Optimization of a Multispectral Imaging System

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Abstract

We have previously presented work using a simple computational model of a multispectral imaging system which we have used to investigate the effect of various parameters (such as the number and properties of the colour channels) on the accuracy of spectral estimation. It was shown that the parameters of a multispectral imaging system interact with each other in a complex way and therefore the optimum set of parameters cannot easily be determined. This paper concerns the development of an optimization technique (based upon simulated annealing) to allow the parameter space of the imaging system to be searched to find the system parameters that give the lowest reconstruction error. Initial results from the optimization analysis show that the optimum spectral properties of the colour channels depend both upon the illuminant under which the image is captured and the goal of the spectral reconstruction process.

Introduction

It is possible to estimate the spectral reflectance function of any surface using a monochrome digital camera with only a small number of filters[1]. Similarly, it is possible to use a simple RGB camera system for the recovery of surface spectral information. However, in order to obtain more reliable estimates of spectral properties it is preferable to use more than three filters or colour channels. Such a system is generally termed a multispectral imaging.[2]

We have previously presented work using a simple computational model of a multispectral imaging system which we have used to investigate the effect of various parameters (such as the number of colour channels) on the accuracy of spectral estimation[3,4.] This paper concerns the development of an optimization technique to allow the parameter space of the imaging system to be searched to find the system parameters that give the lowest spectral reconstruction error. We have used both spectral and colorimetric error measures. The optimization method is based upon simulated annealing and allows the full parameter space to be searched or allows certain parameters to be fixed or constrained. The computational model and the optimization procedure combined provide a useful tool to assist in the design of optimum multispectral imaging systems.

Previous Work

In our previous work and in this paper we have used a simple model of the interaction between light, surfaces and the sensitivities of a camera thus:

$$O_i = \int_\lambda E(\lambda)R(\lambda)S_i(\lambda)d\lambda \qquad \textit{(Equation 1)}$$

where $S_i(\lambda)$ is the spectral sensitivity of each channel i which is given by the transmittance of each filter coupled with the spectral sensitivity of the monochromatic camera, $E(\lambda)$ and $R(\lambda)$ refer to the illuminant power distribution and the surface reflectance function with respect to wavelength λ and O_i is the output of the sensor array for each channel i.

We use the output of this model in conjunction with a linear model of surface reflectance to estimate the spectral reflectance functions of a set of surfaces whose spectral properties have already been measured with a reflectance spectrophotometer.

By using a linear model we are assuming that the reflectance $R(\lambda)$ can be approximated by the linear combination of a set of known basis functions $B(\lambda)$, thus

$$R(\lambda) \approx \sum_j a_j B_j(\lambda) \qquad \textit{(Equation 2)}$$

and then by substituting Equation 2 into Equation 1, we obtain Equation 3

$$O_i = \int_\lambda E(\lambda)\left(\sum_i a_j B_j(\lambda)\right)S_i(\lambda)d\lambda \qquad \textit{(Equation 3)}$$

which is a set of P equations in N unknowns where P is the number of sensor channels and N is the number of basis functions used in the linear model. As long as $P \geq N$, and we assume that $E(\lambda)$, $B_j(\lambda)$ and $S_i(\lambda)$ are known, we can solve this equation for the coefficients a_j using standard linear algebra techniques. Now, in order to estimate a reflectance function $R(\lambda)$ it is sufficient to determine the coefficients a_j, and reconstruct reflectance directly using Equation 2.

Previously published work[3] considered the average error in spectral reconstruction (measured as the median colour difference between measured and reconstructed spectra for a set of 1269 Munsell surfaces[5]) as a function of the number of sensors in the imaging device. The spectral properties of the sensors were Gaussian functions of wavelengths whose peak sensitivities were evenly spaced throughout the visible spectrum. The number of basis functions used in the linear model for the reconstruction process was always equal to the number of sensors (thus, $P = N$). The results of this experiment are summarized by Figure 1 which shows that increasing the number of sensors does not guarantee better spectral-reconstruction performance.

A subsequent experiment[4] relaxed the constraint $P=N$. For each value of P (the number of sensors) the number of basis functions was varied and the results obtained using the optimum number of basis functions in each case are shown in Figure 2.

