

The Effect of Motion on the Perception of Material Appearance

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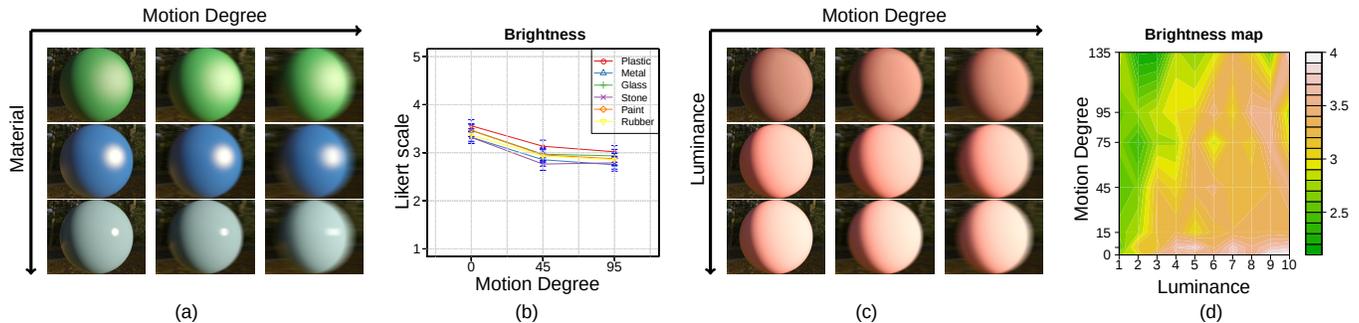


Figure 1: We conduct two large-scale crowdsourced experiments to analyze the influence of motion blur in the perception of material appearance. (a) Representative samples of the stimuli used in our first experiment, in which we analyze the perception of a series of high-level attributes for varying degrees of motion and different materials. (b) The variation of the high-level attribute *brightness* for different motion degrees and material categories tested in our first experiment. (c) Representative samples of the rubber material; part of the stimuli used in our second experiment, in which we look at the influence of varying luminance levels and motion degree on perceived brightness. (d) Results of our second experiment, showing a non-linear influence of motion degree and luminance level on perceived brightness.

ABSTRACT

We analyze the effect of motion in the perception of material appearance. First, we create a set of stimuli containing 72 realistic materials, rendered with varying degrees of linear motion blur. Then we launch a large-scale study on Mechanical Turk to rate a given set of perceptual attributes, such as brightness, roughness, or the perceived strength of reflections. Our statistical analysis shows that certain attributes undergo a significant change, varying appearance perception under motion. In addition, we further investigate the perception of brightness, for the particular cases of rubber and plastic materials. We create new stimuli, with ten different luminance levels and seven motion degrees. We launch a new user study to retrieve their perceived brightness. From the users' judgements, we build two-dimensional maps showing how perceived brightness varies as a function of the luminance and motion of the material.

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SAP '19, September 19–20, 2019, Barcelona, Spain

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ACM ISBN 978-1-4503-6890-2/19/09...\$15.00

<https://doi.org/10.1145/3343036.3343122>

CCS CONCEPTS

• Computing methodologies → Perception.

KEYWORDS

Material Perception, Dynamic Environment, Material Definition Language (MDL), Motion blur

ACM Reference Format:

Ruiquan Mao, Manuel Lagunas, Belen Masia, and Diego Gutierrez. 2019. The Effect of Motion on the Perception of Material Appearance. In *ACM Symposium on Applied Perception 2019 (SAP '19)*, September 19–20, 2019, Barcelona, Spain. ACM, New York, NY, USA, 9 pages. <https://doi.org/10.1145/3343036.3343122>

1 INTRODUCTION

The perception of material appearance is affected by confounding effects such as the shape of the object, illumination, viewing conditions, etc. However, being able to distinguish between materials and to infer their key properties by sight is an inherent process in humans, which is invaluable for multiple tasks. How this is done exactly remains unclear, since human perception is a complex process influenced by a large set of variables. In fact, a unified theory that fully explains such a process does not exist [Anderson 2011; Fleming 2014].

To reduce the dimensionality of the perception of material appearance, many works have focused on developing applications

for material synthesis [Zsolnai-Fehér et al. 2018], editing [Serrano et al. 2016], or filtering [Jarabo et al. 2014]. Other works focus on investigating individual variables that may affect our perception, such as translucency [Gkioulekas et al. 2015], or gloss [Pellacini et al. 2000; Wills et al. 2009].

