Computational Skin Models

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Abstract

Quantitative characterization of skin appearance is an important but difficult task. Skin appearance is strongly affected by the direction from which it is viewed and illuminated. Computational modeling of surface texture has potential uses in many applications including realistic rendering for computer graphics and robust recognition for computer vision. For recognition, the overall structure of the object is important, but fine-scale details can assist the recognition problem greatly. We develop models of surface texture and demonstrate their use in recognition tasks. We also describe a texture camera for capturing fine-scale surface details. Specifically, the texture camera measures reflectance and surface height variation using curved mirrors. We discuss why measurements and models of fine scale detail are important in dermatology applications.

Introduction

Clinical dermatology has not yet benefited from the ability to standardize images in a computationally meaningful way, but the need clearly exists. Consider the impact of meaningful numbers representing skin change. By recording and plotting skin change in response to a treatment, the outcome could be predicted earlier than with visual assessment. Quantitative comparisons could be made between different treatments. The proposed research will open up an new field of quantitatively characterizing skin morphology for treatment, diagnosis and assessing response to therapy. Digital imaging as it exists today in dermatology is woefully insufficient. Point-and-click digital imaging provides almost no quantitative information. In general, the problem of skin imaging is inherently different than internal imaging methods. A camera measures light interaction with the skin surface, so the light source is a major contributing factor in a photograph. The direction at which the light source is incident on the skin has a dramatic effect on skin images (see Figs. 1 and 2.) To fully capture the skin detail, images from multiple source and camera directions should be acquired.

In this paper we discuss recent work in measuring and modeling surface detail. Traditional computer graphics and computer vision represented texture with a single image. This representation is a considerable oversimplification of the complex interaction of light with real surfaces. An important consideration is that texture or surface appearance changes drastically when the viewing and illumination direction is changes. The reason for this change is not only the surface reflectance function but also the fine scale geometry or roughness that causes occlusions, shadows and foreshortening that depends on view/illumination. Work in the literature that addresses texture change with illumination and viewing direction has grown tremendously in recent years. Some early work includes [9-11, 17, 19, 23, 26] and more recent work includes Refs. [2-5, 7, 18, 20, 22, 24, 25, 27-29].

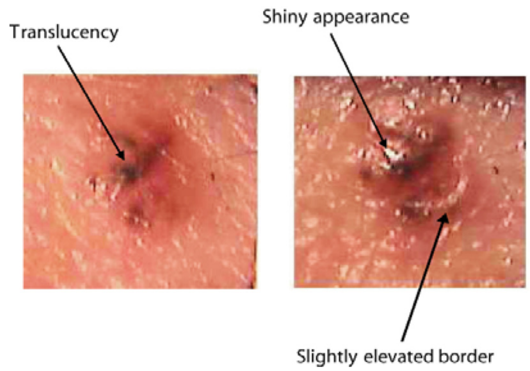

Figure 1. Two detailed basal cell carcinoma images, as the illumination is repositioned. The need for bidirectional imaging is evident from these two images, when one considers that while the left image shows that the skin surface is translucent, the right image captures the shiny aspect of the affected skin, as well as the slightly elevated border of the lesion.

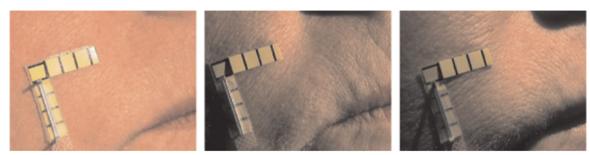

Figure 2. Skin texture in the lip region of the face, as the illumination source is repositioned. The appearance of the skin surface varies significantly, yet only the light direction is changed.

Terminology for texture that depends on imaging parameters was introduced in Refs. [12] and [13]. Specifically, the term bidirectional texture function (BTF) is used to describe image texture as a function of the four imaging angles (viewing and light directions). The BTF can be interpreted as a spatially varying bidirectional reflectance distribution function (BRDF). The BRDF is defined as the the radiance reflected from a scene point divided by the irradiance and can be written as $r(\theta_i, \phi_i, \theta_v, \phi_v)$ where θ_i, ϕ_i are the polar and azimuthal angles of the illumination direction, respectively, and θ_v, ϕ_v are the polar and azimuthal angles of the viewing direction. The dependence of r on two directions is the reason this reflectance function is bidirectional. Models of the BRDF can be quite complex in order to capture the large variation of surfaces in real world scenes. But for a textured surface, reflectance also varies spatially. To capture this additional dimension, accurate models are needed for the BTF (bidirectional texture function) which can be written as $r(x, y, \theta_i, \phi_i, \theta_v, \phi_v)$ where x, y are Cartesian coordinates on the surface.