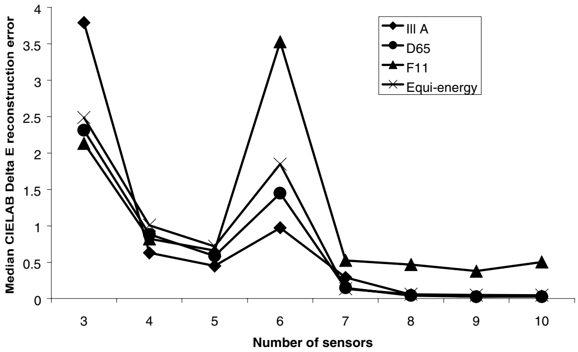

Figure 1. Reconstruction performance as a function of sensor number where P = N.

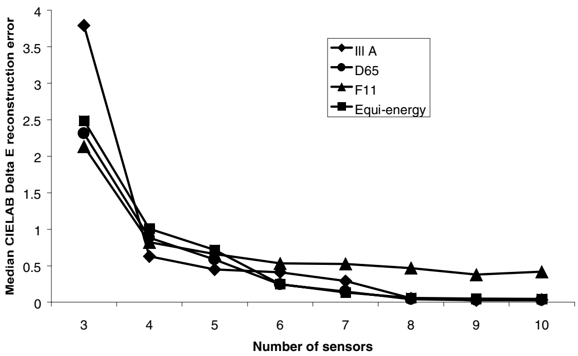

Figure 2. Reconstruction performance as a function of sensor number where the number of basis functions was optimized in each case.

The strikingly poor performance evident for six sensor channels in Figure 1 is interesting but we do not suggest this effect is robust. For example, changing the wavelengths to which the channels are optimally sensitive may well result in much improved performance. We suggest that the poor performance for six sensors shown in Figure 1 occurs because of poor conditioning of Equation 3 which, in turn, is caused by correlations between the spectral sensitivities of the imaging channels and the basis functions in the linear model of reflectance spectra. Indeed, when the number and nature of the basis functions are allowed to vary then the poor performance for six channels disappears (Figure 2).

Thus over-determining the system may result in enhanced performance even though fewer basis functions are used in the linear model than might appear reasonable. For example, six sensors and six basis functions (Figure 1) is out-performed by six sensors and five basis functions (Figure 2).

It is important to note, therefore, that our argument is not that having six sensors in any camera system will always result in relatively poor performance – since relaxing our constraint of equally spaced sensors may also have produced different results – but that increasing the number of sensors alone does not *guarantee* better performance. The interaction of all of the camera properties (in our case, number of channels, width of channel sensitivities, etc) needs to be considered.

The complexity of the interaction of the parameters of the imaging system presents a problem if optimum values of those parameters are to be sought since a multidimensional search procedure is required. The current work was motivated as a solution to this problem whereby an optimization procedure has been used to search the parameter space for a global minimum error (maximum performance).

Experimental

In our previous work we assessed the performance of a camera model whose sensor characteristics were defined as simple Gaussian functions of wavelength. This means that each channel sensitivity function can be expressed as a Gaussian function parameterized by its peak sensitivity, half width, amplitude, skewness and kurtosis. Expressing the channel sensitivities in this way allows us to run a conventional optimization routine known as simulated annealing[6] to minimize the error in the system output by varying the channel parameters. In addition to the channel sensitivities we could vary the number of channels P, the illuminant $E(\lambda)$ and the basis functions $B(\lambda)$ used in the linear model.

In these initial experiments we have only optimized the peak sensitivities and the half-widths of the channels whose spectral properties were assumed to be Gaussian functions of wavelength with zero skewness and kurtosis. The number of channels P and the illuminant $E(\lambda)$ were fixed for any given optimization run. The number of basis functions was also fixed and was equal to the number of channels ($N = P$).

The variables for peak sensitivity and half-width were represented by discrete values at 10nm intervals; the peak sensitivity of each channel was allowed to take on any wavelength from the set [400nm, 410nm, 420nm, … 690nm, 700nm] and the half-width was allowed to take on any value from the set [10nm, 20nm, 30nm, …, 300nm, 310nm]. All filters were normalised so that the integrated sensitivity was always constant.

The simulated annealing optimization procedure aims to minimize a cost function. In our case we used one of two cost functions: the RMS error and the mean CIELAB ΔE error under D65 between the actual reflectance spectra and the reconstructed reflectance spectra. The set of 1269 Munsell reflectance spectra were used both for the determination of the basis functions in the linear model and for the computation of the cost function.

