Seeing jelly: judging elasticity of a transparent object

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Abstract

Taking advantage of computer graphics technologies, recent psychophysical study on material perception has revealed how human vision estimates the mechanical property of objects, such as liquid viscosity, from image features. Here we consider how human perceive another important mechanical material property — elasticity. We simulated scenes in which a transparent cube falling on the floor, while manipulating the elasticity of the cube. We asked observers to rate the elasticity using a 5-point scale. Human observers were quite sensitive to the change in the simulated elasticity of the cube. In comparison with the original condition, the elasticity was overestimated when only the cube contour deformation was visible, whereas underestimated when the cube contour deformation was hidden and only internal optical deformation was visible. The effects of contour and optical deformations on elasticity rating were almost the same when the observers viewed white noise fields that reproduced the optical flow fields of the cube movies. Increasing frame duration (which decreased image speed) also increased the apparent elasticity. These results suggest that human elasticity judgment is based on the pattern of image motion arising from contour and optical deformations. This scientific finding may provide a hint for computationally efficient rendering of perceptually realistic dynamic scenes.

Keywords: material perception, elasticity, deformation

Concepts: •Computing methodologies → Perception;

1 Introduction

A computer graphics with high physical fidelity provide vision scientists a powerful tool to clarify how we visually recognize material properties of objects. In particular, for investigating the perception of optical properties of materials such as specularity [Pellacini et al. 2000], transparency [Fleming et al. 2011] and translucency [Xiao et al. 2014], computer graphics become an indispensable technique to appropriately control experimental stimuli on the basis of simulation of accurate light transports. Not only optical properties, but also mechanical properties such as viscosity and elasticity are the important constituents of material perception [Adelson 2001] and can be well simulated with computer graphics. Taking advantage of physics engine to simulate fluid flows, previous studies have uncovered visual information which was necessary to recognize liquid and its viscosity [Kawabe et al. 2015a; Kawabe et al. 2015b; Paulun et al. 2015; van Assen and Fleming 2015].

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Figure 1: (a) A camera view of three video frames in an experimental movie in which an elastic cube falls on the floor. (b) A top view of the same scene (except for the floor color being changed into black uniform matte) showing how the surface orientation that produces the optical deformation in the camera view dynamically changes.

It has been proved that the judgment for the mechanical properties of materials is sensitive to dynamic image information. For example, [Kawabe et al. 2015a] showed that the human visual system utilized image motion speed as a cue to liquid viscosity and spatial smoothness of motion flow as a cue to liquid flow. [Kawabe et al. 2015b] demonstrated that dynamic image deformation due to refraction of light was a strong clue to seeing the layer of transparent liquid.

Besides liquid, seeing elastic objects is also dependent critically on the dynamic components of visual information. [Warren et al. 1987] found that the human observers exploit the temporal pattern of a ball trajectory as a cue to the elasticity (i.e., a physical ability of an object to resist an external stress and return to an original state when the stress is removed). Based on the trajectory, human observers can estimate the elasticity, and at the same time, predict the future trajectory of the ball [Nusseck et al. 2007]. By using the deformation of a two-dimensional subjective square which was

induced by four pack-men, it has been clarified that an oscillation phase difference between top and bottom sets of pack-men was a strong factor to determine the apparent elasticity of the subjective square [Masuda et al. 2013; Masuda et al. 2015; Warren et al. 1987]. Graphics related research also paid attention to human perception of object deformations to develop perceptually effective rendering techniques. [Garca et al. 2010] has proposed to integrate local and global deformations to simulate perceptually-compelled deformation of objects. [Argelaguet et al. 2013] showed that the simulated local deformation of surface, which was triggered by a users mouse click, could serve as an effective cue to pseudo haptics.

The previous investigation on human elasticity judgment only considered the visual deformation of objects with opaque surfaces. Though a recent study elegantly showed the role of surface appearance in judging the deformability and stiffness of an object [Han and Keyser 2015], it is still unclear what sort of image feature is important for the judgment on the elasticity-related material properties of transparent objects. The present study attempted to unveil image features contributing to the human elasticity judgment in a more complex and photorealistic scene using a transparent elastic jelly-like object which complexly refracts light from its background.

