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PRODUCT SHAPE AND EMOTIONAL DESIGN
AN APPLICATION TO PERFUME BOTTLES

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ABSTRACT

Shape features play a major role in the perception of designed objects. In this paper, we study the relationships between linguistic and numerical shape descriptions, focusing on real images of perfume bottles. The subjective linguistic evaluation of the bottles is obtained through expert annotations using emotional words as labels; the objective numerical description relies on automatically extracted attributes such as elongation or circularity. Statistics and machine learning tools are exploited in order to learn a matching between shape descriptors and subjective labels.

Keywords: emotion detection, image processing, affective computing, machine learning

1. INTRODUCTION

Whereas computer design tools are well spread out into the detailed end phases of design with CAD-CAM systems, they are more difficult to develop for the early phases of design where the information is vague, ill-defined and highly linked to affective processes [1]. In these phases which are a key process in the generative phases of design, designers are used to categorizing information mentally, through a specific way obeying particular cognitive and affective processes [2] and they develop skills that enable them to link shape features with semantic descriptors and emotions. We already explored how to establish automatically some design rules between emotions and design features described by lexical data [3]. Shape features are of great importance because they are the first features expressed by the designers and highly structure the conceptualization. In this study, we explore some machine learning techniques to automatically discover relations established by designers when categorizing shape related information, based on product photos. These relations

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could be used for future computer aided design tools such as information or generation systems.

From the machine learning point of view, many works have been developed to automatically associate emotions with images, based on their visual appearance (see e.g. [4, 5, 6]). While the chromatic properties of the images are widely exploited, shape information is not so often taken into account. This is due to the difficulty of, first, defining relevant descriptors to encode shape, and, second, of automatically extracting them from images. In this paper we present a study based on real images of perfume bottles evaluated both subjectively by expert annotation using emotional words as labels, and objectively through automatically extracted shape descriptors such as area, perimeter, elongation and circularity. We then use statistical tools and machine learning algorithms to study and match these two description spaces.

The paper is organised as follows: the first part describes the data acquisition, detailing the subjective labels selection, the annotation protocol, as well as the numerical shape descriptors. We then discuss the obtained results first focusing on the semantic annotation (Section 3), then on the numerical description (Section 4), and lastly combining both descriptions in Section 5.

2. DATA ACQUISITION

2.1. Images choice

In order to study the relationships between shapes and emotions, we consider women perfume bottles. Indeed these products constitute a rich and expressive domain, covering a very large range of different shapes. Figure 3 and last column of Table 3 illustrate this high variety, through some examples of bottle silhouettes, extracted using the method described in Section 2.3.

The images are retrieved from retailers websites: they provide a uniform presentation, all bottles having the same size and being shown on a white uniform background. On the one hand this guarantees that the annotators will not be distracted by elements other than the bottles, as would be the case if advertisements were used; on the other hand, it makes the extraction of numerical shape descriptors easier. Images where several bottles are shown together or where logos partially cover the bottles are then filtered out. As a result, an image base of 198 bottles is obtained and submitted to two parallel processes: manual annotation by expert designers in order to obtain a linguistic semantic description, as described in Section 2.2; and extraction of numerical shape descriptors, as described in Section 2.3.

2.2. Linguistic semantic annotation

In this section we describe the protocol of the semantic annotation process, presenting the considered linguistic descriptors and the actual annotation step.

2.2.1. Semantic and emotional linguistic descriptors

A list of 40 descriptors has been established after refining an initial list of 300 adjectives, gathered both from the perfume retailers' websites and from designers' verbalisations commenting perfume bottles. This initial list was gradually filtered out according to the following criteria:

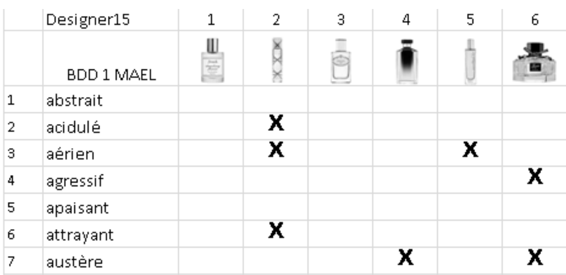
first, the number of occurrences in the text and the overlapping between both sources (retailers' websites and designers' verbalizations), were used. Words too singular in relation to the bottle sample (as *Scottish*) were removed, as well as non discriminant words cited too many times (*inspirational*, e.g.). Furthermore, synonym detection was used: a reduction was done according to the redundancy in meaning (e.g.words such as *attractive*, *arresting*, *captivating*, *exciting*, *stimulating*). Words in relation with some dimensions that are difficult to catch visually were then removed (usability related: *effortless*, olfactory and taste features: *juicy*, *spicy*, or human centred and abstract: *indulgent*, or *innocent*). Lastly negative descriptors were removed. The final list of 40 terms in French providing a certain semantic coverage is shown in Table 1 with their translation.

