Predicting Surface Texture when Seen from Different Distances

Xavier Lladó and Maria Petrou

Abstract— **It is well known that in texture analysis one must distinguish between *image* texture and *surface* texture. The difference between them is easy; image texture is what appears on the 2D image of a physical object, while surface texture provides the variation of the physical and geometric properties of the imaged surface which give rise to the texture in the image.**

The purpose of this work is to analyse what happens to the surface information when the image resolution is modified. We deduce how the same surface appears if seen from different distances. Using 4-source Colour Photometric Stereo, which provides the surface shape and colour information, a method for predicting how surface texture looks like when changing the distance of the camera is presented. We evaluate the performance of the method using real sets of images.

Keywords— **Surface roughness, texture, photometric stereo**

I. Introduction

RECOGNITION of 3-dimensional surface textures from 2-dimensional images is difficult. The 2-dimensional texture in the image, the *image* texture, is produced by the imaging geometry and variation in both surface reflectance and surface relief. The latter two constitute the *surface* texture, which give us the variation of the physical and geometric properties of the imaged surface.While the reflectance properties are intrinsic to the surface, the surface relief produces a pattern of shadings that depends strongly on the direction of the illumination [1]. Thus, the *image* texture created by a 3D *surface* texture changes drastically with the imaging geometry.

This paper uses *Colour Photometric Stereo* (CPS), as described in [2] and [3], to compute the detailed shape and colour of a rough surface when seen by a camera at the zenith of the surface. Photometric stereo is based on the fact that image intensities depend on the surface orientation and its reflectance. Hence, if several images are taken from the same viewing position but with different lighting directions, variation of pixel intensities in these images will be due to changes in the relative positions of the illuminant and the surface [4]. This constraint permits us to calculate the normal vectors, which represent the surface orientation of any point on the surface, and the reflectance factor or albedo, which describes the reflection properties of the surface.

In the last few years photometric stereo has been used to carry out surface texture analysis, determining surface shape and surface roughness [5], [6], [7], [8]. Many researchers in this area have applied this information to develop industrial vision-based inspection systems to detect surface defects. However, our purpose is different and more specific as we try to analyse what happens with the surface information when the image resolution is modified. That means finding out how the same surface appears if seen from different distances. Hence, this work can be used in describing a texture in such a way that it is recognisable from a range of distances.

We have available colour photometric data sets for different camera distances. We use one of the sets to construct the surface information at a given distance. Then we predict how the surface would look like at another distance. We evaluate our surface prediction against the surface shape computed by photometric stereo at the second distance. The method is only appropriate for moving from fine to coarse resolution.

The rest of this paper is organised as follows. In section II, the prediction method is explained. In section III, the performace of the method is evaluated on some real images. Finally, the work ends with conclusions.

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II. Prediction process

A. Image prediction

We shall start by considering two grids referring to the pixels of two images of the same surface, captured from two different distances. One of them must correspond to the higher resolution image and it must be finer than the other. Let us indicate by indices ij a pixel of the coarse grid. This pixel is made up from several pixels of the fine resolution grid, some of which contribute to it only partially. Let us for the moment ignore by how much each pixel of the fine resolution contributes to pixel ij of the coarse resolution, and let us simply say that "superpixel" ij corresponds to a tile of size $K \times L$ of fine resolution pixels. We shall refer to the pixels of the coarse resolution as "superpixels" and the term "pixel" will be used only for the fine resolution pixels. Each superpixel may be thought of as representing a surface patch characterised by a particular gradient vector $(p_{ij}, q_{ij}, 1)^T$ and a particular reflectance function $\rho_{ij}(\lambda)$. The superpixel will have intensity I^u_{ij} in the coarse resolution image, where $u = 1, 2, 3$ or 4, each value corresponding to a different direction of the illumination.