Computational Models of Skin Texture

One model for the BTF is the Bidirectional Feature Histogram.[6] Clearly, a statistical representation makes sense when one models texture for recognition purposes. The standard framework for texture representations consists of a primitive and a statistical distribution (histogram) of this primitive over space. So how does one account for changes with imaging parameters (view/ illumination direction)? Either the primitive or the statistical distribution should be a function of the imaging parameters. Using this framework, the comparison of our approach with the 3D texton method[20] is straightforward. The 3D texton method uses a primitive that is a function of imaging parameters, while our method uses a statistical distribution that is a function of imaging parameters. In our approach the histogram of features representing the texture appearance is called bidirectional because it is a function of viewing and illumination directions. The advantage of our approach is that we don't have to align the images obtained under different imaging parameters.

The primitive used is our BTF model is obtained as follows. We start by taking a large set of surfaces filter these surfaces by oriented multiscale filters and then cluster the output. The hypothesis is that locally there are a finite number of intensity configurations so the filter outputs will form clusters (representing canonical structures like bumps, edges, grooves pits). The clustering of filter outputs are textons. A particular texture sample is processed using several images obtained under different imaging parameters (i..e. different light source directions and camera directions). The local structures are given a texton label from an image texton library (set up in preprocessing). For each image, the texton histograms are computed. Because these histograms are a function of two directions (light source and viewing direction), they're called bidirectional feature histograms or BFH. The recognition is done in two stages: (1) a training stage where A BFH is created for each class using example images and (2) a classification stage. In the classification stage we only need a single image and the light and camera direction is unknown and arbitrary. Therefore we can train with one set of imaging conditions but recognize under a completely different set of imaging conditions. Detailed results for recognizing skin images and samples in the CUReT database can be found in Refs. [5] through [7].

Measuring Skin Appearance

Rutgers Skin Texture Database

We have created a publicly available face texture database.[7] In this study, for each skin surface the BTF is sampled in 32 points, corresponding to 4 camera views, and 8 illumination directions for each camera pose. These images are high magnification and high resolution so that fine-scale skin features such as pores and fine wrinkles are readily apparent. The viewing direction is obtained with a boom stand augmented with an articulated arm allowing six degrees of freedom. Illumination is controlled by a rotating arm which spans two circles of the hemisphere of all possible light directions. The database is comprised of more than 2400 images corresponding to 20 human faces, 4 locations on each face (forehead, cheek, chin and nose) and 32 combinations of imaging angles. The complete database is made publicly available for further texture research at URL http://www.caip.rutgers.edu/rutgers texture.

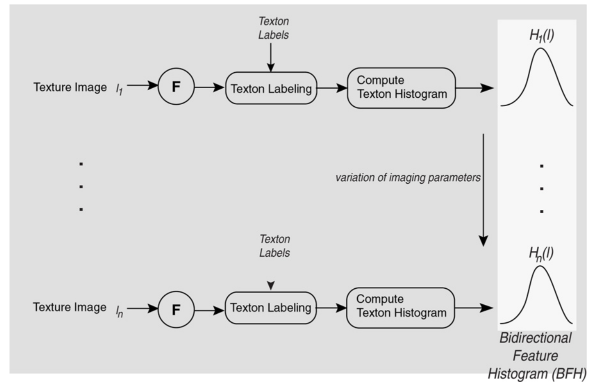

Figure 3. 3D texture representation. Each texture image I_j, j = 1. . . n, is filtered with filter bank F, and filter responses for each pixel are concatenated over scale to form feature vectors. The feature vectors are projected onto the space spanned by the elements of the image texton library, then labeled by determining the closest texton. The distributions of labels over the images are approximated by the texton histograms $H_j(l)$, j = 1. . . n . The set of texton histograms, as a function of the imaging parameters, forms the 3D texture representation, referred to as the bidirectional feature histogram (BFH).

TexCam: Novel Texture Camera

While BTF measurements are useful in texture research, measurement methods are time consuming because the light source and camera must be moved in a hemisphere of possible directions. Our approach for measuring surface detail uses a curved mirror to create a convenient imaging device where multiple views of the same surface point are realized simultaneously. The device has the significant advantage that no parts need to be moved in a hemisphere of directions. Instead, only simple planar motions of the imaging components are needed. Figure 4 illustrates the basic idea. A concave parabolic mirror focuses light to a single point. Therefore, this mirror can be used for convenient orientation of the illumination direction. An incident ray reflecting off the mirror will reach the surface at an angle determined by the point of intersection with the mirror. The light reflected from the surface point at a large range of angles is also reflected by the mirror and can be imaged by a camera. This mirror is the main component in the imaging device and the complete device enables fast multiview or bidirectional surface imaging at high spatial resolution. We summarized the device here, and the full details of the design are presented in Ref. [14].

