interactions. Assessing the quantitative strength of these interactions is a challenge whose results could determine what novel applications the materials might have. In their first-principles electronic-structure calculations[1], the authors establish that the chiral interactions in the atomic layer of manganese are boosted by the spin–orbit coupling of the tungsten substrate — a result in quantitative agreement with their experiment. Besides this, the agreement also nicely illustrates that first-principles electronic-structure calculations can now accurately predict complex magnetic effects[6].

Mirror symmetry is also broken in so-called multiferroic materials, in which the coexistence of magnetic order and ferroelectric order means that the electronic, optical and magnetic properties of the material are interlinked. Spiral magnetic order is known to occur in these materials, but the identification and controlled exploitation of multiferroic effects in artificial nanoscale systems is still in its infancy (see ref. 7 for a review). The effect of surface-induced chiral interactions in thin layers, or at the interfaces of multilayers or granular heterostructures, adds a new twist to the complexity of these materials.

The importance of chiral interactions at the surfaces of magnets is further augmented by the use of spin-polarized electric currents to switch magnetic states in 'spintronic' devices. Spin-polarized currents can exert a torque on magnetic states that is formally related to the chiral spin–orbit coupling observed by Bode *et al.*[1]. This similarity will motivate the study of new classes of system, such as magnetic semiconductors whose chiral interactions are artificially boosted by the choice of substrate.

Finally, Bode and colleagues' results shed new light on unusual mesoscopic-scale magnetic textures. More than a decade ago, for example, it was shown theoretically that chiral interactions support metastable vortex-like excitations, so-called skyrmions[8]. These excitations are the smallest possible micromagnetic objects — just the size of a single magnetic-domain wall[9] — and identifying them experimentally is a tough call for magnetic imaging techniques.

Now that we know that chiral interactions at surfaces can be very strong, many earlier results will have to be revisited. Chiral interactions might, for example, be responsible for a magnetic-superlattice modulation recently found in an iron monolayer on an iridium substrate[10]. These questions are more than an academic challenge: understanding and controlling the twists and turns of thin-film magnetic states could well be handy for new applications such as ultra-high-density magnetic recording media. ■

Christian Pfleiderer is at the Lehrstuhl für Experimentalphysik E21, Technische Universität München, D-85748 Garching, Germany.
Ulrich K. Rößler is at the Institute for Theoretical Solid State Physics, IFW Dresden, D-01171 Dresden, Germany.
e-mails: christian.pfleiderer@frm2.tum.de; u.roessler@ifw-dresden.de

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VISUAL PERCEPTION

A gloss on surface properties

Michael S. Landy

Humans perceive the properties of a surface by interpreting visual input. When estimating gloss and lightness, it seems that neural discrimination of simple image statistics plays a large part.

How do you tell the difference between peaches and nectarines, or between unfinished and polished wood? Many visual attributes help us to distinguish different surface materials, including lightness, colour and texture. The salient attribute shared by nectarines and finished wood is a mirror-like (specular) component of its reflectance, which is perceived as gloss or shininess. On page 206 of this issue, Motoyoshi and colleagues[1] describe a surprising discovery concerning surface perception: a simple characteristic of image statistics — the distribution of luminance values in an image, or the 'skew' — is highly correlated with judgements of gloss and lightness*. The principle can be illustrated by the manipulation of a picture in which a nectarine has been visually transformed to look more like a peach by removing a highlight (Fig. 1).

Motoyoshi *et al.* took calibrated photographs of stucco-like materials varying in albedo (dependent on the amount of black pigment in the material) and gloss (the amount of clear acrylic coating), and found that as gloss was increased, or as albedo was reduced for a glossy surface, the luminance distribution became positively skewed (see Fig. 2a of Motoyoshi *et al.*[1]). In other words, images of glossy materials are predominantly dark, with occasional bright highlights (Fig. 2). They found that human visual judgements of glossiness and lightness were correlated with histogram skew for the stucco images, as well as for photographs of other natural materials. More importantly, simply skewing the histogram of a photograph of a material caused the surface to appear glossier and darker. Finally, they found that if observers adapted to an image with positive skew, a subsequently viewed surface appeared less glossy (with the opposite result for adaptation to negative skew), indicating that humans extract something like luminance skew from images.

