SPATIAL STRUCTURE CHARACTERIZATION OF TEXTURES IN IHLS COLOUR SPACE

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ABSTRACT

We present model based approaches for colour texture characterization in IHLS colour space. Pure chrominance structure information is used in parallel with luminance structure information for colour texture classification. Hue and saturation channels are combined through a complex exponential to give a single channel which holds all the chrominance information of the image. Two dimensional complex multichannel versions of Non-Symmetric Half Plane Autoregressive model and Gauss Markov Random Field model are used to perform parametric power spectrum estimation of both luminance and the "combined chrominance" channels of the image. Colour texture classification is done using k-nearest neighbor algorithm on spectral distance measures both for luminance and chrominance channels individually as well as combined through a combination coefficient. Experimental results show that colour texture characterization obtained by combined luminance and chrominance structure informations is better than the one obtained by using only luminance structure information.

Index Terms— Parametric spectrum estimation, 2D multichannel random field modeling, Colour texture classification.

1. INTRODUCTION

Characterization of spatial variations in colour images has acquired attention of the researchers in the last two decades. Power spectrum information of the colour images can be used to obtain very useful knowledge regarding the spatial feature variations [1]. Frequency domain measures are considered to be less sensitive to noise processes as typical noise processes tend to affect local spatial variation of luminance levels but they present uniform distribution in spatial frequency. Due to these reasons power spectrum estimation of multidimensional random fields has been a point of interest for researchers for a long time.

In [2] model based Spectrum estimation of a single channel by Two Dimensional $(2D)$ Gauss Markov Random Field $(GMRF)$ has been discussed. The method is not able to deal with 2D multichannel data neither real nor complex.

In [3], the authors presented a 2D multichannel autoregressive model based method for the spectrum estimation of real valued data. The authors discussed the autospectra and the cross spectra of the 2D multichannel data but being only limited to the real valued multichannel case, the method is not very well suited for the polar representations of colour images. In [4], the authors used Gaussian Mixture Models for autoregressive model features to classify colour textures. Authors have not considered chrominance structure information at all and they have also considered a non-zero mean case in which AR coefficients do not contain the pure structure information but they are also somewhat influenced by the pure colour information. In [5], authors have presented a Markov Random Field model which combines the colour and texture information to perform the colour texture classification. Gabor filters are used as the texture features while CIE-L*u*v* color values as colour features. Still in this approach they have not considered the chrominance structure information seperately and effects of its fusion with luminance structure information are also not studied.

In this paper we present a model based approach for colour texture classification through 2D multichannel spectral estimation of complex random fields. For this purpose real valued (RGB) colour images are converted to a 3D polar representation of Improved Hue, Luminance and Saturation (IHLS) colour space [6]. Then, an approach for the concurrent spectrum estimation of luminance and chrominance (consisting of both Hue and Saturation) is stated. For this, multichannel complex versions of random field linear prediction models including 2D Non-Symmetric Half Plane Autoregressive (2D NSHP AR) and Gauss Markov Random Field (GMRF) models are used and then finally the results for colour texture classification using spectral distance measures on estimated power spectra for both these models are compared and discussed.

In section 2 colour space conversion used for the work is discussed, while section 3 describes the multidimensional linear prediction models used for power spectrum estimation. Simulations and results are presented in section 4. Finally section 5 concludes the paper.

2. IHLS COLOUR SPACE

The RGB colour space is usually used for image processing and/or analyzing. However the representation of RGB components in a 3D polar coordinate system often reveals characteristics which are not visible in the rectangular representation. To achieve this, we used the IHLS colour space: an improved version of the HLS colour space defined in [6]. Other colour spaces like CIE-L*a*b* may also be used.

