Is Gloss a cue for Real-World Object Size?

James Michael Brown

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of:

Doctor of Philosophy
   in
   Psychology

Anthony D. Cate, Chair
Rachel Diana
Brooks King-Casas
John Richey

June 18, 2020
Blacksburg, Virginia

Keywords: visual perception, gloss, real-world size, image statistics, mid-level vision
IS GLOSS IS A CUE FOR OBJECT SIZE?

Is Gloss a Cue for Real-World Object Size?

James Michael Brown

ABSTRACT

Two separate lines of research in object recognition are studies of materials perception and studies of real-world object size perception. Recent object size investigations of texture indicate mid-level features may cue representations of object size in the absence of object identity. However, these findings are somewhat controversial, and beyond that what mid-level features cue object size is not clear. Mid-level features have always been the focus of materials perception studies of gloss and specular highlights, but to date no research has been conducted that attempts to link findings on the perception of materials to high-level object features like real-world object size. Three separate experiments were conducted to study the relationship between perceived surface glossiness and specular highlights, and perceived real-world object size. Previous research on the relationship between perceived object size and real-world object size were replicated. A significant two-way interaction between ratings of perceived glossiness, object size, and texture was found. Follow-up analyses indicated that perceptions of gloss were present across categorical differences in real-world object size in both the object image and texture image task groups. For the normal object images, small objects were perceived as being glossier than big objects. For the texture images, big objects were perceived as being glossier than small objects. Between the conditions, small normal and small texture object images were not significantly different in perceived glossiness. Between the conditions, glossiness ratings for big texture object images were significantly greater than those for the normal big object images.
The goal of this project was to understand if category level perceptions of surface gloss (i.e. dull/matte surface reflectance versus shiny/glossy surface reflectance) could predict category level differences in the “actual” size of the objects in the real-world (i.e. small objects versus big objects). Previous research on the relationship between perceived object size and real-world object size were replicated. Moreover, in an experiment in which human subjects were tasked with rating the glossiness of images depicting small and large manmade of objects, category level distinctions in the average perceived glossiness of objects also extended to category level distinctions in perceived real-world object size; on average, small objects were perceived as being glossier than big objects. Similar effects were also found for synthetic textures created from the ordinary real-world object images; on average, big objects were rated as being glossier than small objects. Although categorical distinctions in perceived glossiness extended to real-world object size across image conditions, because there were no significant differences in the average perceived glossiness of small objects across the normal image and texture image conditions, the change in perceived glossiness for the big object images suggests that the texture algorithm used may not have preserved the material properties of the big objects. Although more is needed, the category level differences in perceived glossiness across object size and image condition may have been driven by differences in factors related to naturally occurring optical artifacts that are introduced when photographing small and big objects. Overall, results of this study are important because they indicate that the real-world spatial properties of objects may be jointly encoded with materials perceptions of object glossiness.
Dedication

I would like to dedicate this project to my late best friend, Bryce Torian.
Acknowledgments

I would like to acknowledge my PhD advisor Dr. Anthony Cate. You’ve taught me so much over the past 7 years, I can’t thank you enough for providing me with the opportunity to learn psychophysics and visual neuroscience methods from you. Thank you for being both a great mentor and friend.
# Table of Contents

List of Tables .......................................................................................................................... x
List of Figures .......................................................................................................................... xi
Introduction ............................................................................................................................. 1
Motivating Frameworks .......................................................................................................... 4
  Influential Theories of Vision ............................................................................................. 4
  Hierarchical Visual Processing ......................................................................................... 4
  Low-Level Vision .............................................................................................................. 4
  Mid-Level Vision ............................................................................................................... 4
  High-Level Vision ............................................................................................................. 5
Natural Image Statistics ........................................................................................................ 5
Low-Level Image Statistics ................................................................................................. 6
Coarse-Scale Texture Analysis ........................................................................................... 7
Influential Theories of Vision: Overview .......................................................................... 7
Simulating Realistic Visual Appearances ............................................................................ 9
  Attributes of Photorealism ............................................................................................... 9
  Specular Reflections .......................................................................................................... 9
  Diffuse Reflections ........................................................................................................... 10
  Bi-Directional Reflectance Distribution Function (BRDF) ............................................. 10
Three-Dimensional Surface Geometry ................................................................................ 11
Ambient Illumination ........................................................................................................... 11
Attributes of Photorealism: Overview .............................................................................. 12
Materials Perceptions of Surface Gloss ............................................................................. 13
  Gloss ................................................................................................................................. 13
  Apparent Gloss ................................................................................................................ 14
  Specular Highlights ......................................................................................................... 14
Behavioral Studies on Gloss Perception .......................................................................... 14
Gloss Perception Across Changes in Micro and Mesoscale Surface Geometry .................. 15
Gloss Perception and Specular Highlights ...................................................................... 15
Gloss Perception and Real-World Illumination .................................................................. 17
Object Shape Affects the Perception of Materials ............................................................... 18
Object Perceptions of Real-World Size ......................................................... 25
  Object Size ......................................................................................... 25
  Retinal Size ......................................................................................... 26
  Visual Size ......................................................................................... 26
  Familiar Size ......................................................................................... 26
Behavioral Studies on Object Size Perception ............................................. 26
Semantic-Level Perceptions of Object Size ................................................. 27
Coarse-Scale Perceptions of Object Size ..................................................... 28
Behavioral Studies on Object Size Perception: Overview ............................. 30
Neural Correlates of Object Size ................................................................. 30
Semantic-Level Object Size Representations ............................................. 30
Coarse-Scale Object Size Representations .................................................. 32
Neural Correlates of Object Size: Overview ............................................... 32
Behavioral Findings ................................................................................. 34
Neuroimaging Findings ........................................................................... 36
Conclusions Drawn from Converging Evidence .......................................... 36
Dissertation .............................................................................................. 37
Dissertation Contributions ......................................................................... 38
Project Aims ............................................................................................. 39
  AIM 1 ................................................................................................. 39
  AIM 2 ................................................................................................. 39
  AIM 3 ................................................................................................. 40
  AIM 4 ................................................................................................. 40
Stimulus Design ......................................................................................... 42
Real-World Object Images .......................................................................... 42
List of Tables

Table 1: Example of Image Features Across Changes in Surface Glossiness .................................. 72
Table 2: Example of Image Features Across Changes in Surface Glossiness .............................. 73
Table 3: Average Image Skewnes by Factors of Interest .............................................................. 74
List of Figures

Figure 1: Example Image Compression Similar to Human Visual System ........................................... 75
Figure 2: Example of Natural Image Statistics ......................................................................................... 76
Figure 3: Example of Image Luminance Histogram ................................................................................. 77
Figure 4: Example Demonstration of PS-Algorithm .................................................................................. 78
Figure 5: Everyday Examples of Specular Reflections ........................................................................... 79
Figure 6: Everyday Examples of Diffuse Reflections ............................................................................... 80
Figure 7: Distinct Spatial Scales of Where Surface Geometry Influences Appearance .................. 81
Figure 8: Example of Light Probe .......................................................................................................... 82
Figure 9: Everyday Examples of Glossy Surfaces and Objects ............................................................. 83
Figure 10: Everyday Examples of Specular Highlights ........................................................................ 84
Figure 11: Many Fruits and Vegetables are Naturally Glossy ................................................................. 85
Figure 12: Do Biological Needs Drive Aesthetic Enjoyment of Glossiness? ........................................ 86
Figure 13: Manipulating Highlight to be Global Form Incongruent .................................................... 87
Figure 14: Natural Ambient Illumination Makes 3D Objects Appear Glossier .................................... 88
Figure 15: Surface Glossiness Depends on the Overall Shape of ......................................................... 89
Figure 16: Example of Image Features Across Changes in Surface Glossiness .................................. 90
Figure 17: Example of Visual Size .......................................................................................................... 91
Figure 18: Example of Familiar Size ....................................................................................................... 92
Figure 19: Using Perlin Noise to Make a Sphere “Blobby” ................................................................. 93
Figure 20: SYNS Staff Office2 HDR Light Field ................................................................................... 94
Figure 21: Isotropic Ward Reflectance Model ....................................................................................... 95
Figure 22: Gloss Rating Scale using Glossy Blob Stimuli .................................................................... 96
Figure 23: Result of Running Glossy Blobs Through SHINE Toolbox Normalization .......................... 97
Figure 24: SHINE Normalized Object Images .................................................................................. 98
Figure 25: Synthetic Texture Images ................................................................................................. 99
Figure 26: Perceived Weighted Average Size Ranks Predicted by Real-World Size ...................... 100
Figure 27: Gloss Rating Two-Factor Mixed ANOVA: Two-Way Interaction ................................. 101
Figure 28: Differences in Gloss Rating by Size Across Task Groups ............................................... 102
Figure 29: Differences in Gloss Rating Across Task Groups Within Size ...................................... 103
Figure 30: Small Object Heat Maps ................................................................................................. 104
Figure 31: Big Object Heat Maps .................................................................................................... 105
Figure 32: Small Texture Heat Maps ............................................................................................... 106
Figure 33: Big Texture Heat Maps .................................................................................................. 107
Figure 34: Participant Defined Specular Highlight Task Results .................................................... 108
Figure 35: Differences in Image Skew by Real-World Object Size and Image-Type .................. 109
Figure 36: Image Skew Across and Contrast: Synthetic Textures vs Natural Textures .............. 110
Introduction

A long-term goal of cognitive neuroscience research is to solve how the human brain leverages retinal image data for accurate, category-level discriminations about the physical properties of objects and materials in just tenths of a second (Fleming, 2017; Grill-Spector & Kanwisher, 2005; Grill-Spector & Weiner, 2014; Julian et al., 2017; Konkle & Oliva, 2012b; Long et al., 2016).

Our visual perceptions of materials and objects are characterized by patterned activations in the dorsal and ventral visual cortices (Goodale & Milner, 1992; Komatsu & Goda, 2018; Mishkin et al., 1983; Nishio et al., 2012; Wada et al., 2014). Computational models of visual recognition hold that the ventral-temporal cortices utilize information obtained from our past experiences with objects in the real-world to filter and organize cortical inputs of retinal image data (Grill-Spector & Weiner, 2014; Kourtzi & Connor, 2011).

Any physical properties intrinsic to materials and objects that naturally constrain the structure of light reflected from their surfaces should also systematically affect how we visually perceive them (Gibson, 1979). To be sure, independent fields of work on recognition studies of objects and materials have found strong evidence that our visual perceptions are actively informed by our real-world knowledge-based expectations (Buckingham & Goodale, 2010; Goodale, 2011; Goodale & Milner, 1992; Paulun et al., 2019). Although object recognition and materials perception studies both indicate that our real-time visual perceptions are influenced by our previous experiences in the “real-world”, the degree to which these biases are either more sensory or cognitive in nature remains uncertain (Alexander et al., 2014; Fleming, 2017; Long & Konkle, 2017, 2018; Schmid et al., 2020). Considering that objects and materials are fundamentally associated in the real-world, and the empirical similarities observed across
recognition studies of objects and materials, the potential links between these two fields suggest mutual connections that could yield important insights with dedicated study (Schmid et al., 2020). In particular, consider object perception studies of real-world size and materials perception studies of gloss.

Both materials perception studies of gloss and object perception studies of real-world size are currently focused on understanding the contribution of low-level image statistics for human-level visual categorization; for both works, this research topic is an ongoing area of investigation (Long & Konkle, 2017; Long et al., 2016; Marlow & Anderson, 2013; Marlow et al., 2017; Marlow et al., 2019). Moreover, object perception studies of real-world size and materials perception studies of gloss empirically overlap in a few other interesting ways. For example, materials perception work indicates that human perceptions of gloss are sensitive to perceptions of real-world illumination, texture, and overall surface shape (Fleming & Bülthoff, 2005; Fleming et al., 2001, 2003; Fleming et al., 2004; Fleming et al., 2013; Ho et al., 2008; J. Kim et al., 2011; Marlow & Anderson, 2013, 2015; Marlow et al., 2015; Qi, 2012; Qi et al., 2015). Similarly, well-established object perception work indicates that human perceptions of depth and distance are sensitive to knowledge-based representations of real-world size (i.e. “familiar size) (Epstein, 1965; Epstein & Franklin, 1965; Wagemans et al., 2011). Moreover, recent work in object perception indicates that category-level representations of real-world size may be triggered by mid-level visual perceptions of texture and object curvature (Long & Konkle, 2017, 2018; Long et al., 2016; Long, Yu, et al., 2017). Given the parallels between object perception studies of real-world size and materials perception studies of gloss, I conjecture that broad perceptions of gloss may cue categorical perceptions of object real-world size.
In the work presented here I review literature focused on object perception studies of real-world size and materials perception studies of surface gloss. For the purposes of providing motivating frameworks, first I will briefly review literature covering influential theories of vision. Following my review of motivating frameworks, I will provide a detailed overview of research on surface reflectance and related characteristics as they are operationally defined by computer graphics and machine vision researchers. Next, I will then operationally define the characteristics of surface gloss relevant to the work presented here and subsequently review relevant findings from behavioral and neuroimaging studies on gloss perception. Following my review of gloss perception research, I will operationally define the characteristics of real-world object size and review related works from behavioral and neuroimaging studies on real-world object size perception.