This finding is consistent with other work showing that humans are sensitive to image statistics for a variety of judgements. In addition to gloss, perceived surface roughness and translucency also depend on image statistics[2–4]. Skew is an example of one statistic derived from the luminance histogram. But humans are sensitive to at least three statistics of the histogram[5,6]. Perceived brightness and contrast correspond roughly to the mean and variance of luminance[7,8]. In early work[9,10], luminance statistics were found to be insufficient to account for the discriminability of texture patterns. More recent studies, however, indicate that humans are sensitive to the statistics of responses of bandpass filters — for example, simple cells in the primary visual cortex — for both texture discrimination[11] and texture appearance[12,13].

How might the visual system compute statistics such as histogram skew? The initial coding involves spatial linear filtering, which is carried out by various parts of the visual system: the centre-surround receptive fields of ganglion cells in the retina; cells in the lateral geniculate nucleus region of the brain; and the orientation-tuned receptive fields of simple cells in the primary visual cortex. Histogram statistics, and skew in particular, could be recovered from the cells with centre-surround receptive fields, for which darkness and brightness information are separately represented by 'off' and 'on' channels. Motoyoshi and colleagues[1] simulated such a model. Alternatively, such statistics might be recovered from the responses of orientation-selective simple cells in primary visual cortex[5].

Why should positive histogram skew result in both an increased perception of gloss and an apparent darkening of the surface? Many perceptual capabilities are described in terms of 'discounting'. For example, colour constancy refers to the ability, albeit

*This article and the paper concerned[1] were published online on 18 April 2007.

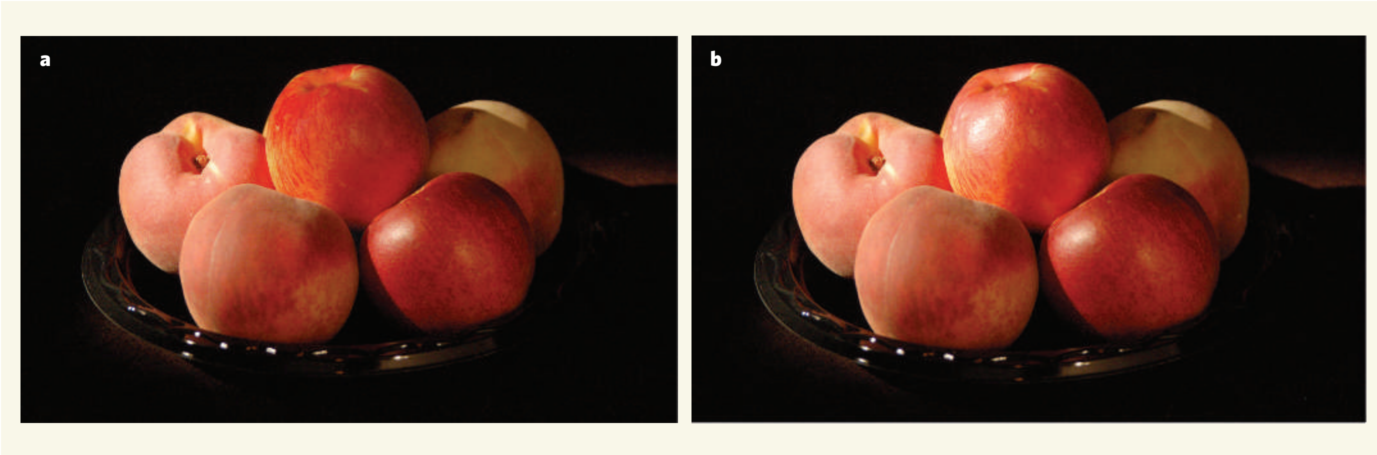

Figure 1 | Highlights from the fruit bowl. **a**, This photograph is a composite of two images, with most of the composite being a photo with highlights from a bright light source coming from the upper left. But the central fruit, which is in fact a nectarine, comes from a second photo in which the glossy highlights were removed by putting a polarizing filter on the light source and a crossed polarizer on the camera. So this normally glossy nectarine looks more like a matt peach. **b**, An unmanipulated image of the same collection of fruit with all highlights present. (Photos by Yun-Xian Ho.)