Let's consider an RGB image whose colours are defined as vectors $[R, G, B]^T$. Each term R, G and B of the vectors belong to the interval $[0, 1]$. Thereby all colours are included in a cube $[0, 1] \times$

$[0,1] \times [0,1]$. For this RGB image Luminance, Saturation and Hue values in IHLS colour space are given as:

$$Y = 0.2126R + 0.7152G + 0.0722B \quad (1)$$

$$S = max\,(R,G,B) - min\,(R,G,B) \quad (2)$$

$$H = \begin{bmatrix} 360^\circ - H' & if & B > G \\ H' & & otherwise \end{bmatrix} \quad (3)$$

where H' is given as:

$$H' = arccos\left[\frac{R - \frac{1}{2}G - \frac{1}{2}B}{(R^2 + G^2 + B^2 - RG - RB - BG)^{\frac{1}{2}}}\right] \quad (4)$$

It gives very small values of Hue independent of Luminance values for achromatic images that makes feature extraction simpler. The inverse transform from IHLS to RGB is given as:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.0000 & 0.7875 & 0.3714 \\ 1.0000 & -0.2125 & -0.2059 \\ 1.0000 & -0.2125 & 0.9488 \end{bmatrix} \begin{bmatrix} Y \\ C_1 \\ C_2 \end{bmatrix} \quad (5)$$

where C_1 and C_2 are given as:

$$C_1 = K \times cos\,(H) \quad (6)$$

$$C_2 = -K \times sin\,(H) \quad (7)$$

and

$$K = \frac{\sqrt{3}S}{2sin\,(120^\circ - H^*)} \quad (8)$$

where $H^* = H - l \times 60^\circ$ where $l \in \{0,1,2,3,4,5\}$ so that $0^\circ \leq H^* \leq 60^\circ$. We use the colour information obtained through this transformation to build a two channel image that contains pure luminance values in one channel and chrominance values in the other channel. We define this chrominance value as an exponential function depending upon two chrominance variables H and S obtained from colour space conversion. This exponential being independent of the luminance values shall give us the pure information about the colour variations in the spatial domain. We define the said exponential as:

$$C = S \times \exp\,(j \times H) \quad (9)$$

We obtain a complex representation of chrominance content of the image which is interesting to analyze the spectrum in a colourimetric point of view. Now the image to be analyzed consists of two 2D channels. The first channel contains the luminance information and second is complex valued channel containing combined chrominance information (hue and saturation) and is written as:

$$X_n = \begin{bmatrix} Y_n \\ C_n \end{bmatrix} \quad (10)$$

where $n = (n_1, n_2) \in \Lambda \subset \mathbb{Z}$ in which Λ is the finite 2-D image lattice region, $Y_n \in \mathbb{R}$ and $C_n \in \mathbb{C}$.

3. LINEAR PREDICTION MODELS

A multichannel 2D random process represented by a vector sequence $X = \{X_n\}_{n\in\mathbb{Z}}$ with dimension L representing the number of channels following a linear prediction model can be defined through the prediction sequence:

$$\hat{X}_n = -\sum_{m\in\,D} A_m X_{n-m}. \quad (11)$$

as

$$X_n = \hat{X}_n + E_n. \quad (12)$$

where $m = (m_1, m_2) \in\ D \subset \mathbb{Z}$ is a point inside neighbour support region defined by D. $A_m, m \in D$, are $L \times L$ coefficient matrices and $E = \{E_n\}_{n\in\Lambda}$ is the prediction error sequence which is supposed to be a multichannel stationary process having a $L \times L$ covariance matrix denoted by Σ_e and Power Spectral Density (PSD) matrix denoted by $S_{e,\nu}$.

The power spectrum estimation is done using 2D multichannel linear prediction model coefficient matrices A_m, $m \in D$, and may be given as:

$$S_\nu = A_\nu^{-1} S_{e,\nu} \left(A_\nu^H\right)^{-1} \quad (13)$$

where $\nu = (\nu_1, \nu_2)$ is the normalized frequency, $\nu \in [-0.5, 0.5]^2$ and A_ν are $L \times L$ dimensional matrices given by:

$$A_\nu = I + \sum_{m\in D} A_m \exp\left(-j2\pi\langle\nu, m\rangle\right) \quad (14)$$

It is to be noted that the frequency response of the filter defined by (12) is $H_\nu = (A_\nu)^{-1}$.

