MEASUREMENT OF PERCEPTUAL ROUGHNESS IN FRACTAL SURFACES

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ABSTRACT

In this paper we present an investigation into visually perceived surface roughness.

First we present psychophysical evidence that suggests that there is a simple relationship between perceived roughness and two well known surface parameters: fractal dimension and rms roughness. And that neither are good estimators, on there own, of perceived roughness.

Second we present a measurement model for deriving the perceived roughness of a surface from its height function which is motivated by the spatial frequency channel model of the human visual system.

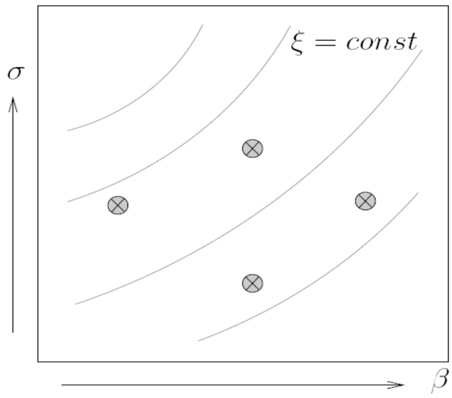
1. INTRODUCTION

Our long-term goal is to establish perceptually relevant measurements for surface texture. By surface texture we understand a stochastic surface which is described by its three-dimensional surface relief and reflectance properties (see Fig. 1(a) and Fig. 2). 'Sand ripples' and 'animal skin' can serve as examples of natural surface textures, while 'textile' and 'wallpaper' are two man-made ones.

To start with a problem of manageable complexity we constrain the study to measuring the perceived roughness of artificially generated fractal surfaces.

- *Fractal surfaces.* Surface textures investigated in this article are constrained to unit-albedo Lambertian surfaces whose geometry is modelled as 1/ frequency$^{\beta}$ noise. They are parameterised by just two terms: β the magnitude roll-off factor, and σ the surface RMS roughness (see Fig. 1(a) for examples).
- *Perceived roughness.* We select perceived roughness (ξ_{PR}), as the only perceptual dimension to be studied.

(a)



(b)

Figure 1. *(a) Examples of fractal surfaces obtained for different values of β (the magnitude spectrum roll-off factor) and σ (the RMS roughness). The surfaces are generated for points as indicated in (b), which is the β − σ space. The contours illustrate the possible form of lines of equal perceived roughness (ξ).*

2. PREVIOUS WORK

There has been surprisingly little work published on experiments that have sort to determine the mapping between the physical description of a surface texture and its perceived characteristics. Most researchers have tried to identify perceptual dimensions by using collections of still images of natural textures such as the Brodatz album [4]. To our knowledge only Ho et al [8] has used surface models. We will therefore divide this survey into two parts: research using image texture, and research using surface models.

2.1 Research using Image Texture

Two broad methods have been used to establish a perceptual space of texture using collections of single still images of texture samples. One method has been to ask observers to judge texture similarity along pre-defined dimensions [17, 1]. While these experiments achieved some agreement in identifying perceptual dimensions, they did not translate well to digital analysis of textures for content-based retrieval. In other experiments [7, 15, 16], multi-dimensional scaling was applied to results from observers asked to sort image textures freely. These authors concluded that visual texture has three major orthogonal dimensions. Long and Leow pointed out that previous authors did not normalise for orientation or scale and argued that such variations would affect texture perception. After normalising image textures in this way, they established a four-dimensional perceptual space which they mapped onto Gabor features using a variety of non-linear functions [11, 12]. Balas [2] manipulated images of natural textures in more sophisticated ways, using Portilla and Simoncelli's algorithm [14] to alter specific statistical properties of synthesised grey-scale images of texture.

2.2 Research using Surface Texture

A characteristic of the above experiments is that they have used image texture. However, our goal is to characterise perception of surface texture. It is well known that images of surface texture, and features derived from such images, are fundamentally affected by illumination and viewing conditions (see Fig. 2) [13, 6]. Moreover, single still images provide relatively poor sensory stimuli – multiple images obtained while moving our heads, the sample orientation, or the illumination greatly enhance our perceptions of surface characteristics.

Koenderink et al [9] used sets of still images of natural surfaces captured under precisely controlled conditions of illumination in order to test observers' ability to estimate the direction of illumination from the images. More relevant to the topic of our work however, Ho et al [8] synthesised surface representations and rendered these under varying conditions of illumination in order to test observers' perception of roughness as a function of illumination angle. They concluded that the perceived roughness of texture patches did not remain constant under varying illumination slant angle. However, the surfaces were obviously artificial (20×20 vertices were used) and the single, still, fronto-planar images subsequently generated provided limited stimuli for observers.

