

Disney Research, Pittsburgh  
4720 Forbes Avenue, Suite 110  
Pittsburgh, PA 15213

April 27, 2012

David Sheinberg, PhD  
Search Committee Chair  
Department of Neuroscience  
Brown University  
Providence, RI 02912

Dear Professor Sheinberg:

I am writing to apply for the assistant professor position in computational neuroscience, as advertised in the CVNet mailing list. I am currently a Postdoctoral Associate at Disney Research, Pittsburgh, an industry research laboratory co-located with Carnegie Mellon University where I am completing my postdoctoral training with Professor Jessica K. Hodgins of the Robotics Institute, Carnegie Mellon University. I completed my PhD degree in Electrical Engineering and Computer Science from Massachusetts Institute of Technology (MIT) in September 2009. While my formal education has been in computer science, I received training in psychology during my doctoral studies in the laboratory of Professor Edward H. Adelson at MIT.

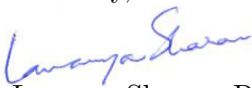
I study human visual perception from a behavioral and a computational perspective. I use psychophysical methods to measure specific visual abilities, and I build computational models in order to understand how the human visual system might support those abilities. My research focuses on explaining visual perception in real-world conditions rather than simplified, abstract settings and brings to bear techniques from the discipline of computer science, including computer vision and computer graphics, to handle and model the complexity of real-world visual inputs. I have employed this interdisciplinary research approach to understand the perception of material properties and more recently, to understand the perception of the static human form.

Additionally, I have strong interests in teaching and mentoring. My unique background has allowed me to experience teaching methods in a variety of disciplines and it has equipped me to teach topics across and between disciplines. I helped develop and teach a new graduate class on human visual perception in the Robotics Institute at Carnegie Mellon University in Spring 2011. I look forward to teaching other classes as well, in particular, sensation and perception, computational neuroscience, and research methods. I have also mentored a number of undergraduate students in research projects, one of which led to a presentation at a top-tier conference.

During my graduate and postdoctoral careers, I have made significant contributions to grant writing. An NIH grant application that I co-wrote with my graduate advisor and a collaborator was funded in 2010 (R01 EY019262-01: Mechanisms for the Perception of Surfaces and Materials).

I have enclosed my curriculum vitae, research statement, teaching statement, and three representative publications. Please let me know if there are any other materials that may assist you in making your decision. I look forward to hearing from you.

Sincerely,



Lavanya Sharan, Ph.D.

# Lavanya Sharan

Disney Research, Pittsburgh  
4720 Forbes Avenue, Suite 110  
Pittsburgh, PA 15213

(617) 840-0672  
lavanya@disneyresearch.com  
<http://people.csail.mit.edu/lavanya>

## Education

---

**Massachusetts Institute of Technology** September 2009  
Ph.D., Electrical Engineering and Computer Science  
Thesis: The perception of material qualities in real-world images  
Advisor: *Edward H. Adelson*

**Massachusetts Institute of Technology** September 2005  
S. M., Electrical Engineering and Computer Science  
Thesis: Image statistics and the perception of surface reflectance  
Advisor: *Edward H. Adelson*

**Indian Institute of Technology Delhi** August 2003  
B. Tech, Electrical Engineering  
GPA 9.62/10.00, awarded *Institute Silver Medal* for academic excellence.

## Research Experience

---

**Disney Research, Pittsburgh** September 2009 – present  
Postdoctoral Associate  
Advisor: *Jessica K. Hodgins*

**Massachusetts Institute of Technology** September 2003 – August 2009  
Research Assistant, Perceptual Science Group  
Advisor: *Edward H. Adelson*

**NTT Communication Sciences Laboratory**, Atsugi, Japan March 2006  
Visiting Researcher, Human and Information Science Laboratory  
Host: *Shin'ya Nishida*

**Indian Institute of Technology Delhi** July 2002 – May 2003  
Undergraduate Thesis, Department of Electrical Engineering  
Advisor: *Subhashis Banerjee*

**University College London** May 2002 – July 2002  
Summer Intern, Gatsby Computational Neuroscience Unit  
Host: *Peter Dayan*

## Teaching Experience

---

**Carnegie Mellon University** Spring 2011  
Instructor, 16-899A Pixels to Percepts: Visual Perception for Computer Vision & Graphics  
Graduate-level class co-taught with *Alexei A. Efros*.

