

WAVELET-BASED TEXTURE-CHARACTERISTIC MORPHOLOGICAL COMPONENT ANALYSIS FOR COLOUR IMAGE ENHANCEMENT

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ABSTRACT

This paper proposes a novel colour image enhancement method which uses wavelet-based texture characteristic morphological component analysis (WT-TC-MCA) to enhance the textural differences in the luminance channel of the colour image. The image enhancement method is intended to be the preprocessing method prior to the use of the colour image segmentation. The input colour image is firstly transformed to CIELab colour space to separate the luminance channel from the chromatic channels. Then only the luminance channel is enhanced by the WT-TC-MCA method to enhance the textural differences between different textures. Therefore, the colour image is enhanced with more differentiate textures while preserving the chromatic information. The experimental results show that the proposed method can enhance different colour image segmentation algorithms more than the state-of-the-art colour image enhancement method.

Index Terms— Colour image enhancement, texture enhancement, morphological component analysis, CIELab colour space

1. INTRODUCTION

The segmentation of colour images are of great importance and challenges in recent image processing works. For better segmentation performances, colour image enhancement is a necessary step to enlarge the differences between different regions in the image. Numerous methods have been proposed to expand the theory of grayscale image enhancement to colour images. The authors in [1] summarized the state-of-the-art colour image enhancement methods, which can be classified in to 2 categories: contrast-based enhancement and texture-based enhancement.

Contrast-based enhancement methods focused on enlarging the differences in pixel intensities. The classical histogram equalization [2] was applied to every RGB channel of the colour image, resulting in an excessive brightness for bright pixels in the image. An adaptive neighbourhood histogram equalization (ANHE) method was proposed in [3] to

equalize the intensities in a variable-shaped neighbourhood containing pixels similar to the seed pixels and update the seed pixels' intensities with the equalized ones. In [4], the histogram of a colour image was newly defined where the cumulative distribution function (cdf) was the accumulation of pdfs within the box of size $R \times G \times B$ in 3D color space. Then the image was enhanced by equalizing this 3D colour histogram with a method preserving both the hue and the gamut constraints as proposed by Naik and Murthy [5]. Multi-scale retinex with modified colour restoration (MSRCR) [6] was the algorithm based on retinex concept [7], improving luminance effects of images without degrading the contrast. However, MSRCR has difficulty distinguishing edges and details while estimating the illumination. In [8], it was proposed to combine a multi-resolution transform with luminance masking and contrast masking based on human visual system (HVS-SWT-LCM), which was capable of adjusting the brightness level of the image and providing both dynamic range compression and contrast enhancement. In [9], spatial entropy-based contrast enhancement using the discrete cosine transform (SECE-DCT) was proposed to enhance both global and local contrast. Transform domain coefficients of an image globally enhanced by SECE is further weighted to obtain both a globally and locally enhanced image. For most of the contrast-based enhancement methods, however, the region of interest can't be highlighted from other regions because image details or edges were over-enhanced or degraded by colour distortion.

Texture-based colour image enhancement methods are typically applied only to image luminance so that the textural differences are enlarged in different regions while the colours are not affected. In [10], histogram equalization and unsharp masking (HE-UM) were used to enhance the texture details of the image. Filters based on partial differential equations (PDE) were also used to enhance colour images due to their good performance in enhancing grayscale textural images [11]. Coherence enhancing diffusion filters (CDF) [12] preserve strong discontinuities at edges while removing artifacts from smooth regions. Shock filtering (SHK) [13] smooths along the coherent texture flow orientations and reduces diffusivity at non-coherent structures which enhances texture details. These methods can enhance the texture details of the

