Comprehensive Perceptual Analysis and Rating of Material Properties from Video Data

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Abstract. The real world is abundant with a diverse array of materials, each possessing unique surface appearances that play a crucial role in our daily perception and understanding of their properties. Despite advancements in technology enabling the realistic reproduction of material appearances for visualization and quality control, the interoperability of material property information across various measurement representations and software platforms remains a complex challenge. A key to overcoming this challenge lies in the automatic identification of materials' perceptual features, enabling intuitive differentiation of properties stored in disparate material data formats. This paper introduces a novel approach to material identification by encoding perceptual features obtained from dynamic visual stimuli. We conducted a psychophysical experiment to identify and validate 16 particularly significant perceptual attributes across 347 materials. Subsequently, we gathered attribute ratings from 20-24 participants for each material, creating a 'material signature' that encodes the perceptual properties of each material.

Keywords: material · appearance · perception · feature · identifier

1 Introduction

The digital representation of materials plays a pivotal role in numerous applications, ranging from virtual reality to industrial design. However, accurately predicting the perceived properties of these materials from a human vision perspective remains a significant challenge in contemporary research. This difficulty in mapping visual appearance to intuitive properties results both from the variety and complexity in material appearances as well as the rich space of human perceptual inferences. Here, we aim to identify some of the most critical appearance attributes of a diverse set of real-world materials including, but not limited to, fabric, leather, wood, plastic, metal, and paper, and use these to characterize the space of appearances. We selected the samples to cover a broad spectrum of textures, colors, and reflective properties, and use them to produce standardized video sequences, to provide a comprehensive overview of material appearances typically encountered in both everyday life and specialized industries. We opted for captured videos showing the genuine material appearance of flat specimens under different viewing conditions [5]. These dynamic material appearance data allowed us to obtain reliable identification of the most important appearance attributes as well as their human ratings. We collected ratings for 347 materials spanning wide range of categories as shown in Fig. 1.

Fig. 1. Frame 30 from a video sequences of the 347 materials in the study.

The primary contributions of our paper are:

– Determination of key perceptual features – through rigorous analysis, we have identified sixteen crucial perceptual attributes of these materials, providing a foundational understanding of material perception.
– Extensive public collection of human observer ratings – we have amassed a substantial dataset by obtaining over 110,000 ratings from human observers for the sixteen attributes across all material samples, offering a rich basis for further analysis.
– Evaluation of the proposed features' performance in material retrieval task and providing their ratings publicly.

2 Related work

Our work is related to human visual perception of comprehensive aspects of real material appearance as a function of illumination and viewing conditions. Namely identification of appearance visual attributes and their changes for different material categories have been a subject of research interest for decades. Researchers attempted to establish a connection between perceptual texture space and computational statistics. Tamura et al. [28] suggested a computational form of six basic texture properties and evaluated their performance in a psychophysical experiment on 56 gray-scaled textures of Brodatz's catalogue [1]. Rao and Lohse [19] identified a perceptual texture space by grouping Brodatz's textures and using hierarchical cluster analysis, non-parametric multi-dimensional scaling (MDS), classification and regression tree analysis, discriminant analysis, and principal component analysis. They concluded that the perceptual texture space can be represented by a three-dimensional space with axes describing repetitiveness, contrast/directionality, and coarseness/complexity. [16] performed an experiment with human subjects to obtain a pattern vocabulary governed by grammar rules. Malik and Perona [13] presented a model of human preattentive texture perception based on low-level human perception. Vanrell and Vitria [29] suggested a texton-based four-dimensional texture space with perceptual textons' attributes along each of the dimensions. Long and Leow [11] presented an approach attempting to solve the missing link between the perceptual texture space and the space of computational texture features, by reduction of Gabor features represented by a convolutional neural network a four-dimensional texture space. Schwartz et al [22] proposed so called visual material traits encoding appearance of characteristic material properties by means of convolutional features of train image patches. In follow up work, researchers discovered space of locally-recognizable material attributes from perceptual material distances by training classifiers to reproduce this space from image patches [26]. Sawayama et al. [21] created dataset of synthetic images with variable illumination and geometries and conducted psychophysical experiments (an oddity task) discriminating materials on one of six dimensions. Schwartz and Nishino [23] avoided fixed set of attributes by proposing a method deriving material attributes annotation based on probing the human visual perception of materials by asking simple yes/no questions comparing pairs of small image patches. Filip et al. [5] analyzed perceptual dimensions of 30 wood materials were analyzed in by means of a combination of similarity and rating studies and compared them to basic image statistics.

