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Abstract

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Keywords

image, restoration, colour, processing, application, visual, modelling

Disciplines

Physical Sciences and Mathematics

Publication Details

Qureshi, A. & Ogunbona, P. (1997). Application of visual modelling in image restoration and colour image processing. IEEE Region 10 Annual International Conference, Proceedings: Speech and Image Technologies for Computing and Telecommunications (pp. 17-20). IEEE.

This conference paper is available at Research Online: https://ro.uow.edu.au/infopapers/2142

Application of Visual Modelling in Image Restoration and Colour Image Processing

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ABSTRACT: This paper describes the application of human visual models in (i) defining a visually uniform colour representation space and (ii) the formulation of visually weighted Kalman filtering for image restoration. The former being useful in colour image quantisation and compression. For (i), the uniformity of chromaticity differences at the ouptut of Frei's colour vision model [3] is tested and compensated for by using MacAdam's uniform chromaticity space. For (ii), the dynamical image model of the Kalman filter is visually weighted using the frequency response of Stockham's model [1] of human vision.

1 INTRODUCTION

In many image processing applications such as image compression, enhancement and restoration, it is desirable to account for the way in which the human visual system processes image information. The human visual system is a complex, non-linear, and time-varying system. Only the early stages of the visual process have been sufficiently understood to be modelled accurately enough to be of relevance in image processing applications. Stockham [1] introduced a basic model of human vision for use in image processing applications. He defined a 'visual domain' at the ouput of the model and related it to Oppenheim's concept of homomorphic processing and filtering [2]. Image data in the visual domain is weighted in accordance to its relative importance to the visual system. Hence, image processing algorithms applied to such visually weighted data produce improved performance in the visual sense. Frei [3] extended Stockham's model of achromatic vision to the case of colour vision.

This paper considers two applications of human vision models in image processing: visually relevant colour image representation and visually weighted image restoration. Both applications are served usefully by the definition of a 'visual' fidelity or error criterion to describe differences between original and processed images. The widely used mean-square error (MSE) measure is not consistent with the visual perception and often leads to de-emphasis of visually important features and vice-versa.

In Section 2, Frei's model of colour vision (which consists of a luminance channel and two chromaticity channels) is extended to provide improved uniformity in its chromaticity representation. This is achieved by employing the experimentally defined MacAdam's uniform chromaticity space [4] to test and specify compensations for Frei's chromaticty representation. In the visual domain of the extended Frei model equal distances represent roughly equal perceived colour differences. This uniformity is beneficial for colour image quantisation, optimal colour selection, and colour image compression.

The restoration of (grey-scale) images using Kalman filtering [5] degraded by deterministic blurring and additive random noise can be described as an optimal estimation problem with respect to the MSE criterion. In Section 3 of this paper, visually weighted Kalman filtering for image restoration is described. The spatial frequency response of Stockham's model is utilised to obtain visually weighted Kalman gain values.

2 COLOUR REPRESENTATION

In this Section, the colour representation spaces are briefly discussed and extension of Frei's vision model is described.

2.1 Colour Spaces

The trichromatic nature of human colour vision is well known, and explained well by the Young-Helmholtz theory

of colour vision [6,7]. It postulates that the human vision's colour receptors (cones) have three types of photo-sensitive pigments whose spectral energy absorption characteristics are linearly independent. This trivariance of colour vision [6], means that most colours can be uniquely represented by a mixture of three primary colours, usually red (R), green (G), and blue (B). These primary colours form the basis of the RGB colour space. A digital colour image is usually represented by assigning RGB intensity values for each of its picture elements. However, it has been experimentally shown that the perception of colour is not a linear function of intensity values. The RGB colour space is therefore non-homogeneous as equal Euclidean distances in it do not correspond to equal appearing colour differences. It also cannot account for the effects of spatial interaction between neighbouring colour points.

The spectral sensitivity curves for the CIE RGB primaries indicate that some colours cannot be obtained additively as they require negative tristimulus values for at least one primary. To overcome this shortcoming of real primary systems, in 1931 the CIE adopted the XYZ primary system which yields positive tristimulus values for all real stimuli. The system has purely imaginary primaries X, Y, Z with respective colour matching functions x(l), y(l), z(l) (where l is the wavelength). The CIE XYZ values are realted to the tristimulus values of a system of real primaries by a 3x3 linear transformation matrix [6].