In the next section, we analyze the temporal pattern of image motion generated by the deformation of a transparent object. We then describe the results of three psychophysical experiments. In Experiment 1, we examined whether human observers could visually recognize the elasticity of the transparent object, and also explored the relationship between the temporal pattern of image motion speed and the elasticity judgment. In Experiment 2, by using noise motion display in which two-dimensional white noises were shifted according to the optical flow fields of an elastic object, we examined whether the dependency of the elasticity judgment on the image motion pattern could be reproduced even with the noise motion display. In Experiment 3, we examined how the frame duration, which changed the temporal characteristics of the image including motion speed, affected the elasticity judgments. In the last section, we discuss the possible implications of the present findings for scientific understanding of human material perception, as well as for vision-realistic rendering of elastic objects by computer graphics.

2 Image analysis and our goal

In this section, we first describe how an elastic cube physically deforms, and second analyze the image motion field that the cube deformation generates. We graphically simulated an elastic cube that falls on to the floor (Figure 1) by using a softbody simulation implemented in Blender (<https://www.blender.org/>). As shown in Figure 1a and 1b, the cube shape non-rigidly deformed across frames. We allowed the surface of the cube to be non-rigidly bended (Figure 1b). The surface bend produced the dynamic change in the local surface orientation across frames. Because we gave the refraction index of 1.5 to the cube surface, the light refraction at the non-rigidly bending surfaces produced the optical image deformation of the background which could be seen through the cube body. In this vein, we would like to focus on the following two image deformations; one comes from the deformation of the cube contour and the other comes from the optical deformation of background image that appears inside of the cube.

We changed the elasticity of the cube by manipulating the push/pull parameters of the Blenders softbody simulation. The push parameter is related to how much the simulated softbody resist being scrunched together, like a compression spring while the pull parameter is related to how much the edges are allowed to stretch (see https://www.blender.org/manual/de/physics/soft_body/interior_forces.html for more details about the model used in soft-

body simulation).

We separately analyzed the image motion pattern coming from the contour deformation and that from the optical deformation. To focus on the image motion pattern from the contour deformation, and to remove the involvement of optical image deformation, we rendered the similar-shaped elastic cube having uniform surface color (with neither shadow nor shading) (Figure 2b) to create the silhouette-like appearance of the cube. To keep the other conditions similar to the original transparent condition, we situated the silhouette cube in the same natural scene. We call this scene condition contour deformation. To focus on the image features from optical deformation, and to remove the involvement of contour deformation, we limited an image region by using a circular aperture (Figure 2c). We call this scene condition optical deformation.

Based on the optical flow fields calculated by means of an established algorithm [Sun et al. 2010], we calculated the mean absolute speed of vertical motion vectors for the contour and optical deformation conditions (Figures 2d-e). We focused on the vertical motion vectors because generated image motion occurred mainly in the vertical dimension.

For the contour deformation condition (Figure 2d), the image motion shows a low baseline. There are a few strong transient peaks for low elasticity (0.55), while not for high elasticity (0.95). The effect of elasticity on image motion is obvious, with the speed being higher for low elasticity. In comparison, for the optical deformation condition (Figure 2e), the base line is high, and transient peaks are not so evident. The effect of elasticity on image motion is qualitatively similar, but small in magnitude. Figure 3 also shows the difference in spatiotemporal patterns of image motion between the contour and optical deformations.

The analysis shows how the image motion pattern of an elastic transparent cube changes according to the contour/optical deformations and the elasticity. In the following experiments, we examined the performance of the human observers to perceive the elasticity under the three presentation conditions. There are three possible results. (a) Observers cannot judge the simulated elasticity at all, since they have no ability to do so, or our simulation was unacceptably wrong. (b) They can correctly judge the simulated elasticity (i.e., the same performance for the three stimulus conditions). (c) They can judge the elasticity with some accuracy, but show biases dependent on the stimulus condition. The last possibility is likely to happen if the observers judgment relies on some dynamic image cues correlated with the physical elasticity, including image speed.