Upon the conclusion of my literature reviews on studies of surface gloss and real-world object size perception I will synthesize conclusions from converging evidence. Based on my conclusions drawn from converging evidence on studies of gloss and real-world object size perception, I will then outline the problem context and posit my dissertation. Finally, I will outline how I intend to evaluate the validity of my dissertation in the form of research questions with proposed study aims, objectives, and hypotheses.
Motivating Frameworks

Influential Theories of Vision

Here, I will briefly review a selection of theoretical frameworks particularly important to the topic of this project. I will use these frameworks to establish the potential relationship between the constructs of material perceptions of surface gloss and object perceptions of real-world size.

Hierarchical Visual Processing

The model of hierarchical visual processing is a seminal model of object recognition that posits that cortical layers in the human visual system are dissociable by the complexity of object information they process and represent (Felleman & Van, 1991; Grill-Spector & Malach, 2004; Van Essen et al., 1992). In this way, object recognition emerges from a stage-wise visual processing hierarchy. Researchers have distinguished three stages of visual processing: (i) low-level vision, (ii) mid-level vision, and (iii) high-level vision.

Low-Level Vision

Low-level vision refers to the stage of vision were retinal inputs to the primary visual cortex are spatially and temporally filtered to extract low-level features. Low-level features are the base units of object representation, low-level features include visual perceptions of spatial frequency, orientation, and color. Low-level features provide the substrates for representing the edges defining shapes, as well as shaded gradients of contrast.

Mid-Level Vision

Mid-level vision refers to an intervening stage of vision that dissociates form from noise. At this stage, low-level visual representations are continuously sampled and analyzed for patterns of spatial and temporal congruence. Statistically regular patterns are extracted and perceptually grouped, forming mid-level features. Mid-level features refer to rectilinear and curvilinear
contours, brightness, hues with saturation, depth, position, and texture. Mid-level features afford
the perception of object and scenes, sans the identity of those objects and scenes (Marlow et al.,
2015).

**High-Level Vision**

High-level vision refers to a stage of vision that intersects with language, memory, and top-
down processing. Without this stage, real-world objects and scenes would only be perceived as
ghostly blobs of light and dark reflecting surfaces varying in texture and material composition.
During this stage, mid-level features of object perceptions are interpreted and semantically
classified into high-level features. High-level features refers to the identities of objects (e.g. “that
face belongs to…”) and categorical distinctions among objects (e.g. “face or scene?”, “animate
or inanimate?”, “small or large?”) (Grill-Spector & Weiner, 2014).

**Natural Image Statistics**

Due to biological constraints, such as the natural down-sampling of retinal afferents, and
constant changes in gaze, ambient lighting, and general viewing context, it is hypothesized that
retinal images input to the primary visual cortex are coarse and unrecognizable from our
apparent high-fidelity visual perceptions (Roland W. Fleming, 2014). See **Figure 1 for graphic
depicting a rough approximation of neurophysiological down-sampling of retinal afferents using a Laplacian Image Pyramid.** Natural image statistics frameworks posit that the visual
system is evolutionarily primed to detect the statistical regularities of structures found in our
natural environment (Lauer et al., 2018; Lescroart et al., 2015). See **Figure 2 for graphic
depicting an example of natural image statistics.** Here, I distinguish two other types of image
statistics, (i) **low-level image statistics** and (ii) **image statistics for modeling mid-level vision.**
A wealth of evidence suggests that the natural environment is structured and remarkably predictable (Oliva & Torralba, 2001, 2006). Importantly, a growing body of evidence from behavioral studies and brain imaging investigations indicate that image statistics may be used by the brain to facilitate a wide variety of visual processes. In particular, in studies where human observers are tasked with making categorical discriminations of either materials (e.g. matte surfaces versus glossy surfaces; wooden surfaces versus metal surfaces), objects (e.g. small objects versus big objects; animate objects versus inanimate objects), and scenes (e.g. landscapes versus cityscapes; indoor scenes versus outdoor scenes), significant differences in behavior and brain activity across factor levels tend to also be predicted by low-level image features (Roland W. Fleming, 2014; Fleming et al., 2003; Josephs & Konkle, 2019; Konkle & Caramazza, 2013; Konkle & Oliva, 2012b; Lescroart et al., 2015; Long et al., 2018; Stansbury et al., 2013).

Low-Level Image Statistics

Low-level image statistics are quantitative summaries of image illumination data; these measures are established as important for low-level image features and coarse-scale image structure (Frank et al., 2020; Roth et al., 2018; Torralba & Oliva, 2002). Examples of methods used to estimate low-level image statistics include computations of the mean, standard deviation, and skew of an images’ luminance histogram, as well as spatial frequency analysis and Fourier decomposition (Oliva & Torralba, 2006; Torralba & Oliva, 2003). See Figure 3 for graphic depicting an example of low-level image statistics.

Because high-level semantic information actively informs visual perceptions of low-level image features, in order to understand how, and to what extent low-level image statistics drive object perceptions apart from high-level cognitions related to being aware of “what” the object is, an increasing number of studies have focused on the study of mid-level object representation
A widely used approach to this problem has been to use texture synthesis algorithms to create synthetic texture images generated from high-level object exemplars.

Coarse-Scale Texture Analysis

Coarse-scale texture analysis is a computational approach to understanding how low-level image statistics contribute to the structure and perception mid-level image features. The goal of this approach is to create images of objects that contain important low-level image statistics and coarse-scale structure, but are not unrecognizable at the level of high-level representations of object identity or category; thus, images created in this way are believed to elicit mid-level object representations (Jeremy Freeman & Eero P. Simoncelli, 2011). In object perception research, an algorithm developed by Portilla and Simonelli (2001) is arguably the most prolific; for simplicity, I’ll refer to the algorithm created by Portilla and Simonelli (2001) as the PS-algorithm, and the textures generated from the PS-algorithm as PS-textures (Balas, 2012; Jeremy Freeman & Eero P. Simoncelli, 2011; Long et al., 2016; Zachariou et al., 2018).

Based on computational models of low-level visual processing, the PS-algorithm works by iteratively filtering images of objects by low-level image features hypothesized to drive the earliest and intermediate stages of visual processing (e.g. spatial frequency, contrast, orientation) (Portilla & Simoncelli, 1999, 2000). Thereby this iteratively pooling of statistical estimates of low-level features, the “textureSynth” algorithm can be used to render images of blobs and other form-like textures profiling an objects mid-level features (Coggan, 2019; Jeremy Freeman & Eero P. Simoncelli, 2011; Freeman et al., 2013). See Figure 4 for graphic depicting example of PS-algorithm applied to an image depicting the author of this project.

Influential Theories of Vision: Overview
The aforementioned frameworks described above have long been (and continue to be) essential to the progress of visual neuroscience and machine vision research. Moving forward, these frameworks will be useful for understanding the relevance of findings from the research on gloss and real-world object size perception reviewed later.
Simulating Realistic Visual Appearances

For the purposes of creating convincingly realistic stimuli, computer graphics (CG) rendering programs, such as Blender 3D and Radiance, have been key to the progress of material perception research (Fleming et al., 2001, 2003; Fleming et al., 2004; Thompson et al., 2016). These programs, and others alike, use ray tracing algorithms designed to quantitatively model the natural propagation of light in real-world scenes and the reflectance properties of surfaces comprising materials and objects (Qi, 2012).

Attributes of Photorealism

In order to understand how materials perception stimuli are designed and created, and eventually discuss the thesis of this project on the relationship between materials perceptions of surface gloss and real-world object size, it is important to consider some of the attributes of photorealism. In this review, I will operationally define and briefly discuss the following attributes of photorealism: (i) specular reflections, (ii) diffuse reflections, the (iii) Bi-Directional Reflectance Distribution Function (BRDF), (iv) three-dimensional surface geometry, and (v) ambient illumination.

All visual representations of the natural world are afforded by light reflected off the material surfaces of our surrounding environment (Roland W Fleming, 2014; Gibson, 1979). There are two types of light reflection, specular reflections and diffuse reflections.

Specular Reflections

Specular reflections are the type of light reflections that occur when light interacts with a surface and reflects in a way that is “mirror-like”. Specular reflections can be found on the surfaces of glossy objects, such as calm bodies of water, oily skin, plastics, and metallic objects; even the part of the human eye where the cornea rests atop the pupil produces specular
reflections (Fleming et al., 2004). See Figure 5 for everyday examples of specular reflections (Thompson et al., 2016).

**Diffuse Reflections**

In contrast to specular reflections, are diffuse reflections. Diffuse reflections are the type of light reflections that occur when light interacts with a surface and reflects in a way that is scattered; diffuse reflections allow us to perceive the color of the materials making up the surfaces they come into contact with (Anderson, 2011). Because diffuse reflections allow us to perceive the color of objects, materials perception researchers hold that the majority of our perceptions of materials and objects are afforded by diffuse reflections (Roland W Fleming, 2014; Fleming, 2017).

While other factors are also important to consider, in general, diffuse reflections cause surfaces to appear more dull or matte (Roland W Fleming, 2014; Fleming, 2017). For example, materials, like clay, marble, and paper have dull visual appearances because they are mostly comprised of diffuse reflecting materials. **See Figure 6 for everyday examples of diffuse reflectance (Anderson, 2011; Thompson et al., 2016).**

**Bi-Directional Reflectance Distribution Function (BRDF)**

For the purposes of simulating photorealistic materials, objects and scenes, computer graphics rendering algorithms often use variants of a radiometric function called the Bi-Directional Reflectance Distribution Function (BRDF). The BRDF provides a succinct description of material appearance in the form of a quantitative model of light reflection (Nicodemus, 1965; Thompson et al., 2016). In materials perception research a BRDF model that is used often is the Ward BRDF (Thompson et al., 2016). The Ward BRDF specifies the visual
appearance of objects with opaque reflecting surfaces as an additive combination of specular and diffuse reflection components (Ward, 1992).

**Three-Dimensional Surface Geometry**

Three-dimensional surface geometry is another important property to consider when rendering photorealistic visual appearances (Fleming et al., 2004). Three-dimensional surface geometry refers to the intrinsic geometric structure, or shape, of a of a three-dimensional surface (Koenderink & Van Doorn, 1996). All real-world objects are characterized by three-dimensional surface geometries (Gibson, 1979; Horn, 1981; Koenderink et al., 2003). Across multiple spatial scales, the surface geometries of objects contribute to how light will interact with their surfaces; thus, across multiple spatial scales, the surface geometries of objects partly determine how they will appear visually (Ho et al., 2008; Koenderink & Van Doorn, 1996; Qi et al., 2015).

In the materials perception literature, three spatial scales of surface geometry have been established as having distinct influence on the visual appearances of surfaces: *megascale*, *mesoscale*, and *microscale*. Megascale surface properties are related to the global shape of a surface (Ho et al., 2008). Mesoscale surface properties are related to the texture of a surface (Ho et al., 2008). Microscale surface properties are related to the material properties of a surface that cause that surface to either appear more matte or glossy (Ho et al., 2008). For visualizations of *mega*, *meso*, and *microsurface* scales, see Figure 7.

**Ambient Illumination**

In the real-world, we are constantly surrounded by light from all directions; in the computer graphics literature, ambient illumination is often referred to as the light field (Thompson et al., 2016). Ambient illumination refers to the field of light that surrounds observers from all directions; objects cannot be seen without a source of light to illuminate their surfaces (Fleming,
2014; Fleming et al., 2003). In order to create photorealistic renderings of three-dimensional materials, objects, and scenes, computer graphics rendering programs often utilize image-based lighting (IBL) (Ward et al., 2008).

Although IBL can be conducted in a variety of ways, all IBL methods require the use of a light probe. Light probes are high dynamic range, panoramic photographs of real-world scenes; light probes capture the complex global illumination properties of the real-world (Thompson et al., 2016). In the context of computer graphics renderings of photorealistic materials and objects, light probes are mapped onto digital environments in such a way that all materials and objects in a given scene are embedded in a spherical projection of the chosen light probe image (Ward et al., 2008). For an example of crude light probe created with a simple smart phone application, see Figure 8.

Attributes of Photorealism: Overview

Having established a focused overview on the attributes of photorealism that must be considered when trying to graphically render realistic materials, objects, and scenes, I will now proceed to introduce the topic of surface gloss, and gloss perception. For further review and more in-depth coverage on these topics, *HDRI and Image-Based Lighting* (Ward et al., 2008) and *Visual Perception from a Computer Graphics Perspective* (Thompson et al., 2016) are excellent source texts.
Materials Perceptions of Surface Gloss

It is important to note that in the real-world, even the smoothest mirrors feature microscopic surface irregularities, and produce both specular and diffuse reflections (Komatsu & Goda, 2018). Every day, we regularly behold and interact with a variety of objects made of different materials that vary in how they reflect light. Despite the large variations of surface materials, humans can quickly and accurately classify what those materials are (Fleming et al., 2004).

One cue that is particularly important for this is ability is the visual perception of surface gloss (Roland W. Fleming, 2014). In the next section, I provide operational definitions for gloss both as a physical property, and as a perceptual phenomenon.