Each superpixel corresponds to a tile of pixels. We wish to keep track of the superpixel to which a pixel contributes. So, we shall give to every pixel three sets of indices: one tells us to which tile it belongs, one tells us where about in the tile it is, and one tells us its location in the fine resolution grid. Let us indicate by indices mn the position of pixels in the fine resolution grid. So, a pixel that contributes to superpixel ij will have indices $ij;kl\ mn$, where $k = 1, 2, ..., K$ and $l = 1, 2, ..., L$. Any other quantity associated with pixel $ij;kl\ mn$ will be indicated by the same notation as for superpixel ij. That is, pixel $ij;kl$ mn corresponds to a surface patch with gradient vector $(p^{mn}_{ij;kl}, q^{mn}_{ij;kl}, 1)^T$ and a reflectance function $\rho^{mn}_{ij;kl}(\lambda)$. Our problem is to predict I^u_{ij}, for a given direction of illumination u, given $\rho^{mn}_{ij;kl}(\lambda)$, $p^{mn}_{ij;kl}$ and $q^{mn}_{ij;kl}$ for all values of i, j, k and l. The values of $\rho^{mn}_{ij;kl}(\lambda)$, $p^{mn}_{ij;kl}$ and $q^{mn}_{ij;kl}$ have been computed from four images by Colour Photometric Stereo. We shall not go into details of this now as they have been published elsewhere [2], [3]. Although the CPS scheme we use can deal with non-Lambertian surfaces, we assume here that the surface we are dealing with is Lambertian.

If the sensitivity of the sensor is $\mathcal{S}(\lambda)$, the spectral distribution of the incident light is $\mathcal{L}(\lambda)$, and the reflectance funcion of the surface patch projected on superpixel ij is $\mathcal{R}(\lambda, N_{ij}, u)$, where N_{ij} is the normal to the surface vector and u the direction of illumination vector, then the intensity value registered by the sensor at superpixel ij is:

$$I^u_{ij} = \int \mathcal{S}(\lambda)\mathcal{L}(\lambda)\mathcal{R}(\lambda, N_{ij}, u)d\lambda \tag{1}$$

$\mathcal{R}(\lambda, N_{ij}, u)$ could be separated in a geometric component $\mathcal{G}(N_{ij}, u)$ and a surface material component, $\rho_{ij}(\lambda)$. Assuming we are dealing with a Lambertian surface,

$$\mathcal{G}(N_{ij}, u) = \frac{N_{ij} \cdot u}{|N_{ij}||u|} \tag{2}$$

where N_{ij} is $(p_{ij}, q_{ij}, 1)^T$.

Superpixel ij is made up from several pixels each of which may have its own reflectance function, and its own orientation. So, $\mathcal{G}(N_{ij}, u)\rho_{ij}(\lambda)$ is really the sum of several such factors, one for each pixel that contributes to the superpixel. Then

$$I^u_{ij} = \int \mathcal{S}(\lambda)\mathcal{L}(\lambda) \sum_{k,l=1}^{K,L} \mathcal{G}(N^{mn}_{ij;kl}, u)\rho^{mn}_{ij;kl}(\lambda)d\lambda \tag{3}$$

By exchanging the order of integration and summation, we obtain:

$$I^u_{ij} = \sum_{k,l=1}^{K,L} \int \mathcal{S}(\lambda)\mathcal{L}(\lambda)\mathcal{G}(N^{mn}_{ij;kl}, u)\rho^{mn}_{ij;kl}(\lambda)d\lambda \tag{4}$$

Note that this formula is quite general: it allows us to predict the value of superpixel ij from the information we have on its constituent pixels, even when seen by a different sensor, under illumination with different spectral distribution and different orientation than those under which the original images, from which the surface information was extracted, were captured.

We shall restrict ourselves here to the case where the sensor and light source are the same. If we assume that the unknown illumination direction is the same as one of the illumination directions in the original data used by the photometric stereo, then this equation collapses to a trivial one:

$$I^u_{ij} = \sum_{k,l=1}^{K,L} I^{u;mn}_{ij;kl} \tag{5}$$

This approach allows us to go straight to predicting how an image of the surface would look like when imaged under different conditions (e.g. different illumination direction), from those under which the images in the database were imaged.

Alternatively, we may try to predict first how the surface itself would be approximated in a different resolution from the original one and then predict the image it would create.

B. Surface prediction

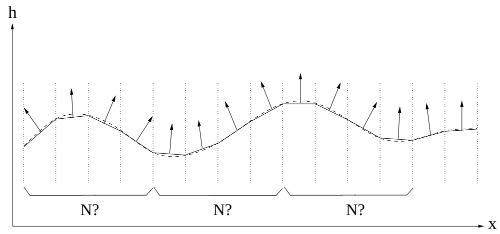

Fig. 1. A surface is approximated by many flat facets in fine resolution. In coarse resolution these are replaced by large flat facets. What is the gradient vector of a large facet as a function of the gradient vectors of the small facets it replaces?