3 Experiment 1

3.1 Purpose

The purpose of this experiment was to examine whether human observers could appropriately judge the difference in object elasticity, and to explore the relationship between the temporal pattern of image motion speed and the resultant elasticity judgments. In the transparency condition, we examined whether the observers could judge the elasticity of a transparent object which complexly refracts light from its background. In the other two conditions, we examined what sort of image features was important for the elasticity judgment. Specifically, the contour and optical deformation conditions respectively focused on how visual information along contours and that within surface could contribute to the elasticity judgment.

Figure 2: Snapshots of stimulus movies as used in (a) transparency, (b) contour deformation, and (c) optical deformation conditions of Experiment 1. The temporal pattern of the mean absolute speed of vertical motion vectors in (d) contour deformation, and (e) optical deformation conditions. Blue thick lines and red thin lines show the image motion speed of an elastic cube with the elasticity of 0.55 (low) and 0.95 (high), respectively.

3.2 Method

3.2.1 Observers

Sixteen people served as observers. They were naive as to the purpose of this study, and had normal or corrected-to-normal visual acuity. This and following experiments were conducted on the basis of ethical approval obtained from the ethical committee at Nippon Telegraph and Telephone Corporation (NTT Communication Science Laboratories Ethical Committee). In addition, the experiments were conducted according to the principles laid down in the Helsinki Declaration. Written informed consent was obtained from all participants except the authors.

3.2.2 Apparatus

To show visual stimuli, we used a 21-in. CRT monitor (GDM-F500R, Sony). The spatial and temporal resolution of the monitor was 1024×768 pixels and 60 Hz, respectively. A computer (Mac pro, Apple) with MATLAB and its extension (PsychToolBox 3, [Brainard 1997; Pelli 1997]) controlled stimulus presentation and data collection.

3.2.3 Stimuli

Blender was used to generate stimulus movies. Each of stimulus movies spatially subtended approximately 16×16 deg of visual angle. The movies contained computer-rendered scenes in which a cube fell on the wooden floor in a white-wall room under global lighting with ambient occlusion and indirect lighting (Figure 1). The simulated size of the cube was $25 \times 25 \times 25$ cm. The cube consisted of 125 subdivided cubes with each of size being $5 \times 5 \times 5$ cm. Geometrical discontinuity among these cubes was smoothed by using the built-in function of Blender. On the first frame of simulation, the center of the cube was positioned at the height of 50 cm from the floor, and on the second frame, started falling on the floor according to the gravity. We used the scenes after the 11th frame in which the cube landed on the floor. Even after the landing, the cube continued to deform vividly. The physics simulation of the elastic cube was sampled at 30 Hz. We created the sequence of 90 frames, of which 60 frames (from 11th to 70th frames) were used as video frames of a single experimental movie. One edge of the cube always faced toward the participants. The elasticity of the cube was controlled by changing the physics engine parameters of pull and push for spring. We manipulated those values between 0.55 and 0.95 with the step size of 0.1. When we made the parameters below 0.55, the cube could not retain an original cube shape after a collision. The maximum value of the parameters was 0.999, but the Blender tutorial recommended to use lower values than this

Figure 3: (a) A density map of the optical flow field between the second and the third video frames of a falling cube with the elasticity of 0.55. Upward and downward image motions are mixed together inside of the cube. (b) The right panel shows the temporal pattern of the vertical speed of the image motions, taken from the rectangle region in the left panel in a pixel-wise manner, and averaged horizontally. Rapid image motions appear not only around the contours, but also deep inside the cube (see, e.g., between 25th and 30th frames and 45th and 50th frames).

because the simulation could go unstable.. Other values such as damp and bending were fixed at 0.5 and 0.025, respectively. Thus, we examined five levels of elasticity. As described in the second section, there were three conditions of the cube surface. First, in the transparency condition (Figure 2a), the cube was given a transparent surface with refractive index of 1.5 (iteration depth was 24), and thus, the three-dimensional surface change of the cube generated the optical image deformation of the background seen through the cube body. The surface of the cube did not have specular reflection components. The surface was also given yellowish color (RGB values were 0.888, 1.000, 0.218) while the color was mixed with the background by means of alpha blending with the alpha value of 0.5. Second, in the contour deformation condition (Figure 1b), the surface of the cube had neither diffuse nor specular components. Only the shadeless yellowish color was given. Third, in the optical deformation condition (Figure 1c), the movies of the refraction-based transparency condition were viewed through a circular aperture in a uniform neutral grey field. The diameter of the aperture was 8 deg.