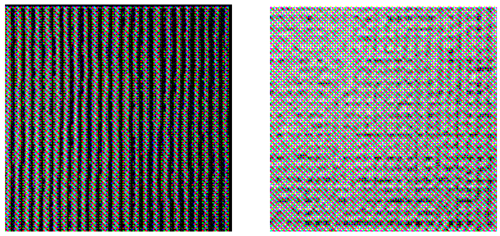


Figure 2. *Effect of illumination variation on images of surface texture. (The two images demonstrate the effect of illumination variation on resulting image texture: both images are of the same physical surface; only the illumination has been changed between photographs.)*

3. EXPERIMENTAL PROCEDURE

In developing our procedure for investigating the perceptual nature and mappings of surface textures we wanted to use stimuli similar to those typically experienced by humans when visually inspecting a surface, but under totally controlled and reproducible experimental conditions. We have therefore used fast computer graphics techniques to render photorealistic imagery of synthesised surfaces in real-time. This provides:

1. Rich real-time stimuli (up to the resolution of the human eye) using self and cast shadowing of Lambertian surfaces,
2. Natural appearing surface textures (very similar to those produced by shattering plaster blocks),
3. Real-time interactive (or pre-programmed) variation of illumination and surface orientation, and

4. Real-time interactive variation of surface characteristics.

Exp. 1 Constant Roughness

Using the methods described above we sought to establish a series of contours of constant perceived roughness in the β-σ space of surfaces. We did this by:

1. Generating a 'reference' fractal surface at a given β and σ, which we plot on a β-σ scatter plot,
2. Generating a second 'test' surface at a different β and a random σ,
3. Presenting the observer with visualisations of both surfaces, during which time the orientations of both surfaces simultaneously follow the same predefined wobbling motion,
4. Asking the observer to interactively adjust the σ of the 'test' surface so its perceived roughness matches that of the reference. Observers were instructed to consider how the surfaces would feel if touched when making these matches.
5. We then plot the final β-σ of the 'test' surface on a scatter plot.
6. We repeat 1–5 with 'test' surfaces of differing β, each time randomising the phase of the 'reference' and 'test' surfaces. This provides one set of iso-roughness points (see Fig. 3).
7. Finally we repeat 1-6 for four other 'reference' surfaces for which we choose a reference β-σ to provide a total of five iso-roughness lines at different perceptual roughnesses.

Exp. 2 Roughness Scaling

Later in a second set of experiments the scaling relationship was analysed by:

1. Generating two 'reference' fractal surfaces at given β and σ values based on the successive contours found in the previous experiments.
2. Generating a third 'test' surface at a similar β and a random σ,
3. Presenting the observer with the three surfaces, during which time the orientations of the surfaces follow the same motion,
4. Asking the observer to adjust the σ of the 'test' surface until it was perceived as being equidistant to the two 'reference' surfaces,
5. Repeat 1-4 with different β, σ and phase values for all possible iso-roughness lines found previously.

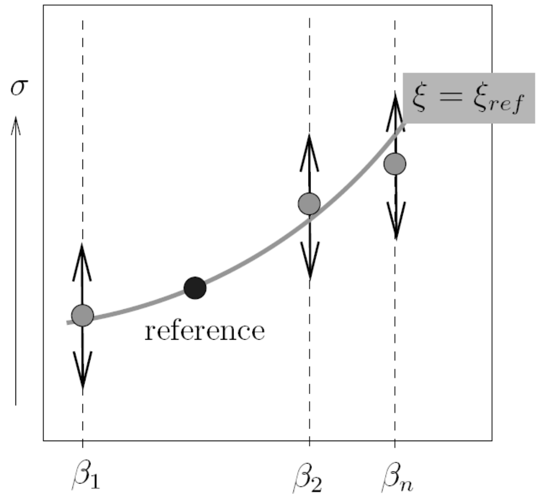


Figure 3. *The principle of identifying the isocontours of perceived roughness. An observer is presented with a pair of textures at a time: the reference texture (the dark point) and a test texture (a light point), and is asked to adjust the RMS of the test texture such that it matches the perceived roughness of the reference. Doing this for several test textures (light points) is a key to obtaining an isocontour corresponding to the reference, ξ = ξ ref.*

The same methods can of course be extended to study the effects of varying any parameters of surface texture on any perceptual judgements.