Many studies represented textureless material appearance by means of bidirectional reflectance distribution function (BRDF) [17] and its parametric models. Matusik et al. [14] psychophysically evaluated large sets of BRDFs, and showed that there are consistent transitions in perceived properties between different BRDFs. They analyzed whether they possess any of the 16 perceptual predefined attributes. They used the observers ratings to build a model in both the linear and non-linear embedding spaces. Such a manifold is then used for editing/mixing between the measured BRDFs. Serrano, et al. [25] psychophysically analyzed isotropic BRDFs to identify smooth and intuitive material appearance transition between different visual attributes. Lagunas et al. [10] presented a deep learning model model measuring the similarity in appearance between different BRDFs, which correlates with human similarity judgments. Serrano et al. [24] collected a large-scale dataset of perceptual ratings of five appearance attributes for combinations of material, shape, and illumination, to analyze the effects of illumination and geometry on material perception across such a large collection of varied BRDFs. Recently, Subias nad Lagunas [27] proposed a single-image appearance editing generative framework that allows to intuitively modify the material appearance of an object by increasing or decreasing high-level perceptual attributes describing such appearance (e.g., plastic, rubber, metallic, glossy, bright, rough, and the strength and sharpness of reflections).

Related research also investigated angle-dependent material appearance represented by more advanced texture models. Jarabo et al. [9] ran perceptual experiments to investigate the visual equivalence [18] of rendered images for different levels of bidirectional texture function (BTF) [2] filtering, and found that blur in a spatial domain is less tolerable than in its angular counterpart. Filip et al. [4] assessed accuracy of advanced material appearance representation using BTF on 16 diverse physical material samples, by comparing human judgements of material attributes made when viewing a computer graphics rendering to those made when viewing a physical sample of the same material. Deschaintre et al. [3] introduced a novel dataset that links free-text descriptions to various fabric materials. The dataset comprises 15,000 natural language descriptions associated to 3,000 corresponding images of fabric materials. Authors identified a compact lexicon, set of attributes and key structure that emerge from the descriptions explaining how people describe fabrics.

What sets our study apart from the previous work is (1) identification of interpretable appearance attributes derived from user studies rather than non-interpretable visual features, and (2) the use videos capturing dynamic light interaction with real materials samples rather than static or synthetic stimuli.

3 Capturing material data

We collected 347 material samples, with a focus on capturing a broad variety of visual appearances but also the most common material categories.

For many material categories with spatially homogeneous appearances, such as metal, plastic, and paper, we can relatively accurately represent individual materials using parametric reflectance models, which encapsulate these materials with compact, physically-related parameters. In contrast, our analysis focuses on more visually complex materials that cannot be easily represented by such models due to local physical effects like shadowing, masking, or subsurface scattering. Therefore, the majority of materials in our collection come from fabric and wood, which are categories with a wide range of appearances due to different fiber types and thread weaving patterns. For the remaining categories, we focus mainly on material samples with specific non-homogeneous structures.

Our dataset consists of 347 samples distributed to the following major categories: fabric (157), wood (67), coating (30), paper (23), plastic (17), metal (14), leather (11), and others (28) (see Fig. 1 showing one frame from the image sequence). Our dataset contains, among others, materials from UTIA BRDF database [6] and MAM 2014 benchmark [20].

