) 9 sets of surfaces. These 9 sets of surfaces are randomly ordered in different sequences to be shown to the participant, regardless the type of objects and size of the surrounding (Figure 2.5). This ordering is very important for making the participants able to classify the surface according to their impression and not by remembering. For instance, if we present the three sets of surfaces (Wc1, Sc1 and Gc1) of the coffee machine one after the other two, we risk that the participant will classify only the first set according his perception and will try to repeat the same classification for the other two. In addition, such a structuring of the IDS will help answering the four main questions as discussed in section 3.

2.3 Definition of surface parameters/attributes using intrinsic geometric quantities

In the proposed approach, the idea is to make use of MLTs to understand the rules linking the classification of free form surfaces, i.e. the level of flatness in the present case, to the free form surfaces themselves. However, MLTs cannot directly work on free form surfaces as depicted on Figure 2.5. Thus, before applying MLTs, a pre-processing step is required and consists in extracting the geometric quantities which best characterize the classified free form shapes (left pillar of the temple in Figure 1.1). Actually, this extraction is performed in two steps: geometric quantities are first extracted (e.g. surface area, volume of the bounding box), and the attributes of the instances are then computed.

To be able to characterize the different surfaces composing the IDS, two sets of geometric quantities have been specified together with a mathematical equation for their computation. The first set represents the geometric quantities related to the surfaces to be classified (Figure 2.6 and

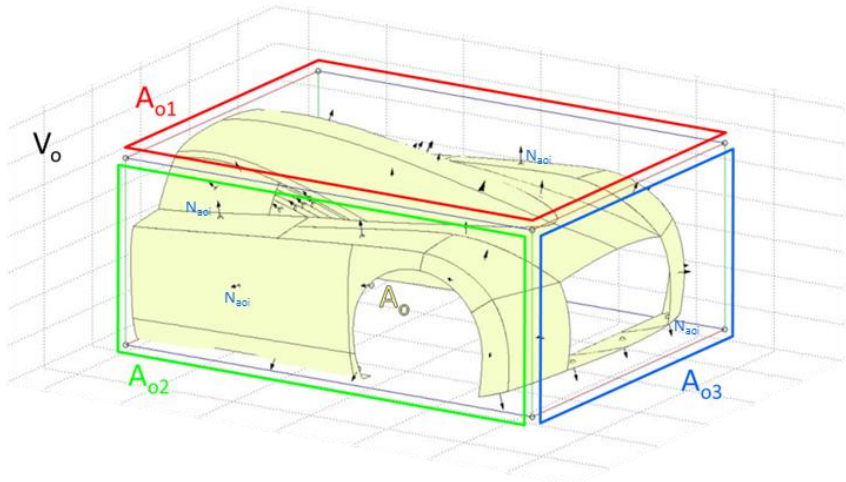

Figure 2.7: Geometric quantities related to the surrounding

Table 2.1) whereas the second set includes those related to the surrounding (Figure 2.7 and Table 2.2). The computation of all of these geometric quantities is done in Matlab using a function from the IGES Toolbox for importing the surface information from IGES file and extracting all geometric entities such as: NURBS curves and surfaces, trimmed patches, and points. Next, the surface triangulation is performed and the specified parameter values are computed using standard mathematical equations and operations (e.g. projection of points cloud onto a plane along projection vector, PCA principles for object orientation vectors, first and second derivative in a given point).

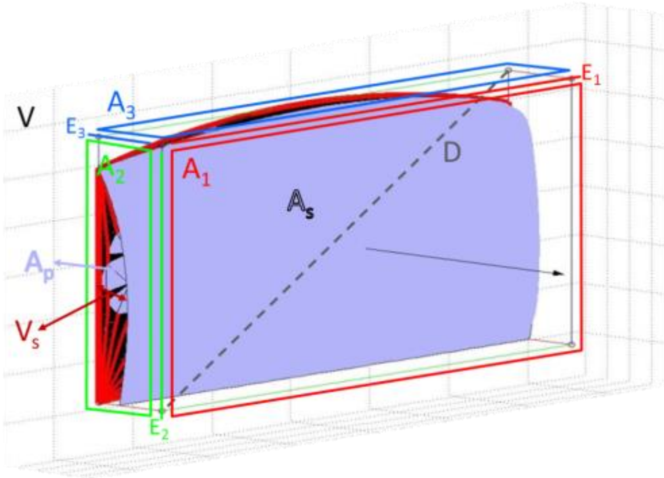

Figure 2.6: Geometric quantities of a surface and associated bounding box

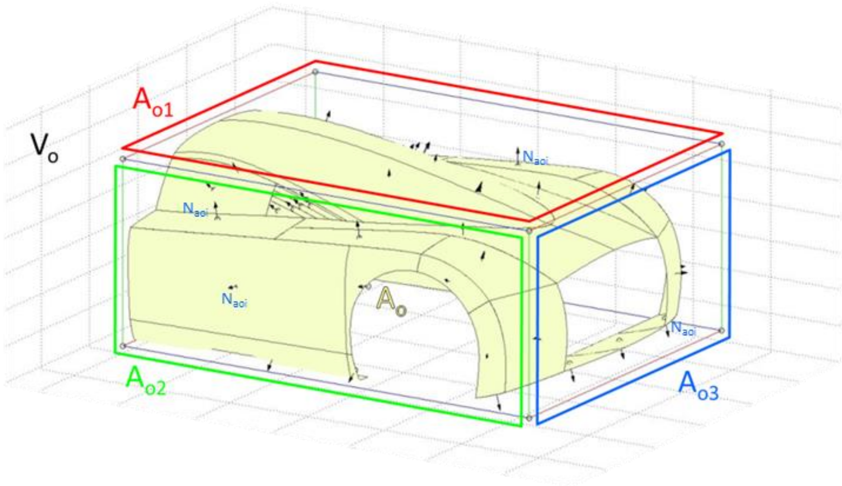

Figure 2.7: Geometric quantities related to the surrounding

Table 2.1: Geometric quantities of a shape and associated bounding box

A_s – Surface area
A_p – Area of the projection of the surface on the plane π defined by the smallest PCA vector
V_s – Volume that is occupied between the surface and its projection on the plane π
V – Volume of the minimum bounding box of the surface
A_1 – The area of the biggest face of the minimum bounding box
A_2 – The area of the second biggest face of the minimum bounding box
A_3 – The area of the smallest face of the bounding box
D – Diagonal of the minimum bounding box
E_1 – The longest edge of the minimum bounding box
E_2 – The second longest edge of the minimum bounding box
E_3 – The shortest edge of the minimum bounding box
M_c – Mean curvature ($\frac{1}{p}\sum_1^p H_i$), where p is the number of the surface discretization points and H_i is the mean curvature value on the *i-th* point on the surface