Experiment 1: Effect of Cost Function

In this experiment the effect of using RMS or ΔE as the cost function was evaluated using an imager with 3 and 4 sensors. The imaging illuminant was D65 and the half-widths and peak sensitivities of the sensor classes were optimized by the simulated annealing algorithm

Experiment 2: Effect of Imaging Illuminant

In this experiment the effect of using D65 or A as the imaging illuminant was evaluated using an imager with 3 and 4 sensors. The RMS cost function was used and the half-widths and peak sensitivities of the sensor classes were optimized by the simulated annealing algorithm

Results

Experiment 1: Effect of Cost Function

Figures 3 and 4 show the results obtained using the RMS and ΔE cost functions respectively for three sensors.

In Figure 3 the spectral half-widths of the three sensors are similar and the peak sensitivities are spread evenly throughout the spectrum. However, this is not the case with the spectral sensitivities in Figure 4, whose similarity with the human cone fundamentals is striking.

Equivalent results are illustrated for the case of four sensors in Figure 5 and Figure 6.

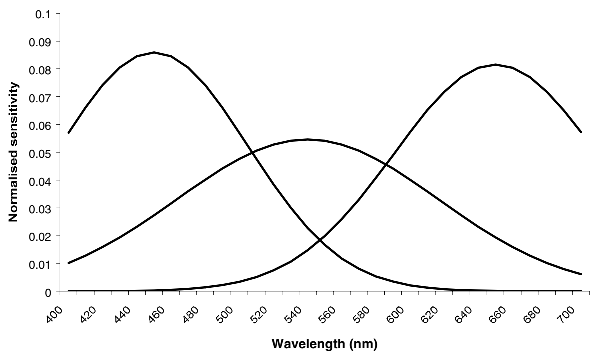

Figure 3. Optimized spectral sensitivities of three sensors using the RMS cost function (imaged under illuminant D65).

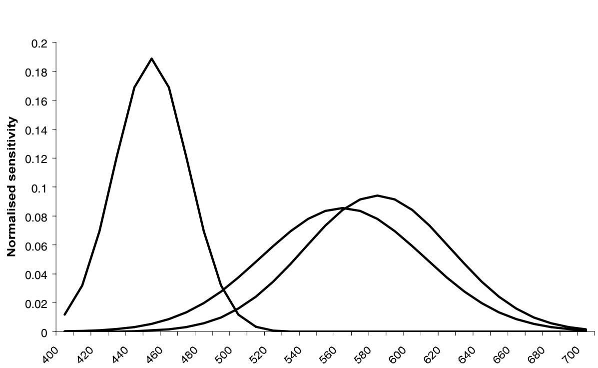

Figure 4. Optimized spectral sensitivities of three sensors using the ΔE cost function (imaged under illuminant D65).

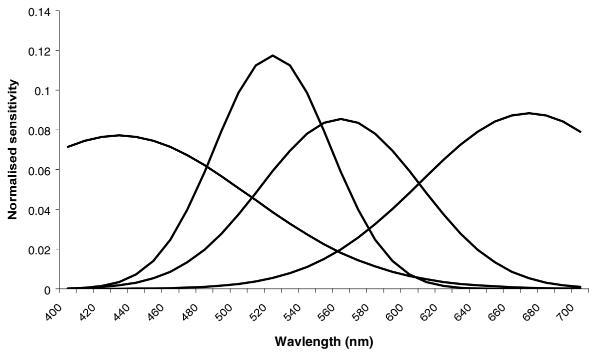

Figure 5. Optimized spectral sensitivities of four sensors using the RMS cost function (imaged under illuminant D65).

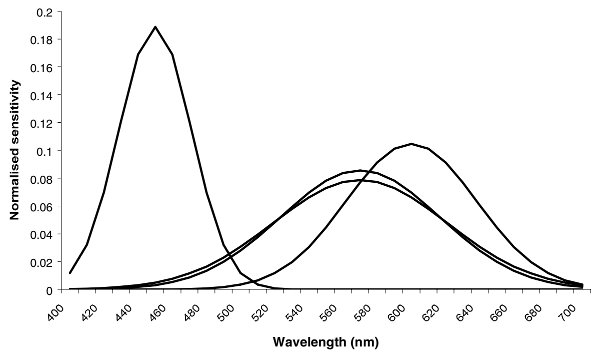

Figure 6. Optimized spectral sensitivities of four sensors using the ΔE cost function (imaged under illuminant D65).

