The Classification of Textured Surfaces Under Varying Illuminant Direction

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Principal Symbols

Signals

Spatial Quantities		Spectral Quanity	Description
Scalar Field	Vector Field		
s(x,y)		S(u,v)	Surface Height
	S(x,y)	P(u,v) Q(u,v)	Surface Derivatives
	L(x,y)		Illuminant Vector
i(x,y)		I(u,v)	Incident Image
d(x,y)		D(u,v)	Measured Data Set
$d_{f\phi}(x,y)$		$d_{f\phi}(u,v)$	Output of filter f,ϕ
	D(x,y)		Filter Outputs Vector
$f_{f\phi}(x,y)$			Feature Response derived from filter f,ϕ
	F(x,y)		Feature Vector
l(x,y)			Label field
n(x,y)		N(u,v)	Noise process
e(x,y)		E(u,v)	Residue Process

Transfer Functions

Spatial Variable	Spectral Variable	Input	Output	Function
o(p,q)		Surface derivative field	Image field	Reflectance function
	R(u,v)	Surface height spectrum	Image spectrum	Illumination
b(x,y)	B(u,v)	Image Spectrum	Data set Spectrum	Imaging
g(x,y)	$G_{\omega\phi}(u,v)$	Data Set Spectrum	Output of filter $\omega\phi$	Gabor filter
	H(u,v)	Surface spectrum	Measure Spectrum	Combined Filter

Surface Parameters

σ_s	Rms Roughness
R_{cla}	Centre line average
m_{rms}	Rms Slope
p_{rms}	Rms slope in the x-direction
q_{rms}	Rms slope in the y-direction
m_{fg}	f^{th} and g^{th} order statistical moment.
β	Power Roll-off
k	Topothesy
λ_0	Correlation length of an isotropic surface
λ_1	Correlation length in the x-direction
λ_2	Correlation length in the y-direction
ω_0	Fundamental frequency
ω_c	Cut-off frequency

Surface Variables

t	Lag
ω	Radial frequency
θ	Polar frequency angle
u	Horizontal frequency index
v	Vertical frequency index
p	Facet slope in the x-direction
q	Facet slope in the y-direction
p_x	Second derivative of surface, in the x-direction.
q_x	Second derivative of surface, in the x-direction.
s(x)	Surface height profile.

$r_c(t)$	Autocorrelation function
$c(t)$	Autocovariance function

Illumination Variables & Parameters

σ	Slant angle
τ	Tilt Angle
R	Correlation matrix of the surface
V[a b c]	Least squares linear model of the illumination process.
i_d	Desired image
a b c	Parameters of optimal linear model.
k_1 k_2 k_3	Parameters of Kube's linear model.

Imaging Parameters

σ_b	Blur
γ_b	Exponent of camera amplification.
σ_t	Standard deviation of temporal noise.
$\sigma_{disparity}$	Standard deviation of the difference between two images
σ_n	Standard deviation of overall noise process.

Gabor Filter Parameters

ϕ	Direction of propagation
σ_x	Standard deviation of the Gabor filter envelope in the x-direction.
σ_y	Standard deviation of the Gabor filter envelope in the y-direction.
u_0	Centre frequency of filter in the x-direction.
v_0	Centre frequency of filter in the x-direction.
B_ϕ	Polar bandwidth of the filter.
B_r	Radial frequency bandwidth of the filter.
σ_p	Measured polar bandwidth

σ_p	Standard deviation of the Gabor filter spectrum in the x-direction.
σ_y	Standard deviation of the Gabor filter spectrum in the y-direction.

Feature Parameters

σ_m	Standard deviation of measure image.
μ_r	Mean of Feature image
σ_r	Standard deviation of Feature image.
a	Parameters of feature/tilt model.
b	" "
M_n	Mean vector of class *n*
Σ_n	Covariance matrix of class *n*
$p_{\mathbf{F}\|l_i}(\mathbf{F}\|l_i)$	Probability that a vector x belongs to class *n*
$k(F\|l_i)$	Probability that a vector x belongs to class *n* over the entire tilt range.

Symbols Associated with Compensation Schemes

$m(\omega)$	Parameters of Chantler' filters.
$b(\omega)$	" "
i_0,i_{90},i_{180}	images obtained from τ=°,90° and 180° respectively.
i_{NL}	Non-linear component of surface to image mapping.
i_p	Image which is a linear function of p-derivative field only.
i_q	Image which is a linear function of qderivative field only.

Abstract

This thesis sets texture analysis in a physical context. Models of the system components are obtained from the literature and integrated into a description of the process linking the rough surface to the feature set on which classification is based. The first component is the rough surface, models of the surface topography are selected from the fields of tribology and scattering. Various reflectance models are considered and a spectral model of the surface/image relationship from the literature, is evaluated and discussed. The relationship between the incident image and the captured data set is investigated and described. This model is integrated with the spectral description of the feature measures to form a model of the transition from surface to feature set.

It is clear from this model that the direction of illumination can affect the directionality of an image obtained from a given surface. Changes in the illuminant direction will result in changes in the feature outputs. If the illuminant direction is altered between training and classification, the classification rule may be inappropriate and classification poor. Several schemes are considered to combat this problem. A technique which uses a representation of the physical surface as the basis for the generation of appropriate training data is selected for further evaluation. The surface derivative fields of the training surface are estimated using photometric techniques. A rendering algorithm uses these estimates to simulate the appearance of the training surface when it is illuminated from an arbitrary direction. It is shown that where illuminant direction is varied this system is able to perform significantly better than a naive classifier, and in some cases approaches the level of accuracy obtained from training the classifier under the conditions at which classification is performed.

Texture analysis is a significant area in the field of machine vision, this is in large part due to the important role of texture in the early visual system. It follows from this that texture has been seen as being critical to general visual systems working in unconstrained environments, consequently, less emphasis has been placed on more controlled inspection tasks. In an unconstrained system it is impractical to adopt a modelling approach and most work in texture analysis takes the image as its starting point. This thesis is concerned with the inspection of rough textured surfaces. By making explicit the circumstances under which classification occurs we are able to employ modelling of the system and describe texture classification in the context of the physical system which gives rise to a textured image.