**Massachusetts Institute of Technology**  
Teaching Assistant, 6.02 Digital Communication Systems Spring 2009  
Teaching Assistant, 6.002 Electronic Circuits Fall 2004  
Conducted tutorials and laboratory sessions for undergraduate-level classes.

## Refereed Publications

---

1. Elizabeth Carter\*, **Lavanya Sharan\***, Laura C. Trutoiu, Iain Matthews, and Jessica K. Hodgins  
Perceptually motivated guidelines for voice synchronization in film  
*ACM Transactions on Applied Perception*, 7(4), No. 23, 2010. (\* denotes equal contribution)
2. Ce Liu, **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson  
Exploring features in a Bayesian framework for material recognition  
*IEEE Conference on Computer Vision and Pattern Recognition*, 2010.
3. **Lavanya Sharan**, Yuanzhen Li, Isamu Motoyoshi, Shinya Nishida, and Edward H. Adelson  
Image statistics for surface reflectance perception  
*Journal of the Optical Society of America A*, 25(4):846-865, 2008.
4. Isamu Motoyoshi, Shinya Nishida, **Lavanya Sharan**, and Edward H. Adelson  
Image statistics and the perception of surface qualities  
*Nature*, 447:206-209, 2007.
5. Yuanzhen Li, **Lavanya Sharan**, and Edward H. Adelson  
Compressing and companding high dynamic range images with subband architectures  
*ACM Transactions on Graphics (SIGGRAPH)*, 24(3), 836-844, 2005.

## Publications under Review

---

**Lavanya Sharan**, Ce Liu, Ruth Rosenholtz, and Edward H. Adelson  
A perceptually guided approach for recognizing materials from single images  
*International Journal of Computer Vision*, **accepted** pending minor revisions.

## Publications in Preparation

---

1. **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson  
Material categorization in real-world images is fast and accurate
2. **Lavanya Sharan**, Leonid Sigal, and Jessica K. Hodgins  
The perception of human body poses and implied actions in real-world images
3. Edilson de Aguiar, **Lavanya Sharan**, Moshe Mahler, Ariel Shamir, and Jessica K. Hodgins  
Perceptually guided capture and stylization of small-scale 3D human figures

## Grant Writing

---

Co-Author (Postdoctoral Role), NIH Grant, **R01 EY019262-01**, Mechanisms for the Perception of Surfaces and Materials, PI: *Edward H. Adelson*, Total award amount: \$573,255, NEI, Neurosciences category.

## Conference Presentations

---

1. **Lavanya Sharan**, Leonid Sigal, and Jessica K. Hodgins  
Recognizing activities and poses: lessons from computer vision  
*Poster* to be presented at Vision Sciences Society Meeting, Naples, FL, 2012.
2. **Lavanya Sharan**, Matthew Kaemmerer, Moshe Mahler, Kwang Won Sok, and Jessica K. Hodgins  
Animated character appearance does not affect judgments of motion trajectory

*Poster* presented at Vision Sciences Society Meeting, Naples, FL, 2011.

3. Elizabeth J. Carter, **Lavanya Sharan**, Laura C. Trutoiu, Iain Matthews, and Jessica K. Hodgins  
Perceptually motivated guidelines for voice synchronization in film

*Oral* presentation at Symposium on Applied Perception in Graphics and Visualization, Los Angeles, CA, 2010.

4. Ce Liu, **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson

Exploring features in a Bayesian framework for material recognition

*Poster* presented at IEEE Conference on Computer Vision and Pattern Recognition, San Francisco, CA, 2010.

5. **Lavanya Sharan**, Ce Liu, Ruth Rosenholtz, and Edward H. Adelson

A computational model for material recognition

*Poster* presented at Vision Sciences Society Meeting, Naples, FL, 2010.

6. **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson

Rapid perception of material properties in natural images

*Poster* presented at International Conference on Cognitive and Neural Systems (ICCNs) Meeting, Boston, MA, 2009.

7. **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson

Material Perception: What can you see in a brief glance?

*Oral* presentation at Vision Sciences Society Meeting, Naples, FL, 2009.

8. **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson

Rapid visual perception of material properties

*Poster* presented at Object Perception Attention and Memory (OPAM) Meeting, Chicago, IL, 2008.