4 RESULTS AND ANALYSIS

Exp. 1 Constant Roughness

Five observers completed the constant roughness experiments (Exp. 1). The scatter plot of the resulting contour lines is shown in Fig. 4. The data is displayed with a logarithmic σ-axis, as it is natural for human observers to appreciate surface height scaling in that way.

The plots show evidence of a linear relationship between log rms roughness and roll-off factor for a constant perceived roughness.

Straight lines were therefore fitted to each of the five sets of results (one for each reference surface roughness). Note the lines were fitted independently to each reference roughness.

We believe that these results clearly indicate a linear relationship between log σ and β for a constant perceived roughness.

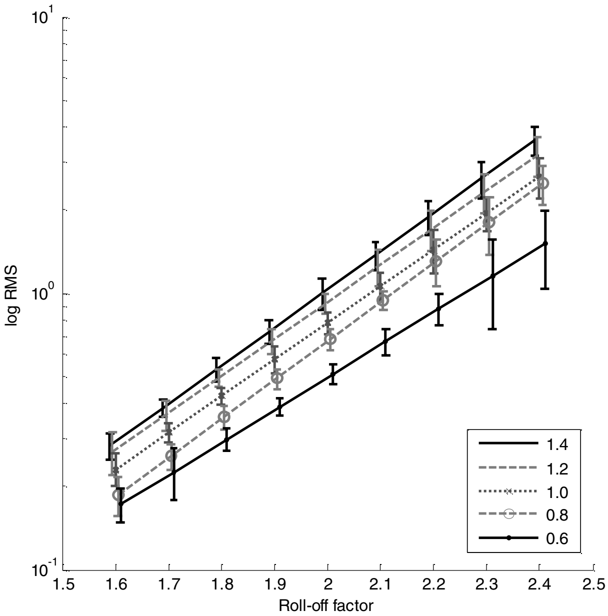


Figure 4. *The results of L1 linear regression of experimental data. The five fitted lines in each graph correspond to reference surfaces whose β's were set to 2, while the reference RMS's (in cm) were as shown in the plot.*

Exp. 2 Roughness Scaling

For the second set of experiments the resulting isocontours are plotted in Fig(5). Again, this shows evidence of the linear relationship, but more importantly gives us the scaling behaviour with which to investigate a measurement model.

5 A MEASUREMENT MODEL OF PERCEIVED ROUGHNESS

In this section we propose a model for obtaining numerical estimates of the perceived roughness (ξ_{PR}) of a surface from its height function. Our proposal was inspired by the common frequency channel model of V1 (the first part of the human visual system). It comprises a number of FRF stages tuned to different frequencies. For the purposes of this modelling, we express the frequency domain description of the fractal surfaces as cycles per degree of visual angle at the experimental viewing distance of 90 cm.

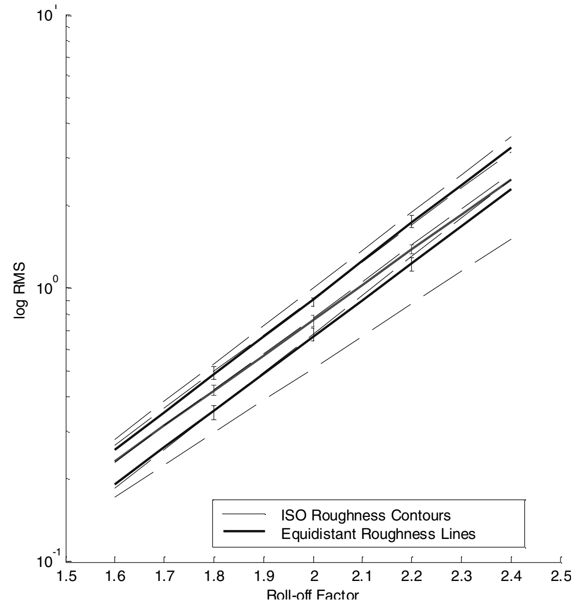


Figure 5. *The results of the experimental data from the second set of experiments. The three solid lines correspond to the perceptual middle contour between the adjacent isocontours from the previous set of experiments.*

Similarly our model comprises of a linear filter stage (F) followed by a non-linear (integrating) stage (RF). It is expressed below in the frequency domain for simplicity.

$$\xi_{PR} = \iint F(\omega,\theta) S(\omega,\theta) d\omega d\theta \qquad (2)$$

where

$S(\omega,\theta)$ is the surface height function expressed in the frequency domain, and

$F(\omega,\theta)$ is the linear filter.

We have found that using a Gaussian function as the linear frequency-domain filter provides a good fit to the psychophysical data. We parameterised it with its width (Gaussian variance) and its weight at 30 cycles/degree.