Table 1: Final list of semantic and emotional descriptors

abstract (abstrait)	extravagant (extravagant)	mysterious (mystérieux)	retro (rétro)
aggressive (agressif)	feminine (féminin)	natural (naturel)	sensual (sensuel)
attractive (attrayant)	fluid (fluide)	original (original)	simple (simple)
austere (austère)	free (libre)	playful (ludique)	soft (doux)
balanced (équilibré)	futuristic (futuriste)	poetic (poétique)	soothing (apaisant)
charming (séduisant)	geometric (géométrique)	powerful (puissant)	sophisticated (sophistiqué)
classic (classique)	glamorous (glamour)	prime (de qualité)	sport (sport)
dynamic (dynamique)	high-tech (high-tech)	pure (pur)	tangy (acidulé)
elegant (élégant)	luxurious (luxueux)	reassuring (sécurisant)	warm (chaud)
ethereal (aérien)	masculine (masculin)	refreshing (rafraîchissant)	young (jeune)

2.2.2. Manual annotation of the perfume bottle images

8 professional designers were recruited for the experiment that lasted 45 to 90 minutes (average 64 min). This panel was composed of 4 professional product designers and 4 design student (50% males, 50% females). They were asked to annotate a set of 50 perfume bottles with the previous list of 40 semantic and emotional descriptors taking into account only the bottle shape: they had to fill up a table where each bottle was represented with a thumbnail, also having at their disposal bigger images of the samples. Each set of 50 bottles was evaluated by two designers independently. Figure 1 illustrates the type of obtained results.



	Designer15	1	2	3	4	5	6
	BDD 1 MAEL						
1	abstrait						
2	acidulé		X				
3	aérien		X			X	
4	agressif						X
5	apaisant						
6	attrayant		X				
7	austère				X		X

Figure 1: Partial view of the manual annotation of perfume bottle images, designer 8

2.3. Numerical shape description

In this section we describe the three-step process we propose to automatically extract of numerical shape descriptors. The first step consists in binarizing the images to distinguish between the bottles and the background, leaving aside colour information. To that aim a simple heuristic is used: pixels that have the same colour (RGB) as a background reference pixel are considered as background, all others are considered as object pixels. Then, in order to reduce noise, object pixels whose 5$\times$5-neighbourhood does not contain at least 13 object pixels are labelled as background pixels.

The second step consists in extracting the silhouette from the detected object. We simply subtract from the image the result of its own erosion obtained using a 3$\times$3 plus-mask. Figure 3 and last column of table 3 show some examples of obtained silhouettes for perfume bottles. It must be underlined that due to the heuristic binarization step, some contour detection errors occur, especially for such objects: because of light reflection and transparency, some parts of the bottle have the same colour as the background and are not assigned to the object, as illustrated with the last bottle on Figure 3. Yet the global result appears to be generally satisfying.

Lastly, 15 classic global shape descriptors are computed, namely width (denoted w), height (h), perimeter (p), area (a), circularity ($cr = p/2 \cdot \sqrt{a \cdot \pi}$, i.e. the quotient between the shape perimeter and the perimeter of the circle with same area), two compactness measures ($cp_1 = p^2/a$ and $cp_2 = l \cdot w/a$), elongation ($e = w/h$) and the 7 invariant moments (φ_1 to φ_7) [7]. It must be underlined that these attributes are not independent one from another.

3. ANALYSIS OF THE EXPERTS' SEMANTIC SHAPE ANNOTATIONS

3.1. Statistical observations

As a result of the annotation phase, he designers provided a total of 2227 associations between bottles and semantic adjectives, we first perform some simple statistical observations from these data. A low inter-annotator agreement is observed as 1827 annotations (82%) appear only once, whereas only 399 (18%) appear twice, i.e. are noted by the two annotators viewing the same bottles. Due to these low values, in the following, we consider for each bottle the union of all annotations, without taking into account their frequency. Besides the data highlight variations in the annotation behaviours, from strict to generous ones: the number of annotations per annotator varies from 97 to 540.

