

# Surface Orientation from Texture Autocorrelation

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## Abstract

We report on a refinement of our technique for determining the orientation of a textured surface from the two-point autocorrelation function of its image. We replace our previous assumptions of isotropic texture by knowledge of the autocorrelation moment matrix of the texture when viewed head on. The orientation of a textured surface is then deduced from the effects of foreshortening on these autocorrelation moments. This technique is applied to natural images of planar textured surfaces and gives significantly improved results when applied to anisotropic textures which under the assumption of isotropy mimic the effects of projective foreshortening. The potential practicality of this method for higher level image understanding systems is discussed.

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properties. Although many of these methods have proven successful, each has been limited by the domain in which it is applicable and its high computational costs. Typical examples of the types of limiting assumptions used include parallel lines [1][2], uniform texture element size, area or spacing [3][4] and statistically isotropic line segments [5][6]. For a complete survey, see [7].

Other methods which make weaker assumptions about the texture properties require complicated or costly features. Many of these can be categorized as structural or syntactic approaches since they are based on complex primitives or a combination of features. Methods which integrate a variety of simpler methods are an example of this [8]. Even in these cases, there are still few methods which are capable of giving good results on natural outdoor textures, a class of textures which, for obvious practical reasons, must play a critical role in any general shape-from-texture system.

One of the earliest attempts to analyze surface parameters of natural outdoor scenery is the work of Bajscy and Lieberman[9]. They proposed a gradient measure based on features computed from the power spectrum of the Fourier transform of local windows for verifying whether surfaces were longitudinal (parallel to the line of sight). A similar but more generalized approach, proposed by Jau and Chin [10], relies on the Wigner distribution, a four dimensional function that involves the Fourier transform at each pixel. The latter has the advantage that it needs to be computed only once for the entire image but unless optical processors are available it is computationally intensive.

In methods proposed by Witkin [5] and Brown and Shvaytser [11], local surface orientation is computed from the effects of foreshortening for textures which are assumed to be isotropic. (By isotropic, we mean, statistically speaking, textures that have no inherent directionality.) Unlike the above methods, which rely on a texture gradient caused by the perspective projection, these methods look at how a statistical distribution, dependent on the direction of textural components in the image, is effected by the foreshortening due to orthographic projection. Witkin proposed to use a histogram of edge directions to determine surface orientation via a maximum likelihood fit. while in our previous work, we used the second order moments of the two-dimensional two-point autocorrelation. The latter has the advantage of being simpler and more robust, broadening the range of

textured surfaces whose orientation could be determined because of the use of information from all parts of the image. Nevertheless, the assumption of isotropy is a very strong and limiting factor for both of these methods.

The method proposed here is an extension of our earlier technique based on the foreshortening of texture autocorrelation. In order to analyze how surface orientation could be obtained for a much broader class of textures, *a priori* information about each texture, specifically the autocorrelation moment matrix of the texture when viewed head on, is used. With this additional information, the original technique can be extended to all textures regardless of whether they are isotropic.

The next section contains a brief explanation of the original method and how it can be extended to use the additional information. Section 3 provides the practical details of our implementation and describes the results we obtained on three commonly found textures: wood, stone and brick.

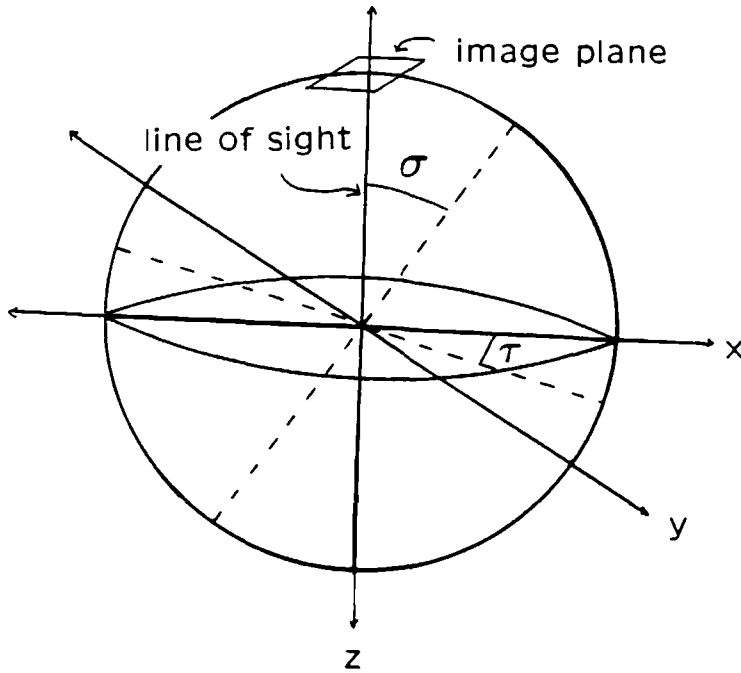
## 2 Foreshortening of Texture Autocorrelation