incomplete, of observers to estimate surface colour independently of the spectral power distribution of the illuminant, thus discounting the illuminant in the interpretation of the retinal signal[14]. When a histogram is positively skewed, apparent glossiness is increased. Thus,

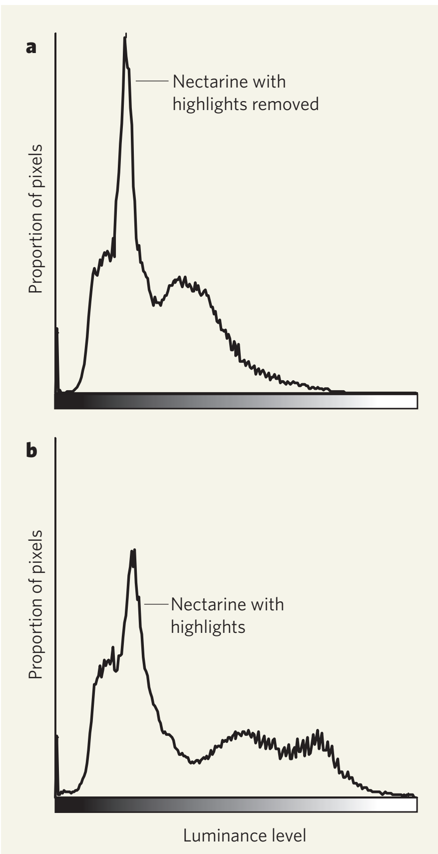

Figure 2 | Luminance distribution. Motoyoshi and colleagues[1] show how the visual system can estimate gloss, or lack of it, from the amount of positive skew in the distribution of luminance in an image. Taking the case shown in Fig. 1, the luminance histogram of the nectarine in the centre of the fruit bowl is less positively skewed without highlights (**a**) than with highlights (**b**).

pixels in the positive tail of the luminance distribution are interpreted as highlights (mirror reflections of the illuminant), and then discounted in interpreting surface lightness[15]. Lightness then becomes a function of the remaining, darker pixel values. This explains why an increase in perceived glossiness is often associated with decreased lightness.

There is, however, another possible explanation of the correlation of image skew with judgements of both gloss and lightness. Parameters of a luminance histogram (mean, variance, skew and so on) are convenient mathematically, but might not correspond precisely to the computations used in making perceptual judgements. In fact, luminance variance is not the form of nonlinearity used by humans for estimates of image contrast[7]. If the impact of different luminance levels on judgements of glossiness were directly measured, one might find that a different nonlinearity (other than skew) is computed, such as the 'blackshot mechanism'[5,6] — which was, by design, orthogonal to the computation of mean luminance, and hence should not correlate with judgements of lightness. It remains to be seen how one can determine the perceptually relevant quantity for estimation of gloss.

Histogram statistics are not the whole story for the perception of lightness, contrast or gloss. Perceived lightness and contrast of a surface depend in a complex way on the surrounding surfaces[16]. For an image to appear glossy, it has to first look like a surface. As Motoyoshi *et al.*[1] point out, the mere presence of a positively skewed histogram is not enough. If an image is modified by randomly permuting its pixels, or by giving random phase values to its sine-wave components, the resulting image may have positively skewed luminance statistics, but will not look like a surface, so the rare, bright pixels will not look like highlights.

For a surface to appear glossy, not only must it include a specular reflectance, but the surroundings must result in a pattern of illumination consistent with the statistics of natural scenes[17,18]. There are many physical dimensions of gloss that affect the perception of surface material. The one studied by Motoyoshi and colleagues is the percentage of ambient light that is reflected in the mirror direction. Another is the degree to which the specular reflection is point-like or blurred (for example in the case of polished versus brushed metal). Its effect on perception has not been studied systematically. But although histogram skew does not explain everything about the perception of surface material, or even of gloss, it is a major step towards a theory of the perception of surface materials. ■

Michael S. Landy is in the Department of Psychology and Center for Neural Science, New York University, 6 Washington Place, New York, New York 10003, USA.
e-mail: landy@nyu.edu

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