Texture classification using Laws' filter in various color spaces

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Abstract-**Color plays an important role in object recognition. In digital images,color spaces are three-dimensional arrangements of color sensations. In this paper, we focus on texture classification using various color spaces with Laws' filter descriptor. The main objective is to determine the contribution of color information for different color spaces to the overall texture classification performances. Initially experiments are conducted for gray-level texture classification by using two datasets VisTex and STex. Then experiments are extended to various color spaces like RGB, HSV, Lab, XYZ, YCbCr and YIQ for the same two datasets for color texture classification. Experimental results indicate that the incorporation of various color information improves the performance of texture classification.**

Keywords: Texture feature, Texture classification, Laws' mask,Color texture.

I. Introduction

Texture provide important characteristics for surface and object identification from aerial or satellite photographs, biomedical images and much other type of images. Many research workshas been done on texture analysis, classification and segmentationfor the last four decades. Despite these efforts, texture analysis is still considered an interesting but difficult problem in image processing. Over the past decade, the study of texture has been extended to the study of texture in color images.Color plays an important role in object recognition. An important topic when processing color images is their representation. The RGB representation is frequently being transformed into other color spaces [1] for analysis. A color space is all possible colors that can be made from a group of colorants. A color space is a method by which we can specify, create and visualise colors. A color is thus usually specified using three co-ordinates or parameters. These parameters describe the position of the color within the color space being used.Two images consisting of the same color but different texture pattern or the same texture pattern but different colors are two different color textures. Two alternatives to feature extraction for color texture analysis appear to be most often used and they consists of:

●   processing each color band separately by applying gray level texture analysis techniques,

●   deriving textural information from luminance plane along with pure chrominance features.

The first method is a straightforward approach of extending the gray level algorithms to color images and has been used in color texture segmentation and classification [2].

Drimbarean and Whelan in 2001 have extended three relevant grayscale feature extraction approaches, namely local linear transforms, co-occurrence and Gabor filtering to color space analysis. The features are extracted on each color channel separately, as well as from luminance plane and alone with pure chrominance features. The results are generated on the VisTex database on different color spaces namely RGB, HIS, CIE-XYZ, YIQ and CIE-LAB. The best classification accuracies are achived in the YIQ space followed by CIE-XYZ space. The worst result obtained for HIS color space [2]. Palm and Lehmann in 2002 have proposed color texture classification by using Gabor filter. They have achieved maximum classification accuracy of 85.6% for feature vector ($RGB_{engA,engP}$) (The indices engA and engP represents energy based on local amplitude, energy based on local phase changes respectively) for VisTex dataset [3]. Palm in 2004 has proposed color texture classification by integrative Co-occurrence matrices and have achieved maximum classification accuracy of 97.7% for feature vector ($RGB_{o,SC,MC}$) (The indices 0, SC and MC indicate histogram features, single-channel Co-occurrence and multi-channel Co-occurrence, respectively, in the RGB color space) for VisTex dataset [4]. Arivazhagan et al in 2005 have achieved classification accuracy of 98.15%, 98.41% and 87.6% for color texture for three different types of VisTex datasets by using WSFs and WCFs [5]. Arivazhagan et al in 2011 have proposed color texture image classification using wavelet texture spectral features. They have achieved classification accuracy of 99.82%, 99.48% and 91.71% for three different types of VisTex datasets [6]. Alternatively, many authors have developed integrated color and texture extraction techniques [7-9].

