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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 output 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.

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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 output 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 output 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 chromaticity 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 \cite{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 \cite{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
respectively 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 \cite{6}.

MacAdam \cite{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 \cite{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 chromaticity 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 information 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 \cite{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: \(G_1\) the luminance
(dark–light) channel, \(G_2\) is the red–green chromaticity
channel and \(G_3\) 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 \cite{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 nonlinearity 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 achieved 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-square error (MSE) functional. Optimization of this weighted 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 up to 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 coefficients (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-square error (MSE) functional. Optimization of this weighted MSE functional leads to ‘visually weighted’ Kalman gains.

The uniformity of chromaticity differences at the output 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.

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

5 REFERENCES