MacAdam [4] experimentally investigated the xy-chromaticity space for homogeneity of colour difference thresholds at fixed luminance levels. Based on these experiments, a new uniform chromaticity space called MacAdam's space was defined via a non-linear transformation of the xy-coordinates [4]. For small localised regions, of the order of a few colour thresholds, the MacAdam's domain forms an approximately homogeneous chromaticity space. In spite of its good homogeneous chromaticity representation, it is not convenient for colour representation as it cannot account for luminance changes or spatial interaction of the visual system.

MacAdam doamin's property of visually homogeneous chromaticity representation provides a tool for quantifying perceived chromaticity differences e.g. within localised regions on it, equal Euclidean distances represent equal perceived chromatcity changes. This property provides a method for objectively assessing the chromatic homogeneity of other colour image representation spaces.

2.2 Evaluation of Frei's Model of Colour Vision

Frei's model of human vision incorporates some of the pre-cognitive processing of image informtion by the visual systems. It does not account for temporal and adaptation effects, and is valid for only medium brightness levels. However, it emulates enough visual behaviour to be of significant value in image processing.
Details of the model are given in [3]. It has three main stages: the first stage represents a linear transformation from RGB space to the eyes' primary system or tristimulus space. The second stage models the eyes nonlinear response to intensity inputs, and the third stage represents the spatial response and interaction of the eye. The output of the model has three channels: G1 the luminance (dark-light) channel, G2 is the red-green chromaticity channel and G3 is the yellow-blue chromaticity channel. Distortion measures applied at the output of the model in the 'visual domain' should weight features according to their visual significance.

To evaluate the colour uniformity of Frei's visual domain, a regularly spaced (and relevantly sized) grid from its chromaticity coordinates was transformed into MacAdam's domain coordinates. The distortion of the grid from a regular and equal spacing revealed the non-uniformity of colour representation in Frei's visual domain. Compensation laws for each chromaticity channel of the Frei's model were calculated by equalisation of Euclidean distance measures between the grid points [10].

Figures 1(a) and 1(b) respectively show the mapping of an equally spaced, regular grid from Frei's visual domain (FVD) and compensated FVD into MacAdam's chromaticity space. The distortion in uniformity of the uncompensated grid are strikingly obvious, while the compensated case shows a much more uniform transformed grid. Uniformity was statistically measured as the ratio of standard deviation to mean (S/M) of the Euclidean distances between transformed grid cross points.

These were noted to be between 100% to 210% before compensation and 13% to 30% after compensation. The significantly increased uniformity in the transformed grid is thus numerically confirmed.

To further validate the compensated Frei's model, subjective assessment of the uniformity of colour difference perception were made. Gaussian noise was added in the visual domain and its effects in the RGB domain were observed. For the compensated model, colour variations seen across the gamut of colours in a test RGB palette, are roughly equal for equal excursions in the G2 and G3 channels. This is in contrast to the subjective observations for the uncompensated space where excursions in G2 and G3 were visible in green areas far more than other colours. The compensated visual domain of Frei's model is useful in defining a more effective 'visual' fidelity criterion for colour image processing. This is useful in many colour image processing applications including colour image quantisation, compression, enhancement and estimation.

3 VISUALLY WEIGHTED KALMAN FILTER

Frei's model of colour vision reduces to an achromatic vision model similar to Stockham's, when only the luminance channel G1 is considered. In this Section, an approach to visually weighted Kalman filtering is presented based on Stockham's model. The latter has two stages: a nonlinearity representing the eyes response to intensity inputs and a second stage to model the spatial response. The incorporation of the non–linearity can create complications in the dynamical signal model and observation model of the Kalman state–space equations. Fortunately, Clark [8] has observed that the nonlinear stage in the visual model is counteracted by the screen gamma of most modern display terminals. He has suggested that the nonlinearty be ignored in working with visually weighted image processing applications. In visually weighting the Kalman filter signal model equations, the non–linearity in Stockham's model is thus ignored.