9. **Lavanya Sharan**, Ruth Rosenholtz, and Edward H. Adelson

Eye movements for material perception

*Oral* presentation at the Vision Sciences Society Meeting, Naples, FL, 2008.

10. Shinya Nishida, Isamu Motoyoshi, Lisa Nakano, Yuanzhen Li, **Lavanya Sharan**, and Edward H. Adelson  
Do colored highlights look like highlights?

*Poster* presented at the Vision Sciences Society Meeting, Naples, FL, 2008.

11. **Lavanya Sharan**, Edward H. Adelson, Isamu Motoyoshi, and Shinya Nishida

Non-oriented filters are better than oriented filters for skewness detection

*Oral* presentation at the European Conference on Visual Perception, Arezzo, Italy, 2007.

12. **Lavanya Sharan**, Edward H. Adelson, Isamu Motoyoshi, and Shinya Nishida

Histogram skewness is useful and easily computed

*Poster* presented at the Vision Sciences Society Meeting, Sarasota, FL, 2007.

13. **Lavanya Sharan**, Yuanzhen Li, and Edward H. Adelson

Image statistics for surface reflectance estimation

*Oral* presentation at the Vision Sciences Society Meeting, Sarasota, FL, 2006.

14. **Lavanya Sharan**, Yuanzhen Li, and Edward H. Adelson

Image statistics and reflectance estimation

*Oral* presentation at the Vision Sciences Society Meeting, Sarasota, FL, 2005.

15. Yuanzhen Li, **Lavanya Sharan**, and Edward H. Adelson

Perceptually based range compression for high dynamic range images

*Poster* presented at the Vision Sciences Society Meeting, Sarasota, FL, 2005.

## Honors & Awards

---

Selected to attend the *Computational Neuroscience: Vision* summer school at Cold Spring Harbor Laboratories, Cold Spring Harbor, NY, June 2008.

Awarded the **Institute Silver Medal** for graduating top of the Electrical Engineering class at the Indian Institute of Technology Delhi, August 2003.

## Professional Activities

---

### *Journal reviews*

Journal of Vision (JoV), Attention, Perception & Psychophysics (AP&P).

### *Conference reviews*

ACM International Conference and Exhibition on Computer Graphics and Interactive Technologies (SIGGRAPH) 2011-2012, IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2010, European Conference on Computer Vision (ECCV) 2010.

### *Program Committee*

ACM Symposium on Applied Perception (SAP) 2012.

## Mentoring Experience

---

Supervisor, CMU graduate student and Research Assistant at Graphics Lab, *Zhe Han Neo*. 2011-2012

Co-Supervisor, Lab Associates at Disney Research, Pittsburgh: Spring & Summer 2010  
*Matthew Kaemmerer, Spencer R. Diaz, and Ishita Kapur.*

Supervisor, MIT undergraduate research assistants (UROPs): 2008  
*William Yee, Aseema Mohanty, and Biyeun Buczyk.*

Supervisor, MIT undergraduate research assistant (UROP), *Cong Luo*. Summer 2006

## Visa Status

---

H-1B (valid until September 30, 2012).

## References

---

1. Edward H. Adelson  
John and Dorothy Wilson Professor of Vision Science  
Department of Brain and Cognitive Sciences  
Computer Science and Artificial Intelligence Laboratory  
Massachusetts Institute of Technology  
43 Vassar St, 46-4115  
Cambridge, MA 02139  
USA  
*Tel:* +1-(617)-253-0645  
*Email:* adelson@csail.mit.edu  
*Relationship:* Ph.D. Advisor

## 2. Jessica K. Hodgins

Professor

Robotics Institute & Computer Science Department  
Carnegie Mellon University  
5000 Forbes Avenue, EDSH 231  
Pittsburgh, PA 15213  
USA

*Tel:* +1-(412)-268-6795*Email:* jkh@cs.cmu.edu*Relationship:* Postdoctoral Supervisor

Director

Disney Research, Pittsburgh  
4720 Forbes Avenue  
Lower Level, Suite 110  
Pittsburgh, PA 15213  
USA

*Tel:* +1-(412)-688-7401

## 3. Ruth Rosenholtz

Principal Research Scientist

Department of Brain and Cognitive Sciences  
Computer Science and Artificial Intelligence Laboratory  
Massachusetts Institute of Technology  
43 Vassar St, 46-4115  
Cambridge, MA 02139  
USA

