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Program Guide

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IEEE

... - 13:00

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... Chao-Ho) Chen, Yi-Fan Li, *Department of Elec-...gineering, National Kaohsiung University of Ap-...ences, Taiwan*

... TWO STAGE VARIABLE BLOCK SIZE MO-...N SEARCH ALGORITHM FOR H.264 EN-...DER
...ki Shimizu, Akio Yoneyama, Hiromasa Yanagihara, ...ki Nakajima, *KDDI R&D Laboratories Inc., Japan*

...ST FULL SEARCH BLOCK MOTION ESTI-...ATION FOR H.264/AVC WITH MULTILEVEL ...CESSIVE ELIMINATION ALGORITHM
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...ZZY NON-RIGID MOTION ESTIMATION RO-...ST TO ROTATION
... Morales Sanchez, Rafael Verdu Monedero, Ricardo ...ez Leon, *Universidad Politecnica de Cartagena,* ... Luis Weruaga Prieto, *Austrian Academy of Sciences,* ...

TA-P4: Feature Extraction and Analysis: Color and Texture

Time: 10:10 - 13:00
Location: Gallery
Chair: Vinod Chandran, *Queensland University of Technology*

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Roberto Cossu, Ian Jermyn, Josiane Zerubia, *INRIA, France*

TA-P4.2 **COMPARISON OF LINEAR SPECTRAL RECONSTRUCTION METHODS FOR MULTISPECTRAL COLOUR IMAGING**
David Connah, Jon Hardeberg, *Gjøvik University College, Norway*; Stephen Westland, *Leeds University, England*

TA-P4.3 **OBJECT TRACKING BY ADAPTIVE FEATURE EXTRACTION**
Bohyung Han, Larry Davis, *University of Maryland-College Park, USA*

TA-P4.4 **COLOR TEXTURAL FEATURES UNDER VARYING ILLUMINATION**
Dimitrios Iakovidis, *Univ. of Athens, Greece*; Dimitrios Maroulis, *Univ. of t Athens, Greece*; Stavros Karkanis, *Technological Inst. of Lamia, Greece*

TA-P4.5 **ADVANCES IN TEXTURE ANALYSIS: ENERGY DOMINANT COMPONENT & MULTIPLE HYPOTHESIS TESTING**
Iasonas Kokkinos, Georgios Evangelopoulos, Petros Maragos, *National Technical University of Athens, Greece*

TA-P4.6 **A FAST PROCEDURE FOR THE COMPUTATION OF SIMILARITIES BETWEEN GAUSSIAN HMMS**
Ling Chen, Hong Man, *Stevens Institute of Technology, USA*

TA-P4.7 **MULTISCALE ASYMMETRY SIGNATURES FOR TEXTURE ANALYSIS**
Gert Van de Wouwer, *Visielab, University of Antwerp, Belgium*; Barbara Weyn, Dirk Van Dyck, *University of Antwerp, Belgium*

BREAK

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COLOR TEXTURAL FEATURES UNDER VARYING ILLUMINATION

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ABSTRACT

In this paper we present a new feature extraction methodology for color texture recognition. It is based on the covariance of 2nd-order statistical features in the wavelet domain of the color channels of the images and it is named as *Color Wavelet Covariance* (*CWC*). The experimentation showed that the CWC features could be used effectively for texture representation even when illumination varies. The use of the linear K-L (Karhunen-Loeve) transformation of the RGB color space for the extraction of the CWC features resulted in a performance that was comparable to the one achieved with more complex non-linear color transformations. The recognition accuracy tested with texture mosaics reached an average of 86%. Using images acquired under varying illumination the performance of the CWC features on the K-L space reached an average of 88%.

1. INTRODUCTION

Texture characterizes any visible surface and this is the major reason that texture analysis methodologies are incorporated into the construction of image analysis systems. During the last years an amount of scientific effort has been directed to the use of color in the texture representation approaches. Recent work includes perceptual approaches [1], the use of chromaticity moments [2], and the derivation of textural information from luminance channel along with pure chrominance features, as well as the processing of each color channel separately by applying gray-level texture analysis techniques [3]. Other approaches exploit the interdependence of the existent textural information within the different channels of a color image, usually captured by means of correlation. Van de Wouwer et al [4] achieved high classification rates using correlation signatures estimated from the wavelet coefficients of color images. Paschos [5] proposed a set of discriminative and robust chromatic correlation features using directional histograms. Vandebroucke et al [6] exploited the correlation of 1st order statistical features between the different color channels for unsupervised soccer image segmentation and Al-Rawi et al [7] proposed Zernike moments of correlation and covariance functions for illumination invariant color texture recognition.