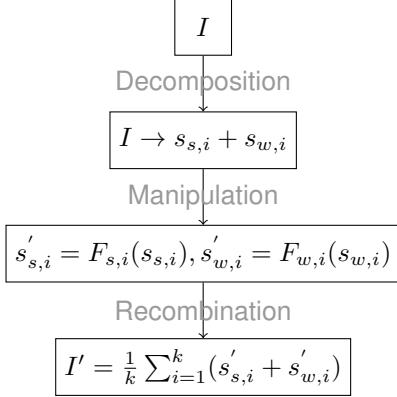


Fig. 1. The WT-TC-MCA based texture enhancement process. The input image undergoes k WT-TC-MCA decompositions (Eq. 1) to extract k pairs of components strongly and weakly exhibiting a particular texture characteristic. These components are manipulated to enhance the strong characteristics and suppress the weak characteristics as Eq. 2. The manipulated components are then recombined as Eq. 3 to form the image where the textural differences are enlarged.

image, but the region of interest is still not well-highlighted because all textures are enhanced to the same extent.

In this paper, the wavelet-based texture-characteristic morphological component analysis (WT-TC-MCA) [14], which has proven to be successful in enhancing the textural differences between different textures in grayscale image, was applied to enhance colour images. We first transfer the image from RGB colour space to CIELab colour space, then the WT-TC-MCA method is used to enhance the luminance (L) channel as a grayscale textural image. After converting back to the RGB colour space with the enhanced L-channel, the colour image is enhanced with more distinguishable texture differences while preserving hue and perceptual effect.

2. IMAGE ENHANCEMENT USING WAVELET-BASED TEXTURE-CHARACTERISTIC MORPHOLOGICAL COMPONENT ANALYSIS (WT-TC-MCA)

Fig. 1 shows the schematic for enhancing image texture by the wavelet-based texture-characteristic morphological component analysis (WT-TC-MCA)[14]. The enhancement process includes three steps.

Firstly, for a given textural image I , the WT-TC-MCA is used to decompose the image into different components corresponding to 4 textural characteristics (coarseness, contrast, line-likeness and directionality) by solving the optimization problems:

$$\{s_{s,i}^{opt}, s_{w,i}^{opt}\} = \arg \min_{\{s_{s,i}, s_{w,i}, T_{s,i}, T_{w,i}\}} \|T_{s,i}s_{s,i}\|_1 + \|T_{w,i}s_{w,i}\|_1 + \|I - s_{s,i} - s_{w,i}\|_2^2, \quad (1)$$

where $s_{s,i}$ and $s_{w,i}$ are components of the original I having strong and weak aspects of the i -th characteristic, $i = 1, \dots, 4$. $T_{s,i}$ and $T_{w,i}$ are wavelet transformations used as dictionaries for components corresponding to strong and weak aspects of i -th characteristic $s_{s,i}$ and $s_{w,i}$ respectively.

After decomposition, the pairs of strong and weak texture characteristic components $s_{s,i}$ and $s_{w,i}$ are manipulated by modifying their wavelet coefficients, leading to enhancement of the texture characteristics they are meant to capture as:

$$\begin{aligned} \alpha_{s,i} &= [a_{s,i}, h_{s,i}, v_{s,i}, d_{s,i}] = \text{wt}(s_{s,i}, j), \\ \alpha_{w,i} &= [a_{w,i}, h_{w,i}, v_{w,i}, d_{w,i}] = \text{wt}(s_{w,i}, j), \\ \alpha'_{s,i} &= f_{s,i}(\alpha_{s,i}), \quad \alpha'_{w,i} = f_{w,i}(\alpha_{w,i}), \\ s'_{s,i} &= \text{iwt}(\alpha'_{s,i}), \quad s'_{w,i} = \text{iwt}(\alpha'_{w,i}), \end{aligned} \quad (2)$$

where $\alpha_{s,i}$ and $\alpha_{w,i}$ are the wavelet coefficients of the image components $s_{s,i}$ and $s_{w,i}$ for the i -th strong and weak characteristic respectively. $\alpha'_{s,i}$ and $\alpha'_{w,i}$ are the modified wavelet coefficients of $\alpha_{s,i}$ and $\alpha_{w,i}$ by the non-linear enhancement methods $f_{s,i}$ and $f_{w,i}$, respectively.