*Tel:* +1-(617)-324-0269*Email:* rruth@mit.edu*Relationship:* Collaborator

## 4. Alexei A. Efros

Finmeccanica Associate Professor

Robotics Institute & Computer Science Department  
Carnegie Mellon University  
5000 Forbes Avenue, EDSH 225  
Pittsburgh, PA 15213  
USA

*Tel:* +1-(412)-268-1234*Email:* efros@cs.cmu.edu*Relationship:* Co-Instructor

## Research Statement

Lavanya Sharan

Our world is composed not only of surfaces and objects, but also of textures and materials. Consider Figure 1. It is easy to recognize the grain patterns of the wooden surface, the dull shine of the copper pipe, and the rows of glazed doughnuts that we know are made of ‘doughnut-stuff’ and not, say, ‘bagel-stuff’. My work has focused on understanding how we infer the *material* properties of surfaces and objects. For images like the one on the right, I have studied questions such as how do we recognize the glaze on the doughnuts, or how do we recognize, almost right away, that the surface beneath the doughnuts is made of wood, and not metal or plastic? The ability to recognize material properties is critical for interacting with our world; metallic surfaces can be hot, shards of glass can be sharp, and glistening surfaces can be slippery.

Most studies of material appearance have relied on a restricted set of stimuli (e.g., planar arrangements of colored patches) to allow stimulus appearance (e.g., color of a patch) to be varied easily. The use of such stimuli has meant that only a restricted set of perceptual qualities have been studied (e.g., color, but not gloss or transparency). My work has advanced our understanding of the perception of material properties by employing *stimuli derived from the real world* (e.g., photographs like the one in Figure 1) and by exploring the rich range of material properties that people can see (e.g., gloss [1, 2] and material identity [5]). By considering real-world surfaces instead of ideal, diffuse surfaces in one set of studies [1, 2], we were able to demonstrate the limitations of previous theories of reflectance perception and to discover a new mechanism for reflectance perception. By using a diverse selection of real-world photographs in a different set of studies [3, 4, 5], we were able to show, for the first time, that the recognition of material categories (e.g., wood) in the real world is fast, accurate, and distinct from the recognition of colors, textures, shapes, and objects.

A significant hurdle to using stimuli derived from the real world is having the ability to perform stimulus manipulations in a consistent, repeatable manner. I use an interdisciplinary approach to overcome this hurdle by employing *techniques from computer science*, in particular, computer vision and computer graphics. These techniques provide ways of manipulating specific aspects of real-world appearance in photographs and computer-generated scenes, and hence, they can be used for stimulus manipulations. Furthermore, these techniques can be used for building models of human visual processing that work directly on real-world inputs and have the potential to offer insights about human vision. In my work, techniques from computer graphics were used to manipulate luminance-based statistics [1, 2] and texture information [4, 5] in real-world images. In addition, we built computer-vision style models to demonstrate the importance of luminance-based statistics for reflectance perception [1, 2] and to reject simple hypotheses based on color, texture, and shape for material category recognition [3, 4].

I want to move the study of problems in visual perception forward by using stimuli and tasks that incorporate the complexity of real-world conditions. Techniques from the fields of computer vision and computer graphics make this goal feasible; they allow us to move beyond the restricted stimulus worlds that have been studied so far. My dual background in computer science and visual psychophysics makes me uniquely equipped to utilize such tools from computer science to study visual perception. I will now illustrate my interdisciplinary research approach with examples from my work on the perception of material appearance [1, 2, 3, 4, 5] and the perception of static human figures [6]. I end with plans for future research.



Figure 1: It is easy to recognize the materials in this image – metal, wood, paper, ‘doughnut-stuff’, etc. (Best viewed in color. Image courtesy Flickr.com user star5112.)

## The importance of using real-world stimuli

It is important to study visual abilities with stimuli that are representative of real-world conditions because nearly all of our visual exposure occurs in the real world with natural or man-made objects and materials. While great strides have been made in our understanding of human vision by studying simple, artificial stimuli and setups, it is likely that many of the visual effects that occur in the real world have been missed. Additionally, it has been argued that our sensory processing might be tuned to the statistical regularities of the natural world, so it is plausible that the knowledge gained by studying the visual system in artificial situations may not generalize to the conditions for which it is most suited.