With a few exceptions, most of the research on material perception has focused on static stimuli. Doerschner et al. [2011] identified three motion cues the brain could rely on to distinguish between matte and shiny surfaces. Aliaga et al. [2015] explore the interplay of cloth and dynamics, while Sakano et al. [2008] studied how self-motion influences the perception of gloss. Nevertheless, a generalized approach that tries to explain the effect of motion on a wide variety of attributes remains an open avenue of research.

In this paper, we study the influence of linear motion in the perception of material appearance relying on a set of intuitive, high-level perceptual attributes [Serrano et al. 2016]. Inspired by previous large-scale studies [Rubinstein et al. 2010; Serrano et al. 2016], we rely on crowdsourced data, from a set of 72 varied, realistic materials. To create a dense space of stimuli, we add additional variations by modifying their luminance, and render them with different levels of motion. This creates a total of 356 stimuli, used in two different experiments.

In the first experiment, we statistically analyze the significant change in how several of these high-level attributes are perceived according to the degree of motion. While brightness decreases significantly, more diffuse appearances remain constant as motion increases. This may be explained by the fact that motion blur has a higher impact on the high frequencies of an image which are usually associated with more specular materials.

In a second experiment, we focus on the perception of brightness, where the first experiment showed a larger influence of motion. We select rubber and plastic materials, with seven motion degrees and ten luminance levels. Using human judgements through Mechanical Turk, we build a brightness map as a two-dimensional function that shows the average perceived brightness for each level of luminance and degree of motion.

Our contributions represent just a step towards a better understanding of how motion affects material perception, a relatively unexplored topic compared to studies on static stimuli. To encourage further research on this topic, all our data will be made publicly available, including the material database, code, and the users' responses.

2 RELATED WORK

2.1 Material perception

To understand the perceptual properties of a given material is a complex task given the ambiguity of the information that arrives at our visual system, influenced by illumination, shape, motion, and other confounding factors. Nevertheless, humans show an outstanding performance recognizing materials [Fleming 2014; Fleming and Bühlhoff 2005; Ged et al. 2010; Li and Fritz 2012]. We are able to infer the physical properties of objects without the need to touch them [Fleming et al. 2015a, 2013; Maloney and Brainard 2010; Nagai et al. 2015; Tanaka and Horiuchi 2015], just by briefly looking at them [Sharan et al. 2009, 2008]. To quantify the contribution of each visual and non-visual cue in our perception remains an open

avenue of research [Anderson 2011; Fleming 2014; Fleming et al. 2015b; Maloney and Brainard 2010]. There exist some evidence that illumination [Fleming et al. 2003; Krivánek et al. 2010], shape [Havran et al. 2016; Vangorp et al. 2007] or motion [Doerschner et al. 2011; Hartung and Kersten 2002] may be one of these factors that alter our perception of a given material. Our work is similar to the latter as we focus on the effect of motion in our perception of material appearance. We launch two experiments using high-level explainable attributes and several stimuli with different degrees of motion and luminance. Then, we analyze the disparity in users' answers as the degree of movement in the stimuli varies and construct brightness maps from participants' responses.

2.2 Materials and motion

The effect of motion in perception has been an active area of research [NEFS 2008; Ullman 1979]. Sakano [2008] study the effect of self-motion in our perception of glossiness. Later extended to describe reflectance properties of a given material [Doerschner et al. 2011] — where they found three visual cues related to motion that our brain could rely on to describe to distinguish matte or shiny surfaces —, and to modulate material appearance [Marlow and Anderson 2016]. Navarro et al. [2011] link perceptual attributes to low-level scene parameters, like the shutter speed of a virtual camera or the anti-aliasing in a scene, for motion blur rendering. The effect of motion has been also studied on the perception we have about liquids [Kawabe et al. 2015], cloth [Aliaga et al. 2015], or depth [Braunstein 2014]. To see if the responses of our visual system change under motion [Kam et al. 2015], or to improve our perception of glossiness [Tani et al. 2013]. Unlike previous work, we do not focus on a particular property or application; instead, we follow a general approach in order to take a step towards the understanding of the effect of motion in a set of high-level attributes that can describe a wide variety of materials.

2.3 Material modeling

In order to faithfully represent the real-world, we need models that capture its richness, are flexible, and can be used easily. There have been many efforts to measure materials and represent them in a digital form. MERL [Matusik et al. 2003] dataset has a set of 100 isotropic materials measured from real samples, UTIA [Filip and Vávra 2014] also adds anisotropy to its set of materials. Objects under Natural Illumination Database [Lombardi and Nishino 2012] includes calibrated HDR information, and the recent database by Dupuy and Jakob [2018] also adds spectral reflectances to its samples. However, measured models usually lack flexibility and are expensive to evaluate, therefore, in our work we decided to work with the database *vMaterials*¹, a curated collection of realistic materials and lights represented in MDL (Material Definition Language) [Kettner et al. 2015] that can be rendered with the OptiX ray tracing engine [Parker et al. 2010]. The ability to model realistic materials together with the studies on material perception has encouraged the development of perceptual applications. Nielsen et al. [2015] present a novel mapping of measured BRDFs, allowing for the extraction of descriptive principal components later used by Serrano et al. [2016] to find a relationship between