Under a similar framework we propose a new feature extraction methodology named as *Color Wavelet Covariance* (*CWC*) that exploits the covariance of 2nd-order textural measures in the wavelet domain of the color channels of the images. We evaluate the performance of these features for color texture recognition in various color spaces and we investigate their performance under varying illumination. The classification task has been assigned to a Support Vector Machine (SVM) classifier, as SVMs have shown remarkably robust performance, even with sparse and noisy data, and they resist to the overfitting and to the "curse of dimensionality" [8][9].

The rest of this paper is organized in four sections. Section 2, includes the description of the proposed methodology for the extraction of color textural features. A short description of the classification model, with the use of SVMs, follows in section 3. In section 4, we appose the results of the application of the proposed methodology for color texture recognition using images from Vistex database [10] and images of objects acquired in different illumination conditions [11]. The conclusions of this study are summarized in the last section.

2. COLOR WAVELET COVARIANCE FEATURES

In the proposed feature extraction methodology we assume that a color image I, is decomposed into three color channels C_i, where $i = 1, 2, 3$. Each channel is raster scanned with a fixed size sliding square window. On each window a K-level 2D-Discrete Wavelet Transform (DWT) is applied. The Daubechies wavelet bases were used due to their orthonormal properties, which are important for the preservation of the textural structure along the different scales of the transform [10]. This transform results in a new representation of the original window, which consists of

$$B = 3K + 1 \tag{1}$$

sub-windows, corresponding to different wavelet bands.

Each band is denoted as $B_j(k)$, where k is the current level of the transform and j = 0, 1, 2, 3 for $k = K$, or j = 1, 2, 3 for $k < K$. $B_0(k)$ corresponds to the low frequency band.

The textural information contained in each window is captured with the use of cooccurrence matrices. Cooccurrence matrices encode the gray level spatial dependence based on the estimation of the 2nd order joint conditional probability density function $f(i, j, d, a)$, which is computed by counting all pairs of pixels at distance d having gray levels i and j at a given direction a. The angular displacement of d = 1 is included in the range of the a-values {0, π/4, π/2, 3π/4}.

The proposed approach for the estimation of color textural features takes advantage of the covariance between statistical measures of the cooccurrence matrix corresponding to each color channel of the image. To investigate the performance of this approach we have considered four Haralick's measures, namely the angular second moment (f_1), the correlation (f_2), the inverse difference moment (f_3) and the entropy (f_4). These four features provide high discrimination accuracy which can only be marginally increased by adding more features in the feature vector [13][14].

The features f_1- f_4 are estimated over each sub-window $B_j(k)$, $j \neq 0$, k = 1, 2, … K, of the color channels C_i, i = 1, 2, 3 of the image and they are noted as:

$$F_{C_i}^{B_j(k)}(a), \qquad (4)$$
$$j \neq 0,\ k = 1, 2, \ldots K,$$

where $F \in \{ f_1, f_2, f_3, f_4 \}$ and a corresponds to the angle considered in the estimation of the cooccurrence matrices, $a \in \{ 0, \pi/4, \pi/2, 3\pi/4 \}$. We define *Color Wavelet Covariance of a feature F* (*CWC or CWC$_F$*), $F \in \{ f_1, f_2, f_3, f_4 \}$ at wavelet band $B_j(k)$, $j \neq 0$, k = 1, 2, … K, between two color channels C_l and C_m as:

$$CWC^{B_j(k)}(C_l, C_m) = Cov\left(F_{C_l}^{B_j(k)}, F_{C_m}^{B_j(k)}\right) \qquad (5)$$

estimated over the different angles a. For K=1, the corresponding feature vectors consist of 72 CWC features ((3 variances + 3 covariances) x 4 cooccurrence matrices x 3 wavelet bands).

The use of these features can lead to a reduced feature space compared to the original feature space defined by Eq.(4).