We optimised this model's parameters to minimise the variation in predicted ξ_{PR} along the lines of constant roughness estimated from experiments Ex.1 & 2. The shape of these optimisation spaces are shown in Figs 6 & 7 respectively.

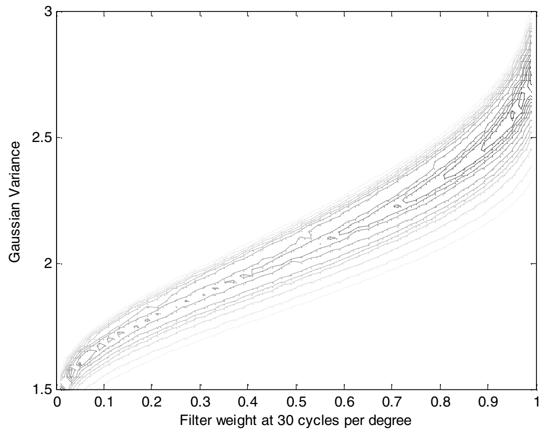


Figure 6. *Fit of the measurement model ξ_{PR} as a function of its parameters for Ex. 1.*

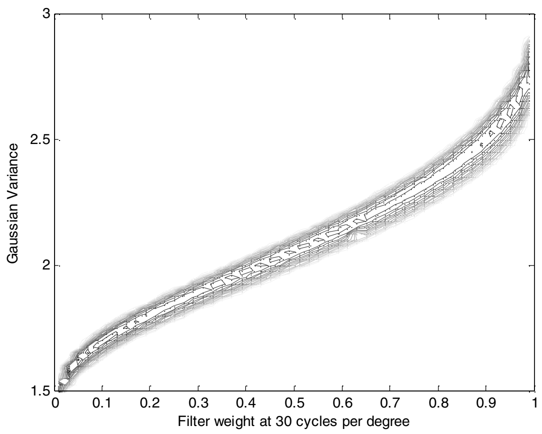


Figure 7. *Fit of the measurement model ξ_{PR} as a function of its parameters for Ex. 2.*

From the above it can be seen that both of the optimisation surfaces follow the same valley shape. The error is not terribly sensitive to traversing along the bottom of the valley and this gives a range of possible filter shapes as shown in Fig. 8.

Contour lines of constant roughness ξ_{PR} predicted by the measurement model (shown in bold in Fig 8) are plotted together with the original psychophysical data in figure 9.

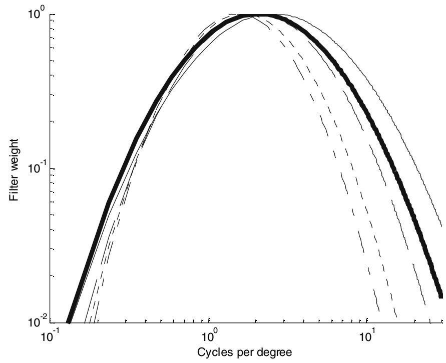


Figure 8. *Possible Gaussian distributions. All the filters have almost similar minimum variances. The bold filter is the most likely filter, which will be used in figure 9 to plot the fitting of the model to the real data.*

6. SUMMARY AND CONCLUSIONS

We have demonstrated that for fractal surfaces of constant perceptual roughness a linear relationship exists between *surface roll-off factor* and *rms roughness*.

Thus neither *rms roughness* or *fractal dimension* (which is directly and simply related to the surface roll-off factor) are good measures of *perceived roughness* on their own.

Finally we have proposed a measurement model for perceptual roughness which is based upon a simple frequency channel of V1 and which we have shown can derive the perceived roughness of a surface from its height function.

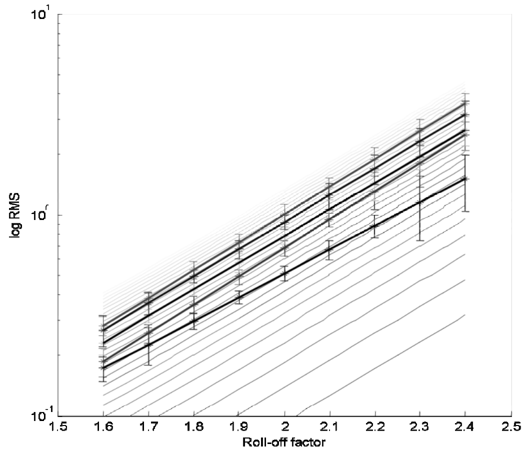


Figure 8. *Fit of the most likely model to the original psychophysical data from Ex. 1.*

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ACKNOWLEDGEMENTS

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