¹<https://www.nvidia.com/en-us/design-visualization/technologies/vmaterials/>

perceptual attributes and an underlying PCA-based representation of BRDFs. To find a metric that models the relationship between human judgements is a long-standing problem not solved yet [Filip and Kolafová 2019; Garces et al. 2014; Lagunas et al. 2018; Soler et al. 2018; Wills et al. 2009]. Lagunas et al. [2019] derive a metric on image space, based on deep learning models, that correlates with human perception and improves previous baselines [Ngan et al. 2006; Pereira and Rusinkiewicz 2012; Sun et al. 2017]. These metrics can also be computed directly over measured BRDFs [Fores et al. 2012; Ngan et al. 2005], or on perceptual traits [Pellacini et al. 2000; Serrano et al. 2016]. Our work diverges from the latter since it does not aim to build a perceptual application, instead, we focus on the more fundamental problem of evaluating the differences in human perception of material appearance under the influence of motion.

3 STIMULI CREATION

The following section explains the process followed in order to create the stimuli for our experiments.

Materials. We use the material library *vMaterials*, a large collection of realistic materials and lights described in Material Definition Language (MDL) [Kettner et al. 2015]. We did not use a measured material database since we can use MDL to directly control the physical parameters of the materials (for instance, the brightness). Moreover, this may facilitate in the future using high-level material features to edit material appearance in real-time. Among all the available options, we selected a subset of 72 materials that span six categories, including glass, metal, paint, plastic, rubber, and stone. We decided to choose materials categories that represent daily items to avoid introducing bias due to unawareness in the participants' answers.

The materials in *vMaterials* include additional layers that add texture or small geometric details at rendering time. These features can alter the information that arrives at our visual system and distract the participant from its real purpose which is to observe the material itself. Therefore, in order to focus the attention of the user, we decided to remove all additional layers included in the material description, obtaining at the end, a homogeneous representation of the material. This procedure is depicted in Figure 2.

Adding motion. To approximate the effect of motion in our stimuli, we use an image algorithm consisting of a two-dimensional filter [Bradski 2000], described in Equation 1.

$$\mathcal{I}_o(x, y) = \sum k(x', y') \times \mathcal{I}_i(x + x', y + y') \quad (1)$$

where $\mathcal{I}_i(x, y)$ and $\mathcal{I}_o(x, y)$ are the input and output images respectively; and (x, y) are the coordinate of the pixel in the image. The expression $k(x', y')$ means a convolution kernel, whose index in the kernel is (x', y') . The range of $k(x', y')$ is $1 \leq x' \leq k_c$ and $1 \leq y' \leq k_r$, where k_c and k_r are the numbers of columns and rows in k . When the aperture is partially outside the image, we interpolate outlier pixel values by mirroring \mathcal{I}_i .

Our experiments only intend to investigate material perception for linear movement, therefore $k(x', y')$ is a horizontal vector, whose value is $1/k_c$. The size of the kernel (k_c), can be considered as the motion degree. In a static situation, the motion degree is 0.

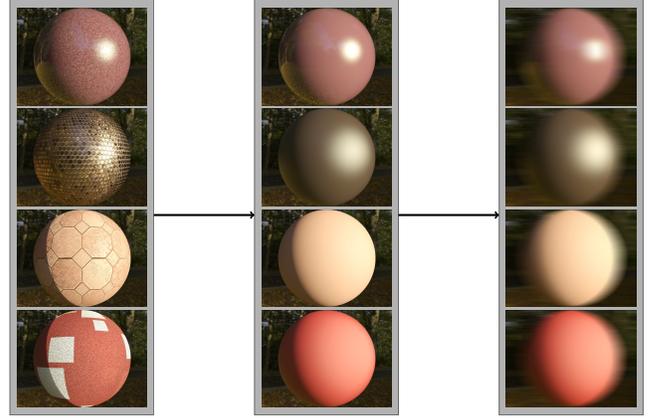


Figure 2: Summary of the process followed to generate stimuli of homogeneous materials with different degrees of motion. From left to right, the first column shows the frameworks used for rendering. The second column is the rendering result using *vMaterials* and ray tracing engine OptiX [Parker et al. 2010], including texture and small geometric details. The third column represents the homogeneous material removing additional information provided in *vMaterials*. The last column shows the stimuli with different degrees of motion.