Let us begin with the terminology and definitions we used previously to specify how surface orientation is related to the second order moments of the autocorrelation of the image. The orientation of a surface (with respect to the line of sight) will be given in terms of the slant and tilt parameters as introduced by Witkin and as shown in Figure 1. An image will be specified by a gray-scale function  $F(\vec{r})$ , where  $\vec{r} = (r_1, r_2)$  denotes a point in the image plane. The image of a textured plane that is viewed head on, *i.e.*, that is perpendicular to the line of sight, will be denoted by  $F_{\perp}(\vec{r})$ .  $F_{(\sigma, \tau)}(\vec{r})$  is then defined as the image produced by the same plane when it is given orientation  $(\sigma, \tau)$  with respect to the line of sight. The autocorrelation of an image,  $A(\vec{r})$ , is defined as

$$A(\vec{r}) = \int \left( F(\vec{r}') - \bar{F} \right) \left( F(\vec{r}' + \vec{r}) - \bar{F} \right) d\vec{r}', \quad (1)$$

where  $\bar{F}$  is the mean of  $F$ . The head-on autocorrelation,  $A_{\perp}$ , and the oriented autocorrelation,  $A_{(\sigma, \tau)}$ , correspond to the images  $F_{\perp}$  and  $F_{(\sigma, \tau)}$ , respectively.

Figure 1. Representation of surface orientation using slant ( $\sigma$ ) and tilt ( $\tau$ ) shown on the Gaussian Sphere. A point on the sphere ( $\sigma, \tau$ ) represents a surface whose normal is the same as the normal to the sphere at this point.



Finally, we introduce the autocorrelation moment matrix,

$$\mu = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{pmatrix},$$

defined as

$$\mu_{ij} \equiv \int r_i r_j A(\vec{r}) d\vec{r}. \quad (2)$$

The moment matrix is trivially symmetric;  $\mu_{12} = \mu_{21}$ . The autocorrelation moment matrices derived from the image of a textured plane viewed head on and the same plane with orientation  $(\sigma, \tau)$  will be denoted  $\mu_{\perp}$  and  $\mu_{(\sigma, \tau)}$ , respectively. As derived in [11], these matrices are related by the following equation:

$$\mu_{(\sigma, \tau)} = \cos \sigma \mathbf{M}(\sigma, \tau) \mu_{\perp} \mathbf{M}(\sigma, \tau). \quad (3)$$

where  $\mathbf{M}(\sigma, \tau)$  is the matrix which foreshortens the vector  $\vec{r}$  in both the image and in the autocorrelation under orthographic projection and is given by:

$$\mathbf{M}(\sigma, \tau) = \mathbf{R}_\tau \mathbf{M}(\sigma, 0) \mathbf{R}_{-\tau}, \quad (4a)$$

with

$$\mathbf{R}_\tau = \begin{pmatrix} \cos \tau & -\sin \tau \\ \sin \tau & \cos \tau \end{pmatrix}, \quad (4b)$$

and

$$\mathbf{M}(\sigma, 0) = \begin{pmatrix} \cos \sigma & 0 \\ 0 & 1 \end{pmatrix}. \quad (4c)$$

That is,  $\mathbf{M}(\sigma, \tau)$  is the matrix which foreshortens the vector  $\vec{r}$  by a factor of  $\cos \sigma$  along the direction of tilt,  $\tau$ , while leaving the direction perpendicular to  $\tau$  unchanged.