As our objective is to describe surface information we need to understand what happens with the surface shape information if the distance of the camera is changed. Figure 1 illustrates this problem and permits us to formulate the following question: what will the normal vectors be if the distance of the camera is changed leading to a new image in which every pixel is the union of several old pixels? This question is answered by deriving the relationship between the normal vectors when they are calculated in different image resolutions. The proposed strategy in order to recover the normal vectors is based on the prediction of the planar patch by which the surface is approximated locally in the coarse resolution. We want to reconstruct the facet of the superpixel by using the information of the facets recovered in the fine resolution.

To predict the planar patch of the superpixel we compute the average plane in the LSE sense passing through the patches of the fine resolution. That means it is necessary to know the height $f(x, y)$ at each point of the surface (*height map*). Using the height information and knowing the facets which contribute to superpixel ij, the average plane can be computed. Consequently, the normal vector of the recovered plane will be the normal vector of the superpixel.

If we define a surface by $(x, y, f(x, y))$ where $f(x, y)$ is the height at point (x, y), the normal as a function of (x, y) is

$$N(x, y) = \frac{1}{\sqrt{p^2 + q^2 + 1}}(p, q, 1)^T \tag{6}$$

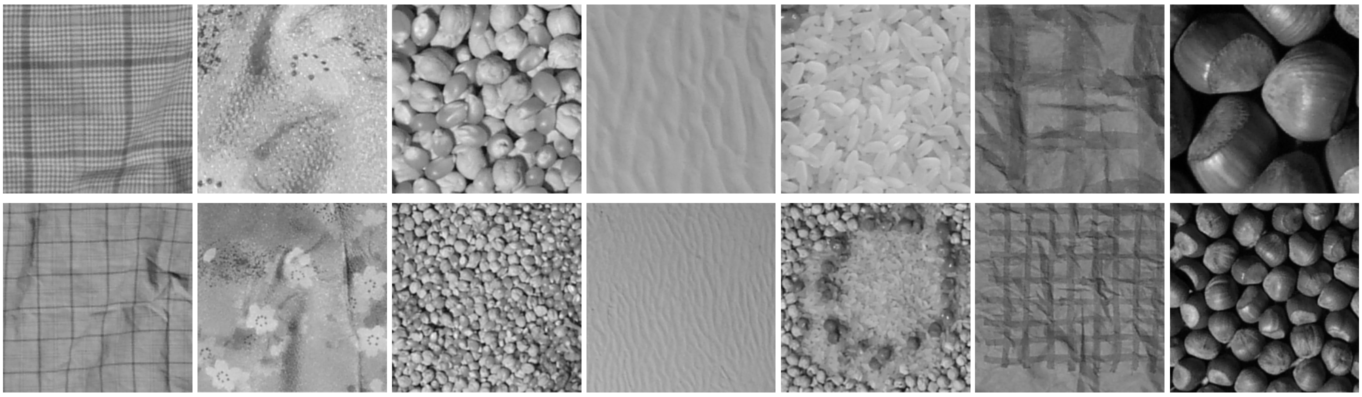

Fig. 2. One photometric image at distance A and C for the seven surfaces.

where the partial derivatives give us the values of the gradient vector $p = \frac{\partial f}{\partial x}$ and $q = \frac{\partial f}{\partial y}$. To recover the height map, we determine $f(x,y)$ from measured values of the unit normal. The partial derivative gives the change in surface height with a small step in either the x or the y direction. That means we can get the surface by summing these changes in height along some path. For example, the surface at (u,v) can be reconstructed by starting at $(0,0)$, summing the y-derivative along the line $x = 0$ to the point $(0,v)$, and then summing the x-derivative along the line $y = v$ to the point (u,v). This is the next integration path

$$f(u,v) = \int_0^v \frac{\partial f}{\partial y}(0,y)dy + \int_0^u \frac{\partial f}{\partial x}(x,v)dx + c \qquad (7)$$

where c is the constant of integration, which represents the unknown height of the surface at the starting point (in our experimental results we have chosen $c = 0$). Any other set of paths would work as well, though it is best to use many different paths and average, so as to reduce the error in the derivative estimates.