As real-world illumination is important for correct matching of material properties especially in interactions between lighting and object geometry [8], we decided to use dynamic stimuli showing material appearance from different observation directions. For each material sample, we produced a video sequence showcasing the material's non-specular and specular characteristics by a slow rotation. These sequences featured close-up views of approximately 42 x 42 mm areas of the samples, captured using the UTIA goniometer [7]. In line with industry standards [15], we maintained a constant polar angle of 45 degrees for both the camera and the light source, varying only the azimuthal angle of the camera to facilitate more rapid measurements. Each sequence commenced with the light and camera azimuthal angles differing by 90 degrees, followed by a 90-degree camera movement, resulting in a final difference of 180 degrees between the azimuthal angles probing specular reflection of the material. Comprising 60 image frames of resolution 632 x 412, each 4-second sequence was played in reverse order after completion, creating an 8-second continuous loop that effectively illustrates the dynamic behavior of the rotating material.

4 Selection of main perceptual attributes

In this section, we describe two studies to identify key visual features for describing the appearance of the material videos in our dataset. The scheme depicting our psychophysical assessment of materials is shown in Fig. 2-a.

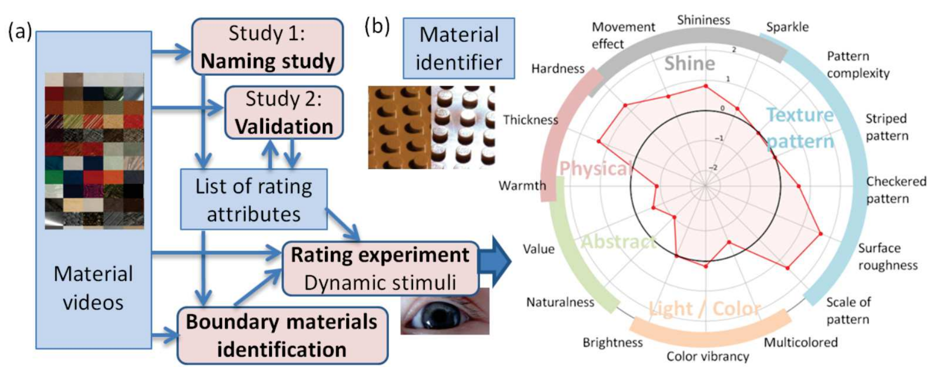

Fig. 2. (a) Scheme of the proposed approach to obtain human ratings of visual attributes. (b) visualization of the attributes for a given material using a polar plot grouping related visual properties.

4.1 Study 1 – Attributes identification

First, we performed an online free naming study. For this, we created three arrangements of 70 material videos each, randomly selected from our full dataset. Participants were then asked to type and rank at least five most visually distinguishing features, in the order of their importance, that they thought sets apart all the materials presented within each arrangement. We collected a total of 451 valid text responses from 32 participants with a mean response duration per arrangement of 2.8 minutes. Subsequently, we grouped synonyms and equivalent terms into clusters, and removed all responses with occurrences < 0.45 % (i.e. with less than two responses) – obtaining a condensed set of 21 visual material attributes. In Figure 2, the plot on the left shows the probability a_p for each attribute (calculated across participants and three trials), as well as the average ranking a_o by participants, and the combination of both, $a_p \cdot (\max(a_o) - a_o)$.