Gloss

To most people, “gloss” is a term reserved for talking about the quality of a printed photograph, or the look of a persons’ eyes after they’ve just woken up from a nap. In fact, gloss is everywhere, for wherever there is a surface that shines in the presence of light, there is also surface gloss (Adelson, 2001; Chadwick & Kentridge, 2015).

Gloss refers to an optical phenomenon of reflective surfaces measured as an index of a surfaces overall ability to reflect light in the specular direction. Surface gloss is an intrinsic quality of surfaces that fail to be fully “mirror-like”, doing so in a way that is aesthetically pleasing to the human eye (Chadwick & Kentridge, 2015). Irregularities in the microscale surface geometry of mirror-like surfaces can cause those surfaces to appear glossy (Qi, 2012; Qi et al., 2015).

I will now provide operational definitions that distinguish gloss as a physical property of material surfaces from the visual perception of gloss, (i) apparent gloss an important feature of glossy surfaces, (ii) specular highlights.
Apparent Gloss

Apparent gloss, also referred to throughout this literature review as “apparent surface gloss”, “perceived gloss”, “perceived glossiness”, or just “glossiness”, regards the subjective perception of gloss on a surface. All surfaces could be described as varying in their apparent surface glossiness. Surface smoothness strongly influences perceived surface glossiness. In general, the rougher a surface is, the more “matte” that surface appears, and the smoother the surface is, the glossier that surface appears (Chadwick & Kentridge, 2015). See Figure 9 for everyday examples of glossy surfaces and objects.

An important feature of surfaces that are often perceived as being glossy is the phenomena of specular highlights (Chadwick & Kentridge, 2015). Specular highlights can appear on any surface made of materials with specular reflecting properties (Chadwick & Kentridge, 2015). I will now provide an operational definition of specular highlights.

Specular Highlights

Specular highlights, or just “highlights”, are localized areas of white that are perceived as bright spots on object surfaces; specular highlights are often described as regions of high contrast. Specular highlights are most often seen on specular surfaces at points of high curvature. Specular highlights are not seen on the surfaces of ordinary flat mirrors (Chadwick & Kentridge, 2015). See Figure 10 for everyday examples of specular highlights.

Furthermore, See Figure 11 for example demonstrating how gloss is a cue to the freshness of foods. See Figure 12 for visuals and brief discussion on why humans may find glossy objects aesthetically pleasing.

Behavioral Studies on Gloss Perception
Now that I’ve established the scope of features most important for understanding the nature of gloss perception, I will briefly review what studies of gloss perception have found in terms of their effects on human behavior.

**Gloss Perception Across Changes in Micro and Mesoscale Surface Geometry**

Previous work on the relationship between gloss perception and surface texture indicates that both the microscale and mesoscale surface geometries of a surface effects the apparent glossiness of that surface (Ho et al., 2008; Koenderink & Van Doorn, 1996). In particular, consider work by Ho, Landy, and Maloney (2008), who conducted a study to understand the conjoint effects of microscale and mesoscale surface geometry on perceptions of texture and glossiness. In the study, observers rated the glossiness images featuring 3D renderings of “bumpy” planar surfaces. In order to achieve different levels of surface glossiness, Ho et al. (2008) designed their materials to have varying levels microscale surface roughness. In order to achieve different levels of mesoscale surface texture, Ho et al. (2008) designed their materials to have varying levels “bumpiness” (i.e. the height of the bumps was manipulated. For the final stimulus set that was presented to subjects, the parameters for microscale and mesoscale surface geometry were jointly varied. Ho et al. (2008) found that bumpier surfaces had higher apparent glossiness, and that glossier surfaces had higher apparent bumpiness (Ho et al., 2008).

Recent studies following methods similar to those used by Ho et al. (2008), such as Qi et al. (2012), as well as Marlow, Kim, and Anderson (2012), also indicate that gloss perception is influenced by microscale and mesoscale surface geometry (Marlow et al., 2012; Qi, 2012; Qi et al., 2015).

**Gloss Perception and Specular Highlights**
Studies of gloss perception suggest that specular highlights can strongly influence the perception of gloss (Adams & Elder, 2014; Park, 2004). Noted earlier, specular highlights are considered to be local features of an objects surface. Studies indicate that perceived surface glossiness is correlated with the spatial extent and intensity of specular highlights, such that increases in the spatial extent and intensity of specular highlights generally makes surfaces appear glossier (Chadwick & Kentridge, 2015).

Observers are also sensitive to the relationship between the phase of the local orientations of specular highlights with respect to global surface shape. For example, when viewing specular highlights on a three-dimensional curved surface, if the local orientations of specular highlights are in phase with the global shape of the surface they are viewed on, that surface will tend to appear glossier compared to when highlight orientations out of phase with the global shape. In other words, when the locations of specular highlights are found in places where they would naturally be found on curved surfaces, surfaces are perceived as being glossier. Moreover, when the local orientations of specular highlights are manipulated to be out of phase with the global form of a 3D curved surface, those surfaces tend to appear matte (J. Kim et al., 2011). See Figure 13 for example where specular highlights are manipulated to be out of phase with the global form of a 3D curved surface.

Although specular highlights are fundamentally local surface features found whole objects, specular highlights can have profound effects on the perceived shape of 3D objects. For example, studies suggest that the visual perception of specular highlights biases observers to perceive objects as having convex surfaces. This effect is presumed to be driven by prior knowledge-based representations of concave and convex 3D shapes and specular surfaces encountered in the real-world (Juno Kim et al., 2011).
Adams & Elder (2014) found that when the shape a highlight is experimentally manipulated to be incongruent with the global form of the object, observers’ judgements of the overall shape of the object becomes more difficult. Similarly, when the shape of specular highlights is congruent with the global form of an object, judgements of object shape are much easier.

Taken together, a sufficient amount of evidence indicates that perceptions of shape, brightness, and glossiness are modulated by presence of specular highlights, and that these effects are context dependent. Although the relationship between specular highlights and perceived surface glossiness is complex and context dependent, it is clear that our perceptions of these visual features are biased by knowledge-based representations of how specular highlights appear on the glossy surfaces of three-dimensional surface geometries found in the real-world (Adams & Elder, 2014; Netz & Osadchy, 2013; Norman et al., 2016).

Gloss Perception and Real-World Illumination

The nature of the ambient illumination projected onto object surfaces also impacts the perception of surface gloss. When computer generated objects are rendered with naturalistic patterns of illumination, they are perceived as being glossier than objects rendered with artificial illumination patterns (Fleming et al., 2003; Olkkonen & Brainard, 2010). See Figure 14 for example where of glossy object rendered using artificial illumination and natural illumination.

Fleming, Torralba, & Adelson (2004) investigated if human subjects could accurately discriminate patterns of illumination found in the real-world from artificial illumination patterns. Even though subjects were tasked with making discriminations of the “realness” of ambient illumination on blobby objects not found in the real-world, humans were found to be quite adept at discriminating real-world illumination from artificial illumination (Fleming et al., 2004).
Object Shape Affects the Perception of Materials

Perceptions of object shape influence perceptions of object material identity (e.g. metal materials versus plastic materials) (Marlow & Anderson, 2015). When observers make comparisons of pairs of objects made with the same materials, qualitative differences in object surface geometry increased the probability that observers would misjudge object surfaces as having different material compositions (Vangorp et al., 2007). The notion that surface geometry strongly influences the perception of gloss is supported by an earlier investigation on gloss perception by Nishida and Shinya (1998). See Figure 15 for example showing how the 3D geometry of an object influence the perception of a given material.

Object Shape and Ambient Illumination Affect the Perception of Gloss

Both the light field an object is embedded in, and the 3D surface shape of an object affect the perception of that object’s surface glossiness (Olkkonen & Brainard, 2011). Olkkonen and Brainard (2011) had observers rate the glossiness of surfaces across different conditions where the ambient illumination projected on to surfaces was either produced by real-world illumination or artificial illumination. Furthermore, the angular complexity of object surfaces was manipulated to either be more rectilinear or curvilinear. Joint contributions of ambient illumination and object shape on perceived surface glossiness were significant; due to a large number of interaction effects between their factors of interest, their results could not predict observers’ perception of surface glossiness in a way that was parsimonious (Olkkonen & Brainard, 2011).

Marlow et al. (2012) had human observers rate the glossiness of object surfaces that varied in a way that was highly controlled. In their study, observers rated the glossiness of surfaces with varying degrees of surface bumpiness. Furthermore, they analyzed the statistics of images for
object surfaces that were found to be highly consistent across observers for ratings on the dimension of perceived surface glossiness. Results of the study indicated that effects of ambient illumination on perceived surface glossiness were mediated by systematic changes in the size, shape, and contrast of specular highlights resultant of changes in surface bumpiness (Marlow et al., 2012).

**Image Statistics and Materials Perception**

A consistent finding in studies where perceptual ratings of surface gloss are measured across a range of different materials is that behavioral effects related to significant changes in material perceptions tend to also be predictable by significant changes in stimulus image statistics.

Motoyoshi et al. (2007) conducted a study in which observers were tasked with rating the lightness and glossiness for images depicting photographed patches of textured stucco-like material that had been painted to vary in surface reflectance characteristics by the factors of interest (Motoyoshi et al., 2007). Motoyoshi et al. (2007) computed the mean, standard deviation, skewness, and kurtosis of the luminance histograms from the stimulus images. Image skewness strongly predicted perceptual changes in observers’ ratings of both surface lightness and surface glossiness. Interestingly, image skewness was inversely correlated with surface lightness ratings, but surface glossiness ratings were positively correlated.

Effects similar to what was observed for image skewness, and ratings surface lightness and surface glossiness, was also found for the standard deviation of the luminance histogram, albeit much weaker. Although mean luminance was found to be predictive of observers’ surface lightness ratings, they were not predictive of observers’ surface glossiness ratings (Kim & Anderson, 2010; Olkkonen & Brainard, 2010; Toscani et al., 2017; Vladusich, 2013).
Findings similar to those observed by Motoyoshi et al. (2007) have been observed in multiple studies across a variety of different material image data sets (Kim & Anderson, 2010; Kim et al., 2016; Wiebel et al., 2015). Under tightly controlled experimental conditions, manipulations of an images’ luminance, such that skewness becomes more positive, is associated with higher ratings in perceived surface glossiness (J. Kim et al., 2011; Marlow & Anderson, 2013).

There is some evidence indicating that the luminance histograms for images of glossy surfaces are often positively skewed, whereas surfaces with matte surface reflectance characteristics are often negatively skewed (J. Kim et al., 2011; Kim et al., 2016; Nishida, 2019; Wiebel et al., 2015). Moreover, deliberate manipulations of an images’ luminance histogram that alter image skewness to become more negative are associated with lowered ratings in perceived surface glossiness. However, it is important to state that image skewness is not a ground truth measurement of surface glossiness (Anderson & Kim, 2009; J. Kim et al., 2011). See Figure 16 for graphical example of changes in luminance histogram across changes in surface glossiness. See Table 2 for breakdown of image statistics for the materials pictured in Figure 17.

Behavioral Studies on Gloss Perception: Overview

Considering the behavioral studies of gloss perception reviewed here, I will now draw attention to a few important key findings.

The perception of gloss is influenced by observers’ previous experiences with objects, and in the context of the real-world; humans can easily discriminate natural ambient illumination from artificial illumination (Fleming et al., 2009; Roland W Fleming, 2014; Fleming et al., 2001, 2003; Fleming et al., 2004; van Assen et al., 2016; Vangorp et al., 2007; Wilder et al., 2019). Furthermore, human observers are sensitive to the structure of specular highlights, such that, the
natural appearance of specular highlights can make a surface appear glossier; moreover, when specular highlights are out of phase with the global shape of a surface, those surfaces will appear less glossy (Scott & Barton, 2014).

The megascale shape of objects can have a profound effect on the perception of surface gloss (Fleming et al., 2004; Nefs et al., 2006; Olkkonen & Brainard, 2011). Mesoscale surface texture can influence perceptions of surface glossiness; moreover, microscale manipulations that make a surface appear glossier can alter perceptions of mesoscale surface texture (Ho et al., 2008; Qi, 2012; Qi et al., 2015). In a similar vein, surface gloss, specular highlights, and specular reflections can have a profound effect on the perception of object shape (Adams & Elder, 2014; Fleming et al., 2009; Fleming et al., 2004).

Image statistics are a useful tool for studying differences in materials perceptions of gloss; however, image statistics are not used by humans to perceive gloss (J. Kim et al., 2011; Marlow & Anderson, 2013; Marlow et al., 2019; Motoyoshi & Matoba, 2012; Motoyoshi et al., 2007). Experimental manipulations that cause surfaces to either appear more glossy or matte tend to be associated with changes in the skewness of an images’ luminance histogram; however, image skew does not necessarily indicate the presence or absence of glossy surface (Anderson & Kim, 2009; Kim & Anderson, 2010; Motoyoshi et al., 2007; Nishida, 2019; Torralba & Oliva, 2003).

Neural Correlates of Gloss Perception

Next, I will briefly review research on the neural correlates of gloss and materials perception.