Obviously, the described prediction method works well if the surface is continuous. When the surface presents discontinuities, i.e. places where its derivatives do not exist, it is not integrable and the above method leads to incorrect normal vectors. The photometric stereo surface reconstruction yields also the set of points where the recovery of the gradient vectors is impossible. In general these are places which are in shadow in more than one of the four images used in the photometric stereo set. Such points are likely to occur at places where the surface has deep "ravines" and they may be associated with the places where the surface is not differentiable and continuous. Thus, when we reconstruct the surface we stop the piecewise integration at these boundaries. The surface shape we reconstruct and the image intensity we predict consist of image patches and not full images.

III. Experimental results

The proposed method was tested with seven photometric sets consisting of four images each, obtained by placing the camera at a certain distance along the zenith of the surface. As well as these photometric stereo sets of images, in order to compare the results of the surface predictions, different sets of the same surface were taken from different distances, without varying the lights or the object position. Therefore, for every surface different photometric sets, consisting of four images each, are available. We shall refer to the photometric sets taken from distance A, B, and C as photometric sets A, B, and C. These sets allow us to make the predictions $A \to B$, and $A \to C$, and the comparision of the predicted results with those obtained by the colour photometric stereo, quantifying exactly the performance of our approach.

The first row of figure 2 shows one of the photometric images for all the surfaces from distance A, while the second row shows the images taken from distance C. In order to evaluate our results we have compared the predicted gradient vectors with those obtained using the photometric set at the second distance. Using the method of section II-B the gradient vectors are directly predicted. However, using the method of section II-A we are only able to obtain image predictions. Therefore, we apply photometric stereo over these predicted images (four images corresponding to four directions of the illumination) in order to compute the surface information. Figure 3 shows four examples of the results of our predictions $A \to C$ with a particular direction of illumination. Note that method II-B can not predict the intensity values for the pixels which contain a discontinuity in the surface because the normal vector can not be computed there. We flag these points with white. It is also possible to visualise the gradient field, producing an image of the surface shape, rendered under a chosen direction of illumination.

In order to do the evaluation it is necessary to solve first the problem of localising which region of the original set corresponds exactly to the region of the prediction. We have done this, computing the correlation of surface shape (gradient components p and q) between the *data* - results obtained by applying photometric stereo directly to the original set - and the *model* - results obtained with our prediction. The correlation method is applied separately for the gradient components p and q, obtaining a set of possible relative shifts between the corresponding images for p and another set of possible relative shifts between the corresponding images from q. Then, the common shifting

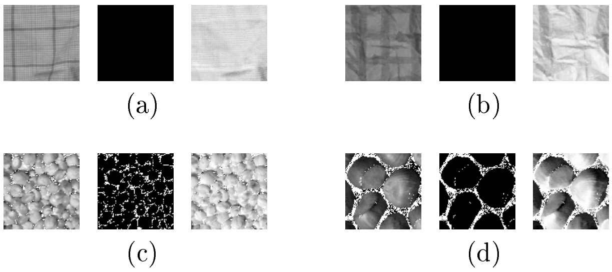

Fig. 3. Prediction $A \rightarrow C$. Image prediction (section II-A), detected discontinuities, surface shape rendered (section II-B).

which maximises both correlations of p and q is chosen, localising exactly the region of the original set.

The shape evaluation is performed by calculating the absolute percentage error distributions for the two gradient components p and q. Table I summarises the results for the predictions $A \rightarrow B$ and $A \rightarrow C$ (method of section II-A), showing the mean and standard deviations of the absolute percentage error distributions. Table II summarises the results using the method of section II-B. Note that similiar results are obtained between the two methods but with method II-B being somewhat better. For almost all the shape predictions, small values in the mean and standard deviation have been obtained. However, the rougher the surface is and the longer the prediction distance, the larger the errors of the prediction.

IV. Conclusions and future work

We presented a general framework for describing textures when seen from different distances. The 4-source CPS has been used in order to obtain the reflectance and the surface shape information of the surface from a close by distance. The proposed method allows one to predict how the texture will look like when seen by a different sensor and under different imaging geometry with an illuminant of different spectral properties. It is based on the assumption of Lambertian surfaces, but it can easily be generalised to other types of surface. The method has been partially evaluated using real sets of images captured from different distances.