3.2.4 Procedure

Each observer was tested individually. The observer was asked to sit 60 cm from the CRT monitor. She/he started each session by pressing the space key on the keyboard of the computer. After 1 second delay, a stimulus movie, which lasted for 2 seconds, was repeatedly presented with the inter-repetition interval of 1 second. On each trial, single movie was selected from 15 (3 surface conditions $\times$ 5 elasticity levels) alternatives, and presented with the observers. The task of observers was to view the movie, and rate the elasticity by using a 5-point scale. They gave "1" for the lowest elasticity and "5" for the highest elasticity. We explicitly asked them to rate the elasticity as material property of the cube, not the shape deformation, by giving them an instruction in Japanese to evaluate Danryoku which has several meanings including elasticity, bounciness, stiffness, and springiness. Each observer received two sessions of 150 trials (3 surface conditions $\times$ 5 elasticity conditions $\times$ 10 repetitions). Within and between sessions, the order of trials was randomized across the observers. It took approximately 10 minutes for the observers to complete single session.

3.3 Results and Discussion

For each observer, the rating values for elasticity impression were averaged for each condition. The data averaged across the observers are shown in Figure 4, which were submitted to the two-way re-

peated measures analysis of variance (ANOVA) with surface conditions (3 levels) and elasticity (5 levels) as within-subject factors. The main effect of surface conditions was significant [$F(2, 30) = 142.56, p < 0.0001, \eta_p^2 = 0.905$]. Multiple comparison tests (Ryan's method) showed that each of three surface conditions was significantly different from another (at least $p < 0.001$). The main effect of elasticity was also significant [$F(4, 60) = 95.60, p < 0.0001, \eta_p^2 = 0.864$]. Multiple comparison tests (Ryan's method) showed that each of five elasticity conditions was significantly different from another (at least $p < 0.005$). Interaction between the two factors was also significant [$F(8, 120) = 10.38, p < 0.0001, \eta_p^2 = 0.408$]. Post-hoc tests revealed that no significant difference was observed between transparency and optical deformation conditions ($p > 0.05$) when elasticity level was lowest (with the pull and push values of 0.55).

Consistent with the previous studies using simpler scenes [Warren et al. 1987; Nusseck et al. 2007], the results show that the human observers were sensitive to simulated object elasticity. (From another perspective, the results indicate the quality of our graphic simulation to be high enough for the observers to reliably judge the objects elasticity.) Furthermore, the rated elasticity changed in accordance with the simulated elasticity either when the observers viewed the outer contour deformation only, or the inner optical deformation only. This implies that either type of image deformation contains the cue to judge elasticity.

The rated elasticity was generally high for the contour deformation conditions, while low for the optical deformation conditions. Between the rated values of the two conditions was the rated elasticity for the transparency conditions, where both contour and optical deformations were available to the observers. The pattern of difference among the stimulus conditions is consistent with the idea that the observers used, at least partially, the image motion speed for judging elasticity. Figure 2 shows that the average image motion speed is higher for low elasticity than for high elasticity. The same figure also indicates that the average speed tends to be higher for the optical deformation than for the counter deformation. If the observers simply exploit the knowledge about the relationship between image motion speed and elasticity, they will estimate the elasticity to be higher for the contour deformation conditions than for the optical deformation condition, as our results actually show.

Figure 4: Experiment 1 results. Error bars represent $\pm$ standard errors of mean.

4 Experiment 2

4.1 Purpose

If the human observers relied their elasticity judgments on the image statistics about motion speed, the similar pattern of elasticity judgments should be obtained even when the cube movies are replaced by dynamic random noise patterns which had the optical flow fields of the elastic cube, but not the spatial pattern. In this experiment, we investigated whether the motion signals of dynamic image deformation was sufficient information for the observer to judge the cube elasticity. Our approach was similar to that [Kawabe et al, 2015a] took to examine image motion features for perceiving liquid viscosity, but here we used a ‘dense noise motion display, instead of a sparse one used by [Kawabe et al, 2015a], in order to present a fine structure of image motion features which were generated by a transparent object.