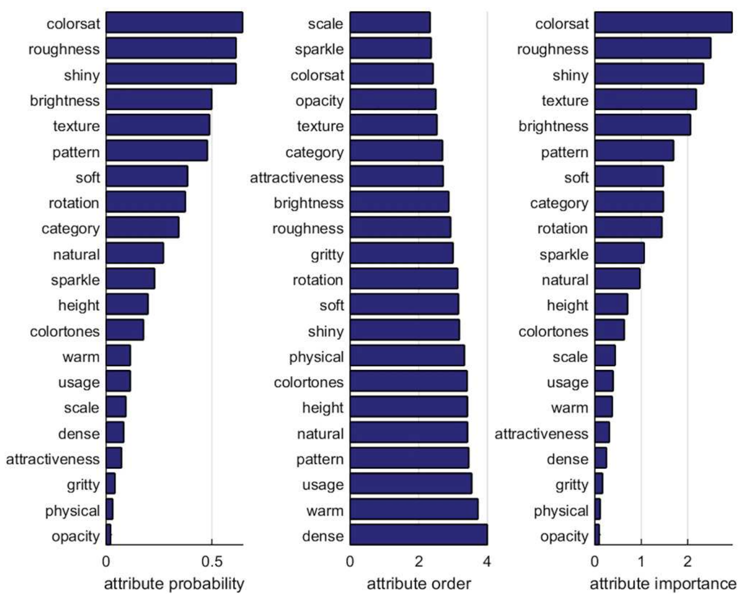

Fig. 3. Attribute statistics obtained from the psychophysical experiment: attribute probability (left), attribute order (middle), and their combination attribute importance (right).

As two of the most frequent terms *texture* and *patterns* are vague without further elaboration we replaced them with the more specific attributes *pattern complexity*, *striped pattern*, *checkered patterns*. The clusters*gritty*, *physical*, and *opacity* were removed as they were rarely mentioned (less than five responses). In total, we did not account only for 1.5 % responses.

The most prominent attributes that participants used to describe the visual appearances of our material videos include common optical attributes such as color variability, saturation, roughness, brightness, shininess, texture, and pattern, but also tactile or subjective attributes like warmth, hardness, naturalness, and attractiveness. The final set of sixteen perceptual attributes used in our rating study is shown in Tab. 1, together with the boundary materials and the instructive questions for all attributes that were given to the participants.

Table 1. A list of 16 perceptual attributes evaluated in the rating study and their description.

ID	attribute	extreme values	description
1.	**color vibrancy**	dull, vibrant	How richly colored is the material, ranging from monochromatic or neutral-colored materials to vibrantly colored materials?
2.	**surface roughness**	smooth, rough	How rough is the material, ranging from fine or smooth to coarse or grainy?
3.	**pattern complexity**	plain, complex	How complex are the patterns on the material, ranging from simple to intricate?
4.	**striped pattern**	no, pronounced stripes	To what extent does the material exhibit stripy patterns?
5.	**checkered pattern**	no, pronounced checks	To what extent does the material exhibit checkered patterns?
6.	**brightness**	black, white	How bright is the material, ranging from dim or subdued to bright or luminous?
7.	**shininess**	matt, mirror	How shiny is the material, ranging from dull or non-reflective to highly reflective?
8.	**sparkle**	none, sparkling	To what extent does the material exhibit sparkling and glittery effects?
9.	**hardness**	soft, hard	How hard is the material, ranging from soft or plush to firm or rigid?
10.	**movement effect**	none, extreme	To what extent does the appearance change due to camera movement?
11.	**pattern scale**	fine, large	How large are the pattern elements, ranging from fine-grained or uniform to large or blotchy patterns?
12.	**naturalness**	manmade, natural	How natural is the material, ranging from man-made to natural origin?
13.	**thickness**	flat, thick	How deep is the material structure, ranging from flat or thin to thick?
14.	**multicolored**	single, many	How multicolored is the material, ranging from a single or uniform color to colorful or many colors?
15.	**value**	cheap, luxurious	How valuable is the material, ranging from low-cost or cheap to extravagant or luxurious?
16.	**warmth**	cold, warm	How warm is the material to the touch, ranging from cool or cold to pleasant or warm?

4.2 Study 2 – Attributes validation

As the clustering of attributes might have been subject to experimenter bias, we performed a second study to validate the 16 attributes. We asked six participants to cluster all 451 valid text responses into the 16 predefined attributes (Tab.1). Overall, the inter-rater agreement was notably high (Fleiss' Kappa score of 0.786) and for 198 out of 451 responses (43.9%), all six raters reached a unanimous decision. For 254 (56.3%) of responses at least three raters agreed, and for 396 (87.8%) responses at least two raters did.