The number of semantic labels assigned to a perfume bottle also varies in a large range, from 3 to 24. It can be noted that the latter bottle thus possesses more than half of the available descriptors, including intuitively contradictory ones, such as *feminine* and *masculine*. On average, the bottles are described by 11.3 terms, with a standard deviation of 4.0. The most frequently used adjective is *feminine*, used for 113 bottles (57% of the bottle base); the least used adjective is *playful* that only applies to 26 bottles (13%). On average a semantic term is used for 55.6 bottles (28% of the base), with a standard deviation of 19.0.

3.2. Study of co-occurrences

Because co-occurrences of semantic terms are globally rare, they provide a good insight on the adjectives. We study them by computing the confidence in rules of the type "$t_1 \Rightarrow t_2$", i.e. the extent to which t_2 is observed when t_1 is. Confidence is classically defined as the quotient of the

Table 2: Co-occurrences with highest confidence c

Rule			c	Rule			c
glamorous	$\Rightarrow$	feminine	77	extravagant	$\Rightarrow$	feminine	63
sensual	$\Rightarrow$	feminine	76	dynamic	$\Rightarrow$	young	63
playful	$\Rightarrow$	young	73	charming	$\Rightarrow$	elegant	62
high-tech	$\Rightarrow$	futuristic	71	luxurious	$\Rightarrow$	elegant	62
poetic	$\Rightarrow$	feminine	69	pure	$\Rightarrow$	simple	61
prime	$\Rightarrow$	elegant	69	sophisticated	$\Rightarrow$	feminine	61
charming	$\Rightarrow$	feminine	69	tangy	$\Rightarrow$	young	61
luxurious	$\Rightarrow$	feminine	64	elegant	$\Rightarrow$	feminine	60
ethereal	$\Rightarrow$	feminine	64	soft	$\Rightarrow$	feminine	60

number of co-occurrences of t_1 and t_2 by the number of occurrences of t_1. Thus this criterion is normalised with respect to t_1 frequency, although that of t_2 still plays a role.

Table 2 shows the rules with confidence higher than 60%. Many of them conclude to the *feminine* adjective, which is due to its high occurrence frequency. Still the premises contain not so frequent adjectives and provide significant associations: the rules with highest confidence e.g. derive *feminine* from the adjectives *glamorous* and *sensual*. Such associations can be interpreted at a semantic level, related to the meaning of these linguistic terms, as are *high-tech* $\Rightarrow$ *futuristic* or *dynamic* $\Rightarrow$ *young*: the designers annotations performed on perfume bottles make it possible to retrieve some common linguistic knowledge. Other associations are more related to shape and design information, such as the rules *pure* $\Rightarrow$ *simple* and *tangy* $\Rightarrow$ *young* and may be more interesting in our framework.

Symmetrically, semantic terms that rarely or never co-occur also provide a good insight on the meaning of the adjectives, at the same two levels: among the 6 term pairs that never co-occur, some are linguistically antinomic pairs, such as (*aggressive*, *soothing*), (*aggressive*, *soft*), others are less directly derived from the adjective meaning, and more related to design (*sensual*, *sport*), (*ethereal*, *powerful*), (*warm*, *pure*), (*high-tech*, *sensual*), (*attractive*, *austere*). On the contrary, it also appears that some expected antonyms are not recovered: the opposition between *masculine* and *feminine* for instance co-occurs for 7 bottles, underlining the fact that seemingly contradictory properties can be perceived from a given perfume bottle, due to the annotator subjectivity and the rich expressive power of the perfume bottle shapes.

4. ANALYSIS OF THE NUMERICAL SHAPE DESCRIPTION

We then explore the properties of the bottle distribution in the numerical space, performing a clustering analysis to highlight the existence of compact and distinct groups of similar bottles.