Scene. We use a sphere as the 3D model, a well-known surface, widely used in previous user-studies [Fleming et al. 2003; Jarabo et al. 2014]. The 3D model is placed in the centre of the scene. In order to render our stimuli, first, we use OptiX [Parker et al. 2010], a general purpose ray tracing engine, with the homogeneous material definition to generate an image of a static material, then we apply the two-dimensional filter explained in Equation 1 to add motion to the scene. Figure 2 summarizes the process of stimuli creation.

4 EXPERIMENT 1: RATING MATERIAL ATTRIBUTES

This section describes the approach followed in order to collect human ratings of perceptual attributes on materials under the influence of a certain degree motion.

4.1 Experiment design

Stimuli. We choose a set of 72 different realistic materials, that span six different material categories, and three degrees of motion: 0, 45, and 95 with a significant difference between them in order to provide a notable change in the stimuli appearance. Further explanation about the stimuli creation is given in Section 3. A subset of the stimuli is shown in Figure 3, all the stimuli are shown in the supplementary material.

Participants. Similar to previous work dealing with large-scale experiments in computer graphics [Lagunas et al. 2019; Rubinstein et al. 2010; Serrano et al. 2016], we rely on Amazon Mechanical Turk (MTurk) to launch our experiments. In the end, a total of 540 users performed the task. Users were unaware of the purpose of the experiment.

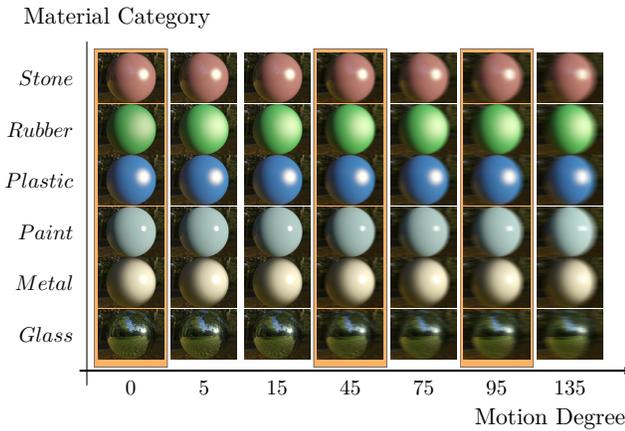


Figure 3: Subset of the stimuli used in the user experiment. Each row corresponds to a material from a material category. The x-axis shows the degree of motion, going from 0 (static stimuli) to 135 (fastest stimuli). For the first experiment, we only use the motion degrees 0, 45, and 95 since they provide significant visual changes in the final renderings.

Procedure. Our user-study deals with the perception of material appearance under the influence of motion. We ask the users to rate a set of perceptual attributes regarding the material in the stimuli. They rate the attributes in a Likert-like scale, which has proven to work reliably in multi-modal problems [Yumer et al. 2015]. Following previous work [Du et al. 2013; Serrano et al. 2016; Zell et al. 2015], our scale ranges from 0 (very little) to 5 (a lot). We consider this range a good compromise between the complexity to fill in the survey and the number of available options for the participants.

Following the work of Serrano et al. [2016], participants rate 14 perceptual attributes, namely: *plastic-like*, *rubber-like*, *metallic-like*, *fabric-like*, *ceramic-like*, *soft*, *hard*, *matte*, *glossiness*, *brightness*, *roughness*, *tint of reflections*, *strength of reflections*, and *sharpness of reflections*. Covering both, high and mid-level features of the material, allowing for a comprehensive evaluation of the participants' perception.

Each test consisted of 12 different trials, 4 groups of three spheres with the same material and different motion degrees, randomly displayed. The participants had to rate all the 14 perceptual attributes in all the trials of the user study (HIT, Human Intelligence Tasks, in MTurk terminology). The experiment was developed to work in standard web browsers. Before the real experiment, there is a thorough description of the task, and a brief training session in order to minimize worker unreliability [Welinder et al. 2010]. During the real test, participants were shown one stimulus at a time. In the end, each stimulus was rated by 30 different users and we collected a total of 6480 answers for 14 attributes, yielding 90.720 ratings.

4.2 Analysis

Among the 14 perceptual attributes rated by the participants, we select a subset of six to perform the statistical analysis, those include *brightness*, *glossiness*, *matte*, *roughness*, *sharpness of reflections* and

strength of reflections. We conducted a Friedman rank sums test, a non-parametric version of ANOVA, [Pohlert 2018] in order to analyze how the factors: *material category* and *motion degree* have affected participants' answers. The *motion degree* contains three levels: 0, 45, and 95 while the *material category* has six: glass, metal, paint, plastic, rubber, and stone. We decided to use a Friedman test since it is suitable for Likert-like ratings and samples do not need to be normally distributed. We chose a significance level of $p = 0.05$ in all our tests.