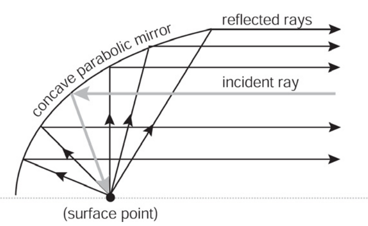

Figure 4. The focusing property of a concave parabolic mirror is exploited to simultaneously measure reflected rays from a large range of angles over the hemisphere. The same mirror is used to direct the incident illumination ray to the sample at the desired angle.

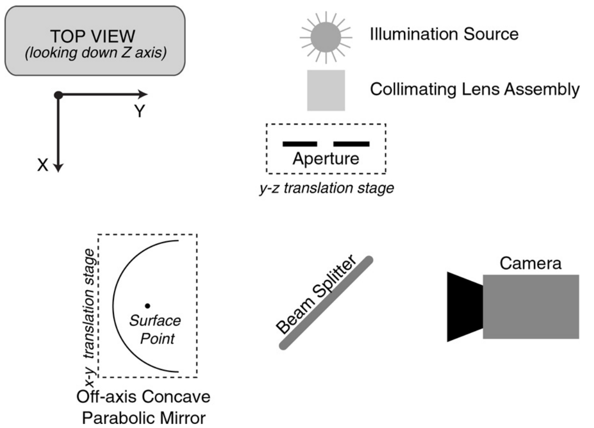

Figure 5. BRDF/BTF Measurement Device. The surface point is imaged by a CCD video camera observing an off-axis concave parabolic mirror to achieve simultaneous observation of a large range of viewing directions. Illumination direction is controlled by an aperture, i.e. translations of the aperture in the X-Z plane cause variations in the illumination angle incident on the surface point. The device achieves illumination/viewing direction variations using simple translations of the illumination aperture instead of complex gonioreflectometer equipment. Measurements of bidirectional texture are accomplished by translating the mirror in the X − Y plane.

The imaging device or *texture camera* uses optical components such as a beam-splitter, concave parabolic mirror, CCD camera, translation stages and is illustrated in Figure 5. The beam-splitter allows simultaneous control of the illumination and viewing direction. A concave parabolic mirror section is positioned so that its focus is coincident with the surface point to be measured. The illumination source is a collimated beam of light parallel to the global plane of the surface and passing through a movable aperture. The aperture ensures that only a spot of the concave mirror is illuminated and therefore one illumination direction is measured for each aperture position. In this approach, the problem of changing the illumination direction over a hemisphere is transformed to the easier problem of translating an aperture in a plane. The light reflected at each angle is reflected from the mirror to a parallel direction and diverted by the beam-splitter to the camera. The camera is equipped with an orthographic or telecentric lens that images the light parallel to the optical axis. The image of the mirror is viewed by the camera that is positioned so that its optical axis lies along the *Y* axis so that a single image corresponds to reflectance measurements from all angles in a partial hemisphere. To obtain a measurement of a surface patch for spatially varying BRDF, the concave mirror is translated along the *X-Y* plane. This arrangement also has the advantage that all light from the measurement point will reflect away from the sample and thus will not reilluminate the surface point changing the intended illumination pattern.

The approach of using curved mirrors was used by Ref. [31] who introduced a method of measuring BRDF using a half-silvered spherical mirror and a fish-eye lens that enables simultaneous measurement of light from all viewing directions without changing camera position. This device is not ideal for BRDF/BTF measurements for a few reasons. First, there is no means of automatically changing the illumination direction over the hemisphere. Second, it is designed for measuring reflectance from a single point and extended samples could cause reflection of light to the mirror and back onto the surface, changing the illumination pattern. Also, the fish eye lens is an imaging component that introduces significant distortion.

Another BRDF measurement device described in Refs. [15] and [21], uses a hemi-elliptical mirror in a hand-held device designed for industrial coating evaluation. Our device differs most significantly from this device in its method of illumination angle control. Specifically, in that device the illumination direction is changed using an additional gimbal mirror which is cumbersome to control automatically. Indeed the commercial version of this device only enables illumination angle variation in a plane instead of a partial hemisphere. Angular variations of a gimbal mirror are more difficult than translational motion of an aperture. Also, when scanning a surface area for BTF measurements, the design in Refs. [15] and [21] requires translation of both mirrors and sensors. In our design, translating a single mirror is sufficient for scanning a small surface region.