4.1. Applied method

To compare perfume bottles in the numerical space, we use the Euclidean distance computed in the 15 dimensional space defined in Section 2.3. In order to avoid one attribute taking very large values to dominate the distance computation, we first normalise the data to $[0, 1]$, so that all

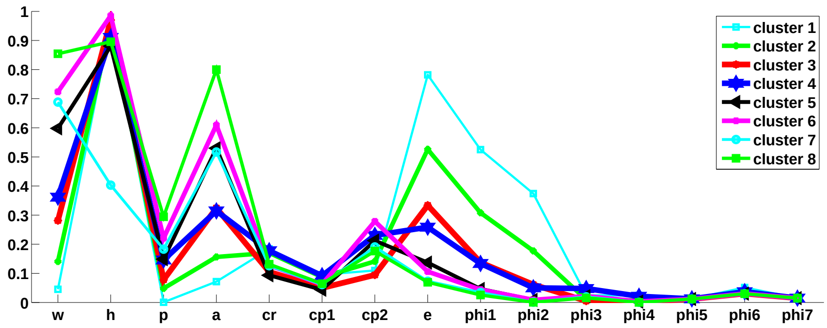


Figure 2: Mainstream cluster prototypes represented in the parallel coordinates view.

attributes vary on the same range.

Regarding the clustering method, we apply the Outlier Preserving Clustering Algorithm, OPCA [8] that identifies both major trends and outliers, defined at several granularity levels. Its use is justified by the structure of the data set that indeed contains both exceptional, atypical bottles and several subgroups corresponding to different bottle types, as described below.

Lastly, to characterise the obtained cluster and interpret the results, it is necessary to define some numerical summary of each cluster. To that aim, we build cluster prototypes [9] that take into account both the common points of the cluster members, and their discriminative features as opposed to the other clusters: for each point, a typicality degree T is computed as the aggregation of its internal resemblance R, i.e. its average resemblance to the other cluster members, and its external dissimilarity D, i.e. its average dissimilarity to the members of the other clusters. In this paper, we consider a weighted mean as aggregation operator, computing $T = 0.75R + 0.25D$. The cluster can then be represented by its member that maximises the typicality degree.

4.2. Obtained results

Applying OPCA to the bottle data set leads to the identification of 25 clusters, 17 of which correspond to outliers, i.e. groups containing only 1 or 2 bottles, and 8 non-exceptional or mainstream clusters. Figure 2 represents the mainstream clusters by their prototypes in the parallel coordinates view, i.e. as a line joining the values it takes for the 15 normalised attributes (values in [0,1]). The width of the line indicates the cluster size: the wider the line, the more bottles in the corresponding cluster. The last column of Table 3 gives the silhouettes of the mainstream cluster prototype bottles, Figure 3 represents some examples of outliers, i.e. exceptional bottles.

It can be observed that the mainstream clusters are mainly differentiated according to elongation e, which, due to the attribute dependence, goes along with width w, area a and the first two invariant moments φ_1 (that sums the variances of the pixel distribution in the vertical and horizontal directions) and φ_2 (that quantifies the covariance of the pixel distribution in the vertical and horizontal directions). Globally, the clustering based on all dimensions leads to a discretization of the elongation values, distinguishing bottle types in terms of their thinness, from very thin bottles to more massive ones: cluster 1 is clearly characterised with its very high elongation, as well as its

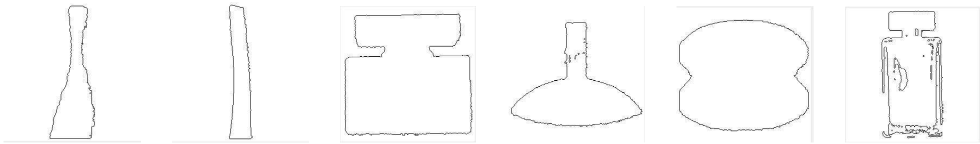


Figure 3: Silhouettes of some exceptional bottles: (1) maximal φ_3 to φ_7 , (2) maximal elongation, (3) maximal area, (4) maximal perimeter, (5) maximal width, (6) incorrect maximal circularity, due to incorrect contour extraction, because of the bottle transparency.

very low width and its high values for φ_1 and φ_2. It corresponds to the thinnest perfume bottles, as illustrated by its prototype (see last column of Table 3). The next clusters then show a graduated decrease in elongation, observed both from Figure 2 and Table 3. The correlation with the area attribute leads to the visual impression of increasing global occupancy of the bottle on the image.

Beside this main characterization in terms of elongation, specific behaviours can be observed, in particular that of cluster 7 whose height h takes very low values that are clearly distinct from all other clusters. In particular it makes the difference with cluster 8 that has similar values of elongation: cluster 8 contains bottles with small elongation with maximal area and occupancy rate, whereas cluster 7 groups smaller bottles whose low elongation is due to lower height.