The influence of motion. A summary with all the p -values for each rated attribute and material category can be found in Table 1, a complete table with all the p -values can be found in the supplementary material. We observe that *glossiness*, *brightness*, *strength of reflections*, and *sharpness of reflections* have a significant change in all the material categories ($p < 0.05$). On the other hand, the attributes *matte*, and *roughness* are not influenced by motion and do not have a significant change for all the material categories ($p > 0.05$). These results may suggest that motion has a bigger effect on our perception of the attributes that describe the specularly of the material instead of on the ones that are used to characterize diffuse appearances.

The influence of the material. The attributes *matte*, and *roughness* are not influenced by motion in all the material categories. Only metal and paint materials for the *matte* attribute will have a significant change ($p < 0.05$). We argue that this significant change is produced because these materials have a characteristic narrow specular lobe that under the effect of motion blur will broaden, giving them a more diffuse and dimmer final appearance.

Given the previous findings, we further investigate the significance of each factor individually. We conduct a Nemenyi post hoc test with a single-step p -value adjustment, suitable to find statistically significant groups after the Friedman test. Table 2 shows the p -values for the attributes *glossiness*, *brightness*, *strength of reflections*, and *sharpness of reflections*; and both factors: *material category*, and *motion degree*.

We can observe a clear trend for all four attributes, there is a significant change in participants' perception when the stimuli change from static to a middle motion degree ($p < 0.05$) and if the stimulus moves from static to the highest analyzed motion degree ($p < 0.05$). However, if the stimulus changes from a middle motion degree (45) to the highest motion degree (95), there are no significant changes in participants' answers ($p > 0.05$). This showcases the non-linear nature of human perception of material appearance [Thompson et al. 2011] and tells us that linear changes in motion do not necessarily correlate with linear changes on the perception we have about the stimuli [Champion and Warren 2017; Zanker 1995]. However, the rubber material category does not show significant changes for attributes *glossiness*, and *strength of reflections* when the degree of motion changes from static to a middle motion degree ($p > 0.05$), but shows significant changes when we move from a static to the highest motion degree ($p < 0.05$). This could be due to the diffuse appearance of rubber, which lacks reflections. Therefore, small changes in motion do not produce perceptually visible changes in the specular appearance of the material, requiring higher motion degrees to perceive those changes.

Table 1: Results from Friedman rank test for all the materials and attributes over all motion degrees. The last two columns show the results from the Friedman test (χ^2 and p -values).

Attribute	Material	χ^2	p -value
Matte	Plastic	0.301	0.860
	Metal	13.942	0.001
	Glass	0.833	0.659
	Stone	1.240	0.538
	Paint	10.033	0.007
	Rubber	2.898	0.235
Glossiness	Plastic	24.958	0.004
	Metal	19.080	0.072
	Glass	52.166	0
	Stone	64.045	0
	Paint	29.110	0
	Rubber	19.648	0.054
Brightness	Plastic	70.490	0
	Metal	52.211	0
	Glass	62.027	0
	Stone	72.240	0
	Paint	71.274	0
	Rubber	59.049	0
Roughness	Plastic	2.924	0.232
	Metal	1.769	0.413
	Glass	2.233	0.327
	Stone	1.347	0.510
	Paint	1.327	0.515
	Rubber	0.003	0.999
Strength of reflections	Plastic	41.848	0
	Metal	42.993	0
	Glass	66.824	0
	Stone	29.444	0
	Paint	18.885	0.079
	Rubber	14.236	0.001
Sharpness of reflections	Plastic	45.868	0
	Metal	51.283	0
	Glass	101.800	0
	Stone	48.995	0
	Paint	38.979	0
	Rubber	34.243	0

Figure 4 shows the trends of participants' ratings for each of the six perceptual properties and motion degrees. As previously discussed *glossiness*, *brightness*, *sharpness of reflections* and *strength of reflections* attributes have significantly different answers under motion. For each attribute, we observe a falloff as the motion degree is increased. This is expected as the blur introduced by the movement of the stimulus dims the image content, soften highlights. Also, if we observe the *sharpness of reflections* attribute, we see that material categories with clear reflections in their materials — like *glass* — have higher ratings in the static stimulus and a steeper

Table 2: Results from the Nemenyi post hoc test. The first column is the name of the attribute rated by the participants. The names of the material categories are placed in the second column. From the third to the fifth column we have the p -values for each change in motion degree.