G_c – Gaussian curvature ($\frac{1}{p}\sum_1^p K_i$), where p is the number of the surface discretization points and K_i is the Gaussian curvature value on the *i-th* point on the surface
A_c – Absolute curvature ($\frac{1}{p}\sum_1^p A_i$), where p is the number of the surface discretization points and A_i is the absolute curvature value on the *i-th* point on the surface
N_a – Average normal of the surface ($\frac{1}{p}\sum_1^p N_{ai}$), where p the number of the surface discretization points and N_{ai} is the normal value on the *i-th* point on the surface
R_p – Radius of a sphere that has same area as A_p ($R_p = \sqrt{\frac{A_p}{4\pi}}$)
R_s – Radius of a sphere that has same area as A_s ($R_s = \sqrt{\frac{A_s}{4\pi}}$)
N_p – Percentage of surface with positive Gaussian curvature (%)
N_n – Percentage of surface with negative Gaussian curvature (%)
N_z – Percentage of surface with zero Gaussian curvature (%), $N_p + N_n + N_z = 1$

Table 2.2: Geometric quantities related to the surrounding

V_o – Volume of the bounding box of the object
A_o – Total area of the object
A_{o1} – Area of the biggest face of the object bounding box
A_{o2} – Area of the second biggest face of the object bounding box
A_{o3} – Area of the smallest face of the object bounding box
N_{ao} – Average normal of the surrounding surface patches in the object ($\frac{1}{p}\sum_1^p N_{aoi}$), where p is the number of the surface patches discretization points and N_{aoi} is the normal value on the *i-th* point on the surface

As discussed in the paper (Petrov A. , Pernot, Veron, Giannini, & Falcidieno, 2014), the use of size independent geometric attributes is recommended such that classification models created in this manner do not depend on the size of the geometric entities (curves and surfaces). This leads to more stable classifications and to the selection of generally valid relevant attributes. Therefore, new size independent surface parameters based on the previous geometric quantities have been defined and will be used to characterize each instance of the IDS. A common way of obtaining size independent parameters is to define ratios between two geometric quantities or two groups of geometric quantities of identical nature (dimension). Thus, 36 surfaces parameters (R_1 – R_{36}) have been defined and are listed in Table 2.3. They all have been specified using the geometric quantities of surfaces listed in Table 2.1 and Table 2.2.

Table 2.3: Surface parameters built on top of the basic geometric quantities

Ratio between the surface area A_s and its projection A_p:	$R_1 = \frac{A_s}{A_p}$
Ratio between the surface volume Vs and bounding box volume V:	$R_2 = \frac{V_s}{V}$

Ratio between the longest edge E_1 and the diagonal D of the Bounding Box:	$R_3 = \frac{E_1}{D}$
Ratio between the second longest edge E_2 and the diagonal D of the Bounding Box:	$R_4 = \frac{E_2}{D}$
Ratio between the smallest edge E_3 and the diagonal D of the Bounding Box:	$R_5 = \frac{E_3}{D}$
	$R_6 = \frac{E_2}{E_1}$
Ratios between the dimensions of the Bounding Box:	$R_7 = \frac{E_3}{E_2}$
	$R_8 = \frac{E_3}{E_1}$
	$R_9 = \frac{A_2}{A_1}$
Ratio between the areas of the planes of the Bounding Box:	$R_{10} = \frac{A_3}{A_2}$
	$R_{11} = \frac{A_3}{A_1}$
	$R_{12} = \frac{A_1}{A_1+A_2+A_3}$
Ratio between the planes areas (A_1, A_2, A_3) and the area of the Bounding Box:	$R_{13} = \frac{A_2}{A_1+A_2+A_3}$
	$R_{14} = \frac{A_3}{A_1+A_2+A_3}$
Multiplication of the Mean curvature with the Radius R_p of a sphere that has same area as the surface projection area (A_p):	$R_{15} = M_c*R_p$
Multiplication of the Mean curvature with the Radius R_s of a sphere that has same area as the surface area (A_s):	$R_{16} = M_c*R_s$
Multiplication of the Mean curvature with the ratio between the surface volume V_s and the surface projection area A_p:	$R_{17} = M_c \frac{V_s}{A_p}$
Multiplication of the Mean curvature with the ratio between the surface volume V_s and the surface area A_s:	$R_{18} = M_c \frac{V_s}{A_s}$
Multiplication of the Gaussian curvature and the surface projection area A_p:	$R_{19} = G_c*A_p$
Multiplication of the Gaussian curvature and the surface area A_s:	$R_{20} = G_c*A_s$
Multiplication of the Absolute curvature with the Radius R_p of a sphere that has same area as the surface projection area A_p:	$R_{21} = A_c*R_p$
Multiplication of the Absolute curvature with the Radius R_s of a sphere that has same area as the surface area A_s:	$R_{22} = A_c*R_s$
Multiplication of the Absolute curvature with the ratio between the surface volume V_s and the surface projection area A_p:	$R_{23} = A_c \frac{V_s}{A_p}$
Multiplication of the Absolute curvature with the ratio between the surface volume V_s and the surface area A_s:	$R_{24} = A_c \frac{V_s}{A_s}$