Gloss Representation in Non-Human Animals

Studies from single-cell recordings of macaque visual cortex indicate that neurons in the ventral visual pathway are sensitive to changes in surface reflection. Nishio et al. (2012) studied how manipulations of 3D object shape, surface contrast, brightness of specular highlights, and
ambient illumination affect the activity of neurons of macaque ventral visual cortex. Neurons in macaque superior temporal sulcus (STS) exhibited preferential responding for glossy stimuli over matte stimuli. Moreover, the activity of the gloss-selective changed linearly as a function of the contrast and brightness of specular highlights (Nishio et al., 2012).

**Material Representation in Humans**

Hiramatsu et al. (2011) investigated whether or not representational patterns of brain activity specific to the representation of material categories and image statistics could be predicted from neural responses in the visual cortex. In their study, subjects viewed images of materials found in the real-world (e.g. metal, wood, leather) projected onto 3D rendered surfaces. Multivoxel pattern analysis (MVPA) was used to create linear classifiers for neural responses as a function of material category and low-level image statistics. Classification accuracy by material category and low-level images statistics was highest in early visual cortices (V1 and V2), and then the fusiform gyrus (FG) (Hiramatsu et al., 2011).

Jacobs et. al (2014) used an adaptation paradigm to differentiate representations evoked by stimuli featuring qualitatively different materials. In their study, subjects viewed images photographs of materials, consisting of wood, stone, metal and fabric surfaces. Patterns of BOLD activity characterizing material adaptation effects were found in both the parahippocampal gyrus and early visual cortices; however, effects of material adaptation were strongest in the parahippocampal gyrus. Interestingly, the response patterns of resultant of material adaptation were quite similar to results observed during fMRI investigations of texture perception (Goodale, 2011; Jacobs et al., 2014).

**Gloss Representation in Humans**
In the first human fMRI study aimed at finding areas of human visual cortex that are sensitive to the perception of gloss, Wada, Sakano, and Ando (2014) found evidence that neurons in the ventral and medial regions of the temporal lobe exhibit increased responding during tasks involving the categorization of glossy and matte materials. Interestingly, the presence of noticeable specular highlight corresponded with preferential activations in the lateral occipital (LO) area, and a distributed pattern of neural activity throughout the collateral sulcus (Komatsu & Goda, 2018; Wada et al., 2014).

In a study by Sun et al. (2016), BOLD activations were measured while human subjects viewed images of 3D rendered objects featuring glossy and matte surfaces. Specifically, subjects viewed images of blob shaped objects whose surfaces varied by the ratio of diffuse and specular reflectance describing their surfaces (i.e. glossier or more “matte”). Results indicated that responses in posterior regions of the fusiform sulcus (pFs) and area V3B responded more for glossy objects than matte objects. Previous investigations found that activations of pFs and V3B are associated with the perception of shape and texture (Schmid & Doerschner, 2019; Sun, Di Luca, et al., 2016; Sun, Welchman, et al., 2016).

**Neural Correlates of Gloss Perception: Overview**

Considering the studies reviewed here, there is sufficient evidence to suggest that the ventral visual pathway is involved in the perception of gloss and materials (Rosenke et al., 2020). I will draw attention to a few key details. Visual perceptions of surface glossiness and materials elicits brain activity in both the dorsal and ventral visual pathways (Jacobs et al., 2014; Schmid & Doerschner, 2019). Material perceptions broadly activate brain areas associated with low-level and mid-level visual processing; previous work associated these brain areas with perceptions of texture and shape (Komatsu & Goda, 2018; Nishio et al., 2012). Regions of the lateral occipital
cortex, posterior fusiform gyrus, and parahippocampal cortices appear to be more sensitive to changes in glossy surfaces than matte surfaces (Sun et al., 2015; Sun, Di Luca, et al., 2016).

Here, I will end my review of findings related to gloss perception and introduce the next topic to be reviewed, real-world object size perception.
Object Perceptions of Real-World Size

Object Size

Object size is a spatial dimension that is intrinsic to all real-world objects; the size of objects constrains the nature of our physical interactions with objects (Konkle & Oliva, 2012a; Konkle & Olivia, 2007). To imagine the way object size influences our physical interactions with objects, consider, as an example, small objects. Small objects, like keys and phones, are things that can be held in our hands and manipulated with our fingers. Furthermore, as another example, consider large objects. Large objects, such as houses and buildings, are things we inhabit that can also serve as landmarks for spatial navigation in the environment (Epstein, 1965; Epstein & Franklin, 1965). Consequently, because the size of objects influences how we can physically interact objects, the size of objects influences how they “look” when we see them (Konkle, 2011; Long & Konkle, 2018; Long et al., 2016; Long, Störmer, et al., 2017).

Regarding the appearance of objects, another important factor that contributes to the appearance of objects that, in previous cognitive science studies on real-world object size has been noted to be related to object size, is object shape (Konkle, 2011). For example, compared to small objects, the overall global shape of large objects tends be rectilinear; conversely, small objects tend to be more “curvy” (Long & Konkle, 2018; Long, Störmer, et al., 2017). Described in terms used materials perception studies discussed earlier, the physical size of objects contributes to the visual appearance of an objects megascale surface geometry (Qi, 2012; Qi et al., 2015).

I will now briefly review findings studies from behavioral and neuroimaging investigations on real-world object size. Before I discuss the findings on the effects of real-world object size
perception, I will provide definitions for terms often used in such studies. First, I will define (i) 

*retinal size*, (ii) *visual size*, (iii) *familiar size*.

**Retinal Size**

Retinal size refers to the size of a visual stimulus as projected onto the back of the retina; also called visual angle (Wagemans et al., 2011).

**Visual Size**

Visual size refers to the size of an object as it’s displayed. Whenever the distance between an observer and an object changes in way that doesn’t alter the viewing perspective, changes in retinal size subtended by the object in the observers’ visual field are referred to as changes in visual size (Konkle & Oliva, 2011a). See Figure 18 for example of visual size.

**Familiar Size**

Familiar size refers to an observer’s knowledge-based representations of object size in the real-world, such that the real-world size of an object is a physical property intrinsic to the object. Familiar size functions as a pictorial depth cue whereby an observer’s prior knowledge of the physical sizes of objects in their environment allows the observer to roughly approximate the relative distances of objects from the observer, and objects from each other (Wagemans et al., 2011). See Figure 19 for example of familiar size.

**Behavioral Studies on Object Size Perception**

Now that I’ve established the scope of features most important for understanding the nature of real-world size perception, I will briefly review a selection of studies discussing the effects of real-world size perception in terms of their effects on human behavior. In the proceeding sections, the term “semantic-level” is used to discuss size perception studies in which subjects
were consciously aware of the stimulus identities, and “coarse-scale” studies are studies in which subjects were not consciously aware of the stimulus identities.

**Semantic-Level Perceptions of Object Size**

Konkle and Oliva (2011) investigated whether or not knowledge-based representations of real-world object size affect the preferred visual sizes of objects. In one experiment, subjects were asked to sort and rank images of everyday objects by their assumed real-world sizes. In a subsequent experiment, three different groups of subjects were instructed to draw pictures of everyday objects from memory on a sheet paper. Moreover, the size of the paper given to subjects for the purposes of drawing pictures of objects differed for each of the three subject groups; in this way, “frame size effects” on the drawn sizes of objects could evaluated (Konkle & Oliva, 2011a).

Analyses revealed that the drawn size of objects correlated significantly with subjects assumed size-rankings, such that small objects were drawn small and large objects were drawn large. Furthermore, the distribution of sizes for drawn objects were found to be predictable as a ratio of object size-rankings to the size of the paper subjects were given to draw on. These findings were consistent across all observers at the individual level and group level.

In a classic study by Epstein (1965), subjects viewed images of coins (e.g. quarters, dimes, half-dollars) with one eye in a darkened room. All images were viewed from the same distance and presented at the same retinal size. Although the retinal size was the same for all coin images, results indicated that subjects distance judgements were systematically biased in a manner that reflected an effect of real-world object size. For example, when observers viewed an image containing both a quarter and a dime (both of which presented at equal retinal sizes), observers
judged the image of the quarter to be farther away than the dime (Epstein, 1965; Epstein & Franklin, 1965).

Extending on the works of Epstein (1965), Konkle and Oliva (2012a) conducted a series of experiments involving the use of image of inanimate, man-made objects of different real-world sizes. In order to study the effects of knowledge-based representations of real-world object size on perceptual judgements of retinal size, subjects were tasked with making retinal size judgements for visual stimuli depicting pairs of exemplar objects of small and large real-world sizes across two experimental conditions. Specifically, the retinal sizes of object exemplars viewed by subjects were either congruent or incongruent with categorical differences in their real-world sizes. Results indicated that retinal size judgements were faster and more accurate for congruent stimuli than incongruent stimuli—an effect referred to by Konkle and Oliva (2012a) as a “familiar size Stroop effect” (Konkle & Oliva, 2012a).

**Coarse-Scale Perceptions of Object Size**

Recent investigations suggest that high-level semantic representations of object identity are not necessary for accurate discriminations of objects across broad categorization of objects by their real-world sizes, and only require an observer be able to perceive mid-level object features. Noted earlier, mid-level features include perceptions of texture and gradients of shading, as well as shape information, like edges and contours with varying degrees of rectilinearity and curvilinearity. Hearkening back to the influential theories of visual processing discussed earlier, mid-level vision is a stage of visual processing that is one step removed from the stage of vision that establishes object identity (i.e. high-level vision).

A number series of studies have been conducted using the PS-algorithm to generate synthetic texture stimuli, and a consistent finding is that behavioral effects are found across categorical
differences in stimulus type, in particular, exemplars of real-world object size (Balas & Conlin, 2015; Balas et al., 2016; Balas, 2012; Long & Konkle, 2017; Long et al., 2016; Long, Störmer, et al., 2017).

For example, in a study by Long et al. (2016), subjects engaged in a visual search task in which they were to search for a target stimulus among an ensemble of stimulus distractors as fast as possible (Long et al., 2016). The experiment featured two different kinds of trial blocks. During half of the trials, the distractor stimulus and target stimulus were from the same object size category (e.g. small real-world size exemplars distractors presented with a small real-world size exemplar target); in the other half of trials, the distractor stimuli and target stimuli were not from the same object size category (e.g. small real-world size exemplars distractors presented with a large real-world size exemplar target) (Long et al., 2016). In a second experiment, selected a highly controlled set of big and small objects that were matched on low-level properties. In a third experiment, Long and Konkle (2016) used the Portilla-Simoncelli (PS) algorithm to generate PS-textures from images of small and large real-world object exemplars; in their work, PS-textures are referred to as “texforms”.

Results from the first and second experiments indicated that participants found target objects faster when the distractor objects differed in real-world size. Intriguingly, although observers could not recognize the identities of PS-textures, the pattern of results found in the first and second experiments were also found in the third experiment, which involved the use of the PS-textures. These results were interpreted as being evidence that small and large objects have reliably different mid-level perceptual features (Long et al., 2016).

Subsequent behavioral studies using the PS-algorithm to generate texture stimuli using exemplars of real-world object size found additional support that exemplars of small and large
man-made objects have reliably different mid-level perceptual features. In particular, following the same methodology used in previous work by Konkle and Oliva (2012a), a familiar-size Stroop effect was found using small and large real-world object size PS-textures (Long & Konkle, 2017).

**Behavioral Studies on Object Size Perception: Overview**

Considering the behavioral studies of object size perception reviewed here, I will now draw attention to a few important key findings. Our visual perceptions of objects are actively informed by knowledge-based representations of real-world size (Epstein, 1965; Epstein & Franklin, 1965). Familiar size is a visual cue to pictorial depth and can be useful for making rough estimates of object distance (Wagemans et al., 2011). Category-level familiar size perceptions can distort low-level perceptual judgments by visual size; this occurs even in cases where semantic information is not available, and only coarse-scale texture information remains (Konkle & Oliva, 2012a; Long & Konkle, 2017; Long et al., 2016). Small and large sized manmade objects are perceptually dissociable by texture and shape (Long & Konkle, 2017, 2018).

Here, I will end my review on behavioral findings related to object size perception and introduce the next topic to be reviewed, the neural correlates of object size perception.

**Neural Correlates of Object Size**

I will now briefly review findings studies from brain imaging investigations on the neural correlates of real-world object size representation. In the proceeding sections, the term “semantic-level” is used to discuss size neuroimaging studies in which subjects were consciously aware of the stimulus identities, and “coarse-scale” studies are neuroimaging studies in which subjects were not consciously aware of the stimulus identities.

**Semantic-Level Object Size Representations**
Konkle and Oliva (2012) conducted an fMRI study in which participants viewed images of everyday man-made objects of small and large real-world sizes. During the experiment participants viewed 200 unique images of small objects (e.g. strawberry, safety pin) and 200 unique images of large objects (e.g. car, piano). In their study, observers viewed one image at a time, and all images were presented at the same small and large retinal sizes. In particular, large objects (e.g., vehicles, pianos, furniture) tended to elicit activations in medial areas of the ventral occipito-temporal cortex, whereas small objects (e.g., coffee cups, coins, paperclips) tended to elicit activations in lateral areas. Strong peaks of differential activations by real-world size voxels for large and small objects were observed within parahippocampal cortices (referred to as “Big-PHC”) and lateral-occipital cortices (referred to as “Small-LO”) respectively (Konkle & Oliva, 2012b).