The manipulated components $s'_{s,i}$ and $s'_{w,i}$, with their own properties enhanced, are re-combined into a final texture-enhanced image I' as follows:

$$I' = \frac{1}{k} \sum_{i=1}^k (s'_{s,i} + s'_{w,i}), \quad (3)$$

where $s'_{s,i}$ and $s'_{w,i}$ are calculated in Eq. 2 as the manipulated strong and weak characteristic components respectively, and k is the total number of characteristics used for image decomposition.

3. COLOUR IMAGE ENHANCEMENT USING WT-TC-MCA

The WT-TC-MCA texture enhancement method is applied to the luminance component from the CIELab colour space. The CIELab colour space transforms the RGB colour space into a luminance channel L and two opponent chrominance channels a and b [15]. By enhancing the L component of the colour image with WT-TC-MCA, the textures are differentiated more whereas chrominance values remain nearly unchanged. As shown in Fig. 2, the WT-TC-MCA based colour image enhancement is implemented as follows:

1. transform the input image I from RGB colour space to CIELab colour space;
2. enhance the L component by the WT-TC-MCA method so that different in l channel are modified to be mutually more different to obtain the enhanced component L' ;
3. replace the L component with L' , then transform the colour image back to the RGB colour space, yielding the texture-enhanced colour image I' .

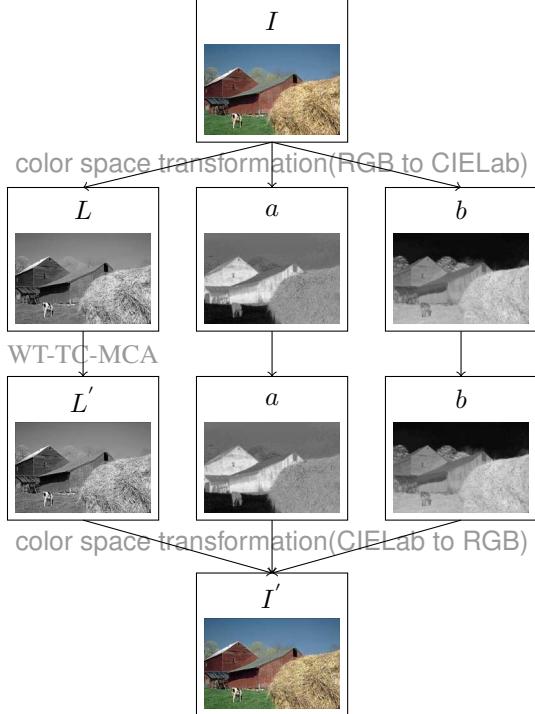


Fig. 2. The WT-TC-MCA based colour image enhancement process. The input image I is transformed to luminance component L and chrominance components a and b . The luminance component L is enhanced by WT-TC-MCA method to L' while the chrominance components a and b are kept unchanged. By transforming the colour image back to RGB colour space, the image I' is enhanced with more differentiable textures.

4. EXPERIMENTS AND DISCUSSION

Our colour image texture enhancement method is evaluated by measuring the improvement in accuracy it yields in texture-based image segmentation algorithms compared with texture enhancement by other methods.

4.1. Experimental Images and Comparator Methods

The colour images utilized in this paper are from the Berkley segmentation dataset [16]. The performance of the proposed method is compared with the state-of-the-art colour image enhancement methods described in [1], including adaptive neighbourhood histogram equalization (ANHE) [3], J. Han, S. Yang and B. Lee's work (HP-ILP) [4], multi-scale retinex with colour restoration (MSRCR) [6], spatial entropy-based contrast enhancement (SECE-DCT) [9], luminance and contrast masking of human visual system based image enhancement (HVS-SWT-LCM) [8], histogram equalization and unsharp masking (HE-UM) [10], coherence enhancing diffusion filter (CDF) [12], and shock filtering (SHK) [13]. Then the segmentation tests are carried out as follows:

- the test images are enhanced as described in Section III, and with the comparator methods listed above;
- the original images and the images enhanced by the proposed method were segmented using several segmentation algorithms: gPb-owt-ucm [16], UCM [17], Mean Shift [18], N-cuts [19], region merging [20] and Canny [21], and evaluated by BSDS500 benchmark;
- the original images and the images enhanced by different image enhancement methods were segmented with the hierarchical segmentation algorithm gPb-owt-ucm [16] and evaluated using the BSDS500 benchmark.