4.2 Method

4.2.1 Observers

Fifteen people served as observers. Of which, six observers had participated in Experiment 1 while they were still naive as to the purpose of the experiment.

4.2.2 Stimuli

In the transparency condition (Figure 4a), stimulus movies consisted of the sequence of dynamic two-dimensional white noises in which pixel values were drawn from a uniform distribution ranging from 0 to 255. We calculated optical flow fields of cube simulation movies as used in Experiment 1. Based on motion vectors of the calculated optical flow, we shifted the pixel values of white noises. We noticed that in the course of this manipulation, there were some

pixels that missed pixel values because of the shift of pixel values toward the outside of stimulus areas and/or the shift towards the identical pixel from different pixels. The vacant pixels were filled with random values drawn from the uniform distribution. The optical flow fields were calculated for 59 sequential pairs of frames. On the initial frame of the stimulus movie, we randomly determined the pixel values in white noise, and on the following 59 frames, the shifted white noise sequences were used. In the contour deformation condition (Figure 4b), on the first frame, the pixel values in a two-dimensional white noise image were randomly determined. On and from the second frame, the pixel values of the white noise in the previous frame were replaced by the new value drawn from the other two-dimensional white noise at the pixel location in which the absolute values of the pixel-value difference between the sequential frames of the graphical simulation movies of the no surface feature cube was non-zero. The non-zero values of the absolute difference mainly appeared at the contour of the cube. Thus, we could efficiently extract the contour motion only. In the optical deformation condition (Figure 4c), the movies in the transparency condition were seen through apertures with an 8 deg diameter.

4.2.3 Procedure

The procedure was identical to the one as used in Experiment 1.

4.3 Results and Discussion

As conducted in Experiment 1, the rating values for elasticity impression were averaged for each condition, and the data averaged across the observers are shown in Figure 4d, which were again submitted to the two-way repeated measures analysis of variance (ANOVA) with surface conditions (3 levels) and elasticity (5 levels) as within-subject factors. The main effect of surface conditions was significant [$F(2, 28) = 68.14, p < 0.0001, \eta_p^2 = 0.829$]. Multiple comparison tests (Ryan’s method) showed that the rating value in the contour deformation condition was significantly different from the other two ($p < .0001$) while the rating value in the transparency condition was not significantly different from the one in the optical deformation condition ($p > 0.5$). The main effect of elasticity was also significant [$F(4, 56) = 56.36, p < 0.0001, \eta_p^2 = 0.786$]. Multiple comparison tests (Ryan’s method) showed that each of five elasticity conditions was significantly different from another (at least $p < 0.005$) except the following pairs of elasticity: 0.65-0.75, 0.75-0.85, and 0.85-0.95 ($p > 0.05$). Interaction between the two factors was also significant [$F(8, 112) = 7.61, p < 0.0001, \eta_p^2 = 0.352$].

The results indicate that the human observers exploit the temporal pattern of image motion speed to judge object elasticity. Similarly to the results of Experiment 1, the judged elasticity in the contour deformation condition was significantly higher than the one in the transparency and optical deformation conditions. Moreover, the observers could differentiate the cube with different elasticity even for dynamic white noise movies.

One notable difference of the results obtained with noise stimuli from those obtained with the original cube stimuli was the lack of difference between the transparency and optical deformation conditions. One possible reason was low visibility of the deforming contour. We therefore conducted an experiment in which a noise-defined elastic cube was presented on a uniform gray field, not on the white noise background, to increase the visibility of the contour. The data ($N = 6$) were submitted to a two-way repeated measures ANOVA, and the results showed that the main effect of surface condition was significant ($[F(4, 20) = 10.658, p < 0.0001]$). Multiple comparison tests showed that the contour deformation condition was significantly different from other two conditions [$p <$

0.0001] while the transparency condition was not significantly different from the optical deformation condition [$p > 0.05$]. The results suggest that the lack of difference between the transparency and optical deformation conditions cannot be ascribed to the low visibility of the contour.