Positive curvature	$R_{25} = \frac{N_p}{N}$
Negative curvature:	$R_{26} = \frac{N_n}{N}$
Zero curvature:	$R_{27} = \frac{N_z}{N}$
Average normal:	$R_{28} = \sqrt{X^2 + Y^2 + Z^2}$ $X = \frac{1}{p}\sum_1^p X_{ai},\ Y = \frac{1}{p}\sum_1^p Y_{ai},\ Z = \frac{1}{p}\sum_1^p Z_{ai}\ N_{ai} = (X_{ai}, Y_{ai}, Z_{ai})$
Ratio between the surface area and the area of the objects:	$R_{29} = \frac{A_s}{A_o + A_s}$
Ratio between surface and object Bounding Box volumes:	$R_{30} = \frac{V}{V_o + V}$
Ratio between surface volume and object Bounding Box volume:	$R_{31} = \frac{V_s}{V_o + V_s}$
Ratio between the smallest plane of the surface MBB (A_3) and the plane of the object BB parallel to it (A_{o1}):	$R_{32} = \frac{A_3}{A_{o1} + A_3}$
Ratio between the second biggest plane of the surface MBB (A_2) and the plane of the object BB parallel to it (A_{o2}):	$R_{33} = \frac{A_2}{A_{o2} + A_2}$
Ratio between the biggest plane of the surface MBB (A_1) and the plane of the object MBB parallel to it (A_{o3}):	$R_{34} = \frac{A_1}{A_{o3} + A_1}$
Ratio between the diagonal of the surface bounding box D and the diagonal of object Bounding Box:	$R_{35} = \frac{D}{D_o + D}$
Distribution of the normal:	$R_{36} = \frac{1}{k}\sum_1^k \frac{dot(N_a, N_{aoi})}{\lvert N_a\rvert\ \lvert N_{aoi}\rvert}$

Clearly this list of surface parameters is only a subset of the possible surface parameters, they have been chosen because they are somehow extending the geometric quantities used for curves straightness in the 3D space for surfaces. Again, those 36 parameters will finally be the only ones which will be used to characterize the free form surfaces and find rules/relationships with their classifications. Thus, we have tried to be quite exhaustive, knowing that the available MLTs will also help identifying the parameters which best influence the classification. In addition, the use of parameters to characterize the surrounding and its influence over the perception of flatness was not treated for curves. It is therefore a complementary part that enriches the understanding of the perception of aesthetic properties of surfaces.

2.4 Fast classification of surfaces by carrying out interviews within a dedicated GUI

The third element of the framework and the second column of the temple is the classification of all instances (Figure 1.1) of the IDS. Before starting with this process, the classification classes of flatness need to be defined. The number of classes has to be, in some way, a compromise between a very fine classification aimed at extracting as much information as possible from the interviewees and a limited one to avoid confusing the participants. In other words, if we propose two classes (e.g., flat and not flat) we will not be able to extract any relevant and significant information or classification patterns. This would provide very poor and irrelevant knowledge because only a very limited set of the instances would be classified as flat and the remaining part would be classified as not flat (depending on the IDS). The other extreme situation would be if we proposed 5 or more classifications. In this case, the participants would be confused and unable to distinguish the difference between some classes. Therefore, in this research, we decided to propose four classes, which we believe is the optimal number considering our experimentations. The next important aspect of defining the classification classes is their naming, which has to be intuitive to the layperson's perceptions. Thus we opted for quantitative judgments (e.g. less, almost, more, very, not, or not at all) of these classes of flatness. As a conclusion, the four levels of classification of flatness are: Flat, Almost Flat, Not Flat, and Very Not Flat. Of course, this can be seen as a parameter and the proposed approach could be set up with more classes or with classes having other names.

To easy and speed up the classification process, a GUI (Guiding User Interface) has been created in Matlab. The classification of the instances corresponds to the right pillar of the temple as described in Figure 1.1. It allows the user to classify surfaces in a very intuitive and simple way, i.e. by only moving a slider and clicking buttons. Effectively, in this work, it was reasonably not possible to ask the user to classify the 8550 instances one by one.

The GUI is split into two parts: the visualization part (red frames) and the control part (blue frame). The visualization top part contains three windows displaying the under classification surface (middle window), the latest classified (left window) and the successive one (right window) in the isometric view. The display of the immediately preceding and successive surfaces allows participants to compare them to decide about the changes of the class. The lowest visualization frame presents the under classification surface from the three standard views, helping the interviewees to understand the surface shape and consequently to decide the class to associate. The controlling part also contains the principal and secondary frames. The principal frame consists of a slider and six buttons: four for associating the class and two for moving to the previous and to the successive surfaces. To speed up the classification process, the user does not have to classify each surface, but only those corresponding to a change of the actual class that is the last attribute selected. This is a key point of the proposed classification techniques which allows the classification of several thousands of instances in very few minutes. Practically, the interviewee classifies the first surface in one of the four classes, automatically this class is associated to all the successive surfaces. Then the user can move to the next surface and if he/she considers that the surface still belongs to the same class of the previous one, then there is no need to click on the appropriate button. The slider allows browsing the surface set under investigation allowing to browse within the same surface category (same color under the slider) or to check the surfaces corresponding to change in the classes, i.e. the ones where there is a color change. The bottom part allows to get the input (i.e.to chose one of the nine sets depicted in Figure 2.5) and to save the results of the classification process. In case the interviewee changes his/her mind about some classification and wants to repeat the classification of a given portion of surfaces, the classification can be repeated by clicking on the buttons Undo or Redo.