4.2. Performance of Enhanced Image Segmentation

Fig. 3 shows an example image enhanced by different colour image enhancement methods, together with the gPb-owt-ucm segmentation results, which performs the best over all images in the dataset. The AHNE method stretches the brightness too much and distorts the colour, leading to weak edges over-enhanced. HP-ILP method focuses on local textures but has unnecessary artifacts in the smooth regions. MSRCR and HVS-SWT-LCM methods both make the images too bright and distort the colour in the dark areas, adding a lot of unnecessary textures. SECE-DCT degrades the textures in bright regions. HE-UM enhances the edges globally however degrades the textures with similar local intensities. CDF and SHK both change the shapes of textures in the images, which cannot highlight textures in the regions of interest either. The proposed method leads to better segmentation results because WT-TC-MCA can enhance textures to different extents with respect to their own properties because it separates the textures into components representing different visual characteristics and modifies these components in different ways.

Fig. 4 shows the evaluation of segmentation algorithms on the BSDS500 images and those enhanced by the proposed method. Table 1 shows the F-measures when choosing an optimal scale for the entire dataset (ODS) or per image (OIS), as well as the average precision (AP). Use of the proposed method prior to segmentation improves the performance of every segmentation method.

	original			WT-TC-MCA		
	ODS	OIS	AP	ODS	OIS	AP
gPb-owt-ucm[16]	0.69	0.72	0.70	0.73	0.75	0.76
UCM[17]	0.66	0.68	0.65	0.68	0.69	0.68
Mean Shift[18]	0.62	0.64	0.58	0.66	0.68	0.63
N-cuts[19]	0.60	0.64	0.54	0.63	0.68	0.58
region merging[20]	0.56	0.59	0.48	0.60	0.62	0.56
Canny[21]	0.54	0.57	0.43	0.56	0.57	0.51

Table 1. The F-measure of segmenting BSDS500 images and images enhanced by the proposed method with different methods.

Then we selected the gPb-owt-ucm segmentation method, which has the best performance in segmenting colour images in the dataset. Fig. 5 shows the evaluation of gPb-owt-ucm in segmenting images enhanced by different enhancing

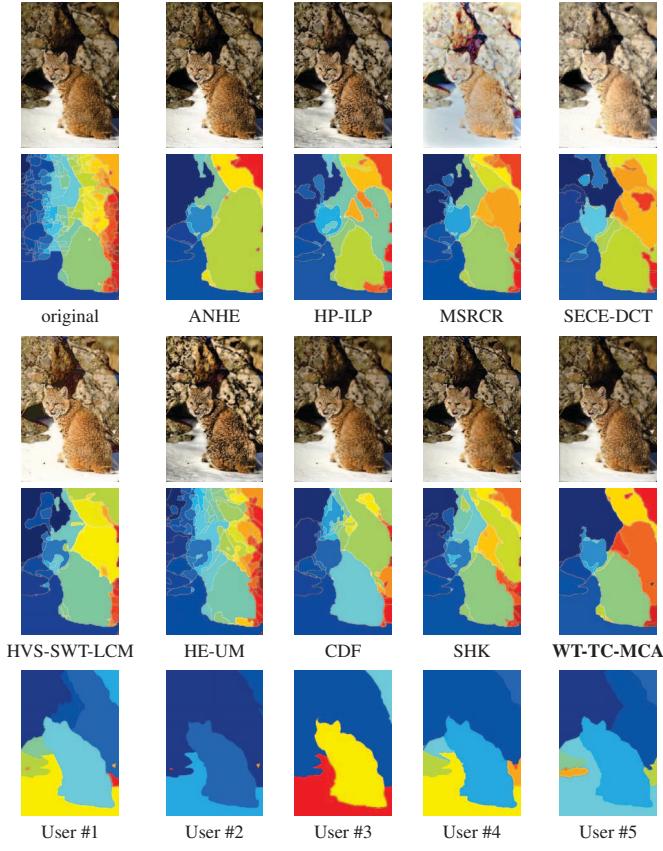


Fig. 3. Segmentation results of colour images enhanced by different colour image enhancing methods. Row 1 to Row 4: colour image enhanced by different methods, as well as the segmentation with gPb-owt-ucm [16]. Row 5: ground truths of segmenting the image by 5 users.

methods. Table 2 shows the F-measure of different enhanced images in the testing dataset. Use of the proposed method prior to segmentation leads to a better segmentation effect than other enhancement methods.