Feature extraction techniques for texture analysis are differing from each other. The main four categories of feature extraction techniques can be defined as (1) statistical methods, (2) structural methods (3) model based methods and (4) transform-based methods.Statistical texture analysis techniques primarily describe texture of regions in an image through higher-order moments of their gray scale histograms. Some examples of statistical texture analysis approaches are gray level co-occurrence matrix (GLCM), run length matrix (RLM), Singular

value decomposition (SVD) and Laws' texture energy measures (Laws) [10-14]. Structural texture analysis techniques describe a texture as the composition of well-defined texture elements such as regularly spaced parallel lines. Model-based texture analysis techniques generate an empirical model of each pixel in the image based on a weighted average of the pixel intensities in its neighbourhood. Transformed-based texture analysis techniques convert the image into a new form using spatial frequency properties of the pixel intensity variations [15]. In the medical image analysis Laws' masks has received wide acceptance [16-18]. However, in texture classification analysis a detailed study of research shows that Laws' masks provided poor classification accuracy [19-23] and there has not been conducted any further research for Laws' mask descriptor for color texture analysis.

In this paper, we propose a scheme for the improvement of classification accuracy by using Laws' mask descriptorfrom gray level intensity to color images in six color spaces on VisTex and STex datasets. In addition, classification performances of gray texture images are performed and are compared with that of color textures. Color texture features are extracted separately from each color panel. Three numbers of features namely mean square, absolute mean and standard deviation are calculated. Laws' mask texture features obtained from three-color channels are concatenated before classification. Simple k-NN classifier is used for classification.

The outline of this paper is as follows: in the next section, we discuss about the theoretical background of Laws' mask descriptor and various color spaces. Section 3 explains in detail about various techniques of the proposed method. In section 4 several experiments are conducted and their results are discussed. In the last section some conclusions are drawn.

II.   Theoretical Background

II.1   Laws' Mask Method

The Laws' method uses filter masks to extract secondary features from natural micro-structure characteristics of the image (level, edge, spot, ripple and wave) which can then be used for segmentation or classification. Laws developed five levelled vectors, which could be combined to form two dimensional convolution kernels. The five vectors are:

L5= [1, 4, 6, 4, 1], E5= [-1, -2, 0, 2, 1], S5= [-1, 0, 2, 0, -1], R5= [1, -4, 6, -4, 1] and W5= [-1, 2, 0, -2, 1].

The level vector describes the average grey level or center weighted local average, edge vector is similar to the gradient operator, spot vector represents the spot extraction, ripple vector detects ripple from the image while wave vector responds to any image pixel changes.2-D filters of size 5×5 are generated by convolving any vertical 1-D vector with horizontal one. Thus, 25 possible combinations of 2-D different masks are produced.

II.2   Various color Spaces

A color space is a mathematical representation of a set of colors. All the color spaces can be derived from the RGB information supplied by the devices.

II.2.1   RGB color space

The red, green and blue (RGB) color space is widely used throughout computer graphics. Red, green and blue are three primary additive colors and individual components are added together to form a desired color. Therefore, colorsare seen as combinations of these so-called primary colors. For this reason, most of the cameras and emissive color displays represent pixels as triple intensities of the primary colors in the RGB colorspace.A disadvantage of the RGB representation is that the channels are much correlated, as all of them include a representation of brightness.

II.2.2   YUV color space

The YUV color space is used by the PAL (Phase Alternation Line), NTSC (National Television System Committee) and SECAM (Sequential Couleur Avec Memoire) as composite color video standards. The black and white system used only luma (Y) information; color information (U and V) is added in such a way that a black and white receiver would still display a normal black and white picture. Color receivers decode the additional color information to display a color picture. The conversion formulae for YUV from RGB are:

$$Y=0.299R'+0.587G'+0.114B'$$

$$U= -0.147R'-0.289G'+0.436B'= 0.492 (B'-Y)$$

$$V= 0.615R'-0.515G'-0.100B'= 0.877 (R'-Y)$$

II.2.3   YIQ color space

The YIQ color space is derived from the YUV color space and is optionally used by the NTSC composite color video standard. The "I" stands for "in-phase" and the "Q" for "quadrature", which is the modulation method used to transmit the color information. The basic equation to convert between R'G'B' and YIQ are:

$$Y=0.299R'+0.587G'+0.114B'$$

$$I= 0.596R'-0.275G'-0.321B'=V\cos33^0-U\sin33^0=0.736(R'-Y)-0.268(B'-Y)$$

$$Q=0.212R'-0.523G'+0.311B'= V\sin33^0+U\cos33^0=0.478(R'-Y)+0.413(B'-Y)$$

II.2.4   YCbCr color space

The YCbCris developed as part of ITU-R BT.601 during the development of a worldwide digital component video standard. YCbCr is a scaled and offset version of the YUV color space. This is the international standard for digital coding of TV pictures at 525 and 625 line rates. It only deals with the digital representation of R'G'B' signals in YCbCr form. Y is defined to have a nominal 8-bit range of 16-235; Cb and Cr are defined to have a nominal range of 16-240.

II.2.5   HSV color space

The HSV color space attempts to characterize colors according to their hue, saturation and value (brightness). The hue of color identifies what is commonly called "color". For example, all reds have a similar hue value whether they are light, dark or intense. The saturation of a color detects the purity or intensity of the color. A fully saturated color is deep and brilliant. When the saturation decreases, the color gets paler and more washed out until it eventually fades to neutral. The degree of saturation is inversely proportional to the amount of white light added. Brightness represents the achromatic notion of intensity.

II.2.6   XYZ color Space

The XYZ color space is accepted by the CIE in 1931. It is designed to yield non-negative tri-stimulus values for each color. In this system, Y represents the luminance of the color. The tri-stimulus values XYZ are related to CIE RGB tri-stimulus values by the following equations

$$X= 0.490R+0.310G+0.200B$$

$$Y= 0.177R+0.812G+0.011B$$

$$Z= 0.000R+0.010G+0.990B$$

II.2.7   CIE LAB spaces

In 1976, the CIE proposed two color spaces (CIELuv and CIELab) whose main goal is to deliver a perceptually equal space. They are nearly linear with visual perception, or at least as close as any color space is expected to sensibly get. The main difference between the two color spaces is in the chromatic adaption model implemented. The CIELabcolor space normalizes its values by the division with the white point while the CIELuvcolor space normalizes its values by the subtraction of the white point. Since they are based on the CIE system of color measurement, which is itself based on human vision. CIELuv and CIELabis device independent but suffer from being quite unintuitive despite the L parameter having a good correlation with perceived lightness.

III. Proposed Methodology

With an aim to improve classification accuracy of color texture images in this paper, we propose a method for extraction of texture features by utilizing Laws' mask descriptor for different color spaces. This section outlines the color spaces and the experimental set-up used for classification.

III.1   Color spaces

In color images, RGB is perhaps the most common format. The RGB space contains three color components, Red, Green and Blue. In our experiment, we use RGB color plane, the color texture images are divided to three sub-images in the color channel of R, G and B. Along with RGB space the other color spaces examined in this paper are HSV, Lab, XYZ, YCbCr and YIQ. The texture features are extracted separately for each color component.

III.3   Experimental set-up for classification

Our proposed method for grayimage texture feature extractionand afterwards extended to color textureimages are examined by using thetraditional Laws' mask descriptor. The different experiments carried out as follows:

a.   First experiment is conducted only for gray images through conventional Laws' mask descriptor. The color texture images are converted to gray images and are passed through Laws' mask descriptors having 25 numbers of masks. We use all the five masks Level (L), Edge (E), Spot (S), Ripple (R) and Wave (W) by which twenty-five different masks are created by using these five masks. Both training and testing images are convolved with twenty five numbers of masks. The convolved outputs are then passed through three different texture energy measurement filters. These are consisted of a moving nonlinear window operation where every pixel of the image is replaced by comparing the pixel with its local neighbourhood based on three statistical descriptors namely mean, absolute mean and standard deviation. The three energy measurement filters are described as follows [17]:

$$\text{Mean=}\frac{\sum_N Neighbouring pixels}{N} \qquad (1)$$

$$\text{Absolute mean=}\frac{\sum_N abs(Neighbouring pixels)}{N} \qquad (2)$$

$$\text{Standard deviation=}\sqrt{\frac{\sum_N(Neighbouring pixels-mean)^2}{N}} \qquad (3)$$

where N represents the window size. Then outputs of energy measurement filters are normalized by min-max normalization method and then the statistical features are extracted. Statistical features like absolute mean, mean square and entropy are extracted. Simple k-NN classifier is used for texture classification.

