UNIVERSITY COLLEGE LONDON

University of London

EXAMINATION FOR INTERNAL STUDENTS

2000-2001

For the following qualifications :-

MSc VIVE

COURSE CODE	:	**PPP**
TITLE OF EXAMINATION	:	**Physics, Psychophysics and Physiology of Vision**
DATE	:	**10 May-2001**
TIME	:	**14.30**
TIME ALLOWED	:	**2 hours 30 minutes**

*Answer **three** questions, at least one from part A and one from part B. Each question is worth 33 marks. The total time allowed is two and a half hours.*

PART A

Question 1

(a) Describe Schafer's dichromatic model for the reflectance of light by an object and show how it leads to an equation for the colour $\mathbf{C}(\mathbf{x}) = \left(R(\mathbf{x}), G(\mathbf{x}), B(\mathbf{x})\right)$ at pixel $\mathbf{x}$ in an image of the form

$$\mathbf{C}(\mathbf{x}) = I_S m_b \mathbf{b} + I_S m_s c_s \mathbf{i} \quad . \qquad (1)$$

Explain what each of the terms on the right hand side of equation (1) above stands for and describe how they depend on the scene geometry, spectral content of the illuminant, and on the reflectance properties of the object.

[6 marks]

(b) Describe how, according to Shafer's dichromatic model, you would expect the observed pixel colours to be distributed in the RGB colour cube for images of:

(1) a piece of clothing, such as a man's shirt,

(2) a mirror,

(3) a coloured, glazed ceramic tile.

Explain what deviations from the distributions in (1)- (3) above you would expect in practice.

[6 marks]

(c) Define the chromaticity rgb and explain under what conditions Schafer's model predicts that the chromaticity will be invariant under changes in the spectral content of the illuminant.

[4 marks]

[Question 1 cont. over page]

[TURN OVER]

[Question 1 cont.]

(d) A camera whose colour channels satisfy the integrated white condition is used to derive opponent colour values at each pixel from the difference of the RGB values.

(i) Explain what is meant by the integrated white condition and describe why it is important.

(ii) Show that, according to Shafer's model, if an object is illuminated by white or grey light, the opponent colours obtained from this camera depend on only one of the terms on the right hand side of equation (1) in (a) above.

(iii) Show that ratios of the above opponent colour values at each pixel should be unchanged under variation of the object's orientation and be independent of the brightness of the illuminant.

[8 marks]

(e) The camera described in (d) above is used to take an image of two differently coloured, flat, glazed ceramic tiles illuminated under white light.

(i) Explain how you would use this image to characterise the colour of each tile. What condition must be satisfied if you are to obtain a good characterisation?

(ii) Describe under what circumstances it would be easy to build a machine vision system, utilising the above camera and white light source, to distinguish examples of these two different types of tile on a conveyor belt.

(iii) Explain why the system should, without change, also be able to distinguish unglazed examples of these two types of tile.

(iv) Describe how the system could further be used to distinguish a glazed tile of a particular type from an unglazed tile of the same type. What condition must be satisfied in this case?

[9 marks]

[Total 33 marks]

[CONTINUED]

Question 2

(a) A machine vision researcher has developed an image segmentation algorithm that is based on a model of the image pixel colour components (R, G, B) being independently distributed as $p_R(R)$, $p_G(G)$ and $p_B(B)$ with means $\overline{R}$, $\overline{G}$, and $\overline{B}$ respectively.

(i) Show that, according to this model, the distribution of pixel intensities may be obtained from $p_R(R)$, $p_G(G)$ and $p_B(B)$ by two successive convolutions.

(ii) Explain why, if each of the distributions $p_R(R)$, $p_G(G)$ and $p_B(B)$ is assumed to be normal with means $\overline{R}$, $\overline{G}$, $\overline{B}$ and variances σ_R^2, σ_G^2 and σ_B^2, respectively, that the distribution of intensity $I = R + G + B$ will also be normal.

(iii) Evaluate the mean intensity, $\bar{I}$, and the variance, σ^2, of the intensity distribution in (ii) above.

(iv) Comment on the validity, in principle, of using such Gaussian model distributions.

[8 marks]

(b)

(i) Describe how you would extend the above Gaussian model so that it can better describe the distributions of pixel colours likely to be encountered in practice from a region of an image corresponding to a uniformly illuminated, uniformly matt painted wall.

(ii) Describe the method you would use to estimate the parameters of the distribution of pixel colours in this case.

(iii) Illustrate how the method you have described in (b)(ii) above works by using it to estimate the mean, $\bar{I}$, and the variance, σ^2, of the intensity distribution. Comment on the formulae you obtain.

[9 marks]

[Question 2 cont. over page]

[TURN OVER]

[Question 2 cont.]

(c) Discuss the limitations of the model you described in (b)(i) above when:

(i) The lighting is uniform, but of variable brightness.

(ii) Parts of the wall are more brightly illuminated than others because of shading effects.

(iii) The paint on the wall contains several different types of small pigment particles.