4.3 Study 3 – Boundary materials identifications

To create a representative visual anchor for the rating study, we asked 9 online participants to pick from the three arrangements of 70 material videos, the material exhibiting the lowest and the highest value of a specified visual attribute (e.g., Which of the materials displays the greatest level of brightness?). Participants completed 96 responses each (3 arrangements x 16 attributes x 2 extrema). Out of 9 participants, the same material video was perceived to express the lowest value of an attribute by 3.6 participants on average, and the highest value by 2.8 on average. We removed double occurrences, yielding the arrangement of 25 materials in Fig. 4 which were used as anchor materials in the following rating study.

5 Rating study

In each trial, we showed a material video stimulus on the left, together with a fixed set of the anchor materials on the right. For each perceptual attribute (Tab. 1), we showed all material videos in random order and online participants provided their evaluation with a slider (Fig. 4). Anchor materials were the same for all tested videos and attributes. We collected a total of 111 040 ratings

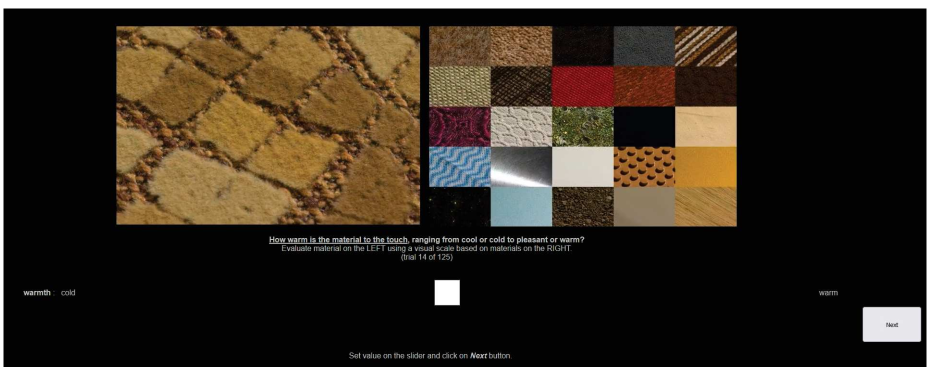

Fig. 4. An example of the rating stimulus with boundary materials on the left.

(20-24 participants/attribute). Data were normalized at the participant level by Z-scoring and then computing mean rating scores across all participants. We excluded participants' ratings from the analysis, when their values had a negative correlation with the mean (typically 1-2 participants per attribute). Finally, we obtained mean opinion score values for 16 attributes and 347 materials.

We can use the obtained ratings of our attributes in various scenarios, such as directly comparing the visual similarity of materials. For instance, during material retrieval, one can filter materials by using only selected attributes. As a similarity measure for comparing sets of attributes of two material samples, we used Pearson correlation; however, other metrics are also possible. Fig. 5 shows rank ordering of materials based on their rating values for individual attributes, where samples are shown in non-specular and specular conditions. Each image illustrates the material appearance under non-specular (left) and specular (right) conditions.