Results also revealed that the preferential responding of lateral-occipital cortices observed for small real-world object size exemplars, as well as the preferentially responded of parahippocampal cortices observed for large real-world object size exemplars, were maintained across significant changes in retinal size. Furthermore, large objects elicited preferential activations in medial regions of the VTC that resembled patterns of activity associated with the perception of scenes and landmarks, and small objects elicited preferential activations in lateral regions of the VTC that resembled patterns of activity associated with the perception of faces, bodies, animals, and tools (Grill-Spector & Weiner, 2014; Kanwisher, 1996; Konkle & Oliva, 2012b).

Thus, findings by Konkle and Oliva (2012b) indicated that the physical size of objects may be a common denominator for representations of both every day and category selective objects. Subsequent investigations of real-world object size using different sets of object images and
different analysis techniques such as MVPA and deep learning algorithms continue to corroborate these findings (Cichy et al., 2019; Coutanche & Koch, 2018; Julian et al., 2017; Konkle & Caramazza, 2017; Lindsay, 2020; Long, Yu, et al., 2017).

**Coarse-Scale Object Size Representations**

Subsequent investigations of mid-level vision and real-world object size representation use of PS-textures also corroborate and extend these findings to; that is to say, a large-scale organization of patterned responding was found to be predictable by the mid-level features of real-world object size exemplars (Collegio et al., 2019). In order to understand the mediating mechanisms of size representation by texture, Long, Yu, et al. (2017) conducted a study in which observers passively viewed synthetic textures created from small and large real-world object size exemplars. Results of the study indicated that low-level image statistics were a weak predictor of size representation; however perceived object curvature was found to be a strong predict of size representation (Long, Yu, et al., 2017).

**Neural Correlates of Object Size: Overview**

Considering the neuroimaging studies of object size representation reviewed here, I will now draw attention to a few important key findings. Brain image research indicates that real-world sizes of objects may be an important principle of organized brain function in the ventral visual cortex (Julian et al., 2017; Konkle & Caramazza, 2017; Konkle & Oliva, 2012b; Long et al., 2018). Lateral-occipital cortices exhibit preferential responding for small objects, and parahippocampal cortices exhibit preferential responding for big objects; although weaker, size elicited neural responses are also found in the absence of semantic-level awareness (Konkle & Oliva, 2012b). Low-level image statistics are a weak predictor of size representation, and
perceived object curvature is a strong predictor of size representation (Long & Konkle, 2018; Long et al., 2018).

Here, I will end my review of findings related to neuroimaging investigations on the neural correlates of real-world object size representation; moreover, I will end my literature review here as well. In the proceeding section I will provide an overview of converging evidence from the reviewed works for studies on the perception of gloss and studies on the perception of real-world object size. Using the influential theories of vision discussed at beginning of this review, I will interpret findings from the studies reviewed throughout this project to synthesize meaningful evidence-based conclusions.
Converging Evidence

Behavioral Findings

Object size and surface gloss perceptions influence behavior in complex, meaningful ways. Evidence consistently supports the notion that human perceptions of gloss and specular highlights are biased by our previous experiences with objects in the real-world (Roland W. Fleming, 2014; Fleming et al., 2003). Mentioned earlier, judgements of shape for three-dimensional objects featuring depth and shading information are assumed to be convex, and in real-life, specular highlights are in fact more likely to be seen on convex surfaces than concave surfaces (Marlow & Anderson, 2015; Marlow et al., 2019; Marlow et al., 2015).

Similarly, when specular highlights appear on three-dimensional surfaces in a way that would naturally occur in the real-world, those surfaces appear brighter and glossier, and discriminations of object shape are facilitated (Adams & Elder, 2014; Adams et al., 2018; Wilder et al., 2019). These findings suggest that perceptions of an objects’ surface depths and 3D geometries are simultaneously informed and biased by our expectations of object surfaces as we have encountered them in the real-world (Adelson, 2001; Fleming et al., 2003).

Much like the reflectance properties of an objects surface, physical size is a property intrinsic to all objects found in the real-world (Gibson, 2014; Konkle & Oliva, 2012a). Object recognition studies also indicate that real-world object size is an important ecological variable that simultaneously informs and biases our perceptions of objects (Konkle & Oliva, 2012a; Konkle & Olivia, 2007). It is well established that familiar size is a cue for human navigation and rough approximations of distance. Importantly, the effects of familiar size are the product of observer’s prior knowledge of the physical sizes of objects in their environment (Epstein, 1965; Epstein & Franklin, 1965; Konkle & Oliva, 2012a; Long & Konkle, 2017).
Similar to the effects of specular highlights on the perception of object shape and surface glossiness, familiar size cues also affect how we perceive objects (Epstein, 1965; Epstein & Franklin, 1965; Konkle & Oliva, 2012a; Long & Konkle, 2017). Retinal size judgements using pairs of small and large familiar object stimuli are easier and more accurate when the objects are presented at retinal sizes that are congruent with their real-world size differences (Konkle & Oliva, 2012a; Long & Konkle, 2017).

Considering the nature of the perceptual biases for specular highlights and familiar size cues, it’s easy to say that their biases are quite different. That specular highlights affect perceptions of surface glossiness, brightness, and depths are not the same familiar size affecting perceptual judgments of retinal size. However, there are two important commonalities to point out, both specular highlights and familiar size cues: (i) simultaneously inform and bias our perceptions of objects, and (ii) are biases caused by our previous experiences with real-world objects. Another interesting parallel between studies of surface reflectance and real-world object size perception regards the non-necessity of semantic awareness for scene and object identity. For example, consider the findings from studies involving categorical discriminations of real versus artificial ambient illumination on warped specular reflecting surfaces (Fleming et al., 2004).

Recent object perception work suggests that the mid-level features of natural images synthesized from images of common real-world objects of different of small and big sizes are systematically driven by patterns of rectilinearity and curvilinearity, the base units for such shape defining factors in relation to object surfaces remains unspecified (Long, Yu, et al., 2017; Long et al., 2018; Zachariou et al., 2018).

Studies from materials perception have demonstrated that human subjects can accurately discriminate real-world illumination from artificial illumination. Moreover, it’s worth noting that
the stimuli used in these tasks are blobby, computer generated objects not found in the real-world; and yet, in these tasks, humans accurately discriminate real-world illumination from artificial illumination with ease (Fleming et al., 2009; Fleming et al., 2004). Similarly, mid-level vision studies of real-world object size have found that humans judgements of visual size are biased by unrecognizable textures extracted from natural images of objects by real-world object size (Long & Konkle, 2017).

Considering these findings, both the judgements of the “realness” of ambient illumination found object surfaces, and the ability to discriminate the physical sizes objects are perceivable at the level of their mid-level features alone (Fleming et al., 2003). Thus, a third commonality I will draw attention to here is (iii) both ambient illumination and real-world object size are ecological factors that do not require the semantic awareness of an objects form.

**Neuroimaging Findings**

Considering the studies reviewed here, there is sufficient evidence to suggest that in both humans and non-human primates that the ventral visual pathway is strongly involved in the perception of gloss and materials (Goda et al., 2014; Nishio et al., 2012; Okazawa et al., 2015). Much like the behavioral findings, activations corresponding to materials perception are subjective (Komatsu & Goda, 2018).

Brain image investigations on perception of real-world object size have consistently found that real-world object size is a large-scale organizing principle of topographic graphic representation in the ventral visual cortex, even when objects are rendered in such a way that they are not recognizable (Julian et al., 2017; Long & Konkle, 2018).

**Conclusions Drawn from Converging Evidence**
After having reviewed the literature on studies of gloss, and real-world object size perception, I will now discuss three conclusions I have drawn. Human behavior is biased by broad dissociations my materials perceptions of gloss and category-level perceptions of real-world size (Roland W. Fleming, 2014; Long et al., 2016). Perceptions of surface reflection and real-world object size elicit selective activations in distinct, yet neighboring regions of the visual cortex. Gloss and materials perceptions elicit activity in brain areas associated with low-level and mid-level visual processes, such as contrast, shape, and texture perception (Komatsu & Goda, 2018). Real-world object size perceptions elicit activations in brain areas associated with high-level visual processing, such as the perception of faces and scenes (Long & Konkle, 2018). In behavioral and neuroimaging studies where categorical discriminations by human observers across broad differences in material surface reflectance and real-world object size are measured, significant changes in behavior and brain activity across dimensions of material surface reflectance and real-world object size tend to also be predicted by stimulus image statistics (Roland W. Fleming, 2014; Fleming et al., 2003; Josephs & Konkle, 2019; Konkle & Caramazza, 2013; Konkle & Oliva, 2012b; Lescroart et al., 2015; Long et al., 2018; Stansbury et al., 2013).

Dissertation

Because category-level perceptions of real-world size and broad-level perceptions of material glossiness are both linked to perceptions of texture, shape, and real-world familiarity biases, I conjecture that broad-level materials perceptions of gloss may cue category-level object perceptions of real-world size. Furthermore, because gloss and texture are both mid-level features, I also hypothesize that dissociations for categorical perceptions of real-world size by materials perceptions of gloss will extend to coarse-scale texture statistics.
Dissertation Contributions

A growing number of object perception and neuroimaging studies suggest that measurable changes in behavior and brain activity measured in experiments where human observers are tasked with making categorical discriminations across high-level object factors can also be elicited using mid-level object exemplars synthesized from high-level object exemplars (Long, Yu, et al., 2017).

Although there is evidence to suggest that the profile of rectilinear and curvilinear features describing the global shape and overall geometries of objects are particularly important for why humans and machines can still make categorical discriminations in the absence of high-level object identity, a full account for these effects remains an on-going topic of interest (Long & Konkle, 2018; Long, Störmer, et al., 2017; Zachariou et al., 2018).

Findings effects of material perceptions related to object size may provide an important source of information for answering this question. Moreover, significant findings may open up additional questions into the nature of associations between perceptions of object materials and other real-world object properties.
Project Aims

AIM 1

Assess the relationship between human perceptions of object size against veridical measurements of object size.

A. AIM 1 OBJECTIVES: Conduct an experiment in which human participants sort exemplar images of manmade objects into ranked groups of increasing real-world size; these rankings will be compared against veridical measurements of size.

a. AIM 1HYPOTHESES: Participant size ranks for object images will be ranked in a manner that is positively correlated with the objects’ real-world sizes, replicating previous findings by others.

AIM 2

Assess the relationship between human perceptions of gloss and across images of categorically different sizes of manmade objects (i.e. small object glossiness vs big object glossiness) and across texture images synthesized from images of categorically different sizes of manmade objects (i.e. small object texture image glossiness vs big object texture image glossiness).

A. AIM 2A OBJECTIVES: Conduct an experiment in which human participants rate the perceived glossiness of manmade objects of categorically different sizes.

a. AIM 2A STUDY HYPOTHESES: Mean gloss ratings for object images will be significantly different across small and big object size categories.

B. AIM 2B OBJECTIVES: Conduct an experiment in which human participants rate the perceived glossiness of texture images synthesized from manmade objects.
a. **AIM 2B STUDY HYPOTHESES**: Mean gloss ratings for texture images will be significantly different across small and big object size categories.

**AIM 3**

Assess the relationship between human perceptions of specular highlights and across images of categorically different sizes of manmade objects (i.e. small object glossiness vs big object glossiness and across texture images synthesized from images of categorically different sizes of manmade objects (i.e. small object texture image glossiness vs big object texture image glossiness).

A. **AIM 3A OBJECTIVES**: Conduct an experiment in which human participants view images of manmade objects of categorically different sizes and digitally mark the top five shiniest regions of the image.

a. **AIM 3B OBJECTIVES**: Conduct an experiment in which human participants view images of texture images synthesized from manmade objects of categorically different sizes and digitally mark the top five shiniest regions of the image.

**AIM 4**

For both synthetic mid-level real-world object size exemplars, and ordinary high-level real-world object size exemplars, explore the relationship between luminance histogram skewness in stimulus images depicting manmade objects across categorical distinctions in perceived real-world object size and glossiness.

A. **AIM 4 OBJECTIVES**: Obtain data on luminance histogram skew from both, mid-level and high-level real-world object size exemplar stimulus images; compare image skew
data to data collected from behavioral tasks in which human subjects judged the size and glossiness of mid-level and high-level real-world object size exemplars.

a. **AIM 4 HYPOTHESES**: For both the mid-level, and high-level real-world object size exemplars, categorical distinctions in perceived real-world object size and surface glossiness will be associated with changes in stimulus image skewness.
IS GLOSS IS A CUE FOR OBJECT SIZE?

Stimulus Design

Here I will summarize the methods used to create the stimuli required to conduct the studies outlined in the project aims and objectives.

**Real-World Object Images**

A collection of 60 full colored images of manmade objects used in multiple studies of perceived object size and texture were provided by the KonkLab; the authors originally obtained these images through Google image searches (Long & Konkle, 2017; Long et al., 2016; Long, Störmer, et al., 2017).

**Glossy Object Images**

Seven glossy object blobs were created using Blender 2.8 and custom Python scripts. Glossy blobs were created with the following procedures.