Another possible reason was the failure of segregation between motion signals coming from the contour deformation and those coming from optical deformation. In general, motion signals are spatially pooled to form the representation of coherent motion [Amano et al. 2009a], especially when the spatial frequency components of adjacent motion signals are similar to each other [Amano et al. 2009b]. In our stimuli, we used dynamic shifts of white noises by optical flow fields of the original graphical simulation, ignoring the spatiotemporal variations of the spatial frequency and orientation components. Thus, it is possible that there were less cues to effectively segregate contour-based from surface-based motion signals in our noise motion display. It is a future task to examine whether the addition of richer form information can enhance the segregation, and consequently restore the relatively high elasticity impression in the refraction-based transparency condition.

Figure 5: (a-c) Stimuli as used in the transparency(a), contour deformation(b), and optical deformation(c) conditions of Experiment 2. (d) Experiment 2 results. Error bars represent $\pm$ standard errors of mean.

5 Experiment 3

5.1 Purpose

The experiments so far suggest that human observers exploit image motion to judge elasticity of objects. The last experiment examined whether the elasticity judgment is based on the negative relationship between that elasticity and the average image speed. Here we manipulated the frame duration of the original simulation movies. As the frame duration is increased, the motion speed decreases. If the human elasticity judgment relies on the negative relationship between elasticity and image speed, the rated elasticity should increase. It should be however noted that as the frame duration is increased, the temporal oscillation becomes slower. As you can see in Figure 2e, the increase in elasticity not only makes the image speed slower, but also makes temporal oscillation faster. Therefore, if the rate of oscillation is a more prominent cue to elasticity judgments than the image speed, as the frame duration is increased, the rated elasticity might decrease.

5.2 Method

5.2.1 Observers

Six people served as observers. All had participated in Experiment 2 while they were still naive as to the purpose of the experiment.

5.2.2 Stimuli

Stimuli were identical to those as used in Experiment 1 except the following. In this experiment, we used four levels of frame durations (33, 66, 133, and 266 msec). The duration of 33 msec was identical to the duration as used in Experiment 1.

5.2.3 Procedure

The procedure was identical to the one as used in Experiment 1 except the following. Each observer received five sessions of 120 trials (4 frame duration $\times$ 3 surface conditions $\times$ 5 elasticity conditions $\times$ 2 repetitions).

5.3 Results and Discussion

For each observer, the rating values for elasticity impression were averaged for each condition. The data averaged across the observers are shown in Figure 5, which were submitted to the three-way repeated measures analysis of variance (ANOVA) with frame durations (4 levels), surface conditions (3 levels) and elasticity (5 levels) as within-subject factors. The main effect of frame durations was significant [$F(3, 15) = 4.85, p < 0.02, \eta_p^2 = 0.493$]. Multiple comparison tests showed that the rating value in the 266 msec condition was significantly different from the value in the 33 msec conditions. The main effect of surface conditions was significant [$F(2, 10) = 30.57, p < 0.0001, \eta_p^2 = 0.859$]. Multiple comparison tests (Ryan's method) showed that the contour deformation condition was significantly different from other two conditions (at least $p < 0.001$). The transparency condition was not significantly different from the optical deformation conditions ($p > 0.05$). The main effect of elasticity was also significant [$F(4, 20) = 20.56, p < 0.0001, \eta_p^2 = 0.804$]. Multiple comparison tests (Ryan's method) showed that "0.95" condition was significantly different from "0.55", "0.65", and "0.75" conditions ($p < 0.001$). "0.55" condition was significantly different from "0.75" and "0.85" conditions, respectively ($p < 0.002$). Interaction between frame durations and surface conditions was significant [$F(6, 30) = 3.38, p < 0.02$]. Post-hoc tests

Figure 6: Experiment 3 results for (a) transparency, (b) contour deformation, and (c) optical deformation, respectively. Error bars represent $\pm$ standard errors of mean.