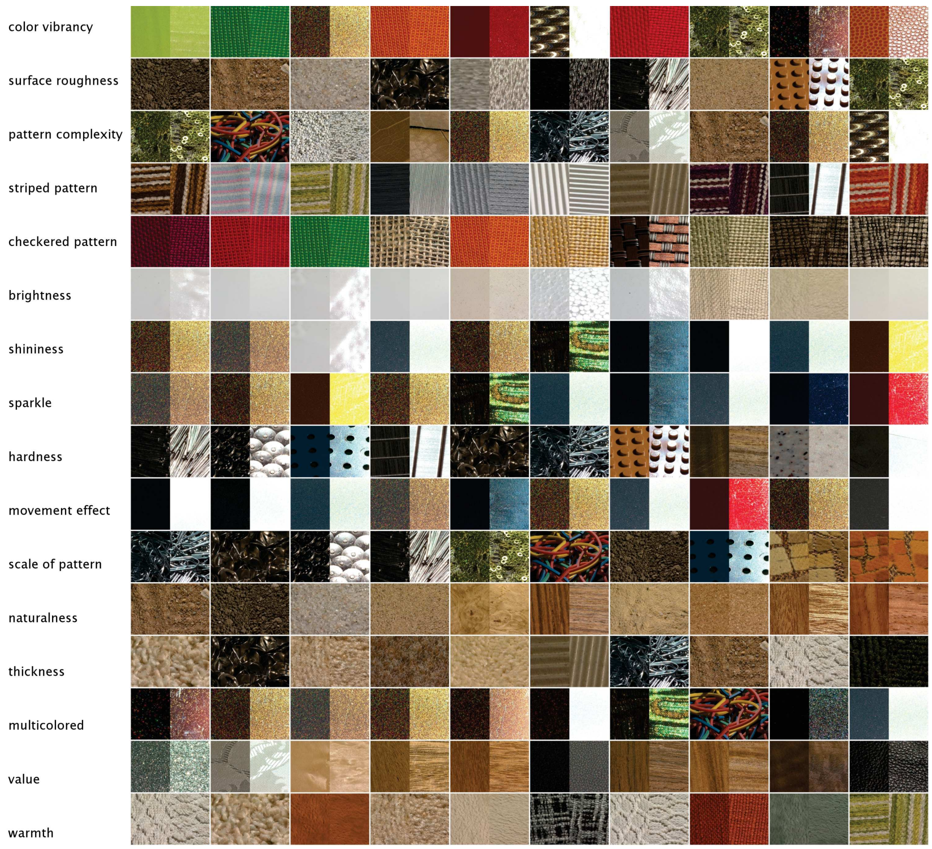

Fig. 5. Ten materials having the highest ranking along individual attributes.

To obtain insight in two dimensional embedding of the material samples, we also performed t-distributed stochastic neighbor embedding (t-SNE) [12] as shown in Fig. 6. For classes *wood*, *fabric, carpet*, and *coating* we observe coherent clusters while for other categories we can see considerable overlaps. This is due to high variability in sample appearance withing this class, e.g. metal in a form of sheet or pins.

This finding is supported by clustering of the similarity matrix between materials' attributes computed using Pearson correlation shown in Fig. 7.

6 Application to Material Retrieval

The material attributes for each material can be visualized in a polar plot, creating a unique visual signature of the material's appearance, as illustrated in Fig. 2-b. The azimuthal ordering of attributes is based on their relationships, forming five clusters loosely related to gloss, texture and pattern, light and color, and both physical and abstract properties. The most significant attributes having