A. **Three-dimensional surface geometry**—following methods used by others in previous studies where perceived glossiness was measured, in the present study, megascale and microscale surface geometry were manipulated (Honson et al., 2020).

   a. **Megascale**—for the present study, megascale surface geometry of the glossiness rating stimulus was designed to be misshapen and “bloppy”. A bloppy megascale surface geometry was achieved by deforming the vertices of a smooth mesh sphere object across two levels of procedural texture noise; Perlin noise was used for both levels. In Blender 2.8, mesh transformations are implemented by adding a “Displace” modifier to an object while in “Object” mode. Further, from the available functions for the displace modifier, the “Distorted Noise” option must be chosen; within the submenu for “Distorted Noise”, for both levels of noise
type, choose the noise type termed, “Improved Perlin”. See Figure 19 for visualization of the process for making the megascale surface geometry.

b. **Mesoscale**—for the present study, all of the stimuli had the same mesoscale surface geometry.

c. **Microscale**—for the present study, the microscale surface geometry of the base glossiness rating stimulus was manipulated to create seven different materials stimuli with different levels of glossiness. In order to achieve this, the specular roughness parameter for the specular component (i.e. the “Glossy BSDF” shader in Blender 2.8) was adjusted to the following levels (.05, .15, .25, .35, .45, .55, .65); all other factors were held constant.

**B. Ambient Illumination**—a real-world, indoors illumination environment was obtained from the Southampton-York Natural Scenes (SYNS) dataset (Adams et al., 2016; Adams et al., 2018; Adams et al., 2015). All blob objects were rendered within the same illumination context. No adjustments were made to illumination context used. This procedure was used to give the blobs a naturalistic glossy appearance. See Figure 20 for visualization of the ambient illumination used.

**C. BRDF**—the reflectance properties were constrained by the isotropic Ward model. The isotropic Ward model holds that light reflections from a material are resultant from the sum of specular and diffuse reflections. The diffuse component controls the degree to which the material surface will scatter light in all directions. The specular component controls the degree to which the material surface will reflect light perpendicularly, produce mirror-like reflections, glossy surfaces, and specular highlights. See Figure 21
for visualization of Ward BRDF components. See Figure 22 for full color image of all glossiness rating stimuli.

**Image Preprocessing**

Images of real-world objects and glossy blobs were rendered to grayscale and normalized by luminance and contrast using the SHINE toolbox. All images were sized to be 440 x 440 pixels (Long & Konkle, 2017; Long et al., 2016; Long, Störmer, et al., 2017). Unlike previous studies of object size, in which small and large object images were normalized separately, in the present study all stimulus images (i.e. small objects, large objects, glossy blobs) were normalized together. See **Figure 19** for Result of Running Glossy Blobs Through SHINE Toolbox Normalization. See **Figure 24** for SHINE Normalized Object Images.

A. **Texture Images:** Following the same procedures used by others, texture images were synthesized from the SHINE normalized object images using the texture synthesis algorithm (Long & Konkle, 2017; Long et al., 2016; Long, Störmer, et al., 2017; Long, Yu, et al., 2017). See **Figure 25** for Synthetic Texture Images.

**Software**

Image processing and texture synthesis were conducted in MATLAB 2019a using custom scripts provided by the KonkLab and the Laboratory for Computational Vision (Long & Konkle, 2017; Long et al., 2016; Long, Störmer, et al., 2017).
Real-World Object Size Rank Study

The present study was conducted for two purposes: (i) Replicating previous work on the relationship between perceived object size and real-world object size, (ii) having a set of images that were verified to be reliably differentiated by categorical differences in real-world object size; essential to the validity gloss perception studies discussed later.

Participants

27 participants were recruited to participate in the study through the Virginia Tech SONA pool. All participants were compensated with 1.5 SONA credits for participating.

Task

Using the 60 normalized object images, participants engaged in a hierarchical image sorting task (Konkle & Olivia, 2007). The specific task was to drag and drop object images into one of eight columns, where each column represented a size rank.

Task Instructions

All participants read the following instructions: “In this experiment you will be presented with images that depict common objects found in the real-world. Across all columns: sort objects into eight groups of roughly similarly sized objects. Try to make sure that the overall size of the objects in each column increases from left to right, such that “Size 1” contains the smallest objects and “Size 8” contains the largest objects. Every column must contain a minimum of four objects, and a maximum of eight objects. Under the "items" field is a column of images. For all images, left clicking an image while moving your mouse will allow you to move that image around the screen. If you've grabbed an image and have positioned that image over one of the eight columns below, releasing the left mouse button will drop that image into the column.
Clicking on the middle of the draggable image will present you with an enlarged view of the object image. When you have finished the task, scroll to the bottom right corner of the screen and click the next button (e.g. an image of an arrow pointing to the right).

**Software**

Participants engaged in the task online via Qualtrics. The main task mechanic was made possible by modifying the Qualtrics question type “Pick, Group, and Rank” to allow for dynamic, user-controlled image binning across eight evenly spaced columns. Task mechanics were implemented by adding custom JavaScript and CSS code to the existing code for the Qualtrics “Pick, Group, and Rank” question type.

**Subject Data Preprocessing**

Of the 27 participants that were recruited, two subjects were removed due to having incomplete task data.

**Preliminary Analysis**

The internal consistency of the object size rankings was assessed using Cronbach’s alpha; Cronbach’s alpha = .99, with a 95% confidence interval from .98 to .99. In order to evaluate the reliability of object size rankings, intraclass correlation coefficients were computed. The average measure ICC was .822 with a 95% confidence interval from .77 to .87 ($F(59, 1121) = 92, p < .001$).

**Calculating Perceived Size Ranks**

Using the data collected from the remaining 25 participants, a weighted average of the frequency counts for each of the 8 possible ranks across all subjects was calculated for each of the 60 images. These weighted averages ranks were used to as the perceived size ranks to be compared against veridical measures of real-world object size.
Physical Size Estimations

In order to compare perceived size against real-world object size, physical sizes of objects were estimated using the diagonal length calculated from the widths and heights of objects found via searches on Google. Diagonal lengths were for each object were converted to centimeters, and the final vector of diagonal lengths was rescaled using a log10 transform. This method of estimating physical object sizes follow the procedures used in previous work on the relationship between perceived object size and veridical size.

Main Analyses

The relationship between perceived object size and veridical size was modeled using a simple linear regression. The weighted averages of perceived size ranks were treated as the dependent variable and the log10 scaled real-world object size estimations were treated as the independent variables.

Hypotheses

1. Perceived object size will have a strong and positive correlation with the log10 scaled real-world object size estimations (Konkle & Oliva, 2011b).

Results

Rankings of perceived object size and veridical object size followed a strong positive correlation ($R^2, .87, p < 0001$). This study replicates previous findings on the relationship between perceived size and real-world object size. Indicating the relationship between perceptions of object size and physical object size are logarithmically scaled in a manner resembling the Weber-Fechner power law.
Discussion

Apart from replicating previous findings, this result is important because it provides evidence that findings differences as a function of another real-world object feature might also be related to perceived object size. For the purposes of investigating the relationship between perceived object size, texture and glossiness, it is important to note that object size from here on is studied categorically (i.e. small vs big.). See Figure 26 for graph of regression of perceived size ranks and real-world size.
Gloss Rating Images of Objects and Textures

The present study was conducted for four purposes: (i) exploring the relationship between perceived glossiness depicting luminance equated images of real-world objects, (ii) exploring the relationship between perceived glossiness depicting luminance equated images of real-world object images, (iii) assessing the degree to which perceived glossiness persists across the normal real-world object images and their synthetic texture counterparts, and (iv) explore the global domain specular reflection.

Method

Participants

44 participants (n = 22 per study) were recruited to participate in the study through the Virginia Tech SONA pool. All participants were compensated with 1.5 SONA credits for participating.

Procedures

Participants engaged in an image rating task in which they had to rate the glossiness of object images on a Likert scale that ranged from 1 to 7. Participants rated the glossiness of each object image one at a time. The order of images was randomized across all subjects. In both task groups (i.e. normal image task group, texture image task group), all participants rated the glossiness of 30 small objects and 30 big objects (normal images or PS-textures depending on the task group in question).

Software

Participants engaged in the task online via Qualtrics. The task was designed much like a standard multiple-choice survey.
Gloss Matching Objects Task Instructions

All participants read the following instructions: “In this experiment you will be presented with images that depict common objects found in the real-world paired with computer generated blobs. The blobs presented here were designed to simulate different levels of object surface reflectance; during the experiment you will see seven different blobs. For each question try you’re best to: Consider the overall appearance and reflectance a given real-world object. Then, when you’re ready, select the image with the blob that best matches the overall appearance and reflectance of the real-world object”.

Gloss Matching Textures Task Instructions

All participants read the following instructions: “In this experiment you will be presented abstract, computer generated images of textures created from images of common objects found in the real-world paired with glossy computer-generated blobs. The blobs presented here were designed to simulate different levels of object surface reflectance; during the experiment you will see seven different blobs. For each question try you’re best to: Consider the overall appearance and reflectance the given textured image. Then, when you’re ready, select the image with the blob that best matches the overall appearance and reflectance of the textured image”.

Preliminary Analyses

The internal consistency of the perceived gloss ratings for normal object images and texform object images was assessed with Cronbach’s alpha. For normal object images Cronbach’s alpha = .93, with a 95% confidence interval from .9 to .95. For PS-texture images Cronbach’s alpha = .83, with a 95% confidence interval from .77 to .89.

In order to evaluate the reliability of gloss ratings across subjects in each task group, intraclass correlation coefficients were computed for both normal object images and PS-texture
images ratings of perceived glossiness; results revealed the ratings were not reliable. For normal object images the average measure ICC was .261 with a 95% confidence interval from .19 to .35 ($F(59, 884) = 13.3, p < .001$). For the PS-textures images the average measure ICC was .135 with a 95% confidence interval from .09 to .20 ($F(59, 922) = 4.82, p < .001$).

**Calculating Perceived Gloss Ratings**

For each subject, gloss ratings for each image were collapsed across small and big object categories.

**Main Analyses**

The relationship between perceived glossiness, object size, and task-type (normal images vs PS-texture images) was modeled using a two-factor mixed ANOVA. For the independent variables, task-type was included as a between-subjects factor, and object size category was included as a within-subjects factor. Mean gloss rating was treated as the outcome variable. Prior to reviewing the results of this analysis assumptions of normality and homogeneity of variance were checked and no violations were found.

**Hypotheses**

1. Mean responses for gloss ratings will be significantly different across object size.
2. Mean responses for gloss ratings will be significantly different across task types.

**Results**

Results of the mixed effects ANOVA revealed a statistically significant two-way interaction between task group and object size on mean gloss rating, ($F(1, 42) = 33.02, p < 0.001, \eta^2_p = .44$). Planned comparisons for the simple main effects for the between-subjects effect of task-type (normal object images vs texture objects images) were conducted using two-sample t-tests. Planned comparisons for the within-subjects effect of size were conducted using paired t-tests.
These planned comparisons for the simple main effects based on a priori hypotheses indicated that mean gloss ratings for both the small and large objects in the normal image task condition were significantly different from the mean gloss ratings for large objects in the texture image task conditions ($p < .001$ with Bonferroni).

Planned comparisons also indicated that mean gloss ratings between the small and large objects within the normal image task were significantly different. Planned comparisons also indicated that mean gloss ratings between the small and large objects with the texture image task were significantly different ($p < .001$ with Bonferroni). See Figures 27, 28, and 29 for graphs depicting the significant two-way interaction and graphs depicting significant pairwise comparisons by the task variables of interest.

Discussion

Overall, hypotheses were supported, however the findings were not necessarily expected. As normal images, small objects had higher mean gloss ratings compared to large objects. As texture images, large objects had higher mean gloss ratings compared to small objects. Across the normal image and texture image task groups, small object gloss ratings were not significantly different. Across the normal image and texture image task groups, big object gloss ratings were significantly different; big object gloss ratings were higher in the texture group than the normal image group. In particular, it noteworthy that big object gloss ratings increased in the texture image condition. These findings are discussed in detail in the general discussion.
Detecting Specular Highlights in Images of Objects and Textures

The present study was conducted for four purposes: (i) exploring the relationship between perceived local shininess depicting luminance equated images of real-world objects, (ii) exploring the relationship between perceived local shininess depicting luminance equated images of real-world object images, (iii) assessing the degree to which perceived local shininess persists across the normal real-world object images and their synthetic texture counterparts, and (iv) providing a qualitative exploration of surface reflectance characteristics of high-level and mid-level real-world object size exemplars at a local level of surface reflection.

Method

Participants

44 participants (n = 22 per study) were recruited to participate in the study through the Virginia Tech SONA pool. All participants were compensated with 1.5 SONA credits for participating.

Procedures

Participants were tasked with identifying specular highlights in images of objects. For both the normal image and texture image conditions, participants were presented images one at a time. In order to advance to the next screen, participants were required to make no more than five selections.

Software

Participants engaged in the task online via Qualtrics. The main task mechanic was made possible by the Qualtrics question type “Heat Map”.
Highlights in Images of Objects Task Instructions

All participants read the following instructions: “In this experiment you will be presented with images that depict common objects found in the real-world. For each question try you’re best to: Consider the overall appearance and surface reflectance of the real-world object when you’re ready, click on the top five shiniest parts of the real-world object displayed in the image. Clicking a marker that has already been place will remove that marker”.