Attribute	Material	Motion Degree Pairs		
		0-45	0-95	45-95
Glossiness	Glass	0	0	0.209
	Metal	0.269	0.003	0.178
	Paint	0.017	0	0.373
	Plastic	0.004	0.800	0.892
	Rubber	0.070	0.003	0.553
	Stone	0.002	0	0.665
Brightness	Glass	0	0	0.988
	Metal	0.019	0	0.649
	Paint	0	0	0.645
	Plastic	0.002	0	0.380
	Rubber	0.005	0	0.783
	Stone	0	0	0.946
Strength of reflections	Glass	0.006	0	0.357
	Metal	0.014	0.004	0.108
	Paint	0.029	0.012	0.946
	Plastic	0.003	0.005	0.274
	Rubber	0.056	0.040	0.991
	Stone	0.003	0	0.768
Sharpness of reflections	Glass	0	0	0.592
	Metal	0.003	0.002	0.192
	Paint	0.002	0.071	0.703
	Plastic	0	0.008	0.729
	Rubber	0.006	0	0.728
	Stone	0.027	0.004	0.918

decreasing slope. On the other hand, *matte* and *roughness* attributes, not considered statistically significant, have slight changes as we increase motion, showing an almost uniform behavior.

5 EXPERIMENT 2: BRIGHTNESS UNDER MOTION

Given the results of the previous experiment (Section 4), here we further investigate the influence of motion on the perceived brightness of some materials, focusing on rubber and plastic. We run new experiments for these materials, from which we will plot the perceived brightness as a function of the luminance level and motion degree of the stimuli.

5.1 Experiment design

Stimuli. We generate a series of stimuli for the materials rubber and plastic, with ten continuous-changed luminance levels (1 to 10) under seven different motion degrees (0, 5, 15, 45, 75, 95, 135). The stimuli used in this experiment for the material rubber can be seen in Figure 1, c). All the stimuli are shown in the supplementary material.