For example, in our work on the perception of surface reflectance [1, 2], we showed that the visual effects observed with flat, diffuse surfaces do not extend to real-world surfaces. Consider Figure 2. It is easy to distinguish the white, matte surface from the black, glossy one. Equating the mean luminance values of these surfaces does not, unlike the case of flat, diffuse surfaces, fool observers into believing that they have the same reflectance properties. Most theories of reflectance perception only consider mean luminance information, and therefore, they cannot explain the effect in Figure 2.

In our work on the perception of material categories [3, 4, 5], we were confronted with the challenge of designing a stimulus set that would test the ability to recognize high-level visual categories (e.g., wood) and not low-level stimulus characteristics (e.g., a color like brown). To address this challenge, we used an intentionally diverse selection of real-world photographs as stimuli. These photographs, some of which are shown in Figure 3, were selected carefully so as to include appearance variations due to reflectance properties, 3-D shapes, object associations, and imaging conditions within each material category. The diversity of our stimuli made it unlikely that simple heuristics could be used to judge the material category (e.g., brown surfaces denote wood and high spatial frequencies denote fabric). Because our stimuli capture the natural range of material appearances, we were able to dissociate high-level material categories from low-level properties like color or related surface properties like shape and texture in our stimuli.

The study of human figures, like the study of material appearance, has been limited by the use of artificial stimuli (e.g., stick figures or moving dots that convey human motion). In recent work [6], we studied the perception of human actions (e.g., kicking, running, and bending) in real-world photographs of everyday scenes. We found that standard actions like walking or sitting can be predicted even when the human figure is occluded, which demonstrates the importance of support surfaces and scene context for recognizing actions. Findings like these highlight the importance of examining visual judgments in real-world conditions instead of abstract, idealized settings.

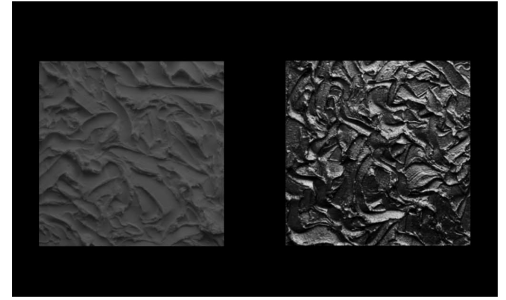


Figure 2: A classic visual effect observed with flat, diffuse surfaces does not work with complex, real-world surfaces [2]. Unlike the original effect, the surfaces shown here do not appear to have the same reflectance properties.



Figure 3: We can tell that these surfaces are made of fabric, and not of plastic or glass, even when we only get 40 ms to look at these photographs [5]. From left to right, close-up of a taffeta gown, crochet cap made of nylon, flannel bedding, plush toy, and an Oreo cookie made of wool.



## The significance of computer-vision and computer-graphics techniques

The goal of computer vision research is to produce automated systems that can interpret images of the real world in the same way as human observers (e.g., by automatically recognizing surfaces, objects, materials, and people). In computer graphics, the goal is to recreate the appearance of the real world. These goals are complementary; computer vision researchers focus on analyzing real-world appearance while computer graphics researchers focus on synthesizing it. Together, the techniques developed in these fields provide us with tools for manipulating real-world stimuli (e.g., by changing texture properties in photographs) and building models of human visual processing that work on real-world inputs (e.g., by building a computer-vision style system to recognize gloss or transparency).

We studied the luminance distributions of surfaces using imaging techniques from computer graphics, in an effort to explain the effect in Figure 2. We observed that luminance distributions of light vs. dark and matte vs. glossy surfaces differ in systematic ways, and that these differences can be captured by certain statistics of luminance other than the mean (e.g., standard deviation, skewness, and 90<sup>th</sup> percentile). In our experiments [1, 2], not only were these statistics correlated with the physical reflectance (e.g., high values of skewness for glossy surfaces), but they were also correlated with the perceived reflectance (e.g., high values of skewness for surfaces that were perceived as glossier). When we digitally manipulated these statistics in our stimuli, as shown in Figure 4, using a texture-synthesis technique from computer graphics, observers’ judgments were correspondingly altered. A computer-vision style model based on these statistics was able to estimate surface reflectance from our stimuli with an accuracy similar to that of human observers ( $r^2 = 0.7$ ) [2]. These findings, along with a novel visual aftereffect based on the skewness statistic [1], led to the conclusion that there is a strong connection between the luminance-based statistics we identified and the perceived reflectance for surfaces like the ones in Figure 2.