Our futher studies will be focused on the classification of textures seen from different distances. We will use the presented method in order to predict how each surface would look like seen from different distances and different directions of illumination. The idea is to generate a "virtual" database of image textures at another distance against which we will compare unknown image textures in order to classify it.

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TABLE I

Evaluation of predictions $A \rightarrow B$ and $A \rightarrow C$ using the photometric results obtained by the predicted images of method II-A. Absolute percentage error distributions of p and q.

	Set	p		q	
		mean	std	mean	std
	AB	0.0907	0.1129	0.0861	0.1808
Texture 1	AC	0.1359	0.2287	0.1394	0.1675
	AB	0.1346	0.1273	0.0740	0.1569
Texture 2	AC	0.1028	0.1846	0.1974	0.2874
	AB	0.3188	0.2672	0.2230	0.3551
Texture 3	AC	0.1992	0.2317	0.3653	0.4732
	AB	0.0845	0.1744	0.1070	0.1669
Texture 4	AC	0.1090	0.1130	0.1668	0.2426
	AB	0.1439	0.2008	0.1867	0.2144
Texture 5	AC	0.1840	0.2347	0.2036	0.2358
	AB	0.0829	0.1419	0.1182	0.1631
Texture 6	AC	0.1646	0.1768	0.1883	0.2409
	AB	0.3771	0.4715	0.3378	0.4471
Texture 7	AC	0.2114	0.3507	0.3410	0.4736

TABLE II

Evaluation of predictions $A \rightarrow B$ and $A \rightarrow C$ using the method of section II-B. Absolute percentage error distributions of p and q.

	Set	p		q	
		mean	std	mean	std
	AB	0.0998	0.1001	0.1134	0.1966
Texture 1	AC	0.1214	0.2045	0.1411	0.2171
	AB	0.0354	0.2314	0.0651	0.1902
Texture 2	AC	0.0528	0.1923	0.0887	0.1757
	AB	0.1778	0.2809	0.1547	0.1795
Texture 3	AC	0.1687	0.1825	0.2223	0.2997
	AB	0.0522	0.1235	0.0747	0.1413
Texture 4	AC	0.1150	0.1653	0.0843	0.2125
	AB	0.1152	0.2305	0.1406	0.1820
Texture 5	AC	0.1106	0.1653	0.0843	0.1325
	AB	0.0973	0.2050	0.1648	0.2786
Texture 6	AC	0.0868	0.1553	0.1504	0.1959
	AB	0.2336	0.3425	0.2004	0.4227
Texture 7	AC	0.3374	0.4972	0.2366	0.4380

References

[1] M.J. Chantler. Why illuminant direction is fundamental to texture analysis. *IEE Proceedings in Vision, Image and Signal Processing*, 142(4):199–206, August 1995.

[2] S. Barsky and M. Petrou. Colour photometric stereo: Simultaneous reconstruction of local gradient and colour of rough textured surfaces. *In Proceedings 8th International Conference on Computer Vision*, pages II: 600–605, 2001.

[3] M. Petrou and S. Barsky. Shadows and highlights detection in 4-source colour photometric stereo. *In Proceedings International Conference on Image Processing*, Stereoscopic and 3-dimensional Image Processing II. Thessaloniki, October 2001.

[4] R.J. Woodham. Gradient and curvature from the photometric-stereo method, including local confidence estimation. *Journal of the Optical Society of America, A*, 11(11):3050–3068, November 1994.

[5] G. McGunnigle and M.J. Chantler. Rough surface classification using point statistics from photometric stereo. *Pattern Recognition Letters*, 21:593–604, 2000.

[6] M.L. Smith, G. Smith, and T. Hill. Gradient space analysis of surface defects using a photometric stereo derived bump map. *Image and Vision Computing*, 17:321–332, 1999.

[7] M.L. Smith. The analysis of surface texture using photometric stereo acquisition and gradient space domain mapping. *Image and Vision Computing*, 17:1009–1019, 1999.

[8] F. Solomon and K. Ikeuchi. Extracting the shape and roughness of specular lobe objects using four light photometric stereo. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18:449–454, November 1996.