b.   In the second experiment, we have examined the classification accuracy of color texture images. In this step we have used six different color spaces namely RGB, HSV, Lab, XYZ, YCbCr and YIQ. Color texture features are extracted separately from these color planes. For example for RGB color space the three color components, Red, Green and Blue of color texture images are passed through Laws' mask individually and results are generated for each color band by following the procedure of experiment one. Then all the features obtained from three color channels are concatenated. Simple k-NN classifier is used for texture classification. Same procedure is followed for all the color spaces. The block diagram of the experiment is given in Fig. 1.

IV. Experimental results and Discussion

To validate the efficiency of the proposed methodtwocolor databases VisTex andSTex are used. Experimental results demonstrate significant improvements of our proposed method. The results of each database are discussed separately below.

STex database

The Salzburg Texture Image Database (STex) is a large collection of 476 color texture image that have been captured around Salzburg, Austria [24]. We have selected 25 texture images of size 512×512 as shown in Fig. 2 from STex database and each image is divided into sixteen 128×128 non overlapping samples. Thus there are total 400 samples available, out of which 200 samples are used for training and 200 samples are used for testing. The classification results are illustrated in Table 1. It is observed that classification accuracy of 72.50% is achieved for gray level intensity by using the mean filter of Laws' mask. For the same mean filter of Laws' mask highest classification accuracy of 92% is obtained for CIELab color space. The second highest classification accuracy of 91.50% is achieved by YCbCr for the mean filter.Classification accuracy of 67% is obtained for gray level for absolute mean filter of Laws' mask descriptor. For the absolute mean filter the highest classification accuracy of 89% is obtained from both CIELab and YCbCr color spaces. Classification accuracy of 63.5% is obtained for gray level for standard deviation filter of Laws' mask descriptor. For standard deviation filter highest classification accuracy of 91.50% is achieved from YCbCr color space. The lowest classification accuracy is delivered by XYZ color space. Classification results for various color spaces are presented in Fig. 4.

VisTex Database

The Vision Texture (VisTex) dataset is prepared by the Massachusetts Institute of Technology (MIT). VisTex database contains color texture images [25]. The challenges of VisTex database are different view points and illumination orientations. Also from VisTex database we have selected 25 texture images of size 512×512 as shown in Fig. 3. Each image is divided into sixteen 128×128 non overlapping samples. Thus there are total 400 samples available, out of which 200 samples are used for training and 200 samples are used for testing. It is observed that classification accuracy of 59%is achieved for gray level intensity by using the mean filter of Laws' mask. For the same mean filter of Laws' mask highest classification accuracy of 84% is obtained for CIELab color space. The second highest classification accuracy of 83% is achieved by YCbCr for the mean filter. Classification accuracy of 52.50% is obtained for gray level for absolute mean filter of Laws' mask descriptor. For the absolute mean filter the highest classification accuracy of 75% is obtained from both CIELab and YCbCr color spaces. Classification accuracy of 55% is obtained for gray level for standard deviation filter of Laws' mask descriptor. For standard deviation filter highest classification accuracy of 77.50% is achieved from CIELab color space. The lowest classification accuracy is delivered by XYZ color space. Classification results for various color spaces are presented in Fig. 5.

From the results it is observed that all the enegy measurement filters of Laws' mask desscriptor achieved better classification accuracies than gray images for all the color spaces. The classification percentages obtained in this study are of minor importance. The important finding is that the addition of color can increase the classification results. The different classification results obtained for various color spaces suggest that color has an important contribution to the discriminative power of the features.