Incorporating human vision models in image processing can be accomplished by either weighting the data to be processed such as in homomorphic processing [9] or by weighting the parametric equations specifying the data. The latter approach is more suitable for use with Kalman filtering given that it employs signal prediction and signal update equations.
The restoration of (grey–scale) images using Kalman filtering [5] degraded by deterministic blurring and additive random noise can be described as an optimal estimation problem with respect to the MSE criterion. For linear observations and Gaussian signals, the Kalman algorithm can provide the minimum mean–square error (MMSE) estimates of the signal. The Kalman algorithm consists of prediction and update equations. The optimal update equation for the Kalman gain is derived by an unconstrained minimisation of a mean square error functional.

Visual weighting of the Kalman filter is acheived by weighting the minimum mean–square error prediction coefficients with the inverse Fourier transform (impulse response function) of the spatial frequency response of Stockham's model. These weighted MMSE coefficients define a weighted mean–sqaure error (MSE) functional. Optimization of this wieghted MSE functional leads to 'visually weighted' Kalman gains.

The performance of the visually weighted Kalman filter has been evaluated using 256x256 test digital images. The images were blurred using a uniform point spread function and degraded by additive white Gaussian noise. Distorted images were generated for a range of blurred signal to noise ratios (BSNRs) (10 dB to 50 dB). The degraded images were then restored using the well known reduced–update Kalman filter (RUKF) [5] algorithm and a visually weighted RUKF (VRUKF).

The restoration results obtained using the two algorithms were compared both numerically and subjectively. It was seen that the visually weighted filter consistently produces better subjective restorations. The RUKF which is based on minimising the MSE provides the better MSE improvements in intensity domain. This reveals the inconsistency of the MSE measure (when applied in the intensity domain) with visual relevance. However when the

MSE is measured in visually weighted domain, then the VRUKF was observed to perform upto 3 dB better.

4 SUMMARY

This paper has qualitatively described the application of human visual models in the formulation of visually weighted Kalman filtering for image restoration and in defining a visually uniform colour representation space. The dynamical image model MMSE predictor coefficents (of the Kalman filter) are visually weighted using the frequency response of Stockham's model of human vision. These weighted MMSE coefficients define a weighted mean-sqaure error (MSE) functional. Optimization of this wieghted MSE fucntional leads to 'visually weighted' Kalman gains.

The uniformity of chromaticity differences at the ouptut of Frei's human colour vision model is tested and compensated for by using MacAdam's uniform chromaticity space. In the visual domain of the extended Frei model equal distances represent roughly equal perceived colour differences. This forms the basis of a visually relevant fidelity criterion which can be beneficial for colour image quantisation, compression, enhancement, and optimal colour selection.

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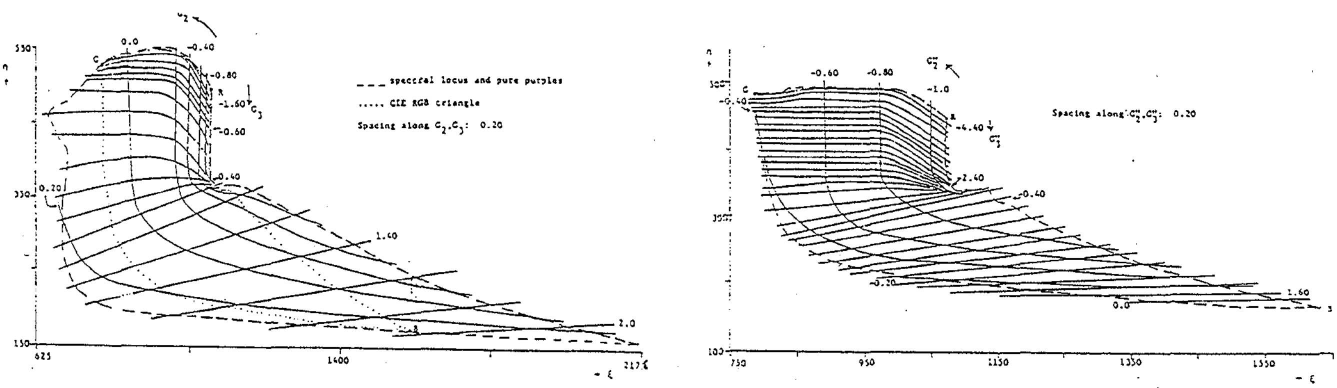

(a) (b)

Figure 1: Distorted G1, G2 grid in MacAdam's Domain (a) uncompensated (b) compensated