3. SUPPORT VECTOR MACHINES FOR PATTERN CLASSIFICATION

Let Φ be a non-linear mapping from the input space $I \subseteq \Re^n$ to the feature space $F \subseteq \Re^m$. The SVM algorithm is capable of finding a hyperplane defined by the equation

$$w\Phi(x) + b = 0 \qquad (6)$$

so that the *margin of separation* is maximized. It is easy to prove [8][9] that for the *maximal margin* hyperplane,

$$w = \sum_{i=1}^{N} \lambda_i y_i \Phi^{\mathrm{T}}(x_i) \qquad (7)$$

where the variables λ_i are Lagrange multipliers that can be estimated by maximizing the quantity

$$L_D = \sum_{i=1}^{N} \lambda_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \lambda_i \lambda_j y_i y_j K(x_i, x_j) \qquad (8)$$

with respect to λ_i, where the following constraints should be satisfied: $\sum_{i=1}^{N} \lambda_i y_i = 0$ and $0 \le \lambda_i \le c$, for i = 1, 2, …, N, and a given value c. $K(x_i, x_j)$ is called kernel function and it is defined as the inner product

$$K(x_i, x_j) = \Phi^{\mathrm{T}}(x_i)\Phi(x_j)\,. \qquad (9)$$

Linear, polynomial, Radial Basis Function (RBF) are the most common functions used as SVM kernels. The *one-against-one* strategy is used for the classification of multiple classes [9].

4. RESULTS

The aim of the experimentation apposed in this paper is the evaluation of the recognition performance of the new feature set using SVMs. The color images used were digitized at 3x8=24bit and the window size used for feature extraction was 32x32 pixels. The windows' sliding step was chosen to be one pixel, so as to produce detailed output images. Concerning the choice of the SVM kernel, preliminary experiments showed that the 2nd-order polynomial kernel $\mathrm{K}(x_i, x_j) = (x_i \cdot x_j + 1)^2$, is more suitable for the classification of the CWC features than the linear, 3rd-order polynomial or RBF kernel, since it can achieve high generalization performance at a relatively low computational cost. The classification performance is estimated in terms of Mean Classification Error (MCE %).

The results are organized in two parts. In the first part, standard textures from Vistex database and mosaics are used for the evaluation of the performance of the CWC features for texture recognition. In the second part, an assessment of their performance under varying illumination is attempted.

4.1. Texture recognition using Vistex images

The texture recognition performance of the proposed methodology was measured using 32 color texture images from the Vistex database [10]. The texture images were

128x128 pixels size and were grouped into two test mosaics of 16 images each as illustrated in Fig. 1. The mosaics were 512x512 pixels size.

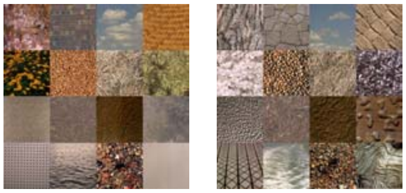

Fig. 1. 16-Texture test mosaics

For each group, the SVM was trained with the 16 texture images independently. The trained SVM was used to recognize the different textures in the corresponding 16-texture mosaic images. The same procedure was repeated in different color spaces that have been used in various texture recognition applications in the literature. The MCE achieved in RGB was 17.58±0.85%, in K-L (linear approx.) was 14.07±0.77%, in YIQ 15.10±0.84%, in YES 15.08±0.62%, in HSV 13.80±1.19%, in HLS 15.10±1.15% and in $L^*a^*b^*$ 17.24±0.70% [4][15][16]. The results are summarized in Fig. 2 and they are compared to the results achieved by using the gray-level cooccurrence features on the wavelet domain (21.39±2.10%).

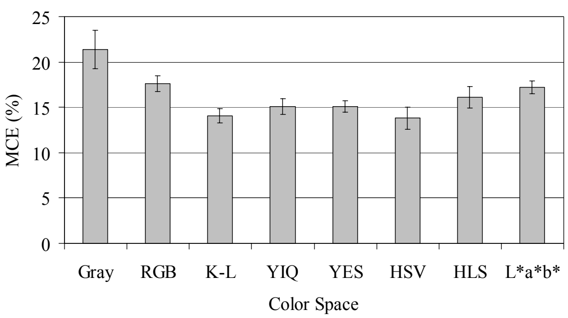

Fig. 2. Classification results in different color spaces.