Another device employing concave mirrors for BRDF measurement is described in Ref. [1]. This device uses two mirrors to achieve a similar functionality to the device described here. The device is consequently more complex and more difficult to prototype. Also, scanning a surface requires traversal of two mirrors instead of one. The design has two focal points and the distance between the two focal points limits the size of the object to be measured.

A "kaleidoscope" approach to BTF measurement is given in Ref. [16]. This device measures texture appearance for a discrete number of imaging parameters since the mirrors are not curved. The advantage is that scanning is not necessary for acquiring the appearance of a region. The disadvantage of this device is that only a few discrete samples of the full imaging parameters space can be explored.

The prototype device has an off axis parabolic mirror (Janos Technology A8037-175) that is a section of a full parabolic mirror. Figure 7 shows a closer view of this parabolic mirror and a test sample (blue glossy cardboard).

Additional equipment includes a beam splitter (K54-823 Edmund Scientific), fiber optic illuminator (Schott Fostec, DCR II), and an iris diaphragm with 0.8 mm minimum aperture and 25.4 mm maximum aperture (K53-915 Edmund Scientific). Figure 6 shows an image of the main components of the current system prototype. Not shown in the figure are the *X-Z* and *X-Y-Z* mechanical stages (Velmex Inc.). These stages are used for automatic scanning by placing the illumination aperture on an *X-Z* stage and the mirror on an *X-Y-Z* stage. The light source is DC-regulated and equipped with a quartz halogen bulb. Light collimation is implemented with a convex lens series so that the incident illumination is sufficiently bright and nearly parallel. Note that several variations of the illumination source can be made within the context of the original design. For instance, spectral filters on the illumination source would enable BRDF measurements as a function of spectral wavelength. In addition, polarizers may be used at both the source and detector for measurements as a function of polarization angle. Also, scanning a non-planar sample will require an additional system component to estimate the depth of the object. While this prototype is mounted on an optical board for convenience of testing and modification, portable implementations are foreseeable extensions.

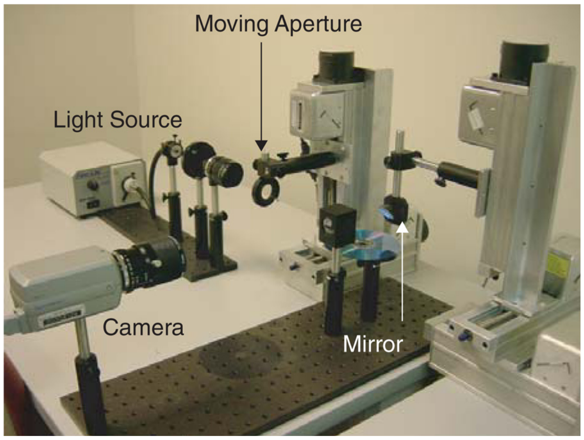

Figure 6. Device prototype including camera, illumination source, collimating lens assembly, illumination aperture, beam splitter and off-axis concave parabolic mirror. A CD is the imaged sample placed at the focus of the mirror.

Figure 7. Off-axis concave parabolic mirror used in prototype.

To obtain a texture image, the desired viewing direction and illumination direction are specified. The illumination aperture is positioned to achieve the correct illumination direction. A single pixel from each camera image is identified that corresponds to the correct viewing direction. This pixel is acquired for each mirror position along a 2D grid in the $X - Y$ plane.

To illustrate the image texture acquired by the texture camera, we show representative examples from various surface samples (Figure 8). For each of these examples the spatial sampling is dense with an effective pixel size of 0.075 mm. The images in Figure 8 correspond to a fixed illumination direction and three different viewing directions. These images also reveal the changes in the overall appearance of each surface sample with viewing direction.

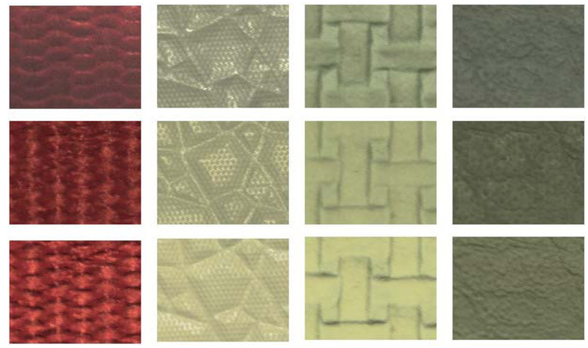

Figure 8. Texture images for sample surfaces: (from left to right) canvas, rough plastic, rubber mat, and leather. Each image corresponds to a frontal illumination (i.e. $\theta_i = 0$). The width is 10.5 mm and the height is 8.25mm. The top row corresponds to $\theta_v = 22^\circ$. For the middle row $\theta_v = 0$. For the last row $\theta_v = -22^\circ$. For each image $\varphi_v = 0$, i.e. the point of interest on the mirror is in the $y - z$ plane. Note that the brightness of the first row has been manually enhanced so that structure is better visible.