The outliers, that correspond to exceptional perfume bottles, can be justified by their deviation from the main data trends for one or more attributes. In particular, invariant moments of high order, φ_3 to φ_7, that do not contribute to distinguish among the mainstream data, isolate several asymmetrical bottles, as illustrated by the first contour on Figure 3. The other silhouettes of figure 3 represent some of the exceptional bottles together with their justification. It can be noted that some outliers are due to incorrect contour extraction, as illustrated with the last example, but such cases remain rare.

5. MATCHING OF THE SEMANTIC AND NUMERICAL SHAPE DESCRIPTIONS

Lastly we study the matching between the obtained clusters and the semantic description of the perfume bottles to characterise the obtained clusters semantically.

5.1. Applied method

For each semantic term t and each cluster c, we compare the proportion of bottles in c the term describes and this proportion computed across all data: formally, denoting n the total number of bottles, n_t the number of bottles described with term t, n_c the number of bottles in cluster c, and n_{ct} the number of bottles in cluster c described with the adjective t, we compute the local proportion $Lp(t, c) = (n_{ct}/n_c)$ / (n_t/n). This is identical to the classic lift criterion used in association rule analysis. High values above 1 mean that the adjective is significantly more present in the cluster than it is globally, implying that the term is somehow representative of the cluster. On the contrary, low values smaller than 1 mean that the adjective is much more absent from the cluster than it is globally: this indicates that the cluster may be characterised by the absence of the term.

5.2. Obtained results

Table 3 presents all pairs (cluster, semantic term) for which Lp is higher than 1.5 or lower than 0.5 together with the cluster prototype. It must be underlined that the significant present (resp. absent) adjectives are not necessarily present in (resp. absent of) the prototype that has been computed in the numerical space without considering the semantic annotations.

Some of the observed associations can be justified from the numerical shape characterisation presented in the previous section, in particular from the proportion variation in terms of thinness: the important thinness of cluster 1 can justify its description as *ethereal* and can provide a fragile look accounting for the significant absence of *powerful*. Moreover, in contrast with bottles of cluster 7 and 8 for instance, whose center of gravity is very low, cluster 1 bottles can be seen as having a dynamic look due to their thinness, explaining the adjectives *dynamic*, *young*, *sport*. Cluster 2 contains bottles that are smaller but still elongated: they can still provide the idea of lightness, but without the fragility semantics and only with the notion of sport performances. This may explain why the presence of *sport* is more significant for cluster 2 than for cluster 1. Cluster 3 goes further in increasing width and area, as well as decreasing elongation. These proportions can be seen as providing a robust character, accounting for the significant presence of *powerful*. Further decreasing elongation along clusters, through a combined increase of width and decrease of height, can make a feeling of balance and security emerge, while the words *ethereal* and *sport* become characteristically absent (clusters 6 and 8).

Other adjectives seem to be more difficult to interpret when matching the clusters with their numerical description as presented in the previous section. Yet, from visual inspection of the cluster content, they appear to be relevant: for instance the *fluid* term for cluster 7 can be justified by the predominant curve lines in the bottles assigned to this cluster that soften the shape. Likewise the significant presence of the *warm* adjective in cluster 6 can be explained by the colours of the bottles and perfumes assigned to the cluster. Although these interpretations cannot be explained by the exploited attributes, and should be confirmed by the introduction of new descriptors, as histograms of local line directions, or average curvature radius, it seems promising that they can already be made: they may indicate correlations used in the design process, that relate e.g. the presence of curves or specific colours to specific proportions of the bottles and their elongation.

The introduction of such additional descriptors could also enable to refine the identified clusters, and lead to the characterization of adjectives that are not highlighted in the present experiment, such as *geometric*, as well as the better interpretation of some associations that still require further investigation, as *mysterious* or *playful*, that provide descriptions at a higher abstraction level.

6. CONCLUSION

In this paper we studied the shape of perfume bottles, both from the subjective and the objective points of view, using two different description spaces: a semantic and linguistic one obtained by manual annotation and a numerical one made of automatically extracted shape attributes. We then considered the matching of these two description spaces using statistics and machine learning tools. The obtained results led to the identification of associations within and between these two spaces, that can be interpreted and justified, in particular using the thinness attribute of the bottle that appears to play a major role.