According to these results it is obvious that color features perform better than grayscale features. The lowest MCE was achieved in the K-L and in the HSV space. It should be noted that the SVM was not trained with the areas between the different textures of the texture mosaics. The percentage of these "unknown" to the system areas reaches 6.25% of the test images. In the less realistic case of using 6% of the test images for training, which is commonly used in the literature [17], the classification performance increases by 12.22% - 15.76% depending on the color space used. The images illustrated in Fig. 3, validate the fact that the SVM failed to recognize the "unknown" areas and prove that the classification accuracy of the "known" textures is high.

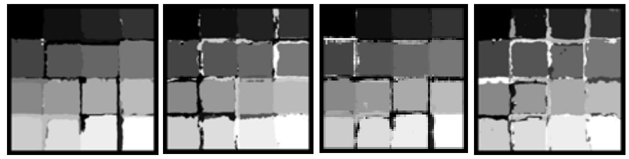

Fig. 3. Classification results using HSV (left pair) and K-L (right pair) CWC features.

4.2. Texture recognition under varying illumination

The images used in the experiments for the evaluation of the texture recognition performance under varying illumination were taken from a database containing 20 objects acquired in different orientations and views under 11 different light sources [11]. Out of these objects we have selected 4, containing strong textural patterns as illustrated in Fig. 4. Each object corresponded to a different texture class. The folds of the objects and the shades made the recognition task harder but more realistic. The images were sized at 128x128 pixels and equalized.

Fig.4. Sample images "coffee", "shirt1", "shirt2", "shorts".

The SVM was trained with 4 images of the objects acquired under the same illumination conditions. The rest of the images of the objects that were corresponding to different illuminations were used for testing. The same procedure was repeated for all the 11 different illumination conditions and in different color spaces. In addition to the color spaces used in the previous experiment, we have also included rgb (normalized RGB) and $l_1l_2l_3$ as they are invariant to illumination changes [18]. The classification results are summarized in the diagram illustrated in Fig.5.

The CWC features perform equivalently in RGB (18.08±2.47%), YES (17.57±6.72%), HSV (18.12±1.81%), HLS (17.09±2.30%), rgb (16.26±4.31%) and *l1l2l3* (16.15±1.91%) color spaces. The performance of the gray-level features (32.23±5.93%) was significantly inferior to the performance of the CWC features.

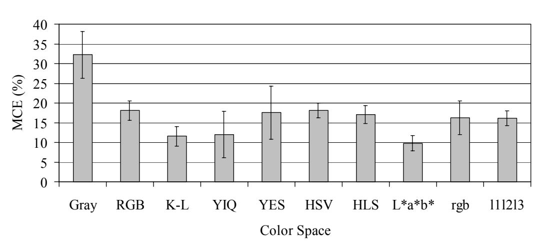

Fig.5. Classification performance under varying

illumination in different color spaces.

The lowest MCE was achieved in $L^*a^*b^*$ (9.79±1.95%), K-L (11.54±2.51%) and YIQ (12.02±5.87%) spaces. The variance in the case of K-L and $L^*a^*b^*$ is lower that in the case of YIQ. Figure 6, illustrates indicative classification results for the “shirt1” image corresponding to different illumination conditions.

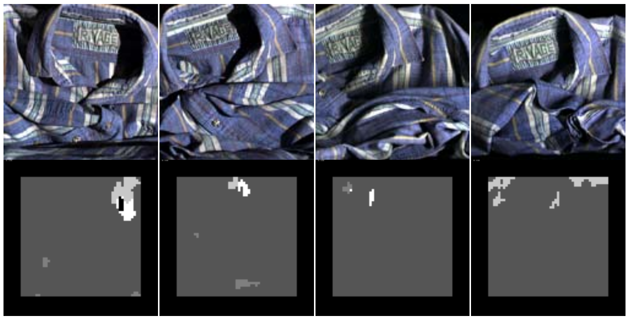

Fig.6. Classification results for the “shirt1” image using K-L (2rd row).

5. CONCLUSIONS

In this paper we introduced a new set of features for color texture representation, named CWC. We attempted to evaluate their recognition performance under varying illumination using SVMs. Different color spaces were considered for the evaluation. The results show that the linear K-L transformation of the RGB color space can be used effectively for the representation of texture using the CWC features even when the illumination varies. K-L model consists of statistically uncorrelated axes and requires less computational effort than non-linear transformations of the RGB. From the experimentation it can be concluded that the CWC features in the K-L color space lead to high recognition performance and could be used in real texture analysis applications involving image acquisition under different light sources.

7. REFERENCES

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