In the original method, it was possible to compute the surface orientation directly from equation (3) since  $\mu_\perp$  was known to be a multiple of the identity since the texture was assumed to be isotropic. The slant and tilt could be specified as simple functions of the autocorrelation moment matrix. Without this assumption, further information is necessary to resolve the orientation. We have chosen to use the autocorrelation moment matrix for the texture when viewed head-on as an additional input. Given this prior information, it is now possible to use equation (3); in this case, we can solve for the slant and tilt by an iterative solution using Newton's method.

### 3 Implementation and Results

To test this method, a series of images were taken of three commonly found textures: brick, wood and stone. The brick and wood were both highly anisotropic while the stone was sufficiently anisotropic that the original method gave unsatisfactory results. In each case a single planar surface was photographed from a sufficient distance that orthographic projection was a good approximation, and that the entire image consisted of an image with a single orientation. For each texture, several photographs were taken of each texture at varying surface orientations including one which was a head-on view. An attempt was made to keep the same location on the

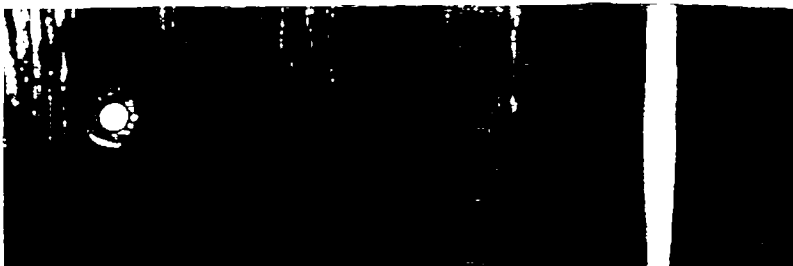
surface in the center of each photograph and to keep the camera at a fixed distance from the surface. The actual orientations were obtained, as in the previous study, using an identical picture for each orientation, in which a flat circular object was placed on the surface.

As before, photographs were digitized to yield  $256 \times 256$  8-bit gray-scale images, and the autocorrelation was computed as the Fourier transform of the power spectrum of the image. Based on our previous results, to compensate for statistical noise, the second order moments were summed only over those autocorrelation values which were greater than the average value found in a ring of radius 10 pixels.

The nonlinear system of equations given in (3) was solved using Newton's Method. This was guided by an initial estimate of the foreshortening matrix determined from the solution obtained if we assume the surface is isotropic (i.e. we let  $\mu_{\perp}$  be proportional to the identity.) Convergence with insignificant computational cost occurred in all instances except one in which the autocorrelation moment matrix was not positive definite, presumably due to statistical error. This was confirmed by another picture of the same texture (wood) whose orientation was similar. In this instance, the matrix was marginally positive definite, convergence was slower, but a good estimate of the orientation was found. Over the whole sample, the average error in the slant and tilt estimates was 8 and 4 percent respectively. The worst errors were 17 and 10 percent respectively. A 5 percent error is estimated in the measurement of the actual orientation.