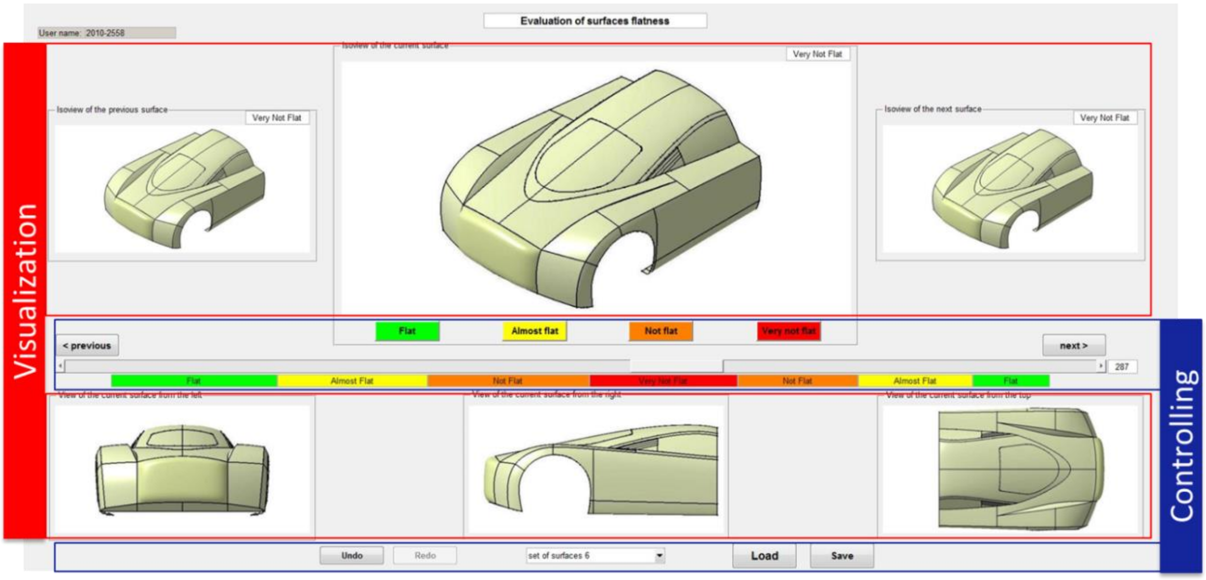

Figure 2.8: Workbench for the flatness classification of surface

The classification has been conducted by interviewing participants from three different countries (France, Italy, and Macedonia) and with different backgrounds (engineers, mathematicians, students, PhD candidates, researchers, and so on). The composition of the participants is given in Table 2.4 together with some figures which characterize them as well as the time they spent to perform the classification. At the end of the interviews, the 8550 instances have been classified by the 65 participants. Said differently, each instance has been classified 65 times. Of course, the participants do not have the same feeling and the instances are therefore not classified in the same way.

Table 2.4: Structure of interviewed sample

Place	Number of participants	Status	Sex (M/F)	Age range	Common comments	Average duration
France	20	PhD student – 11 Masters – 4 Engineers – 5	15/5	23 – 33	Very well done Time consuming	20 – 45 minutes
Italy	15	PhD degree – 7 Researcher – 7 Technical staff – 1	7/8	25 – 54	Good interface Too many views confuse the interviewees	35 – 60 minutes
Macedonia	30	PhD degree – 5 Engineers – 17 Students – 8	25/5	21 – 51	Interesting Time consuming	30 – 50 minutes

3 Experiments

Now that the framework has been set up, several experiments can be conducted to answer to four main questions: 1) Is there a common perception of the flatness, 2) Is the amount of surrounding influencing the perception of flatness?, 3) Is the type of surrounding influencing the perception of flatness?, 4) What are the most relevant attributes to characterize the flatness? Before detailing the fours studies which have been designed to answer those questions, the adopted methods are first introduced.

3.1 Grouping instances of the IDS

In order to conduct the studies and answer the four questions, the IDS and associated sets of Figure 2.5 have been further decomposed. Table 3.1 details how the decomposition has been performed and the studies for which the groups have been designed. For example, Group 2 gathers together all the surfaces which have no context, i.e. 2850 instances, to be used for the second study, i.e. to answer the question 2) Is the amount of surrounding influencing the perception of flatness ?

Table 3.1: Decomposition of the IDS in seven groups

Group ID	Group type	Sets of surfaces	Nb of instances	Studies
1	All the surfaces	1 to 9	9 x 950 = 8550	1 and 4
2	Without context	1, 3 and 8	3 x 950 = 2850	2
3	Smaller context	4, 5 and 7	3 x 950 = 2850	2
4	Greater context	2, 6 and 9	3 x 950 = 2850	2
5	Car door	5, 8 and 9	3 x 950 = 2850	3
6	Car back	3, 6 and 7	3 x 950 = 2850	3
7	Coffee machine	1, 2 and 4	3 x 950 = 2850	3

3.2 Identifying the best learning algorithm

There exist a huge amount of learning algorithms (classifiers) which all have their own characteristics and capabilities to solve specific problems. In order to avoid testing all the algorithms for the four studies, it has been decided to first identify what could be considered as the best classifier in our context. Thus, the seven groups of classified instances introduced in section 3.1 have been introduced in five classifiers: classification tree (C4.5), Naïve Bayes (NaiveBayes), Support Vector Machine (SMO), k-nearest neighbors (IBk) and classification rules (RIPPER). The results are shown in Figure 3.1. The percentages are the average of the percentages of well-classified instances obtained when training a distinct classifier for each participant and using the 10 folds cross-validation strategy. For example, using the 8550 instances classified by the 65 participants (group 1), and using the classifier C4.5 for each participant separately with 10 folds cross-validation, we obtained 65 percentages whose average is equal to 83.31%. The same applies for the other groups and classifiers. At the end, the C4.5 classifiers appear to be the best to solve our classification problem. Only this algorithm will be used for the next experiments.

		Classifiers	C4.5	NaiveBayes	SMO	IBk	RIPPER
Single-label dataset Study 1 and 4	1	**Participant classification (8550)**	83,31 %	46,78 %	68,87 %	75,93 %	78,88 %
Grouping by context Study 2	2	Without context (2850)	81,62 %	49,08 %	69,57 %	74,81 %	78,68 %
	3	Smaller context (2850)	83,41 %	51,49 %	72,72 %	76,34 %	80,09 %
	4	Greater context (2850)	83,75 %	51,58 %	72,09 %	76,74 %	80,61 %
Grouping by Object Study 3	5	Car door (2850)	76,99 %	57,48 %	72,63 %	66,30 %	74,94 %
	6	Car back (2850)	84,28 %	64,33 %	73,31 %	71,89 %	80,97 %
	7	Coffee machine (2850)	89,16 %	61,54 %	77,02 %	85,18 %	86,45 %

Figure 3.1: Selection of the best classifiers

3.3 Handling multi-label classification

As explained at the end of section 2.4, the 8550 instances of the IDS have been classified 65 times. In other words, multiple (i.e. 65) class labels have been assigned to each instance. In order to keep use of basic learning techniques and do not make use of multi-labeled classification techniques, two methods have been designed and tested throughout the four studies :

1) Use of a general classification (Method 1) obtained using the majority principle. The problem of dealing with multiple labelled dataset of instances can be solved by replacing the multiple labelled classifications with a single labelled classification by using the majority principle. In our case, it represents the perception of flatness of the majority of participants. For instance, if a surface has been classified as flat by more than 33 out of 65 participants, then this class is chosen as the final surface class. Following this principle, the final class of some surfaces can be automatically defined. This is illustrated on Figure 3.2. For example, the surface 1 has been classified as flat (F) by 36 participants, as Almost Flat (AF) by 14 participants and so on. Thus, using the majority principle, this instance can be classified as Flat (F).