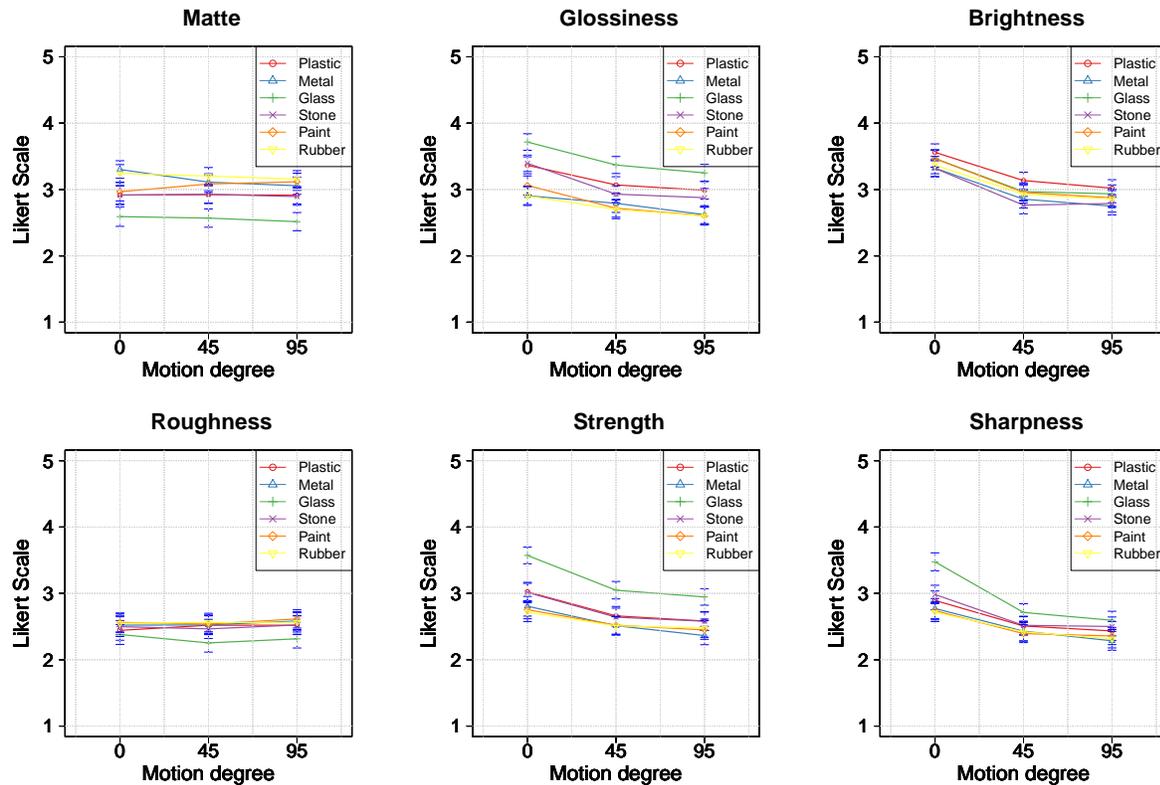


Figure 4: Plot showing the average rating given in the user-study for each of the six perceptual attributes analyzed, for each material type and for all the motion degrees. The x -axis shows the variation in motion of the stimuli, the y -axis displays the average rating given by the participants. Each color of the line plot represents one of the material categories. Error bars correspond to a 95% confidence interval. We see how for the attributes *glossiness*, *brightness*, *sharpness of reflections* and *strength of reflections*, there is a clear decreasing trend while *matte* and *roughness* shows an almost uniform behavior. All the plots for each attribute can be found in the supplementary material.

Participants. Similar to the previous user-study, we relied on Amazon Mechanical Turk to launch the experiment. A total of 210 unique workers took part in it. Users were unaware of the purpose of the experiment.

Procedure. This experiment follows a similar scheme to the one explained in Section 4. Participants are asked to rate a subset of six different attributes (introduced in Section 4) on a continuous 5-point Likert-like scale. Also, although we are only interested in brightness, in order to avoid participants to know the real purpose of the experiment, they are asked to rate all the subset of 6 attributes. We reduce the number of attributes to rate from 14 to 6 in order to avoid distractions in the user [Di Cicco et al. 2019]. Each experiment has 10 different trials containing all the brightness levels and random motion degrees. The trials are presented randomly to the participants. We collect 15 answers for each sphere, brightness, and motion degree. In the end, we gather a total of 2100 answers.

5.2 Analysis

After collecting all the data, we have a set of brightness ratings for stimuli with variations in their motion degree and luminance.

With it, we can build two-dimensional maps that tell us the average perceived brightness for each luminance and motion degree level.

Brightness map construction. In Figure 5, we can see the brightness maps for the materials rubber (left) and plastic (right). The brightness maps are constructed for all 10 luminance levels, in the x -axis, and 7 motion degrees, in the y -axis, of the stimuli. In order to build the brightness map, we get the average perceived brightness values of the participants using the ratings of the experiment. Since we cannot generate an infinite set of stimuli, the points that are not sampled are generated using linear interpolation.

Compensation between luminance and motion degree. Both brightness maps confirm the results from the previous stimuli (Section 4), as motion increases our ratings of perceived brightness decrease. However, when the stimulus reaches a high motion degree our perception of its brightness keeps almost constant.

Also, if we follow an isocontour in the brightness maps the lines that have the same average perceived brightness, we can observe how, in order to keep a constant perceived brightness, the slope of the isocontour bends. Moreover, if we compare both

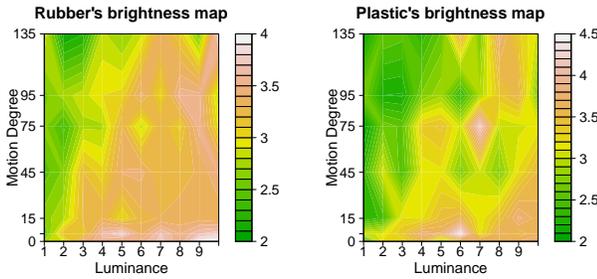


Figure 5: On the left, the rubber brightness map created using the stimuli from the experiments. On the right, the plastic brightness map. For both brightness maps, the x -axis is the luminance of the stimulus while the y -axis is its motion degree. Both figures show how as motion degree increases, brightness will decrease non-linearly.

brightness maps, we can observe how the plastic has an overall less perceived luminance. We argue that this happens due to the blur in the highlights of the plastic, a specular material, produced by the effect of motion blur. While on the rubber, since it is a diffuse material, there are no significant highlights and the effect of motion has a reduced impact compared to the case of plastic.

Luminance region split. Isocontours show how in order to keep the same level of perceived brightness, luminance levels have to increase non-linearly when motion degree is increased linearly. Moreover, if we follow the isocontour generated between the values 2 and 3 of luminance, we can see a clear separation; on the left, we would have the dim area with values of perceived brightness around 2.5 while on the right side of the isocontour we can see a constant area with perceived brightness of 3.5. These two regions are separated by the isocontour where our perceived brightness takes a value of 3. This exhibits the non-linear behavior of human perception, and also how, although the values of luminance and motion degree are changing, our perception of brightness remains constant.