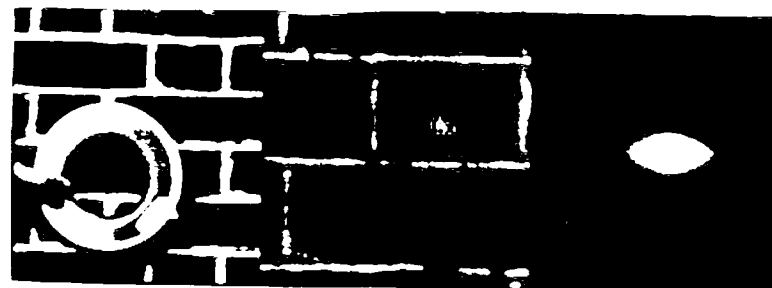
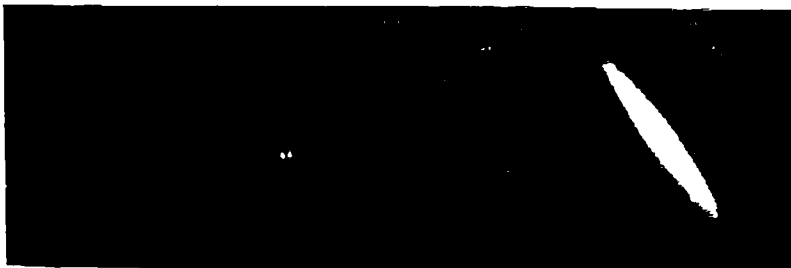
Examples of two of the pictures and their autocorrelation are given in Figure 2. From the autocorrelations in this figure you can see that the textures are anisotropic. If the texture was isotropic the autocorrelation would be composed of concentric scaled elliptic iso-contours (which are circular if the surface is viewed head on.) For each view of a textured surface contained in the figure, one picture depicts the surface with a flat circular object laying upon it. This makes the surfaces orientation explicit just as it would for the autocorrelation if the texture were isotropic. Since the textures are anisotropic, the comparable orientation information is contained only in the autocorrelation relative to the head on autocorrelation. Our technique measures this distortion, due to foreshortening, which transforms the autocorrelation in the same way it transforms the image under orthographic projection.

Figure 2. Autocorrelation of Anisotropic Textures. The two centermost pictures in each set, show the textured surface from which the autocorrelation was computed. The respective autocorrelations are shown on the right. On the left are the surfaces with a circular object laying flat upon them from which the orientation of the surface is apparent. One row of pictures are from the head-on view while the other row of pictures represent the textured surface at an orientation which was to be determined. Both textures are highly anisotropic as can be seen by the autocorrelation of the head-on views which are not circular. It is possible to see the distortion due to projective foreshortening in the pictures and the autocorrelations by comparing the head-on with the oriented view.



Actual Orientation  
 Slant =  $56^\circ$ , Tilt =  $38^\circ$

Computed Orientation  
 Slant =  $66^\circ$ , Tilt =  $37^\circ$



Actual Orientation  
 Slant =  $29^\circ$ , Tilt =  $-4^\circ$

Computed Orientation  
 Slant =  $30^\circ$ , Tilt =  $-9^\circ$

In all but the previously mentioned case, surface orientation estimates were accurate even though in many cases textural anisotropy mimicked the effects of foreshortening. Use of prior knowledge of the autocorrelation moments from a head-on view was chosen for simplicity, but any other view would suffice as long as its orientation was known. Since, in practice, it is not feasible to have prior information about each texture, the next step would be to use multiple views of each texture in which the orientations of all the views are unknown. From the change in autocorrelation moment matrices, relative orientations could be computed which a surface reconstruction algorithm would ultimately fit into a coherent 3-D perception of the scene.

## 4 Concluding Remarks

We have examined a refinement of our technique for determining the orientation of a textured surface from the two-point autocorrelation function of its image. The previous assumption of textural isotropy was replaced by knowledge of the autocorrelation moment matrix of the texture when viewed head on. The orientation was then deduced from the effects of the foreshortening on the autocorrelation moments. The new technique can successfully determine surface orientation for anisotropic textures. This technique suggests an image understanding system guided by a texture classification scheme would be capable of determining surface orientation for a broader class of textures than has been previously possible.

We believe that, as Bajscy and Lieberman contend, texture is the most significant feature of outdoor scenes. Shape-from methods based on stereo or motion often have inherent difficulty dealing with highly textured scenes since feature matching becomes intractable. On the other hand, enormous information is available for explicit surface reconstruction where surfaces are textured; indeed, many surfaces cannot be unambiguously reconstructed unless they are textured. (See [12] for a good example.) Guidance and recognition tasks could be greatly improved with the assistance of a shape-from-texture systems if they were able to deal with a broad range of natural textures without complex structural knowledge or extreme computational costs.



The results of this work confirm that powerful cues for 3-D perception can be extracted from textured surfaces. We have presented a simple method which, given prior knowledge about the type of textured surface under consideration, is capable of measuring surface orientation for a wide variety of natural images.

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