Surface instances	classification by participants				classification classes				final class (>n/2)
	label 1	label 2	....	label 65	F	AF	NF	VNF	
surface 1	F	F	AF	NF	36	14	10	5	F
surface 2	F	F	F	F	30	25	6	4	
surface 3	F	F	AF	AF	15	38	8	4	AF
surface 4	AF	F	AF	AF	4	31	28	2	
surface 5	AF	NF	NF	AF	3	21	37	4	NF
surface 6	AF	NF	NF	NF	2	10	22	31	
…………………….	…	…	…	…	…	…	…	…	
surface N	VNF	VNF	VNF	VNF	5	8	13	39	VNF

Figure 3.2: Assigning a final class to a surface using the majority principle

However, following this principle, some instances remain unclassified. Actually, one of the most important rules followed during the generation of the sets of surfaces is the continuity in the modification of the shapes for the creation of the intermediate surfaces. This means that if the surface k is classified as class1 and surface k+2 is classified in class2 then the surface in between the two (i.e. surface k+1) must belong either to class1 or class2. Therefore, if surface k+1 cannot be associated to a class by the majority of participants, then the surface should be classified as some of the neighbor surfaces. Neighbor surfaces are the nearest neighbor surfaces that are classified with a final class by using the majority principle. For instance, 30 participants have classified the surface 2 as Flat (F) and 25 as Almost Flat (AF), thus surface 2 can be classified as Flat (F).

Following those two principles, we obtained a general single labelled classification that will be used in the following studies.

2) Use of mutual comparisons (Method 2) between the classifications of the participants. Here, the idea is to transform the multi-labelled classification problem in a set of n(n-1) mutual comparisons between individual classifications (n=65 in our case). For example, the classification of the participant k is first used to find the classification rules of participant k. Then, the classification rules of participant k are applied to the instances classified by the (n-1) other

participants. Following this method, a comparison can therefore be performed to understand how much the classification of participant k is shared by the other (n-1) participants. This method will be exemplified in the next subsection.

Finally, to be able to manage the results and be more synthetic, some of the percentages will be averaged. For example, instead of showing 64 percentages to characterize how much 64 participants have the same understanding of a given participant, it will be possible to average them so as to conclude globally how much the understanding of this participant is shared by the 64 others.

3.4 Study 1 : Is there a common perception of flatness ?

The investigation on the existence of a common perception of flatness can be carried out by evaluating the differences between the individual classifications and a general classification model, or by carrying out n(n-1) mutual comparisons between the individual classifications. For this study, the 8550 instances of group 1 are to be used (Table 3.1).

3.4.1 Method 1 : Use of a general classification

This approach consists in first extracting a general classification model and then testing it with the classification of the interviewees to estimate how representative the general classification is. In this case, the dataset of surfaces classified according to the general classification (method 1 introduced in section 3.3) is used to train a classifier, and then the trained classifier is tested with the dataset classified by the interview participants. As discussed in section 3.2, the learning algorithm C4.5 (classification tree) has been used to train the classifier.

The comparison of the classification of all participants with respect to the general classification is given in Figure 3.3. For example, when using the classifier (classification tree) built from the general classification on the dataset classified by the first participant, the percentage of well classified instances is 67.7%.

%	Participants	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Single label	Accuracy	67,7	45,0	43,6	53,6	40,5	35,9	48,4	68,4	49,6	58,1	57,3	57,0	45,8	59,1	50,1	47,3	51,2	63,1	39,0	50,1	51,2	71,7
	Ranking	3	51	54	29	58	64	45	2	43	21	22	26	48	18	42	47	36	10	59	41	37	1

%	Participants	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
Single label	Accuracy	38,3	38,8	50,4	58,9	45,5	58,2	54,1	51,6	57,1	50,1	59,8	42,9	53,2	50,2	48,4	37,8	44,8	43,4	51,8	56,1	45,5	62,8
	Ranking	61	60	38	19	50	20	28	35	25	40	17	57	31	39	46	63	52	55	34	27	49	11

%	Participants	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	Av.
Single label	Accuracy	53,0	66,0	65,5	61,1	57,2	52,3	37,9	64,3	22,7	62,6	43,2	48,5	60,1	57,3	44,7	63,9	65,4	61,6	66,1	53,5	62,6	52,7
	Ranking	32	5	6	15	24	33	62	8	65	13	56	44	16	23	53	9	7	14	4	30	12	

Figure 3.3: Comparison between the classification of 65 interviewees and the one obtained using the general classification model

Taking into account the accuracy of all participants, the average accuracy is 52.7%. If we rank the classification of all participants by accuracy and take the top-ten ranked classifications (red numbers), we can see that their average accuracy is 66.3%. Additionally, the highest accuracy, i.e. participant 22 with accuracy of 71.7%, indicates the participant who share the most similar classification rules to the ones of the general classification.

Method 2 : Use of mutual comparisons To understand if the classification rules followed by a person are also shared by the others, a mutual comparison is carried out by using the classification of each participant to train a classifier (still using C4.5 classification tree), then the obtained classifier is tested using the classifications of the other 64 participants and finally the results of the testing are used for the comparison. This process is repeated for the 64 other participants, and the results are given in Figure 3.4. For example, when the classifier trained on the classification suggested by participant 1 is applied on the dataset classified by participant 2, the accuracy is 48.0%.

Overall, the average accuracy for the classifier of participant 1 applied on the other 64 participants is 48.4%. The average accuracy of the classification model for a participant can be considered as an overall and orientation measure for the "level of share-ability" of the classification for this participant.

%		Training set					
	Participants	Participant 1	Participant 2	Participant 3	Participant 4	.....	Participant 65
Testing set	Participant 1	/	45,7	40,2	54,3	.....	59,8
	Participant 2	48,0	/	36,9	46,7	.....	44,5
	Participant 3	40,9	36,9	/	44,5	.....	44,8
	Participant 4	50,8	44,3	40,9	/	.....	57,6
	Participant 5	41,2	44,9	36,0	42,2	.....	40,9
	.....	.....	.....	.....	.....	.....	.....
	Participant 65	58,3	42,9	43,9	60,7	.....	/
Average accuracy		48,4	39,5	36,9	44,7	.....	47,3

Figure 3.4: n(n-1) mutual comparisons of individual classifications

The average accuracy of all the participants is given in Figure 3.5. Taking into account the average accuracy of all participants, the overall average accuracy is 42.1%. If we rank the classification of all participants ordered by their average accuracy and take the top-ten ranked classifications (red numbers), we get an average accuracy of 47.76%.