Highlights in Images of Textures Task Instructions

All participants read the following instructions: “In this experiment you will be presented abstract, computer generated images of textures created from images of common objects found in the real-world. For each question try you’re best to: Consider the overall appearance and surface reflectance of the textured image. When you’re ready, click on the top five shiniest parts of the texture displayed in the image. Clicking a marker that has already been place will remove that marker”.

Analyses

Inferential statistics were not computed on these data. However, heat maps were created to visualize the distributions of participant defined specular highlights in the object image and texture image task groups. Future work on this data may utilize hierarchical clustering methods, such as linear discriminant analysis (LDA), to identify clusters of spatial features related to participants perceptions of specular highlights.

Results

Looking at the heat maps, it is possible that structural features related to object size and texture are present in the heat maps. See Figures 30-34 for plots made from the participant defined specular highlight data across the different factors of interest.
Categorical Distinctions in Image Skew and Real-World Object Perceptions

Because previous studies of surface gloss and materials perception found evidence indicating that image skewness tends to predict significant changes in apparent surface glossiness, image skewness values were calculated from the luminance histogram of each stimulus image used in the present study (Kim & Anderson, 2010; Kim et al., 2016; Motoyoshi et al., 2007; Wiebel et al., 2015). Image skewness values were calculated using the open source program, ImageJ. For the purposes of this study, ImageJ data analytics of image moments were used to obtain image skewness values. These procedures were applied to all 120 images (60 object images (30 small objects, 30 big objects), and 60 texture images, (30 small objects, 30 big objects)). See Table 2 for image skew values across the stimulus images (the normal big, normal small, texture big, and texture small images).

Method

Quantifying Image Skew

Although is typically evaluated on the basis of graphical examinations of the shape data viewed as a histogram, as a general rule, skewness values between -.5 and .5 are considered to be approximately symmetric, skewness values between -1/1 and -.5/5 are considered to be moderately skewed, and skewness values less than -1 or greater than 1 are considered to be highly skewed. By these criteria, the average luminance histogram of big objects characterized by deviations in distribution shape symmetry; these effects were found for both the normal object images and the texture images. Both the normal big object images and the texture big object images were found to be moderately skewed; the directionality of the skew was positive in both cases as well. Similar effects were not found for either the small objects across image type.
Main Analyses

For both the object images condition and texture images condition, independent samples t-test were used to compare the average skewness of the stimulus images across levels of real-world object size (small objects vs big objects).

Results

Results indicated that normal object images were significantly different across levels of real-world object size category, \( t = (2.13), p < .05 \); specifically, big object skewness was higher than small object skewness. Differences across levels of real-world object size were not observed for the texture images.

Discussion

Comparisons of average skewness across real-world object size category found significant differences for the normal object images; specifically, big object skewness was higher on average than small object skewness. See Figure 35 for plot titled “Differences in Image Skew by Real-World Object Size and Image-Type”.
Summary of Key Findings

Object Size, Image Type, and Apparent Glossiness

Perceived glossiness differences were observed across categorical differences in real-world object size in both the object image and texture image task groups. In the object image task group, on average, small objects had higher gloss ratings than big objects. In the texture image task group, on average, big objects had higher gloss ratings than small objects. Across the object image and texture image task groups, glossiness ratings for small objects were not significantly different. Compared to the object image task group, average glossiness ratings for big objects, were significantly higher in the texture image task group.

Image Skew, Image Type, and Object Size

Because previous work suggests that modulations in apparent surface gloss and materials perception can, to a large extent, be predicted by low-level image features, in particular image skewness, image skewness from the luminance histograms of the stimulus images were examined (Kim & Anderson, 2010; Motoyoshi et al., 2007). Using the general rules for quantifying the amount of image skewness, both the normal big object images and the texture big object images were found to be moderately skewed; the directionality of the skew was positive in both cases as well (Doane & Seward, 2011). Comparisons of average skewness across real-world object size category found significant differences for the normal object images; specifically, big object skewness was higher on average than small object skewness.
General Discussion

The results for the normal object image task group may indicate that, on average, the surfaces of small objects are composed of shinier materials than big objects. The uniqueness of this study makes it somewhat difficult to offer an explanation of the glossiness difference observed by real-world object size without some speculation.

Some have stated that the ability of mid-level, synthetic texture stimuli to influence behavior in ways that is similar to high-level object perceptions is driven by the shape of objects (Long & Konkle, 2018; Zachariou et al., 2018). In particular, there is evidence that the degree to which an objects’ shape is comprised of rectilinear and curvilinear features is important, and that big objects are perceived as being boxier than small objects, and small objects are perceived as being curvier than big objects (Long & Konkle, 2018; Long, Störmer, et al., 2017; Zachariou et al., 2018). Considering the focus of the present study, this would make sense with previous findings in materials perception research, where perceptions of object materials are influenced by perceptions of shape, and vice versa.

Another important factor to consider is that, due to the square cube law, object size and material composition are physically correlated properties for both animate and inanimate objects (Haldane, 1926; Konkle, 2011; LaBarbera, 2003; Long et al., 2016). Consider the material compositions of the objects depicted in the stimulus images used in the work presented here. Most of the small objects appear to be uniformly made of no more than one or two materials (e.g. dustpan object is only made of plastic, light bulb object is mostly made of glass, but the base contains a tiny bit of metal). In comparison to small objects, the objects depicted in the big object images appear to have a more heterogenous material composition. For example, most of the big objects appear to be made of at least three or more materials (e.g. there were objects like the
exercise bike, elliptical machine, and fire truck that were clearly more variable in the material surface makeup).

Apart from material differences, optical artifacts are another factor that may have contributed to the size-related differences in perceived glossiness (Dragnea & Angelopoulou, 2005; Fleming & Bülthoff, 2005; Kunsberg & Zucker, 2018). For example, small objects tend to be photographed close-up, whereas big objects are more often photographed from afar (Konkle & Oliva, 2011a). As a result, upon being photographed, images of the small objects may have been more susceptible to photometric artifacts, such as light emitted by the flash of a camera (Zavagno et al., 2011). Similarly, differences in the distance at which the small and big objects were photographed would invariably also lead to differences in ambient illumination overall (Rempel, 2012).

**Differences Across Mid, High-Level Object Size Exemplars**

While the previous interpretations make intuitive sense for the normal object images, they do not clearly account for the observed increase in big object glossiness ratings across the normal and texture image task groups. The interpretation of this result is important because if small object surfaces are actually perceived as being glossier than big object surfaces on average in the real-world, and categorical distinctions by perceived real-world object size are a high-level property of visually perceived objects, then categorical distinctions in materials perception by real-world object size are also a property of high-level object perceptions.

**Similarities to Previous Work**

Recent studies have found evidence to suggest that the Portilla-Simoncelli (PS) algorithm does not preserve the illumination properties of natural image statistics of photographed materials (Balas & Conlin, 2015). Balas et al. (2015) found that the accuracy of observer
judgments for detecting changes in the lighting of photographs depicting materials in different illumination contexts, and their synthetic texture counterparts, were negatively impacted; illumination changes were much less accurate for the synthetic texture images. This is noteworthy because perceptions of illumination influence perceptions of object shape and surface glossiness. Similar findings have been found by others (Wallis et al., 2016).

There is evidence to suggest that the ability for observers to accurately discriminate contrast negated natural textures from PS generated textures varies in a way that is stimulus category dependent (Balas, 2012). In a study conducted by Balas et al. (2012), two separate stimulus categories, images of fruit and vegetables, and images of abstract art, were used to generate PS-textures; contrast negations of the original images and the PS-textures were also created. In conditions where the fruit/vegetable images were used, contrast negation lead to significant decreases in task performance; this effect was found for both the original and PS-textures images. However, in conditions where the abstract art images were used, oddball detection performances were best for the PS-textures; moreover, PS-texture performances were virtually identical across manipulations of image contrast (Balas, 2012).

A second experiment found that participants ability to discriminate changes in image contrast were significantly compromised for PS-textures generated from either image category (Balas, 2012). Balas et al. (2012), interpreted the category-dependent behavioral effects observed for the PS-stimuli to be the result of differences in the higher-order image statistics of the stimulus images, citing image skew as a potential source (Balas, 2012). See Figure 36 for visualization of image histogram obtained from images created in a manner the followed the methods of Balas (2012).
In the present study, moderate levels of asymmetry in the shape of the luminance histograms were detected for both the normal, and texture big object images; however, similar effects were not observed for either the normal, or texture small object images. Furthermore, texture big object images had significantly higher glossiness ratings compared to the normal big object images, but significant changes in small object glossiness across the normal and texture image conditions by glossiness were not observed.

Through the lens of findings by Balas et al. (2012; 2015; 2016), and others (Wallis et al., 2016), there is evidence to suggest that there are at least some cases where the mid-level surface reflectance characteristics of object surfaces and natural images are not fit by the PS-algorithm (Balas & Conlin, 2015; Balas et al., 2016; Balas, 2012; Wallis et al., 2016).

Hearkening back to the observed changes in perceived glossiness for the normal big object and texture big object images, and the consistency of the perceived glossiness for small object images across the normal and texture image conditions, it is possible that the surface reflectance characteristics of big objects may not be preserved by the PS-algorithm.

Regarding the source of the effects observed for the big object images, the average skewness of the luminance histograms observed for the original big object images may provide insight. Any number of factors related to the context of how the big object images were photographed could have caused them to have more image skew on average (Motoyoshi & Matoba, 2012; Olkkonen & Brainard, 2010, 2011; Pas et al., 2017).

**Study Limitations**

This study is novel, and the methods used here could be improved upon. All of the studies were conducted online, and compared to most gloss perception research, gloss perception research is typically conducted in highly controlled settings, involving the use of specially
calibrated CRT monitors, gamma correction, etc. (Thompson et al., 2016). Furthermore, the light field used to render glossy blobs was obtained from an indoor illumination context. It could be argued that the light field used biased the results in a way that confounded the differences observed across object size and image type (Adams et al., 2018). With these limitations in mind, more work is needed.

**Conclusion**

The present study found evidence to suggest that categorical distinctions in perceived real-world object size are dissociable by similarly broad distinctions in perceived surface glossiness. Although differences in perceived glossiness were found using stimulus images for high-level real-world object size exemplars, and synthetic textures designed to simulate mid-level real-world object size exemplars (i.e. metamers), perceptions of surface glossiness were not constant between the two stimulus image types. These results may suggest that in certain cases, synthetic texture algorithms designed to simulate mid-level visual perception are not necessarily accurate for the surface reflectance characteristics of materials.
References


Specular Highlight Deformation, Boundary Contour Deformation, and Active Haptic Manipulation. *II*(2), e0149058. https://doi.org/10.1371/journal.pone.0149058


Scott, & Barton. (2014). Specular Image Structure Modulates the Perception of Three-Dimensional Shape. 24(22), 2737-2742. [https://doi.org/10.1016/j.cub.2014.09.074](https://doi.org/10.1016/j.cub.2014.09.074)


Wagemans, J., Van Doorn, A. J., & Koenderink, J. J. (2011). Pictorial depth probed through relative sizes. 2(9), 992-1013. [https://doi.org/10.1068/i0474](https://doi.org/10.1068/i0474)


Table 1: Example of Image Features Across Changes in Surface Glossiness

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>219.391</td>
</tr>
<tr>
<td>SD</td>
<td>84.53</td>
</tr>
<tr>
<td>Min.</td>
<td>0</td>
</tr>
<tr>
<td>Max.</td>
<td>255</td>
</tr>
<tr>
<td>Skew</td>
<td>-2.074</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.449</td>
</tr>
</tbody>
</table>

*Note.* Image statistics computed for the image shown in Figure 3.
Table 2: Example of Image Features Across Changes in Surface Glossiness

<table>
<thead>
<tr>
<th>Material</th>
<th>A (matte)</th>
<th>B (neutral)</th>
<th>C (glossy)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>66.666</td>
<td>72.71</td>
<td>71.981</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>8.188</td>
<td>11.489</td>
<td>12.545</td>
</tr>
<tr>
<td><strong>Min.</strong></td>
<td>50</td>
<td>52</td>
<td>45</td>
</tr>
<tr>
<td><strong>Max.</strong></td>
<td>88</td>
<td>142</td>
<td>242</td>
</tr>
<tr>
<td><strong>Skew</strong></td>
<td>0.269</td>
<td>1.571</td>
<td>4.545</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>-0.652</td>
<td>4.947</td>
<td>48.591</td>
</tr>
</tbody>
</table>

*Note. A. Artificial matte material image statistics. B. Artificial neutral glossy material image statistics. C. Artificial glossy material image statistics. All image statistics were obtained using ImageJ.*
Table 3: Average Image Skewnes by Factors of Interest

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Small</td>
<td>.07</td>
<td>1.44</td>
</tr>
<tr>
<td>Normal Big</td>
<td>.89</td>
<td>1.48</td>
</tr>
<tr>
<td>Texture Small</td>
<td>.34</td>
<td>1.48</td>
</tr>
<tr>
<td>Texture Big</td>
<td>.65</td>
<td>1.15</td>
</tr>
</tbody>
</table>

*Note.* Image statistic
Figure 1: Example Image Compression Similar to Human Visual System