Experiment 2: Effect of Imaging Illuminant

Figure 7 shows the optimized spectral sensitivities of an imager with three sensors where the imaging illuminant was illuminant A. The cost function was the RMS error and therefore Figure 7 (illuminant A) can be compared with Figure 3 (illuminant D65).

Figure 7 illustrates that the optimum spectral sensitivities of a multispectral imaging system are dependent upon the spectral properties of the illuminant. The product of the illuminant and the channel sensitivities can be combined to give the effective spectral sensitivity of the imaging system under that illuminant. Figure 8 shows the spectral sensitivities of Figure 7 multiplied by the spectral power distribution of the imaging illuminant A. It can be observed that the peak sensitivity of the sensor class at 400nm (Figure 7) is effectively shifted to a longer wavelength when the illuminant is considered (Figure 8). This arises because the large band-widths of the sensors in Figure 7 interact with the spectral properties of the illuminant to give the effective spectral sensitivities that are shown in Figure 8. Of course, we note that intrinsically it is the effective spectral sensitivities of the imaging system (not the spectral sensitivities of the channels alone) that are optimally determined.

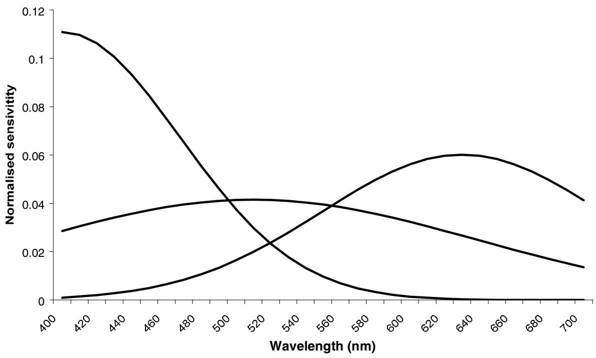

Figure 7. Optimized spectral sensitivities of three sensors using the RMS cost function (imaged under illuminant A).

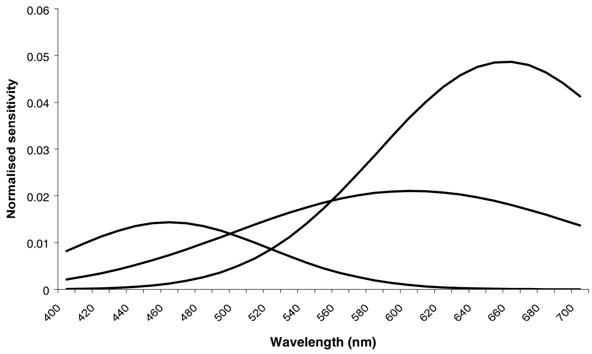

Figure 8. Effective spectral sensitivities of the optimal sensors shown in Figure 7 under illuminant A.

Discussion

Other authors have attempted to optimize aspects of multispectral imaging systems. Particular attention has been paid to the optimization of filter characteristics[7,8,9] in the design of multispectral systems. These are generally based upon vector space methods such as projection onto convex sets.

In this work we have shown that the nature of the cost function that is used in the optimization procedure affects the spectral properties of the filters that are found. In particular, we have found differences between a simple RMS measure and a colorimetric error based upon CIELAB ΔE under illuminant D65. The RMS error is attractive in that it is illuminant independent. However, it does not take into account any properties of the human visual system and may not yield the most practically effective imaging parameters. The colour-difference approach does take into account the human visual system but in our work is restricted to a single illuminant (D65). The use of a colour-difference metric also allows for metamers and therefore the choice of a suitable metric depends upon the goals of the reconstruction procedure; i.e. is it to recover accurate spectral properties or is it to recover estimates of spectral properties that colorimetrically match the original spectra? Recent work on the choice of a suitable metric for optimizing the filters of a multispectral imaging system has considered Vora and Trussell's μ-factor[10] and a unified-measure-of-goodness colorimetric measure.[11]

We have also shown that the properties of the optimal colour channels depend upon the illuminant under which the imaging system operates. Current work is underway to extend our analysis to include the illuminant in the optimization procedure and to ensure that realistic noise characteristics are included in the system.

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Biography

David Connah was awarded a BSc in Biology by Keele University in 1997, and an MSc in Machine Perception and Neurocomputing, also from Keele University, the following year. He began work on his PhD in the Colour and Imaging Institute at the University of Derby in October 1999. His research work is focussed on factors relating to the design of multispectral imaging systems.