In (14), I is an identity matrix of dimensions $L \times L$ which represents the coefficients at origin (0,0) and $< .,. >$ represents scalar product.

In (13), S_ν denotes the PSD matrix of the 2D vectorial random process X at normalized frequency ν. A_ν^H represents the hermitian transpose of the matrix A_ν.

For colour images defined by (10), $L = 2$. The PSD for a 2D L channel random process defined by (11) and (12) is estimated using (13) and (14). The PSD matrix gives us the auto spectra and the cross spectra of the two channels. The structure of the PSD matrix is given as:

$$S_\nu = \begin{bmatrix} S_{YY}(\nu) & S_{YC}(\nu) \\ S_{CY}(\nu) & S_{CC}(\nu) \end{bmatrix} \quad (15)$$

where $S_{YY}(\nu)$ denotes the auto spectrum of real valued luminance channel and $S_{CC}(\nu)$ denotes the autospectrum of the complex valued chrominance channel, while $S_{YC}(\nu) = S^*_{CY}(\nu)$ are the cross spectra of the luminance and chrominance channels respectively. In the following, the power spectrum estimation is done using 2D NSHP AR and GMRF prediction models. Details of these two models are given in following subsections.

3.1. 2D NSHP AR Model

A multichannel 2D NSHP AR process is represented by (11) and (12) with a neighbour support region $D = D_{M_1,M_2}$ defined as:

$$D_{M_1,M_2} = \{(m_1, m_2)\,/ 1 \leq m_2 \leq M_2 \text{ for } m_1 = 0, \; -M_2 \leq m_2 \leq M_2 \text{ for } 1 \leq m_1 \leq M_2\} \quad (16)$$

where $(M_1, M_2) \in \mathbb{N}^2$ is the model order and in the case of 2D NSHP AR model, $E = \{E_n\}_{n\in\mathbb{Z}}$ is supposed to be a multichannel white noise stationary process having $S_{e,\nu} = \Sigma_e$. We use least squares estimation method to estimate the model parameters by a matrix solution of a system of normal equations using Moore-Penrose matrix inverse. Then these AR coefficients are used to estimate the PSD matrix of the real valued luminance and the complex valued chrominance channel. As E is a multichannel white noise therefore the estimate of PSD matrix for multichannel 2D NSHP AR model takes the form:

$$\hat{S}_\nu = \hat{A}_\nu^{-1} \hat{\Sigma}_e \left(\hat{A}_\nu^H\right)^{-1} \quad (17)$$

and structure of this PSD matrix is given in (15).

3.2. Gauss Markov Random Field Model

It is possible that an observation in a 2D random field may depend on its neighbouring observations in all directions unlike the case in NSHP and thus making the model non-causal. A multichannel 2D GMRF process is represented by (11) and (12). For a model order M, $D = D_M$ is a non-causal, symmetric neighbourhood excluding the origin $(0,0)$ such that if $\{m \in D_M\}$ then $\{-m \in D_M\}$. Such a support is defined as:

$$\Omega_1 = \left\{ m, \underset{m \neq (0,0)}{\operatorname{argmin}} \; \|m\|_2 \right\} \tag{18a}$$

$$\Omega_k = \left\{ m, \underset{m \notin \bigcup\limits_{1 \leq p \leq k-1} \Omega_p}{\operatorname{argmin}} \; \|m\|_2, m \neq (0,0) \right\}, k \geq 1 \tag{18b}$$