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V. Conclusion

The aim of this research is to study the impact of color texture features through Laws' mask descriptor by means of comparative study. The classification results illustrate that use of color is an important component that improves the performance standard of gray level texture analysis techniques.

References

[1] G. Van de Wouwer, P. Scheunders, S. Livens and Van Dyck, "Wavelet correlation signatures for color texture characterization", Pattern Recognition, Vol. 32, pp. 443-451, 1999.
[2] Drimbarea A. and Whealn P. F., " Experiments in colour texture analysis", Pattern Recognition Letters, Vol. 22, pp.1161-1167, 2001.
[3] Palm C. and Lehmann T. M., "Classification of color textures by Gabor filtering", Machine GRAPHICS & VISION, Vol. 11, no. 2/3, pp. 195-219, 2002.
[4] Palm C., "Color texture classification by integrative Co-occurrence matrices", Pattern Recognition, Vol. 37, pp. 965-976, 2004.
[5] Arivazhagan S., Ganesan L. and Angayarkanni V., "Color Texture Classification using WSFs and WCFs", Multimedia Cyperscape Journal-Special Isssue on Multimedia Data Processing and Compression, Vol. 3 (4), pp. 35-40, 2005.
[6] Arivazhagan S., Ganesan L. and Joyson C. T., "Color Texture Image Classification using Wavelet Texture Spectral Features", International Journal of Biomedical Engineering and Consumer Health Informatics, Vol. 3, No. 1, pp. 21-27, 2011.
[7] Wouwer V., Scheunders P., Livens S. and Dyck D. V., "Wavelet correlation signatures for color texture characterization", Pattern Recognition, Vol. 32, Issue. 3, pp. 443-451, 1999.
[8] Jain A. and Healey G., "A Multiscale Representation Including Opponent Color Features for Texture Recognition", IEEE Trans. Image Process., Vol. 7, Issue. 1, pp. 124-128, January 1998.
[9]   Palm C., "Integrative AuswertungvonFarbe und Texture", PhD thesis, RWTH Aachen, Osnabruck, 2003.
[10] R. M. Hralick, K. Shanmugam and I. Dinstein, "Textural features for image classification", IEEE Trans. System Man. Cybernetics, Vol. SMC-3, pp. 610-61, 1973.
[11] M. M. Galloway, "Texture analysis using gray level run lengths",, Computer Graphics Image Process., Vol. 4, pp.172-179, 1975.
[12] B. Ashjari, Singular Value Decomposition Texture Measurement for Image Classification, PhD thesis, University of Southern California, Los Angeles, CA, 1982.
[13] Laws K. I., "Texture energy measures", Proc. Image Understanding Workshop, pp. 47-51, 1979.
[14] Laws K. I., "Textured image segmentation", Image Processing Institute, Univ. of Southern California, Report 940, 1980.
[15] Manish H. Bharati, J. Jay Liu and John F. MacGregor, "Image texture analysis: methods and comparisons", Chemometrics and Intelligent Laboratory Systems, Vol. 72, pp. 57-71, 2004.
[16] Rachidi M., Marchadier A., Gadois C., Lespessailles E., Chappard C. and Benhamou C. L., "Laws' Masks Descriptors Applied to Bone Texture Analysis: An Innovative and Discriminant Tool in Osteoporosis", Skeletal Radiology, Vol. 37, No. 6, pp. 541-548, June 2008.
[17] ElnemrHeba. A., "Statistical Analysis of Law's Masks Texture Features for Cancer and Water Lung Detection.", IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 6, No 2, November 2013.
[18] Sagiterry Arden Setiawan, Elysia, Wesley Julian and PurnamaYudy, "Mammogram Classification using Law's Energy Measure and Neural Network", Procedia Computer Science, Issue 59, pp. 92-97, 2015.
[19] ManianVidya, Vásquez Ramón and Katiyar Praveen, "Texture Classification Using Logical Operators", IEEE Transactions on Image Processing, vol. 9, Issue 10, October 2000.
[20] OjalaTimo, PietikäinenMattiand JarkkoNisula, "Determining Composition of Grain Mixtures by Texture Classification Based on Feature Distributions", Pattern. Recognition Artificial Intelligence, Vol.10, Issue 73, 1996.
[21] Harwood David, OjalaTimo, PietikäinenMatti, Kelmanc Shalom and Davisa Larry, "classification by centre-symmetric auto-correlation using Kullback discrimination of distributions", Pattern RecognitionLetters, Volume 16, Issue 1,1-10, January 1995.
[22] Harwood D., Subbarao M. andDavis L. S., "Texture classification by local rank correlation", Graphics and Image Processing, Vol. 32, pp. 404-411, 1985.
[23] F. Ade, "Characterization of textures by eigenfilter" , Signal Processing, Vol. 5, pp. 451-457, 1983.
[24] Department of Computer Sciences, U. S., Salzburg texture image database stex (www.wavelab.at/sources/stex), 2007.
[25] Massachusets Institute of Technology, Vision texture database vistex. http://www.outex.oulu.fi/index.php?page=contributed, 2002.

