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Parametric models of linear prediction error distribution for color texture and satellite image segmentation

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ABSTRACT

In this article we present a Bayesian color texture segmentation framework based on the multichannel linear prediction error. Two-dimensional causal and non-causal real (in RGB color space) and complex (in IHLS and $L^*a^*b^*$ color spaces) multichannel linear prediction models are used to characterize the spatial structures in color images. The main contribution of this segmentation methodology resides in the robust parametric approximations proposed for the multichannel linear prediction error distribution. These are composed of a unimodal approximation based on the Wishart distribution and a multimodal approximation based on the multivariate Gaussian mixture models. For the spatial regularization of the initial class label estimates, computed through the proposed parametric priors, we compare the conventional Potts model to a Potts model fusioned with a region size energy term. We provide performances of the method when using Iterated Conditional Modes algorithm and simulated annealing. Experimental results for the segmentation of synthetic color textures as well as high resolution QuickBird and IKONOS satellite images validate the application of this approach for highly textured images. Advantages of using these priors instead of classical Gaussian approximation and improved label field model are shown by these results. They also verify that the $L^*a^*b^*$ color space exhibits better performance among the used color spaces, indicating its significance for the characterization of color textures through this approach.

1. Introduction

Texture segmentation in color images is a challenging problem. In supervised color texture segmentation, a known color texture sample is used to identify and/or extract the regions having the same color texture in a given scene or image. A large number of algorithms have been proposed for color texture segmentation during recent years, based on different techniques for the description of textural content in a color image like Gabor filters [14,15], JSEG [9], Quaternion representation of color textures [25], transform based texture descriptors [18] and model based techniques [11,17].

Model based approaches have been extensively used to segment the textured regions in gray level and color images. In [12], an unsupervised multispectral texture segmentation method is presented. Single decorrelated texture factors in each color plane are assumed to be represented by a set of local models evaluated for each pixel centered image window and for each color plane. In this work, the authors have based the segmentation framework on the parameter space describing the multichannel textures. This method on the other hand requires a contextual neighborhood selection and two additional thresholds.

In [5], authors used the 2D single channel real valued linear prediction models for the multiple resolution segmentation of gray level textured images. The initial class label field of the image was estimated by approximating the linear prediction error (*LPE*) with a Gaussian probability distribution. Once the initial class label field of the image is estimated, this field is modeled as a Markov random field (*MRF*). In this work, the authors did not discuss the modeling and subsequently the segmentation of the color images using these models. Another work [4] presents an improved version of the approach discussed in [5]. This work also addresses the gray level textures and approximates the LPE with a Gaussian probability distribution.

An MRF based color texture segmentation method is proposed in [15]. The authors represented the feature distributions of the different classes in the image by Multivariate Gaussian Mixture Model *(MGMM)*. They used Gabor filters as texture features

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whereas pixel values in CIE $L^*u^*v^*$ color space are considered as color feature cue. In [18], the authors used autoregressive model features to classify color textures. They have used several methods to represent the structure information of the color images including wavelet and DCT coefficients. Authors achieved color texture classification by fusing this structure information with the pure color information obtained through the mean and covariance information of the image.

In this paper we present a comparison between different parametric approximations of the 2D multichannel LPE distribution for a supervised color texture segmentation algorithm. This work is an extended and detailed analysis to the basic concepts presented in [21].

In the first step of our proposed segmentation algorithm, we estimate the 2D multichannel linear prediction model parameters using a small training sub image. These models are complex valued in the case of Improved Hue, Luminance, Saturation (*IHLS*) [13] and $L^*a^*b^*$ [7] color spaces for a two channel complex valued color image representation (see Section 2.2). In the case of RGB color space, the model is real valued as the three color planes are real. Then, we estimate the multichannel LPE sequence of test image using the 2D multichannel linear prediction model computed in the training step. 2D multichannel versions of non-causal (Gauss Markov Random Field (*GMRF*)) and causal (non-symmetric half plane autoregressive (*NSHP AR*) and quarter plane autoregressive (*QP AR*)) models are used as image observation models. We estimate the overall color distribution of the image from the multichannel prediction error sequence. Classically, the distribution of this multichannel LPE sequence E can be approximated using a multivariate Gaussian approximation. Although this approximation is simple and mostly used, it may not be an accurate approximation when the distribution of the LPE is neither gaussian nor unimodal. Segmentation results are therefore not robust or stable as our preliminary study tends to show [21]. To address this problem, we discuss two other parametric models for approximation of the distribution of multichannel LPE sequence E:

1. Wishart probability distribution.
2. MGMM probability distribution.

Once these approximations are estimated, initial class label field is computed with the help of these approximations. This coarse class label set for the test image is assigned according to a global criterion which maximizes the probability of the multichannel LPE sequence E computed through one of the proposed parametric models.

During the spatial regularization process of the initial class labeld field, we compare the use of a conventional Potts model and a Potts model fusioned with a Gibbs distribution based on region size energy term to model the distribution of the class label field. In this context, we also compare the deterministic Iterated Conditional Modes (ICM) algorithm to the stochastic Simulated Annealing (SA) in order to study the dependence of the segmentation results against the used algorithm. The results of the approach for the segmentation of synthetic color textures using three different image observation models, three parametric approximations of the multichannel LPE distribution in three color spaces *i.e.* RGB, IHLS and $L^*a^*\ b^*$ are presented, compared and discussed. The effects of different hyperparameters on the final segmentation results for synthetic color textures as well as high resolution satellite images are also presented and discussed.

Section 2 presents the used two channel complex color image approach and image observation models. Different approximations of LPE distribution are discussed in the Section 3. The estimation of the class label field is presented in the Section 4. The Sections 5 and 6 present the experimental procedures and results for color texture and satellite image segmentation respectively. Finally conclusion of the presented work and a few perspectives are discussed in the Section 7.

2. Image observation models

In this section we will discuss the used color spaces, the two channel complex color image and the causal and non-causal linear prediction models used as the image observation models.

2.1. The color spaces

The analysis presented in this paper is carried out in three different color spaces including RGB, IHLS (Fig. 1a) and $L^*a^*b^*$ (Fig. 1b) color spaces.

The RGB color space is the most widely used color space in computer applications and image processing. It is defined by the three chromaticities of the red, green, and blue additive primaries, and can produce any chromaticity that is the triangle defined by those primary colors. This space is easier to use for color image analysis but all possible colors can not be represented in this color space. Also the color distances computed in the RGB color space are not correlated to perception.

Many color space conversion systems define a saturation coordinate which is dependent on the brightness coordinate of the image and hence are not very suitable for image analysis applications. To overcome this shortcoming of conversion systems, an improved

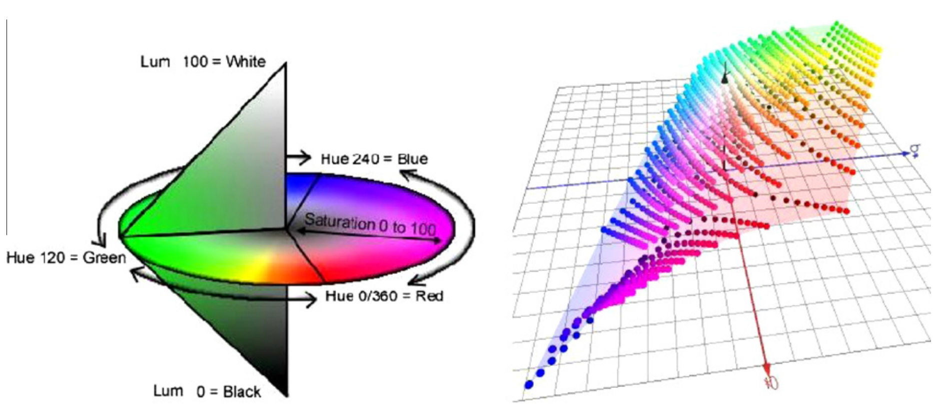

Fig. 1. Color spaces: (a) IHLS color space and (b) $L^*a^*b^*$ color space.