%	Participants	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Single label	Average accuracy	48,4	39,5	36,9	44,7	37,2	35,9	39,5	47,4	42,5	45,8	45,6	44,0	39,8	44,3	42,3	40,3	41,0	47,3	37,4	42,9	41,7	48,4
	Ranking	3	49	56	20	55	60	50	6	36	13	15	28	48	23	37	46	43	8	54	31	40	2

%	Participants	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
Single label	Average accuracy	36,8	34,0	42,6	44,7	40,8	44,9	44,1	43,7	44,2	42,0	42,2	40,3	40,7	38,4	38,7	34,1	39,0	36,4	44,2	45,9	42,6	44,7
	Ranking	57	64	34	19	44	17	27	29	26	39	38	47	45	53	52	63	51	58	24	12	33	18

%	Participants	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	Av.
Single label	Average accuracy	41,1	46,3	46,3	47,6	44,2	43,5	34,6	49,2	26,4	45,4	34,2	41,4	42,6	44,5	36,2	47,4	45,7	44,6	47,9	42,8	47,3	42,1
	Ranking	42	10	11	5	25	30	61	1	65	16	62	41	35	22	59	7	14	21	4	32	9	

Figure 3.5: Average accuracy of all the participants when using n(n-1) mutual comparisons

The two methods can now be compared to answer the initial question of this first study, i.e. is there a common perception of flatness ? The Figure 3.6 highlights the ten top-ranked classifications when following the two methods, i.e. the n(n-1) mutual comparisons of method 1 and the comparisons to a general classification of method 2. Here, one can notice that 8 classifications are in the 10 top-ranked classifications of the two methods, thus there is a 80% overlap. As a conclusion, the general classification can be considered as relevant to express a common perception of flatness. Furthermore, considering that the n(n-1) mutual comparisons indicate how much provided classifications are recognized by the others, they can also help in defining the relevant attributes (see study 4 in section 3.7).

mutual comparisons

No	Participant	Accuracy	Rank
1	1	48,4	3
2	8	47,4	6
3	18	47,3	8
4	22	48,4	2
5	46	46,3	10
6	48	47,6	5
7	52	49,2	1
8	60	47,4	7
9	63	47,9	4
10	65	47,3	9

referential comparisons

No	Participant	Accuracy	Rank
1	1	67,7	3
2	8	68,4	2
3	18	63,1	10
4	22	71,7	1
5	46	66	5
6	47	65,5	6
7	52	64,3	8
8	60	63,9	9
9	61	65,4	7
10	63	66,1	4

Figure 3.6: Parallel between the ten top-ranked classifications when using the mutual comparisons (left) and comparisons to a general classification (right)

3.5 Study 2 : Is the amount of surrounding influencing the perception of flatness ?

The investigation on the influence of the amount of surrounding on the perception of flatness can be carried out following the two previously introduced methods. For this study, the 8550 instances of the IDS are still used but split in three groups 2, 3 and 4 of 2850 instances each (Table 3.1). Being the two methods already introduced and applied for the study 1, there will be less details in this section.

The main hypotheses which have driven the reasoning is as follows. If the surrounding does not affect the perception of flatness, then the participants will follow the same classification rules for the same surfaces regardless the surrounding. On the contrary, their classification rules will be affected in case the surrounding has an influence in the perception of the surface flatness.

%	Participants	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Single label	without context	64,2	44,9	30,1	49,4	37,7	38,6	46,9	67,6	48,3	52,6	59,8	63,4	38,9	54,6	49,4	37,6	46,2	59,8	37,2	50,8	51,7	70,0
	smaller context	70,2	42,9	38,0	56,6	43,9	33,1	44,2	65,6	48,5	69,7	57,5	59,9	44,8	60,8	48,4	52,3	50,2	58,3	34,0	52,8	49,9	72,1
	greater context	65,4	46,6	60,6	54,4	37,4	38,8	51,5	71,7	51,9	55,1	56,6	50,9	52,7	62,5	52,4	53,7	57,8	70,7	46,3	47,4	51,2	71,9

%	Participants	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
Single label	without context	37,6	45,8	50,1	58,2	40,2	51,4	57,5	58,2	42,7	50,1	67,4	53,7	54,2	42,9	50,5	34,3	45,2	49,4	54,6	44,2	50,2	60,8
	smaller context	34,0	39,4	47,9	53,6	48,3	63,5	49,5	50,9	63,8	44,9	58,9	42,2	49,9	47,2	43,6	42,7	48,0	45,3	50,8	57,7	46,9	62,9
	greater context	40,6	33,0	52,8	65,5	45,7	59,8	55,4	48,1	59,5	56,4	54,1	35,7	55,3	57,6	48,4	36,5	40,8	35,2	54,2	66,4	41,3	64,3

%	Participants	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	Av.
Single label	without context	55,8	59,2	55,2	66,1	56,6	49,5	40,1	63,3	20,6	60,6	33,3	40,9	71,7	60,5	44,2	69,0	64,7	62,8	64,9	44,2	60,3	51,4
	smaller context	44,3	65,0	69,9	58,3	55,1	45,9	33,2	60,2	22,8	59,6	50,4	49,2	59,1	60,3	41,5	56,8	70,6	58,4	64,9	52,8	68,9	52,2
	greater context	60,7	74,5	71,5	60,0	60,8	59,1	39,1	70,1	23,5	66,7	44,6	52,0	50,1	51,7	49,1	68,5	62,1	63,1	69,0	63,1	58,9	54,3

Figure 3.7: Comparison of the individual classifications with general classification models and according to different amounts of surrounding contexts (without, smaller and greater contexts)

Following the first method, i.e. comparison to a general classification model, three general classification models are created and then applied on the classification of each participant. The three general classification models refer to the three groups used in this study, namely group 2 – without context, group 3 with a smaller context and group 4 with a greater context. They are created using the majority voting principle as explained earlier. Figure 3.7 shows the results for the accuracy obtained for the three groups. For example, when the general classification created for group 2 (without context) is applied on the instances of this group 2 classified by the participant 1, an accuracy of 64.2% is obtained. Once the three general classification models have been tested for the 65 participants, the average accuracies can be computed (last column of Figure 3.7). This result indicates that the average accuracy of the classification of the shapes without context is 51.4%. It also shows that when the size of the context increases (smaller and greater contexts), the classification accuracy increases

(52.2% and 54.3%, respectively). Such an ordering of the accuracies confirms our hypothesis that the surrounding context influences the perception of flatness. Actually, the amount of surrounding information is correlated to the strength and consistency of the classification among individuals.