Table1.Classification results of conventional Laws' masks descriptor (5×5) of various color spaces including gray-level for STex dataset.

Different color spaces	No. of features for each image	Classification accuracy (%)		
		Mean	Absolute Mean	Standard Deviation
Gray	75	72.50	67.00	63.50
RGB	225	87.00	72.50	72.00
HSV	225	85.00	74.00	77.00
Lab	225	92.00	89.00	90.00
XYZ	225	75.00	67.50	64.00
YCbCr	225	91.50	89.00	91.50
YIQ	225	80.00	74.00	74.50

Table2.Classification results of conventional Laws' masks descriptor (5×5) of various color spaces including gray-level for VisTex dataset.

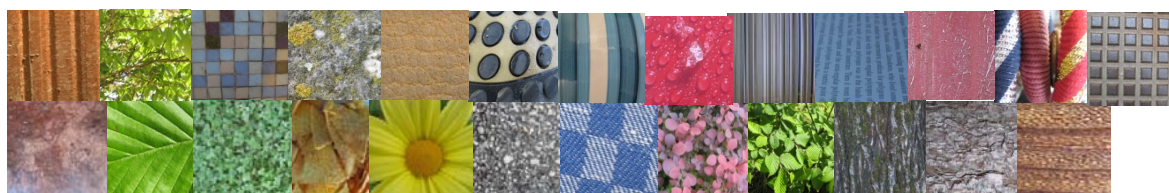| Different color spaces	No. of features for each image	Classification accuracy (%)		
		Mean	Absolute Mean	Standard Deviation
Gray	75	59.00	52.50	55.00
RGB	225	65.00	60.50	59.50
HSV	225	64.00	62.00	63.00
Lab	225	84.00	75.00	77.50
XYZ	225	62.00	58.50	59.00
YCbCr	225	83.00	75.00	74.50
YIQ	225	70.50	61.00	64.00
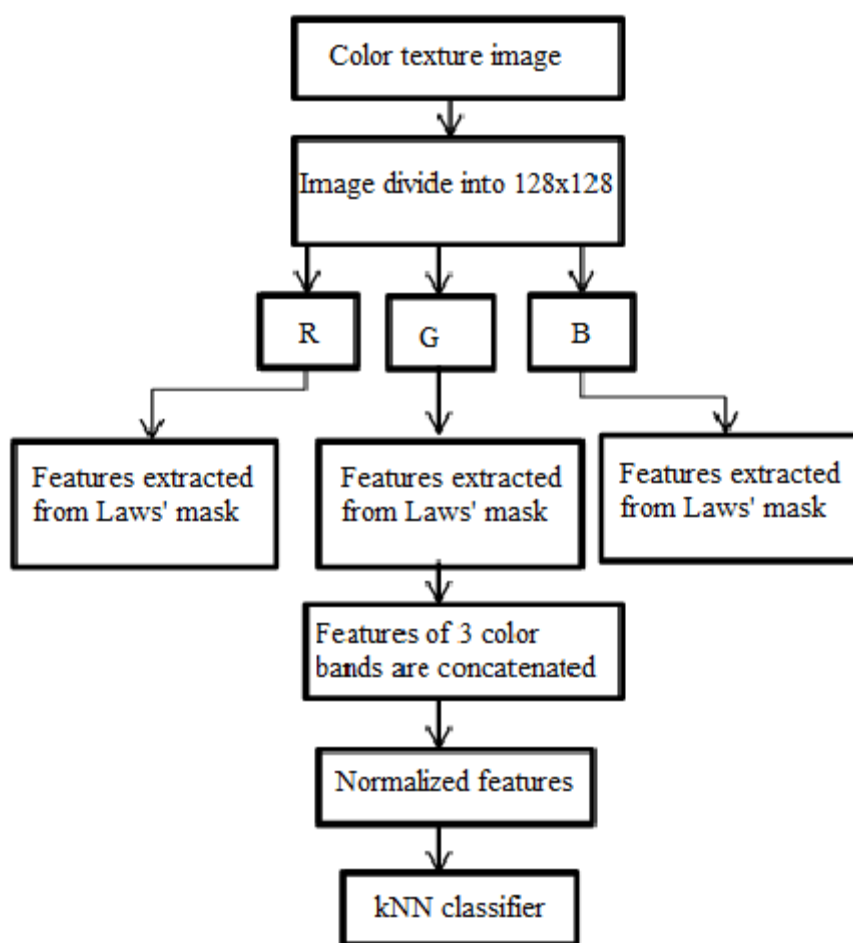
Fig.1. Block diagram.

