The effect of variation in illuminant direction on texture classification

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Abstract

Texture analysis has been an extremely active and fruitful area of research over the past twenty years. Many advances have been made, but the effect of variation in lighting conditions on automated texture classification and segmentation has received little attention. This thesis shows that the direction of the illuminant is an important factor that should be taken into account when analysing images of three-dimensional texture.

A frequency domain model is presented which predicts that both the directional characteristics and the variance of images of three-dimensional texture can be affected by changes in illuminant vector. Results of simulations and laboratory experiments support these predictions.

The responses of three sets of texture measures are analysed using a test set of isotropic and directional textures. The results show that the feature measures' outputs are affected by changes in illuminant direction. These changes are also shown to significantly increase the error rates of statistical classifiers implemented using the three feature sets. Normalisation of images is shown to reduce the error rates in some cases.

The frequency domain model of image texture is further developed using empirical data and the resulting model used to design a set of tilt-compensation filters. These filters are used to pre-process images to reduce the effects of changes in the angle of tilt of the illuminant. Application of the filters to the test image set reduced the classification errors associated with directional textures.

Principal symbols and abbreviations

Symbol	Meaning	Section first introduced
σ_S	angle of slant of the surface	2.1.3
τ_S	angle of tilt of the surface	2.1.3
$\mathcal{F}[g(x,y)]$	the Fourier transform of the function $g(x,y)$	2.2.1
σ	angle of slant of the illuminant vector **L**	2.2.1
τ	angle of tilt of the illuminant vector **L**	2.2.1
L	unit vector pointing at the light source	2.2.1
n	unit vector normal to the surface	2.2.1
$I(x,y)$	normalised intensity image	2.2.1
$F_I(\omega,\theta)$	Fourier transform of the normalised intensity image	2.2.1
$V_H(x,y)$	surface height map	2.2.1
$F_H(\omega,\theta)$	Fourier transform of the surface height map	2.2.1
$F_s(\omega,\theta)$	surface response component of $F_H(\omega,\theta)$	2.2.1
$F_\tau(\omega,\theta)$	tilt response component of $F_H(\omega,\theta)$	2.2.1
$F_\sigma(\omega,\theta)$	surface response component of $F_H(\omega,\theta)$	2.2.1
ω	angular frequency (polar co-ordinates)	2.2.1
θ	angle of direction w.r.t. the *x*-axis (polar co-ordinates)	2.2.1
β_H	surface power roll-off factor	2.2.1
β_I	image power roll-off factor	2.2.1
S	height scaling factor	3.1.1
s_H^2	surface height variance	3.1.3
s_H	surface height deviation	3.1.3
$\hat{\alpha}$	average estimated slope angle	3.1.3
b_τ	*y*-intercept parameter of the raised cosine model of the tilt response component $F_\tau(\omega,\theta)$	3.3.4(c)
m_τ	slope parameter of the raised cosine model of the tilt response component $F_\tau(\omega,\theta)$	3.3.4(c)
ω_1	angular frequency in the *x* direction	5.1
ω_2	angular frequency in the *y* direction	5.1
$H(\omega_1,\omega_2)$	transfer function	5.1
$P(i,j)$	un-normalised co-occurrence matrix	5.2
$p(i,j)$	normalised co-occurrence matrix	5.2
d	co-occurrence matrix displacement vector	5.2
D^2	Mahalanobis distance	5.4
$\overline{D_\tau^2}$	mean tilt sensitivity	5.4
ω_s	sampling frequency	6.4.1

Abbreviation	**Meaning**	**Section first introduced**
ARMA	autoregressive moving average (model)	4.3.3
ASM	angular second moment (co-occurrence feature)	5.2
CON	contrast (co-occurrence feature)	5.2
cooc1	feature set/classifier based on co-occurrence features	6.2.2
COR	correlation (co-occurrence feature)	5.2
ENT	entropy (co-occurrence feature)	5.2
FBM	fractional Brownian motion	2.1.3
frac1	feature set/classifier based on Linnet's features	6.2.2
GLCM	grey-level co-occurrence matrix	4.4.1
laws1	feature set/classifier based on Laws' features	6.2.2
MRF	Markov random field	2.1.1
PCA	principal components analysis	4.3.1
PSD	power spectral density	2.2.1
rms	root mean square	2.1.4.
ROV	remotely operated vehicle	1.1
TEC	total error of classification	6.1.1