	F-measure		
	ODS	OIS	AP
original	0.69	0.72	0.71
ANHE[3]	0.69	0.71	0.69
HP-ILP[4]	0.71	0.74	0.74
MSRCR[6]	0.70	0.72	0.71
SECE-DCT[9]	0.71	0.74	0.75
HVS-SWT-LCM[8]	0.71	0.74	0.75
HE-UM[10]	0.68	0.71	0.71
CDF[12]	0.72	0.74	0.75
SHK[13]	0.71	0.72	0.73
WT-TC-MCA	0.73	0.75	0.76

Table 2. The F-measure of segmenting BSDS500 images and the images enhanced by different methods using the gPb-owt-ucm segmentation method.

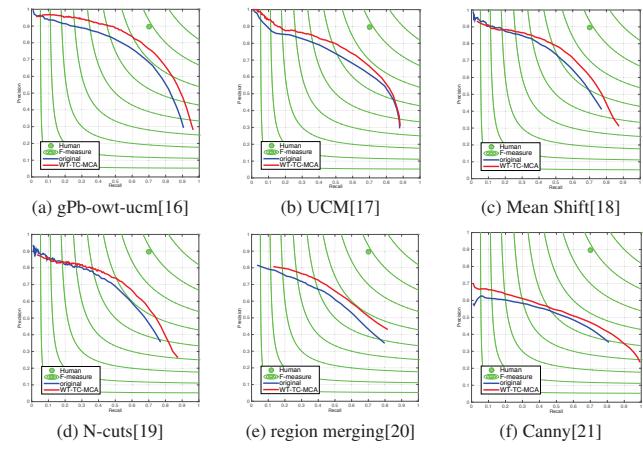


Fig. 4. Evaluation of different segmentation algorithms on the BSDS500 images and those enhanced by the proposed method. Blue curves are the precision-recall curves of segmenting the original images, red curves are the precision-recall curves of segmenting the enhanced images.

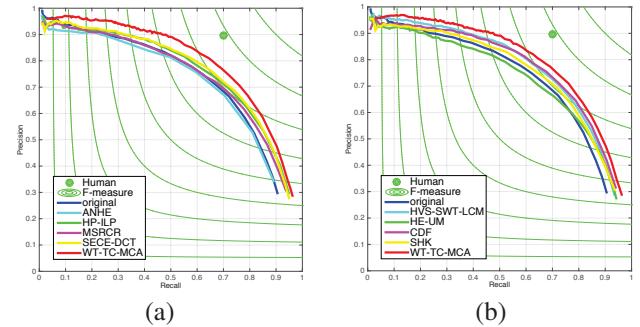


Fig. 5. Evaluation of the gPb-owt-ucm segmentation method on the BSDS500 images and those enhanced by different image enhancing methods. (a) The comparison among the original images (blue), ANHE (cyan), HP-ILP (green), MSRCR (magenta), SECE-DCT (yellow) and the proposed method (red); (b) the comparison among the original images (blue), HVS-SWT-LCM (cyan), HE-UM (green), CDF (magenta), SHK (yellow) and the proposed method (red).

5. CONCLUSION

We novelly enhanced the textures in colour images using the wavelet-based texture characteristic morphological component analysis (WT-TC-MCA) method. The luminance channel of the image was extracted then enhanced by WT-TC-MCA to enlarge the textural differences. The experimental results showed that the proposed image enhancement method enlarged the textural differences without affecting chrominance of colour images, leading to improved colour image segmentation results.

6. REFERENCES

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