Following the second method, i.e. using n(n-1) mutual comparisons, the same order of the classification accuracy is obtained (Figure 3.8). For example, the accuracy of 86.51% is an average value computed from the accuracies obtained when testing the classifier (C4.5 classification tree) learned from group 2 (without context) on the same group 2 classified by the 65 participants. The results show that the average accuracy (88.67%) of the classifiers trained and tested on group 4 (greater context) is greater than the average accuracy (88.26%) of the classifiers trained and tested on group 3 (smaller context) which is greater than the average accuracy (86.51%) of the classifiers trained and tested on group 2 (without context). Again, this result validates what has been also concluded with method 1, i.e. by increasing the context the perception of flatness became more stable.

Av		Training set		
Testing set	Size of context	Without context	Smaller context	Greater context
	Without context	86,51	45,91	47,47
	Smaller context	58,65	88,26	55,16
	Greater context	59,78	51,31	88,67

Figure 3.8: Mutual comparisons according to different amounts of surrounding contexts

3.6 Study 3 : Is the type of surrounding influencing the perception of flatness ?

The investigation on the influence of the type of surrounding on the perception of flatness will also follow the two previously introduced methods. For this study, the 8550 instances of the IDS are still used but split in three groups 5, 6 and 7 of 2850 instances each (Table 3.1).

In this study, the idea is to analyze whether not only the amount but also the type of surrounding influences the perception of flatness. For instance, when a participant classifies a set of surfaces with a different amount of surrounding but for a same object (e.g. the coffee machine), he/she will intuitively follow classification rules. However, these classification rules might differ greatly from those he/she would follow when classifying surfaces belonging to other shape environments and objects (e.g. the car door and car back).

%	Participants	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Single label	Car door	54,7	39,5	31,2	52,3	50,1	27,5	32,7	63,5	50,6	54,7	66,4	59,8	42,5	42,8	36,6	48,1	41,3	57,8	27,6	61,0	23,0	66,3
	Car back	73,1	45,8	39,4	49,9	28,9	32,5	53,4	80,4	39,4	60,3	43,9	49,0	61,6	73,2	44,2	39,1	56,1	58,7	32,0	42,3	60,3	82,3
	Coffee machine	73,3	49,0	57,8	57,4	39,6	50,9	56,8	61,1	60,0	64,4	64,2	65,3	32,5	61,8	69,1	56,4	56,3	73,2	58,1	48,5	68,7	66,3

%	Participants	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
Single label	Car door	43,9	59,8	50,4	39,4	25,1	59,0	58,6	45,3	55,8	35,7	66,6	31,8	37,5	48,3	37,9	34,1	49,4	27,2	49,9	48,1	40,8	53,6
	Car back	25,6	16,8	51,0	73,4	49,6	55,0	54,4	47,1	46,4	49,1	75,7	33,6	53,8	60,1	59,1	45,4	51,1	45,5	46,8	54,0	40,9	80,3
	Coffee machine	44,0	41,4	49,6	66,0	61,1	62,4	50,8	64,9	64,6	65,6	38,9	66,0	69,1	38,8	45,2	34,7	34,2	56,6	63,4	66,6	56,1	57,1

%	Participants	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	Av.
Single label	Car door	54,6	49,1	66,7	62,2	46,4	37,0	25,8	59,2	15,2	51,9	43,4	30,9	62,9	43,8	72,5	61,5	65,3	55,6	71,5	50,4	54,6	47,8
	Car back	39,9	77,0	64,5	49,0	58,8	54,7	57,9	59,3	20,7	81,5	57,3	55,7	70,1	68,5	15,0	54,7	72,7	56,6	55,6	69,3	58,2	53,2
	Coffee machine	67,2	73,0	67,1	74,0	66,2	62,6	27,9	75,7	29,5	54,7	28,5	55,8	49,1	60,4	47,0	78,1	60,9	73,3	72,1	41,7	75,0	57,4

Figure 3.9: Comparison of the individual classifications with general classification models and according to different types of surrounding contexts (car door, car back and coffee machine)

Following the first method, i.e. comparison to a general classification model, three general classification models are created and then applied on the classification of each participant. The three general classification models refer to the three groups used in this study, namely group 5 (car door), group 6 (car back) and group 7 (coffee machine). They are created using the majority voting principle as explained earlier. Figure 3.9 shows the results for the accuracy obtained for the three groups. For example, when the general classification created for group 5 (car door) is applied on the instances of this group 5 classified by the participant 1, an accuracy of 54.7% is obtained. Once the three general classification models have been tested for the 65 participants, the average accuracies can be computed (last column of Figure 3.9). These results indicate that the average accuracy of the classification of the shapes for the car door is 47.8%, while the average accuracy of the classification for the car back is 53.2%, and the accuracy of the classification for the coffee machine is 57.4%. Thus, there is a quite large difference between the average accuracies for the car door (47.8%) and the coffee machine (57.4%).

Following the second method, i.e. using n(n-1) mutual comparisons, similar results have been obtained (Figure 3.10). The accuracy value of 81.79% is the average value of the accuracy of testing group 5 on itself for all 65 participants. The results show that the average accuracy of the classifiers trained and tested on group 7 (93.16%) is quite different from the average accuracy of the classifiers trained and tested on group 6 (89.53%) which is also quite different from the average accuracy of the classifiers trained and tested on group 5 (81.79%).