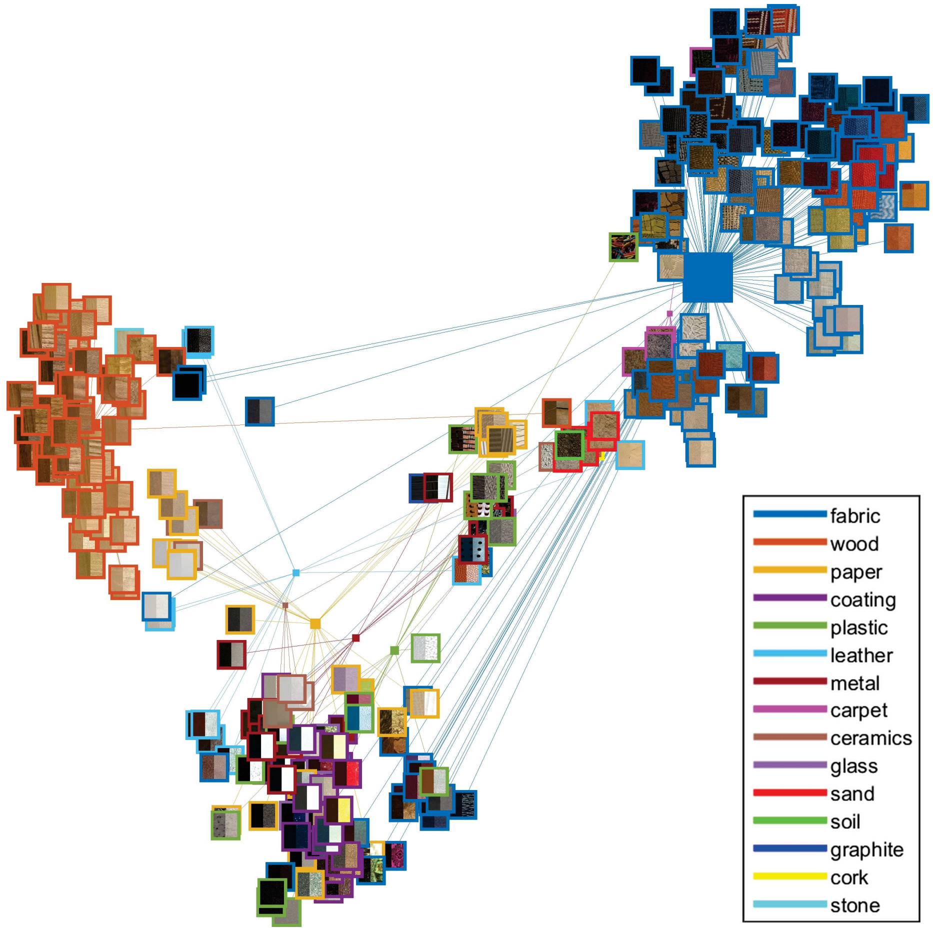

Fig. 6. Material samples proximity obtained as two-dimensional embedding of the samples obtained using t-SNE.

higher values are positioned near the plot's boundary, while the less important ones are closer to its center. Fig. 8 displays the visual attributes computed as the median value across all samples in seven major material categories. This allows us to clearly distinguish between categories; for example, fabric is characterized as thick and warm, whereas coatings and leather are identified as hard and shiny.

We utilized Pearson correlation between material attributes as a measure for retrieving materials with similar appearance and presented the results in Fig. 9, where the three materials most similar to the query are displayed. Size of the retrieved images indicate their correlation to the query image and can serve as approximate measure of material typicality in the dataset. We observe that the retrieval is highly effective when similar materials are present in the category,

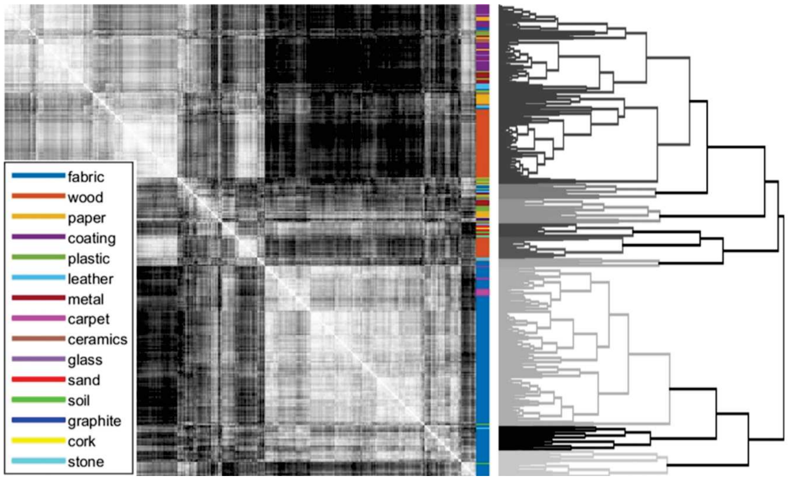

Fig. 7. Material samples proximity obtained a similarity matrix between the materials with corresponding clustering.