(multiple comparison tests of the significant simple main effect) revealed that the transparency condition was significantly different from the optical deformation condition when the frame duration was 66 msec ($p < 0.05$) while the difference was marginally significant when the frame duration was 33 msec and 133 msec ($p < 0.08$) and not significant when the frame duration was 266 msec ($p > 0.05$). Interaction between frame durations and elasticity was also significant [$F(12, 60) = 2.16, p < 0.03$].

The frame duration influenced elasticity judgment. Namely, the rated elasticity increased with the frame duration, indicating that the slower image motion speed likely increases the apparent elasticity. The results support the idea that the human visual system is sensitive to the image motion speed in judging an object elasticity.

6 General Discussion

We reported that the temporal pattern of image motion speed was critical to the elasticity judgment. In particular, human observers judged object elasticity by utilizing image motion patterns coming from both contour deformation and optical deformation. Moreover, image motion speed with temporal oscillation served as important cue to the apparent elasticity.

It has been already shown that image motion cues are important to recognize materials. For example, optical flow patterns are used to discriminate matte from glossy surfaces [Doerschner et al. 2011; Yilmaz and Doerschner 2014]. Moreover, the pattern of image motion speed can be utilized to discriminate the rigid from non-rigid cylinders [Jain and Zaidi 2011]. As described above, image motion/deformation is a cue to see liquid and its properties [Kawabe et al. 2015a; Kawabe et al. 2015b]. The present results provide another line of evidence that image motion provides the visual system with useful information for material perception.

Although our results showed the importance of image motion speed in the elasticity judgment, the image motion speed is not possibly a sufficient factor to judge how much elastic the object is. Computationally, elastic motion is categorized into a different class from fluid motion [Aggarwal et al. 1994; Huang 1990]. It is still an open question how human vision differentiates the two sorts of motion from each other. The previous study has shown that image motion

speed is a critical cue for the human visual system to recognize liquid viscosity [Kawabe et al. 2015a]. Hence, in order for human observers to utilize image motion speed as effective cue to elasticity or viscosity, it is necessary to in advance recognize whether the object is made of elastic or fluid material. One potential information for differentiating elastic from fluid motion is local oscillation of image motion [Masuda et al. 2013; Masuda et al. 2015]. On the other hand, the local oscillation likely occurs in a transparent water flow which distorts its background image according to refraction law [Kawabe et al. 2015b]. A previous study showed that smooth motion flows are the cue to see liquid from image motion [Kawabe et al. 2015a]. Thus, the existence of the higher-order smooth motion flow defined by local oscillation is possibly a potential cue for the human visual system to differentiate whether the object is made of elastic or fluid material. It also remains to be studied how much one can judge objects elasticity only from static shape of the object.

The present study tested human elasticity judgment only for a single scene, and introduced a hypothesis in a top-down manner. In a sense, our results only propose a working hypothesis for the mechanism to see an elasticity object. Besides image motion features that we highlighted here, there are possibly many other features that are correlated with the physical elasticity, and human vision indeed uses. It is an intriguing future direction to pursue such image features and/or perceptual rules underlying human material perception by analyzing the relationship between a variety of image features and perceptual responses to many naturalistic scenes by means of, say, machine learning and deep neural network. As a first step, it would be interesting to see the effect of changing the pattern of the objects background which likely alters the optical flow of image deformation due to refraction.

Finally, the findings about human vision could be useful to create compelling graphics of an elastic object. Our experiments suggest that given the identical elasticity in simulation, the observers judge the elasticity of the object to be different depending on whether image deformation comes from the outer contour deformation or from inner optical deformation. Even if creators tried to generate computer graphics with high physical fidelity, it is possible that the graphics are not seen in a way as the creators desire. Based on the scientific knowledge on how we see things and stuffs, we will be able to develop effective and economical techniques of the com-

puter graphics. For example, without faithfully simulating the elastic object, it may be possible to manipulate the apparent elasticity by directly modulating the magnitude of image deformation and/or spatiotemporal frequency, both of which significantly affect image motion features. Actually, based on human vision studies, useful presentation techniques have been proposed [Kawabe et al. 2016], in which addition image motion features to a static object is able to produce a vivid perceptual deformation of the object. By cheating the brain, we can get compelling expressions of computer graphics.

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