Av		Training set		
	Objects	Car door	Car back	Coffee machine
Testing set	Car door	**81,79**	**29,86**	**28,37**
	Car back	**36,00**	**89,53**	**30,03**
	Coffee machine	**38,36**	**40,18**	**93,16**

Figure 3.10: Mutual comparisons according to different types of surrounding contexts

Finally, the results obtained when applying the two methods, i.e. comparison to the general classifications and n(n-1) mutual comparisons, are consistent and do validate the fact that the type of surrounding does influence the perception of flatness. Furthermore, let us define the sharpness of a transition between the classified surface and its surrounding surfaces using the angles between the average normal vector and the surrounding average normal vectors (Figure 3.11). When comparing the three types of surrounding contexts, it clearly appears that the more the transition between the classified surface and its surrounding is sharp, the more the accuracy of the trained classifiers increases. Thus, participants better classify the surfaces when they are surrounded by surfaces connected with sharp edges.

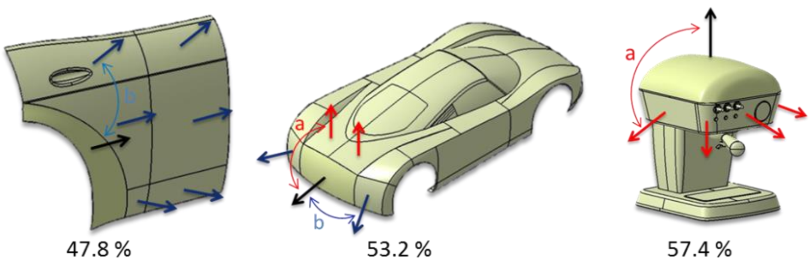

Figure 3.11: Influence of the sharpness on the accuracy of the classifiers

3.7 Study 4 : What are the most relevant attributes to characterize the flatness ?

To answer this question, the group 1 containing the 8550 instances is used (Table 3.1). Again, the two previously introduced methods are to be used and compared.

To solve the problem of identifying which surface parameters (among the 36 parameters introduced in section 2.3) best characterize the flatness property, the Attribute Selection (AS) approach has been adopted. AS allows the identification of which attributes can be omitted without affecting the results of further classifications. The adopted technique uses a correlation-based algorithm to evaluate the correlation of various subsets of attributes with the given classification. Then, it applies appropriate search algorithms to rank and propose the best subset of attributes, among the entire set of parameters that are highly correlated to the classification but independent to each other.

Following the second method, i.e. using n(n-1) mutual comparisons as previously introduced, the AS method has been successively applied over the 65 single labelled datasets to select for each dataset the subset of parameters which best influence the classification of the associated participant. Then, the most recurring ones have been identified by counting the number of times that one parameter is selected. Those results are shown in Figure 3.12. For example, we can see that the parameter 1 (i.e. the ratio A_s/A_p as defined in section 2.3) is ranked second most influencing parameter among the 36 parameters. This parameter appears in 42 lists of most influencing attributes of the 65 participants. Finally, following the second method, the top-seven most influencing parameters are the parameters 2, 1, 28, 4, 17, 36 and 25.

	Parameters	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Single label	Selected	42	44	4	36	5	10	0	6	0	1	0	11	0	5	2	11	31	13
	Ranking	2	1	25	4	20	16	29	19	30	28	31	13	32	21	27	14	5	11

	Parameters	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Single label	Selected	5	8	0	0	0	0	21	4	20	41	17	5	16	5	7	12	11	31
	Ranking	22	17	33	34	35	36	7	26	8	3	9	23	10	24	18	12	15	6

Figure 3.12: Relevant attributes/parameters ranked according to the number of times their appear in the list of most influencing parameters of all participants

Following the first method, i.e. the comparison to a general classification model, similar results have been obtained. In this case, the top-seven most influencing parameters are parameters 1, 2, 4, 8, 17, 28 and 36.

Thus, there is a clear overlap of 80% of the top-seven best-ranked attributes obtained with the two methods. Actually, only the parameter 25 for the second approach and the parameter 8 for the first method do not match. Said differently, the six attributes listed in Figure 3.13 correspond to the most relevant and commonly shared attributes which best characterize the classification of the 65 participants. Thus, modifying those attributes of a given surface may affect significantly the judgment of flatness.

index	Selected parameters
1	Ratio between (As/Ap)
2	Ratio between (Vs/V)
4	Ratio between (E_2/D)
17	Mean curvature (Mc*Vs/Ap)
28	Average normal |Na|
36	Distribution of the normal

Figure 3.13: Selection of the most relevant parameters

4 Conclusion and future works

The advent of low cost 3D printing and Flexible Manufacturing Systems (FMS) allowing the production of personalized products is opening the possibility to normal customers to become themselves designers of their products. Current CAD technologies are not suitable for general customers. The so-called declarative modelling allowing the shape generation and modification through set of commands easily understandable would be a suitable way to define more customer-oriented shape modelling capabilities. The realization of such an approach is possible only if easy and generally understandable terminology of shape properties and modelling operations can be identified. In this perspective, this paper addresses the verification of a common perception and judgment of a specific surface shape property, the so-called flatness, together with the identification of the concerned shape characteristics. This is performed through the set up and use of a general framework exploiting Machine Learning Techniques for the detection of hidden classification rules and the selection of the most prominent involved parameters. A supervised learning approach has been applied, using the results of surface classification sessions carried out in three different countries. Considering that the surface shape perception can be affected by its surrounding (adjacent shape behavior and extension) and context (object in which the surface is inserted), surfaces in different types of objects and with different types and extensions of the neighboring surfaces have been considered. The results obtained even if promising are indicating some differences in the perception of flatness quality. Additionally, it resulted that considering the flatness of a surface embedded in a shape reduces these differences, and in particular, the differences diminish when increasing the extension of the surrounding shape and the shape differentiation between the surface and the surrounding. This aspect is important since in the foreseen modelling scenario, the user should modify a part of the object and not a single surface out of its context, thus more generally valid rules can be determined. Even if we considered a large number of surfaces, additional tests should be carried out with more surfaces and more contexts (surrounding shapes and products) to confirm the prediction capabilities of the detected rules and of the importance of the extracted geometric properties. Future work would also include the consideration of geometric properties more distributed along the surface to detect other possible significant parameters for the flatness characterization. Finally, to actually implement the declarative modelling approach for non-expert designers, modelling operators should be defined and developed able to modify the surfaces through changes of such parameters.

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