We measured the ability to identify material categories with photographs like the ones in Figure 3 and found that observers could categorize materials (e.g., fabric vs. non-fabric) in exposures as brief as 40 ms. We wanted to understand if this performance, in spite of our careful stimulus design, was due to observers merely recognizing color, shape, texture, or object properties. Therefore, we conducted additional experiments with stimulus manipulations that either preserved *only* the color, shape, or texture information (e.g., by using a technique from computer graphics as shown in Figure 4) or dissociated object and material information (e.g., by using images like the one of the woolen Oreo cookie in Figure 3). We found that observers were unable to distinguish material categories when given only one type of information (color, shape, or texture), and that they did not require object information (e.g., Oreo cookie) to recognize material properties (e.g., that the cookie was made of wool). A computer-vision style model [3, 4] based on local color, texture, and edge information supported these perceptual findings (performance at material category recognition, humans: 91%, our model: 44.6%, competing model: 23.8%, chance: 11%). Taken together, our results demonstrate that material category recognition is a basic visual ability that is distinct from simple judgments of either color, texture, shape, or shape-based object identity.

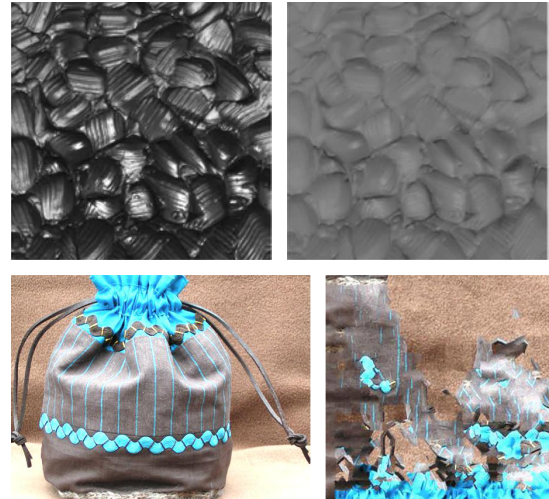


Figure 4: Examples of stimulus manipulations. (Top) A well-known computer-graphics technique was used to force the luminance-based statistics of (left) a dark, glossy surface to match those of light, matte surface producing (right) a significant change in perception. (Bottom) A different computer-graphics technique was used to isolate texture information from (left) an image containing fabric surfaces to create (right) a ‘texture-only’ version where it is hard to identify the original materials.

## Future Directions

I plan to continue incorporating techniques from computer vision and computer graphics into the study of visual perception. As these techniques evolve and are able to capture and model more of the complexity of real-world conditions, we will gain newer ways of probing visual abilities. In addition, I plan to extend my research program to include the study of problems like the perception of *illumination*, *texture*, *3-D shapes*, and *human form* as well as *applications* of perceptual methods in computer science.

**Surface appearance.** Aspects of surface appearance such as color, reflectance, texture, 3-D shape, and materials, as well as the factors that influence surface appearance like illumination have mostly been studied in isolation from each other. In images of the real world, all of these variables are confounded with each other and are difficult to separate. Studying the different aspects of surface appearance in isolation is not always possible and not always desirable either. In our work on reflectance perception [1, 2], studying reflectance properties in the presence of complex surface geometry helped identify limitations of previous theories of reflectance perception. For material category recognition, our results suggest that color, texture and shape information while not useful in isolation can be combined to improve recognition performance [3, 4]. In ongoing work, we are investigating the influence of the 3-D geometry on the ability to spot illumination inconsistencies in real-world photographs. I believe that the various aspects of surface appearance that have traditionally been studied as separate problems are connected to each other in ways we do not yet understand. Studying these problems with real-world stimuli forces us to address their connections. In future work, I plan to actively explore such connections between the variables that determine surface appearance.

**Human form.** My recent work has focused on the perception of the human form [6]. While there has been extensive research aimed at understanding how we perceive human bodies and human movements, most studies have considered a restricted set of stimuli (e.g., moving dots to convey human motion). I believe that the use of realistic stimuli in the form of photographs, videos, or simulations can advance our understanding of the topic. Moreover, ideas from the field of computer vision can be informative for perceptual investigations; computer-vision systems that attempt to identify human figures in real-world images and videos can lead to computational hypotheses about human visual processing. I plan to explore such hypotheses in future work on the perception of human figures.