$$D_M = \bigcup_{1 \leq k \leq M} \Omega_k \tag{18c}$$

where $\|m\|_2 = \sqrt{{m_1}^2 + {m_2}^2}$. In case of GMRF $E = \{E_n\}_{n \in \mathbb{Z}}$ is a 2D multichannel Gaussian correlated noise sequence which has a $L \times L$ covariance matrix denoted by Σ_e. GMRF model parameter matrices A_m are estimated again by solving a system of normal equations using least squares method using Moore-Penrose matrix inverse. These GMRF model parameters are then used to estimate the PSD matrix of the process X. It can be verified that the PSD matrix for the 2D multichannel complex valued GMRF is given as:

$$S_\nu = \Sigma_e \times \left(A_\nu^H \right)^{-1} \tag{19}$$

where A_ν is given by (14), leading us to:

$$S_{e,\nu} = A_\nu \Sigma_e \tag{20}$$

This shows that E is a correlated noise sequence. As in the case of 2D NSHP AR spectrum estimation, the PSD matrix contains both the auto and cross spectra of the luminance and chrominance channel as given in (15).

4. SIMULATIONS AND RESULTS

Simulations for the estimation of model parameters, for the estimation of Power spectrum and consequently for colour texture classification using multichannel complex versions of 2D NSHP AR and GMRF models were carried out. The experiments were conducted on the MIT Vision Texture (VisTex) database. We chose randomly 10, 512×512 textured color images from the Vistex database, shown in Fig 1.

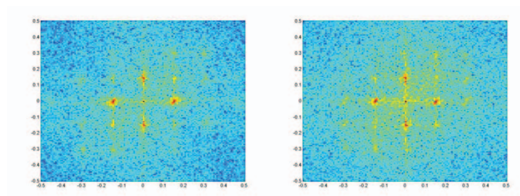
The spectrum estimation was done on blocks of size 32. First 96 subimages of each texture were used for training, while the remaining 160 subimages were used for testing. In Fig 3 absolute frequency content of the luminance and chrominance channel of texture 8 (Fig 2) are shown. In Fig 4 and Fig 5 estimated luminance and chrominance spectra for the same image are shown, which are computed in cartesian coordinates for normalized frequency range ν where $\nu = (\nu_1, \nu_2) \in [-0.5, 0.5]^2$.

4.1. Spectral Distance Measure

To measure overall closeness of luminance and chrominance spectra at all frequencies, following spectral distance measure was used:

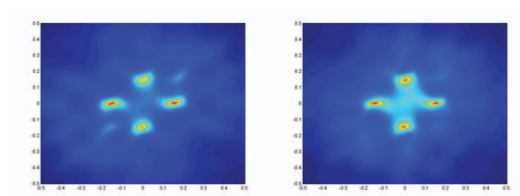
Fig. 1: The tested texure database

Fig. 2: Test texture 8



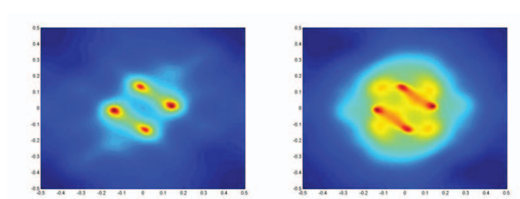
(a) Luminance Channel (b) Chrominance Channel

Fig. 3: Absolute frequency content using 2D FFT



(a) Lum. Channel, S_{YY} (b) Chrom. Channel, S_{CC}

Fig. 4: Auto Spectra using 2D NSHP AR of order $(2,2)$



(a) Lum. Channel, S_{YY} (b) Chrom. Channel, S_{CC}

Fig. 5: Auto Spectra using GMRF of order 4

$$K_\beta \left(S_{1,\beta}, S_{2,\beta}\right) = \frac{1}{2} \times \sum_{\nu_1,\nu_2} \left| \sqrt{\frac{S_{1,\beta}(\nu_1,\nu_2)}{S_{2,\beta}(\nu_1,\nu_2)}} - \sqrt{\frac{S_{2,\beta}(\nu_1,\nu_2)}{S_{1,\beta}(\nu_1,\nu_2)}} \right|^2 \tag{21}$$

	$k=1$	$k=3$	$k=5$	$k=7$
α	0.69	0.82	0.81	0.93
L	88.125	86.750	87.125	85.937
C	86.250	85.812	85.812	84.937
LC	94.500	94.875	94.437	93.125

Table 1: Total percentage classification of 10 colour textures using 2D multichannel complex NSHP AR model of order $(2, 2)$.