6 DISCUSSION AND FUTURE WORK

6.1 Conclusion

We have presented an analysis of the effects of motion blur on our perception of a wide set of material attributes, for different material categories. To do it, we analyze 38,880 ratings (72 (materials) \times 3 (motion degrees) \times 30 (answers/stimulus) \times 6 (attributes)) given for six different material attributes: *brightness*, *glossiness*, *matte*, *roughness*, *sharpness of reflections* and *strength of reflections*. Please refer to the supplemental material for the complete analysis of all 14 attributes included in the experiments.

A reasonable concern when using Mechanical Turk as a source for participants in user studies, is the possible effect of uncontrolled viewing conditions (such as display characteristics or viewing environment). Nevertheless, previous studies have shown that MTurk can actually be used in visual psychophysical experiments, and its results matched those under controlled lab conditions, since a large

number of participants reduces variance (e.g. [Heer and Bostock 2010; Jarabo et al. 2014]). Similarly, participants were not screened for proficiency in English, so it may be that some subtleties in the description of material appearance were lost.

Our results indicate that motion blur has a significant effect on our perception of attributes related to the specular nature of the material, namely *glossiness*, *brightness*, and *strength and sharpness of reflections*, whereas no significant influence exists on the attributes *matte* and *roughness*. The four aforementioned attributes—*glossiness*, *brightness*, and *strength and sharpness of reflections*—are given significantly lower ratings as the motion degree increases. This can be due to the removal of high frequencies of the stimuli as a consequence of motion blur, since it has been shown that these relate to specularity [Durand et al. 2005]. When looking at the nature of this influence through post-hoc analysis, we observe that, among lower motion degrees the influence of motion blur on the perception of attributes is larger than among higher ones; actually, there is no significant difference between motion degrees 45 and 95, while there is between degrees 0 and 45. This seems to indicate a stabilization of perceived attribute magnitudes for higher motion degrees, i.e., from a certain motion degree, increased motion blur does not change the perception of these attributes.

Moreover, we select an attribute and material category to do a more in-depth analysis of the influence of motion blur on perceived brightness. In this second experiment, we not only vary the motion degree, but also the luminance of the material shown in the stimuli. We seek to observe how the isocontours (i.e., lines of constant brightness) behave as we vary both motion degree and luminance level. Despite the limited extent of our experiment, we observe how the non-linear behavior with motion degree persists. Further, this behavior is different for different luminance levels, falling back to an almost constant (independent of motion degree) behavior for both very high and very low luminance levels. This intricate relationship suggests the need for more detailed experiments, covering a wider range of appearances and perceived attributes; this work takes the first steps in this direction, but a comprehensive model of the influence of motion blur in material perception remains as future work.

6.2 Future work

In this work, we have just investigated the effect of motion blur due to linear motion in our perception of material appearance; other kinds of motion, including rotation, multidirectional paths, accelerated movement, etc., would require further analysis, for which we hope our work can provide a solid basis. Similarly, we make the reasonable assumption that motion blurred images are a good proxy for actual moving stimuli for the purposes of our test.

Our stimuli have been rendered using homogeneous material files in MDL. Exploring how the missing information encoded in the heterogeneities of some materials (like stone, or wood) affects appearance perception is an interesting extension, not included in our work. Some materials, especially specular ones, may require a wider dynamic range than what a typical display provides, an aspect of appearance perception not covered in this work since our stimuli were tone mapped. Also, since users, in general, tend to

avoid extrema in Likert-based tests, it would be interesting to find if using a 7-point scale would have an influence in their responses.

Finally, extending this work to find a correlation between image statistics and the set of perceptual attributes analyzed remains unexplored. Human perception of appearance is a sophisticated process, not fully understood, which poses many challenges and opens interesting avenues of future research, and we hope our work will inspire future exploration of the influence of motion in our perception. For instance, our findings could be used to optimize the performance of rendering pipelines where motion can have a big influence like in the emerging fields of virtual reality or real-time ray-tracing.

ACKNOWLEDGMENTS

We want to thank the anonymous reviewers for their encouraging and insightful feedback on the manuscript; the members of the Graphics & Imaging Lab for fruitful discussion, and in particular Ana Serrano Pacheu for the website building, IbÅşn Guillen, Sandra Malpica, Julio Marco, Marta OrtÅşn ObÅşn and Incheol Kim for help on the pilot experiments. Ruiquan Mao also would like to thank Davide Deflorio, PhD candidate in SyMoN Lab, University of Birmingham, for the valuable suggestions. Manuel Lagunas is funded by the European Research Council (ERC) under the European UnionÅşs Horizon 2020 research and innovation programme (CHAMELEON project, grant agreement No 682080). Ruiquan Mao is funded by Marie SkÅşodowska-Curie Action (MSCA-ITN/ETN) under the European UnionÅşs Horizon 2020 research and innovation programme (DyViTo project, grant agreement No 765121).

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