The identified associations depend on the considered data; they are thus specific to perfume bottles, which is not in contradiction with the fact that some of them may be due to linguistic correlations. All of them reflect true associations underlying designer appreciations of the perfume bottles. Future works aim at performing a similar experiment with other products, so as to compare the identified associations and highlight those constant across several domains. Other perspectives concern the refinement of the established relations, especially through the addition of more expressive numerical shape descriptors, e.g. regarding the decomposition and separate characterizations of the bottles themselves and their caps. The combination with colour and texture of the perfume bottles may also provide useful information: although annotators were asked to focus on the bottle shapes, these other perceptions may have biased their judgment and taking them into account may help to improve the quality of the association of the numerical and semantic description spaces.

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REFERENCES

[1] Hsiao, H and Huang, H. A neural network based approach for product form design. *Design Studies*, 23:67–84, 2002.

[2] Bouchard, C, Omhover, J.-F, Mougenot, C, Aoussat, A, and Westerman, S. TRENDS, a content-based information retrieval system for designers. In *Proc. of DCC08*, 2008.

[3] Omhover, J.-F, Bouchard, C, Mantelet, F, and Aoussat, A. Formalizing design rules appearing in early design: an application of agglomerative clustering. In *Proc. of ICED07*, 2007.

[4] Hayashi, T and Hagiwara, M. Image query by impression words - the IQI system. *IEEE Transactions on Consumer Electronics*, 44(2):347–352, 1998.

[5] Colombo, C, Del Bimbo, A, and Pala, P. Semantics in visual information retrieval. *IEEE Multimedia*, 6(3):38–52, 1999.

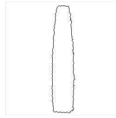
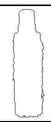
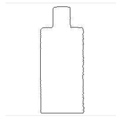
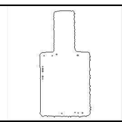
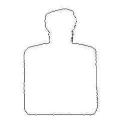
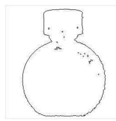
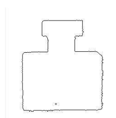
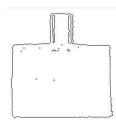
[6] Li, Q, Luo, S, and Shi, Z. Fuzzy aesthetic semantics description and extraction for art image retrieval. *Computers and Mathematics with Applications*, 2008.

[7] Hu, M. Visual pattern recognition by moment invariants. *IEEE Transactions on Information Theory*, 8:179–187, 1962.

[8] Lesot, M.-J and Bouchon-Meunier, B. Descriptive concept extraction with exceptions by hybrid clustering. In *Proc. of Fuzz-IEEE'04*, pages 389–394, 2004.

[9] Lesot, M.-J, Rifqi, M, and Bouchon-Meunier, B. Fuzzy prototypes: From a cognitive view to a machine learning principle. In *Fuzzy Sets and Their Extensions: Representation, Aggregation and Models*, pages 431–452. Springer, 2007.

Table 3: Characteristic adjective presence or absence for the non-exceptional clusters

	Significant presence		Significant absence		Cluster shape prototype
Cluster number	adjective	Lp value	adjective	Lp value	
1	ethereal	3.12	powerful	0.36	
	tangy	2.10	attractive	0.38	
	dynamic	1.72	extravagant	0.43	
	mysterious	1.65	aggressive	0.46	
	young	1.63	high-tech	0.49	
	sport	1.57			
2	sport	1.96	glamorous	0	
	high-tech	1.70	charming	0.21	
			warm	0.40	
3	powerful	1.53	fluid	0.42	
			sensual	0.47	
			mysterious	0.48	
			playful	0.49	
4	playful	1.52	reassuring	0.21	
			natural	0.41	
			soothing	0.45	
5	reassuring	1.82	fluid	0.21	
	high-tech	1.66	ethereal	0.25	
	retro	1.51	playful	0.36	
			sensual	0.46	
			charming	0.47	
6	playful	1.83	sport	0.38	
	warm	1.55	ethereal	0.43	
	sensual	1.55	high-tech	0.47	
			austere	0.48	
			masculine	0.49	
7	fluid	2.30	aggressive	0.37	
	charming	1.98	masculine	0.41	
	reassuring	1.70			
	mysterious	1.65			
	original	1.62			
	high-tech	1.55			
	feminine	1.52			
	playful	1.52			
8	aggressive	1.83	pur	0	
	warm	1.61	sport	0.26	
			charming	0.28	
			ethereal	0.30	
			high-tech	0.32	
			reassuring	0.35	
			balanced	0.36	
			soft	0.40	