	$k=1$	$k=3$	$k=5$	$k=7$
α	0.5	0.69	0.65	0.72
L	78.000	77.938	78.875	79.188
C	71.313	72.938	72.563	72.688
LC	87.375	88.687	88.625	88.750

Table 2: Total percentage classification of 10 colour textures using 2D multichannel complex GMRF model of order 5.

where $\beta \in \{L, C\}$. The spectral distance measure given in (21) gives the closeness of each channel individually. Therefore, in order to combine the luminance and chrominance channel spectral information and make it useful for improvement of colour texture classification results we define the following combined spectral distance measure:

$$K_{LC}(\nu_1, \nu_2) = \alpha \times K_L(\nu_1, \nu_2) + (1 - \alpha) \times K_C(\nu_1, \nu_2) \quad (22)$$

This distance combines the information from both spectra using a combination coefficient α, where $0 \leq \alpha \leq 1$. The optimal combination coefficient value was learned through the classification of the same training subimages. For each k, the value of α which gives the maximum classification percentage for these training subimages, is used during the classification of test subimages.

Once the individual and combined spectral distances of both luminance and chrominance channels are calculated, the k-nearest neighbour algorithm was used to classify the colour textures. Experiments were carried out for different values of k including $1, 3, 5$ and 7.

Experimental results indicating the percentage colour texture classification using 2D multichannel complex NSHP AR and GMRF models for colour texture classification are shown in tables 1 and 2 respectively. First row in each table indicates α, the combination coefficient being calculated for different values of k, the number of nearest neighbours calculated for texture classification. Second and third rows in the tables indicate the total percentage colour texture classification results for 10 colour textures using luminance and chrominance channel spectral information separately. In row three total percentage colour texture classification using pure luminance and chrominance structure information is given. Both multichannel 2D NSHP AR and GMRF models have shown reliable results for different values of k. Two very important results can be deduced from these tables.

Firstly it is clear that the percentage classification of colour textures increases significantly if we use pure chrominance structure information as an additional information with standard luminance structure information and which was the primary purpose of this study. Secondly we also see that if we increase the number of nearest-neighbours that we consider, percentage classification results are not disturbed on a large scale indicating the robustness of the approach.

Another important observation is that 2D multichannel complex NSHP AR model gives us better results in terms of colour texture classification as compared to the 2D multichannel complex GMRF model. Total percentage classification of colour textures obtained by this approach are quite good and can easily be compared to the total percentage classification results of colour textures computed through other existing approaches.

5. CONCLUSION

The aim of this research paper is twofold. First: In this study we have theoretically adapted and successfully used the two dimensional multichannel complex linear prediction models for modeling of images in a perceptual colour space like IHLS which has not been addressed so far. In this paper we have also presented a new approach for model based combined power spectrum estimation for both luminance and chrominance channels in IHLS colour space.

Second: A useful information of pure chrominance structure, considering a zero mean case is computed and is fused with pure luminance structure information to get better colour texture classification results. The results obtained are interesting and indicate that these type of parametric models are efficient for precise spectral estimates. These precise spectral estimates are very useful in applications like colour texture classification as shown in this paper, colour texture segmentation and also in colour texture reconstruction.

The results obtained from this approach can further be improved if pure colour information like histogram cubes in RGB or any perceptual colour space like IHLS can be fused to this combined luminance and chrominance structure information like it has already been proposed in [4], [5].

In future studies we would like to contribute to the existing work by doing a comprehensive and detailed comparative study of these approaches in other perceptually uniform colour spaces which include CIE-L*a*b* and CIE-L*u*v*.

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