Note. From A, and ending at G, from left to right, the image gradually becomes coarser in detail and overall spatial resolution. This graphic depicts the results of Laplacian image pyramid. This image is created by first applying a gaussian blur to the original image, then reducing the pixel size of that image by half; this procedure is then applied to the blurred and halved image. This process is continued until the lowest spatial resolution possible. A Laplacian image pyramid is then created by iteratively taking the differences between the resultant levels of the Gaussian (Burt & Adelson, 1983). A. Image resolution (256x256). B. Image resolution (128x128). C. Image resolution (64x64). D. Image resolution (32x32). E. Image resolution (16x16). F. Image resolution (8x8). G. Image resolution (4x4). This example was created using “pyrtools”, open source Python software developed by the Lab for Computational Vision. The person pictured here is the author of this project.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 2: Example of Natural Image Statistics

A

B

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 3: Example of Image Luminance Histogram

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 4: Example Demonstration of PS-Algorithm

*Note.* A. A photograph of the author of this project. B. A white noise image. C. The image resultant from coercing the white noise image depicted in B to gradually take on the PS-algorithm defined texture characteristics from the photograph of the author (50th iteration). The person pictured here is the author of this project.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 5: Everyday Examples of Specular Reflections

Note. A. The warped images of an office setting are featured as specular reflections cast onto the surface of a ceramic coffee mug. B. The warped images of a bathroom specularly reflected onto the metallic surface of a water faucet. C. The warped images of a hallway and building exit specularly reflected onto the polished floor of Williams Hall.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 6: Everyday Examples of Diffuse Reflections

Note. A. A close-up photograph of bricks made of “Hokie” stone (a.k.a. limestone). B. A close-up photograph of a leafy plant. C. A close-up photograph of an old tree.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 7: Distinct Spatial Scales of Where Surface Geometry Influences Appearance

Note. A is a normal sphere with neutral reflectance properties and B represents a change to the sphere that influenced the sphere megascopic surface geometry. C is a normal sphere with neutral reflectance properties and D represents a change to the sphere that influenced the sphere mesoscopic surface geometry. E is a normal sphere with neutral reflectance properties and F represents a change to the sphere that influenced the sphere microscale surface geometry. All objects were created in Blender 2.8. These objects were created in a manner that was inspired by previous works (Ho et al., 2008; Marlow & Anderson, 2013, 2015; Qi, 2012; Qi et al., 2015).

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 8: Example of Light Probe

Note. This light probe was created by the author of this project in a reserved laboratory space located in the department of psychology at Virginia Tech; the light probe created using an iPhone application called “360”.
Figure 9: Everyday Examples of Glossy Surfaces and Objects

Note. A. The painted black surface of a car. B. The surface of red Christmas bauble. C. The eyes of a graduate student at three in the morning. The person pictured here is the author of this project.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 10: Everyday Examples of Specular Highlights

Note. A. Specular highlights on the surface of a clear light bulb. B. Specular highlights on the surfaces of shiny brown dress shoes. C. A specular highlight on the spherical surface of a blue exercise ball. D. A specular highlight on a cheap plastic cup.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 11: Many Fruits and Vegetables are Naturally Glossy

*This figure was created by the author of this project, and it is NOT a reproduction*

\[\text{Note.}\] Previous work by Arce-Lopera (2012) indicates that human perceptions of fruit freshness are influenced by visual perceptions of luminance distribution. A. Photograph of eggplant. B. Photograph of apples. C. Photograph of bell peppers. D. Photograph of habanero peppers.
Figure 12: Do Biological Needs Drive Aesthetic Enjoyment of Glossiness?

*Note. Following an evolutionary approach, findings by Meert et al. (2014) suggest that humans’ preferences for shiny objects and material surfaces are driven by our innate, biological needs for water (Meert et al., 2014).

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 13: Manipulating Highlight to be Global Form Incongruent

A. A 3D blob with a matte material surface featuring specular highlights copied from a glossy blob of the same geometry. B. Colored map of the orientation gradients for A. C. A 3D blob with a matte material surface featuring specular highlights copied from a glossy blob of the same geometry; compared to A, the highlights depicted in C are incongruent with the 3D geometry of the 3D blob. D. Colored map of the orientation gradients for C.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 14: Natural Ambient Illumination Makes 3D Objects Appear Glossier

*Note. A. Glossy blob rendered with an unrealistic light field. B. Glossy blob rendered with real-world illumination using the StaffOffice2 light field (provided by the SYNS dataset). Objects were created using Blender 2.8.*

*This figure was created by the author of this project, and it is NOT a reproduction.*
Figure 15: Surface Glossiness Depends on the Overall Shape of

Note. A glossy material was created in Blender 2.8 using a natural light field provided by the SYNS dataset; the light field used was “StaffOffice2”. Four different objects featuring surfaces significantly different megascale surface structure (i.e. shape) were created; each mesh object and then all objects were rendered with the same material. A. Standard image outputs from Blender. B. Histogram normalized and contrast enhanced versions of the images depicted in A.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 16: Example of Image Features Across Changes in Surface Glossiness

Note. A. Artificial matte material and the matte material luminance histogram. B. Artificial neutral glossy material and the neutral glossy material luminance histogram. C. Artificial glossy material and the glossy material luminance histogram. All materials were created using Blender 2.8. See Table 2 for breakdown of image statistics for the materials pictured here.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 17: Example of Visual Size

*Note.* Expressed in inches, the visual size of the tiny man being measured is about 4 inches. The person pictured here is the author of this project.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 18: Example of Familiar Size

*This figure was created by the author of this project, and it is NOT a reproduction*

Note. The familiar-sizes’ of the objects in the room add to the weirdness of this photograph. While the person reflected in the mirror does not look out of place, or oddly sized, editing the photograph and placing the person in the mirror elsewhere in the room makes them appear out of place and tiny. The person pictured here is the author of this project.
Figure 19: Using Perlin Noise to Make a Sphere “Blobby”

Note. A. Smooth sphere. B. Perlin noise. C. A sphere made “blobby”; result of global and local surface geometries of the sphere being disturbed by Perlin noise.

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 20: SYNS Staff Office2 HDR Light Field

*This figure was created by the author of this project, and it is NOT a reproduction*

Note. A. 360 scene perspective. B. Stereographic scene perspective.
Figure 21: Isotropic Ward Reflectance Model

*Note. A. Diffuse ("Lambertian") reflectance component. B. Specular reflectance component.*

*This figure was created by the author of this project, and it is NOT a reproduction*
Figure 22: Gloss Rating Scale using Glossy Blob Stimuli

Note. All seven glossy blobs used to create a glossiness ratings scale.

*This figure was created by the author of this project, and it is NOT a reproduction*
Note. All seven glossy blobs used to create a glossiness ratings scale (SHINE normalized).

*This figure was created by the author of this project, and it is NOT a reproduction*
Note. All real-world object used (SHINE normalized).
Figure 25: Synthetic Texture Images

Note. PS-textures.
Figure 26: Perceived Weighted Average Size Ranks Predicted by Real-World Size

Note. Results of Experiment 1.
Figure 27: Gloss Rating Two-Factor Mixed ANOVA: Two-Way Interaction

Note. Results of Experiment 2.
Figure 28: Differences in Gloss Rating by Size Across Task Groups

Note. Results of Experiment 2.
Figure 29: Differences in Gloss Rating Across Task Groups Within Size

Note. Results of Experiment 2.
IS GLOSS IS A CUE FOR OBJECT SIZE?

Figure 30: Small Object Heat Maps

Note. Small object heat maps.
Figure 31: Big Object Heat Maps

*Note.* Big object heat maps.
Figure 32: Small Texture Heat Maps

Note. Small texture heat maps.
Figure 33: Big Texture Heat Maps

*Note.* Big texture heat maps.
Figure 34: Participant Defined Specular Highlight Task Results

*Note.* Combined heatmaps for the specular highlight task across the factors of interest.
Figure 35: Differences in Image Skew by Real-World Object Size and Image-Type

*Note.* Image statistics.
Figure 36: Image Skew Across and Contrast: Synthetic Textures vs Natural Textures

Note. This images in this figure are recreations of the stimuli used in Balas (2015) et al.’s study.
A. A positive contrast image patch made from a photograph of an art piece created by a friend of the author of this project. B. A positive contrast image patch depicting a synthetic texture made from the photograph depicted in A. C. A positive contrast image patch made from a close-up photograph of a bowl of raspberries. D. A positive image patch depicting a synthetic texture made from the photograph C. E, F, G, and H are contrast negated versions of A, B, C, and D respectively. To the right of each image patch is a graphic of the luminance histogram for that image patch. For A, B, C, D, E, F, G and H, note the differences in the shape of histograms.

*This figure was created by the author of this project, and it is NOT a reproduction*
Appendix A

Procedures for Creating 3D Geometry for Glossy Blobs

*This figure was created by the author of this project, and it is NOT a reproduction*
Appendix B

Interface Working with Real-World Light Fields in Blender 2.8
Appendix C

Custom Material Shading Rig in Blender 2.8
Appendix D

Size Rank Task Demo

Size Ranking Task: Instructions

• In this experiment you will be presented with images that depict common objects found in the real-world.

Across all columns: sort objects into eight groups of roughly similarly sized objects.

1 2 3 4 5 6 7 8

Small Large

• Try to make sure that the overall size of the objects in each column increases from left to right, such that “Size 1” contains the smallest objects and “Size 8” contains the largest objects.

• Every column must contain a minimum of four objects, and a maximum of eight objects.

Task controls:

• Under the “Items” field is a column of images. For all images, left clicking an image while moving your mouse will allow you to move that image around the screen.

• If you’ve grabbed an image and have positioned that image over one of the eight columns below, releasing the left mouse button will drop that image into the column.

• Clicking on the middle of the draggable image will present you with an enlarged view of the object image.

• When you have finished the task, scroll to the bottom right corner of the screen and click the next button (e.g. an image of an arrow pointing to the right).
Appendix E

Object Gloss Matching Task Instructions

- In this experiment you will be presented with images that depict common objects found in the real-world paired with computer generated blobs.

- The blobs presented here were designed to simulate different levels of object surface reflectance; during the experiment you will see seven different blobs.

- For each question try you’re best to:
  - Consider the overall appearance and reflectance a given real-world object.
  - Then, when you’re ready, select the image with the blob that best matches the overall appearance and reflectance of the real-world object.
Appendix F

Object Gloss Matching Task Demo
Appendix G

Texture Gloss Matching Task Instructions

- In this experiment you will be presented abstract, computer generated images of textures created from images of common objects found in the real-world paired with glossy computer generated blobs.

- The blobs presented here were designed to simulate different levels of object surface reflectance; during the experiment you will see seven different blobs.

- For each question try you’re best to:
  □ Consider the overall appearance and reflectance the given textured image.
  □ Then, when you’re ready, select the image with the blob that best matches the overall appearance and reflectance of the textured image.
Appendix H

Object Shine Mapping Task Demo

Shine Mapping Task: Instructions

- In this experiment you will be presented with images that depict common objects found in the real-world.
- For each question try you’re best to:
  - consider the overall appearance and surface reflectance of the real-world object
  - when you’re ready, click on the top five shiniest parts of the real-world object displayed in the image
- Clicking a marker that has already been place will remove that marker.
Appendix I

Texture Shine Mapping Task Demo

Texture Shine Mapping Task: Instructions

- In this experiment you will be presented abstract, computer generated images of textures created from images of common objects found in the real-world.
- For each question try you’re best to:
  - Consider the overall appearance and surface reflectance of the textured image.
  - When you’re ready, click on the top five shiniest parts of the texture displayed in the image.
- Clicking a marker that has already been placed will remove that marker.
Appendix J

IRB

(see next two pages)
MEMORANDUM

DATE: May 29, 2020

TO: Anthony Cate, James Michael Brown, Maria Delleman

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires October 29, 2024)

PROTOCOL TITLE: Perceiving Real-World Object Features

IRB NUMBER: 19-679

Effective May 29, 2020, the Virginia Tech Human Research Protection Program (HRPP) and Institutional Review Board (IRB) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104(d) category(ies) 3(i)(B).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit a new request to the IRB for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All Investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Determined As: Exempt, under 45 CFR 46.104(d) category(ies) 3(i)(B)

Protocol Determination Date: January 3, 2020

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.
**SPECIAL INSTRUCTIONS:**

*** The Virginia Tech IRB/HRPP has requested that research involving person-to-person contact or gatherings of human research participants be paused as soon as possible. The duration of the pause is unknown, but to reduce disruption to the extent possible, we will be reassessing daily. Although we continue to issue approval notices, Virginia Tech guidance should be followed. Please visit https://www.research.vt.edu/covid-19-updates-impacts.html for updates.

This amendment, submitted May 14, 2020, updates research protocol, recruitment materials, and consent forms to revise eligibility criteria to be 18 years of age or older and English speaking, and to revise compensation procedures from 1.5 SONA credits to a $5 electronic Visa gift card.

<table>
<thead>
<tr>
<th>Date*</th>
<th>OSP Number</th>
<th>Sponsor</th>
<th>Grant Comparison Conducted?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this protocol is to cover any other grant proposals, please contact the HRPP office (irb@vt.edu) immediately.