Polarization Multiplexing

Another recent method for bidirectional imaging is polarization multiplexing.[8] Multiple unknown light sources can illuminate the scene simultaneously, and the individual contributions to the overall surface reflectance can be estimated. This method relies on the relationship between light source direction and intensity modulation. Inverting this transformation enables the individual intensity contributions to be estimated. In addition to polarization multiplexing, we show that phase histograms from the intensity modulations can be used to estimate scene properties including the number of light sources.

Measuring Skin Shape

In addition to measuring skin appearance, the geometric structure of the skin is of interest for modeling. While several scanning devices exist to capture the global shape of an object, few methods concentrate on capturing the fine-scale detail. Fine-scale surface geometry (relief texture) such as surface markings, roughness, and imprints, are essential in highly realistic rendering and accurate prediction.We present a novel approach in Ref. [30] for measuring the relief texture of specular or partially specular surfaces using a specialized imaging device with a concave parabolic mirror to view multiple angles in a single image. Laser scanning typically fails for specular surfaces because of light scattering, but our method is explicitly designed for specular surfaces. Also, the spatial resolution of the measured geometry is significantly higher than standard methods, so very small surface details are captured. Furthermore, spatially varying reflectance is measured simultaneously, i.e. both texture color and texture shape are retrieved.

The method directly calculates the surface normal map from multiview images of globally planar surface patches. Here we use the term "multiview image" to refer to a set of surface images observed over a range of viewing angles. Normally such images are difficult to obtain, requiring numerous cameras and/or mechanical positioning devices. However, by employing the bidirectional imaging device we can instantaneously obtain the multiview observation of a point. Multiview images are obtained by scanning the surface point-by-point in scan-line order. The spatial pixel size is controlled by the scanning step and not the CCD array, and we can achieve a spatial resolution of 0.1 mm.[14] Our approach assumes that the object is at least partially specular so that a specularity is visible in the multiview images. There is no need for registration of geometry and images and there is no need for computing point correspondence as in stereobased methods. The imaged surface point is exactly the same point where the surface normal is measured. We applied this technique to recovering skin geometry. A skin replica which is provides a solid cast of the skin details was scanned. This result is shown in Figure 9.

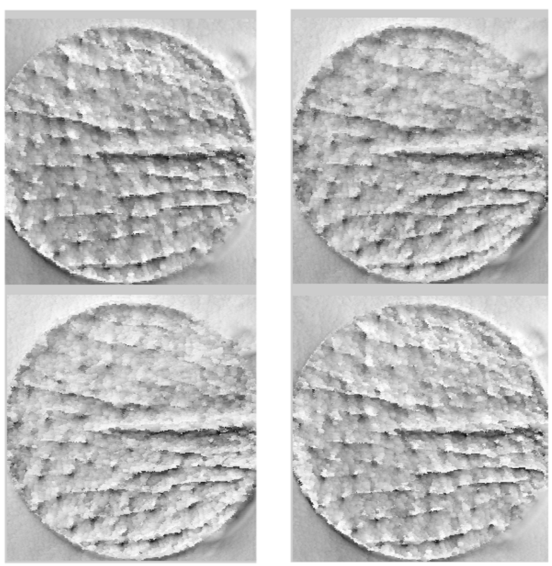

Figure 9. Rendered surface shape obtained by applying Lambertian shading to the estimated surface normals. The four panels show the rendering with different illumination directions to enhance the observed detail. (Skin replicas were provided courtesy of Dr. Hawkins of Unilever Research

Discussion

Using clustering and other computational techniques from pattern recognition and machine learning, our methods can describe skin computationally. Such descriptions can be used for comparing skin appearance to an ideal, comparing skin appearance before and after a topical product application or comparing skin appearance with different formulations of a cosmetic in development. Computational skin modeling relies on accurate and convenient skin measurements. We discuss multiple methods of measuring skin appearance including: (1) a traditional method with skin appearance captured under different viewing and illumination directions (2) a texture camera comprised of custom optics to obtain multiview images of skin and (3) a polarization multiplexing method where multiple illumination directions are obtained using polarization. In addition to skin appearance, we discuss a method to measure skin shape. Typically such fine scale geometry is difficult to aquire with conventional shape detection methods. However recently developed methods enable the detection of very fine scale skin details such as small wrinkles.

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