**Applied perception.** My research in visual perception has benefited greatly from the ideas and techniques developed in computer vision and computer graphics. I believe that the knowledge of visual perception and the use of perceptual techniques can similarly benefit research in computer vision and computer graphics. The emergence of Amazon’s Mechanical Turk as a tool for computer vision research has meant that computer vision researchers now regularly conduct online perceptual experiments to evaluate their systems. However, a fast and cheap way of presenting images to human observers and obtaining their (often noisy) data is not sufficient for progress; critical thinking about the perceptual variables being tested is still required. For example, it is important to understand how the choice of the real-world images used to develop a computer-vision system affects the conclusions one can draw about the success of that system at visual recognition. In our work on material recognition, we found that a computer-vision system that could successfully recognize specific instances of real-world surfaces (> 95% accuracy) could barely distinguish high-level material categories (23.8%). Understanding when and why various computer vision (or graphics) techniques work is crucial for assessing progress. Similar to the practice in computer vision, perceptual methods are used to evaluate the success of systems in computer graphics. The correct application of perceptual techniques can help identify achievements in visual realism, and as we showed in [7], guide the development of a computer-graphics pipeline. The importance of perceptual methods in computer science is becoming increasingly apparent, and through collaborations like the ones I have pursued during my postdoctoral training at Disney Research, I plan to bridge the gap between the study of visual perception and the development of techniques in computer vision and computer graphics.

## References

- [1] Motoyoshi, I., Nishida, S., **Sharan, L.**, & Adelson, E. H. (2007). Image statistics and the perception of surface qualities, *Nature*, 447, 206–209.
- [2] **Sharan, L.**, Li, Y., Motoyoshi, I., Nishida, S., & Adelson, E. H. (2008). Image statistics for surface reflectance perception, *Journal of the Optical Society of America A*, 25(4), 846–865.
- [3] Liu, C., **Sharan, L.**, Rosenholtz, R., & Adelson, E. H. (2010). Exploring features in a Bayesian framework for material recognition, *IEEE Conference on Computer Vision and Pattern Recognition*, 239–246.
- [4] **Sharan, L.**, Liu, C., Rosenholtz, R., & Adelson, E. H., A perceptually-guided approach for recognizing materials in single images, *under review*.
- [5] **Sharan, L.**, Rosenholtz, R., & Adelson, E. H., Material categorization in real-world images is fast and accurate, *in preparation*.
- [6] **Sharan, L.**, Sigal, L., & Hodgins, J. K., The perception of human body poses and implied actions in real-world images, *in preparation*.
- [7] De Aguiar, E., **Sharan, L.**, Mahler, M., Shamir, A., & Hodgins, J. K., Perceptually guided capture and stylization of small-scale 3D human figures, *in preparation*.

## Teaching Statement

Lavanya Sharan

I received an undergraduate education in electrical engineering, a graduate education in computer science, and training in the field of psychology during my doctoral studies. My unique background has allowed me to experience teaching methods in a variety of disciplines and it has equipped me to teach topics across and between disciplines. My approach to teaching is influenced by my experiences as a student and later, as a teacher. Conveying *why* a particular topic is interesting, or even exciting, is as important as teaching the specifics at hand. Engaging students in classroom or online discussions and making them active participants in the learning process is also crucial for effective teaching.

**Teaching Approach and Teaching Experience:** As I made my way through different departments and institutions in my student career, I encountered many wonderful teachers who left a lasting impression on me. I remember these teachers fondly not only because they could explain concepts clearly and were effective teachers, but also because I enjoyed their classes. Like a favorite television show, I looked forward to each lecture and I was a little sad when the semester was over. Not all classes were as memorable. There were many where I did not feel as engaged, or as excited. When I look back and try to understand which teaching strategies worked and which ones did not (at least for me), a few themes emerge:

- *Good teachers love teaching.*

When a teacher enjoys the process of teaching, the students can sense it and they respond to it. Learning becomes much easier and more fun.

- *Show them the big picture.*

A good teacher understands that conveying every detail of a particular topic is not the point of teaching. Details can be found in books or lecture notes or online tutorials. Conveying high-level ideas and conveying why these ideas are important or interesting or novel (for their time) is far more useful.