Fig.2.STex database.
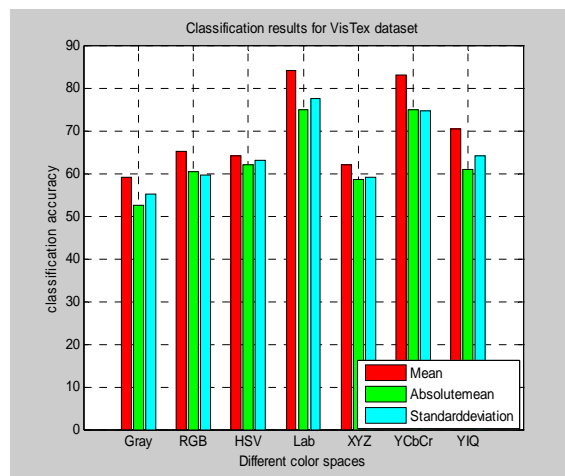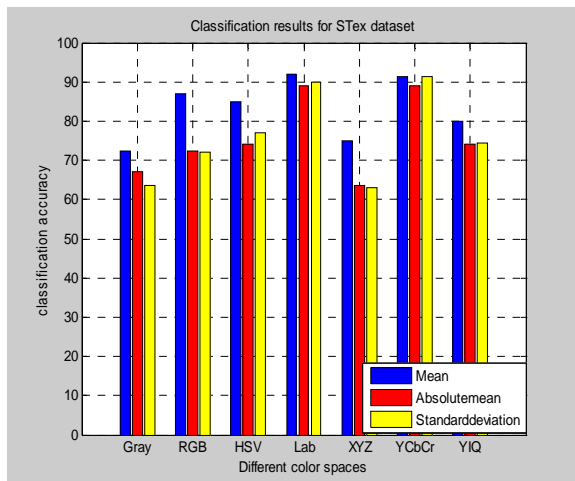
Fig.3.VisTexdatabase.

Fig.4. Results of different color spaces for STex.Fig.5. Results of different color spaces for VisTex.

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