(iv) The wall has been covered with a regularly patterned, matt paper.

[8 marks]

(d) Discuss how the model may be further generalised in order to describe images of rough surfaces and describe, how you would characterise the roughness and how you would estimate it from image data.

[8 marks]

[Total 33 marks]

Question 3

(a) A Markov random field $F(m,n)$ used to model image texture is often described by the probability density function

$$P(\mathbf{F}) = \frac{\exp\left(-\sum_{m,n} U(m,n)\right)}{Z} \quad . \qquad (2)$$

(i) Explain what each of the terms in equation (2) stands for and describe what conditions $P(\mathbf{F})$ and $U(m,n)$ must satisfy in order for $F(m,n)$ to be a Markov random field.

(ii) Describe how the $U(m,n)$ may be represented in terms of interactions between pairs of pixels and over larger pixel cliques.

[6 marks]

(b)

(i) Illustrate your answer to (a)(ii) above by means of models designed to encourage smooth variations of the field F, (1) with minimum gradient variation, and (2) with minimum curvature variation.

[Question 3(b) cont. over page]

[CONTINUED]

[Question 3 (b) cont.]

(ii) Describe how interactions in the $U(m,n)$ such as those in (1) and (2) in (b)(i) above can lead to long range correlation in the field F.

(iii) Explain why these interactions make it difficult to calculate a realisation of the field F consistent with the distribution in equation (2) above.

[7 marks]

(c)

(i) Describe one method that may be used to calculate a field F consistent with (2).

(ii) Describe what in principle must be done to ensure that the field F obtained by the method you have described in (c)(i) above does, for example, have minimum gradient variation. Comment on the significance of this requirement in practice.

(iii) Explain what you would do in a practical implementation of this technique to overcome the difficulties arising from the requirements in (c)(ii) above.

[10 marks]

(d)

(i) Explain what is meant by "hidden variables" and describe why you might wish to include such terms in the Markov random field appearing in equation (2) in part (a) above.

(ii) Explain how the hidden variables that you would introduce in (d)(i) affect the interactions between pixels in the Markov random field model you described in (b)(i)(1) above.

(iii) Describe how the hidden variables you would introduce in c(i) affect each other. Indicate the strength of these interactions relative to each other and to the original interactions in model (b)(i)(1) above and explain why these interactions should be so.

(iv) Explain why it is difficult to estimate the strengths of these interactions in practice.

[10 marks]

[Total 33 marks]

[TURN OVER]

PART B

Question 4

(a) Derive the Fourier transform of the image signal

$$I(x,y) = c + [1 + m\cos(\delta k_1 x + \delta k_2 y)]\cos(kx) \quad ,$$

where $k > (\delta k_1)^2 + (\delta k_2)^2$, and $c > 1$ and $m < 1$ are constants.

[5 marks]

(b) The Canny edge detector is applied to the image signal given in question 4(a). Explain, using illustrations where appropriate, how the edges detected by the model will vary as a function of the magnitude of the parameter m and whether these edges reflect visual perception.

[8 marks]

(c)

(i) Explain how a compressive non-linear transfer function like a Naka-Rushton receptor equation, may introduce distortion products into the processed image signal.

(ii) Let the visual image signal be composed of two sinusoidal gratings of similar spatial frequency and contrast. The image signal is processed by a compressive non-linearity, which may be approximated by a power series expansion. By use of these assumptions, provide an estimate of the magnitude and frequency of the distortion product with the lowest spatial frequency that is introduced into the visual signal.

[8 marks]

(d) What evidence, if any, suggests that the visual system has specialised processes whose purpose it is to detect contrast changes that might be present in the visual signal?

[12 marks]

[Total 33 marks]

[CONTINUED]

Question 5

(a) Describe the respective assumptions used by ordinary least-squares (OLS) and by total least-squares (TLS) minimization procedures.

[5 marks]

(b) Explain the perceptual consequences of motion adaptation on motion perception.

[8 marks]

(c) Is motion adaptation a consequence of neural fatigue? Your answer should contrast and compare those predictions made by "fatigue models" with those made by "optimisation" models of visual adaptation.

[8 marks]

(d) Provide an account for effects of motion adaptation on motion perception by contrasting and comparing the predictions made by OLS and TLS models of motion perception.

[12 marks]

[Total 33 marks]

Question 6

(a) Define the binocular correspondence problem, explain why it can occur and show how the problem can be tackled by a coarse to fine strategy. You should use one computational model of binocular depth perception to help illustrate your answer.

[8 marks]

(b) What constraints can be applied to explain one's perception of monocular transparency? In what respect are these constraints incomplete?

[5 marks]

(c) What is the two-channel model for binocular depth perception? Your answer should include empirical evidence to support the two-channel model over the single channel model.

[12 marks]

(d) Explain how monocular constraints on perceptual transparency may be applied to explain the asymmetric binocular depth relations found for contrast envelopes.

[8 marks]

[Total 33 marks]

[END OF PAPER]