- *Engage them or lose them.*

When students are engaged in the classroom, they ask questions and they participate in discussions. Good teachers encourage students to ask questions, they promote discussions, and in general, they make learning an interactive process.

I incorporated these lessons into my teaching, first as a graduate teaching assistant and then as a co-instructor for a graduate class. Along the way, I also learned several new lessons. For example, as a teaching assistant for *6.002 Electronic Circuits*, I conducted weekly tutorial sessions where the goal was to ensure that the students had understood the lecture material and were in a position to solve the problem sets. I realized that getting students to speak up during these sessions was not as easy as simply posing a question to the class. Our teaching policy discouraged ‘cold calling’ on students, so I had to find a way to get the students in my tutorial sections to participate in the classroom. After trying a few different strategies, I found that the strategy that worked best involved posing a question of medium difficulty and asking students to come up with ideas for finding the answer, rather than the answer itself. By making the question accessible to most students, and by arriving at the answer in a series of steps, I was able to get my students to participate in the classroom.

Another aspect of teaching that I learned on the job was helping someone think through a problem. As a teaching assistant for *6.02 Digital Communication Systems*, I was responsible for helping students complete weekly problem sets and for grading their solutions. Some students would come to me during

office hours or laboratory sessions because they were stuck on a problem and they wanted me to give them the solution. I could understand their frustration, but I wanted them to arrive at the solution on their own. I found that asking the students to present their efforts to me while thinking aloud would often make them realize where they had gone wrong. Sometimes, students needed a few hints. Sometimes, the process of thinking aloud helped identify gaps in their understanding of the lecture material that I could then rectify. In all cases, it was rewarding as a teacher to help students achieve a breakthrough in their thinking about a problem.

One piece of advice that I received about teaching is that teaching is really re-learning what you thought you knew. As I began to co-teach a graduate class, I realized how true that was. Explaining complicated material to a new audience forces one to rethink the key ideas and to find ways to connect those ideas with what the audience already knows. This process of revisiting and rearranging ones' thoughts can be quite illuminating. The graduate class that I co-taught, *16-899A Pixels to Percepts* (<http://graphics.cs.cmu.edu/courses/P2P/>), involved preparing lectures on visual perception for a computer science audience. As an interdisciplinary researcher, I have often had to do the opposite, i.e., explaining computer science concepts to visual perception researchers. In both cases, I find that convincing the audience *why* the knowledge of a different field can be useful in their own fields is essential. Once the audience is sold on a few applications of this new knowledge, they are willing to learn more. Making such a case for visual perception in my lectures gave me a new perspective on my own research on visual perception. I plan to use this principle of addressing the 'why' question first in my future teaching endeavors to motivate students about learning new topics.

**Mentoring Experience:** In addition to teaching, I have also had the opportunity to advise and mentor undergraduate students in research projects. As a graduate student, I mentored four such students, most of whom had never had any exposure to research. Teaching someone how to do research while I was still learning how to do it myself was quite enlightening. I encountered two challenges in mentoring these students. First, I had to convince students that research requires far more patience and perseverance than they were used to in their classes. Second, I had to teach them that simply getting a result is not enough; one needs to ask what the result tells us about the problem at hand. Different students reacted differently to these lessons. For some, the experience contributed to their excitement about research in general and led them to graduate school. For others, the uncertainty of research made them realize they wanted to create applications for existing knowledge rather than contribute to the discovery of new knowledge.

In my postdoctoral career, I have mentored two senior undergraduate students and one Masters-level student in research projects. These students had some research experience already and had more clearly defined interests and career goals. With these students, the challenge was finding the right research project for each person. I was able to guide these students in directions that played to their strengths and interests, but also gave them opportunities to acquire new skills and to participate in graduate-level research. One of the undergraduate student projects led to a presentation at a top-tier conference. Given the opportunity to advise doctoral graduate students, I would similarly encourage them to pursue projects within my research program that are the right fit for their individual goals.

**Teaching Interests:** I look forward to teaching and mentoring undergraduate and graduate students. I feel confident about teaching classes in my area of expertise, human visual perception, at introductory and advanced levels. I can also teach certain introductory classes in psychology (e.g., sensation and perception, computational neuroscience, and research methods). I am particularly excited about designing interdisciplinary graduate-level classes on computational methods for studying perception and on the applications of perception for computer science, similar to the class I co-taught at Carnegie Mellon University.