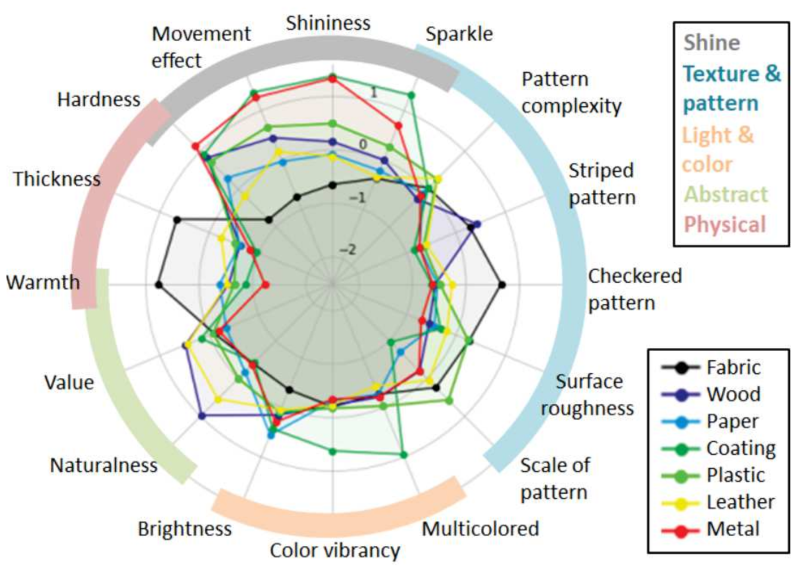

Fig. 8. A comparison of typical visual attributes for major material categories in our dataset.

such as carpet (013), fabric (067, 093), leather (114), sand (176), or wood (210). However, even in the absence of similar materials in the dataset, the retrieval system suggests plausible materials, such as fancy fabric (103), crinkled paper (123), or paper clips (137). Retrieval performance for all materials can be found in a supplementary material.

Fig. 9. Examples of similar materials retrieval based on a correlation between attributes' values: material in query, its visual signature and five retrieved images from our dataset having the closest appearance.

7 Discussion

The main contribution of this paper is definition of the crucial visual attributes for identification of material visual properties. Although our study uses one of the largest sets of material samples used in a psychophysical analysis to date, and we carefully selected this set from a portfolio of real-world materials, the number of samples per material category varies. The highest number of samples is in the categories of fabric and wood due to their inherited high visual variability. This could potentially impact selection of our visual attributes and skew their generalization towards these categories. On the other hand, including more samples would have made our similarity experiment much more demanding.

Our current study is limited to a fixed level-of-detail of the material surface. It analyzes the sample area of 40 x 40 mm and thus is limited to materials with relatively fine and stationary textures and cannot describe visual behavior of materials beyond our sample size, i.e., textures with too low spatial frequencies or slow gradient changes over the sample. Also our dynamic stimuli represented a limited subset of all possible lighting-sample-viewer configurations. We had to limit camera and light trajectories so that movies were of reasonable duration. Therefore, we do not account for specific retroreflective, goniochromatic, or anisotropic behavior of materials due to changes in viewing and lighting angles which are not present in our stimuli.

We consider this work as a proof-of-concept study, which can be extended in the future by collecting ratings of even wider range of materials. To support future research in this area, we have made all stimuli data and rating responses available in a public repository.

8 Conclusions

In a series of psychophysical studies involving 347 materials across various categories, we identified a set of sixteen material attributes and had them rated by twenty observers. Our findings indicate that these attributes perform well in facilitating intuitive, human-centered comparisons and retrievals of material appearances, thereby creating a unique visual signature for each material. This signature enables effective material retrieval based on perception-related features. In future work, we aim to predict human ratings of these attributes using image statistics derived from photographs of the materials, which would allow for the automatic computational identification of the material appearance fingerprint.

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