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Morphological Component Analysis to Enhance Textures of an Image

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ABSTRACT:*This paper gives the insight to use a new texture enhancement method which uses an image decomposition that allows different visual characteristics of textures to be represented by separate components whereas previous methods either enhance texture indirectly or represent all texture information using a single image component. This method uses a modified morphological component analysis (MCA) which allows the texture to be separated into multiple morphological components each representing a different visual characteristic of texture. By selecting four such texture characteristics and propose new dictionaries to extract these components using MCA. Then the procedures are applied for modifying each texture component and recombining them to produce a texture-enhanced image.*

Keywords: Enhancement, Image Decomposition, Morphological Component Analysis, Texture.

I. INTRODUCTION:

Some existing texture enhancement methods indirectly highlight textures of an image by reducing noise or artifacts in the image. For instance, the median filter [6] and the Weiner filter [10], these filters have low pass filter like characteristics so they degrade the textures in addition to removing noise. Whilethe non-local means filter [9] which can smooth the noise in the image while preserving image detail as much as possible. Wavelet-based methods removes noise by shrinking coefficients in high-frequency sub-bands not exceeding certain thresholds, while preserving the image textures in high-frequency sub-bands that exceed these thresholds.

Some other methods enhance the image textures directly. Unsharp masking (UM) was proposed to improve the visual appearance of an image by emphasizing its high frequency contents [8]. However, the high passfilterlike nature of UM causes enhancement of noise and artifacts in the image as well. The same is true of histogram equalization methods [7]. Shock filtering [14] is a transformation of anisotropic diffusion which smooth's along the coherent texture flow orientations, and reduces diffusivity at non-coherent structures which enhances the textural detail.

All of the above mentioned methods either enhance or suppress all the different "textural" components of the image to the same extent, because the image is treated as a single "texture" component.

The morphological component analysis (MCA) concept was developed for separating the texture from the image, for inpainting applications or more generally for separating several components which have different morphologies in the single image. Some textural characteristics are selected based on human visual perception. Then, MCA is used to decompose textures into *multiple* morphological components according to the desired characteristics by introducing dictionaries. The obtained morphological components are then modified so that textures become enhanced.

II. TEXTURE BASED IMAGE DECOMPOSITION USING MORPHOLOGICAL COMPONENT ANALYSIS:

A texture characteristic is to quantify the perceived texture of an image.The image decomposition and texture

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enhancement is performed as shown in below steps:

1) The input image is decomposed to several different pairs ofcomponents where each pair consists of a component that strongly exhibits a particular texture characteristic and a component that weakly exhibits it, or exhibits opposite characteristics, e.g. a “coarse” component and a “fine” component;

2) The components are manipulated to enhance the texture characteristics they are meant to capture, e.g. a high-coarseness component is manipulated so that so it becomes coarser, a low-coarseness (fine) component is manipulated so that it becomes finer;

3) The manipulated components are recombined to obtain an image in which textures are more different from each other than in the original image with respect to the chosen texture characteristics.

Algorithm: MCA decomposition algorithm

1. Initialize the number of iterations I_m , dictionary parameters $\mu_{s,i}$ and $\mu_{w,i}$, threshold for stopping decomposition δ and threshold for updating parameters λ and $s_{s,i}$=$s_{w,i}$=0.
2. Start Decomposition:

Assume $s_{w,i}$ as fixed and Update $s_{s,i}$

Calculate the residue, $r = I - s_{s,i} - s_{w,i}$

for n = 1: I_m

$$d = s_{s,i} + r$$

If $n == 1$

$$s'_{s,i} = T_{s,i}(s_{s,i} + r)$$

else

$$s'_{w,i} = T_{w,i}(s_{s,i} + r)$$

end

update$\mu_{s,i}$

update$s_{s,i}$ $w \quad h\, s'_{s,i}\, a \quad s_{w,i}\, w \quad h\, s'_{w,i}$

end

3. update threshold with $\delta = \delta - \lambda$
4. if $\delta - \lambda$, return to step-2 else finish

Input Image ⇨ **Image Decomposition (MCA)** ⇨ **Manipulation (Textures)** ⇨ **Image Recombination** ⇨ **Enhanced Image**

Fig. 1 shows the schematic diagram for the proposed texture enhancement method by decomposing image.

The proposed texture enhancement process schematic diagram is shown in Fig. 1. The input image undergoes MCA decompositions using dictionaries to extract pairs of components that strongly and weakly exhibit a particular texture characteristics. Adjustable parameters has been used for dictionaries so that decomposition performance is more consistent for different images.

The Morphological Component Analysis [2] used to extract different textures of an image is given in(1)

$$\{S^o_{s,i}\ ,S^o_{w,i}\ ,T^o_{s,i}\ \ ,T^o_{w,i}\ \} = \arg\min_{\{S_{s,i},S_{w,i},T_{s,i},T_{w,i}\}} \left\|T_{s,i}, S_{s,i}\right\|_1 + \left\|T_{s,i}, S_{w,i}\right\|_1 + \left\|I - S_{s,i} - S_{w,i}\right\|_2^2 \tag{1}$$

where$S_{s,i}$and $S_{w,i}$ are the components having strong and weak textures, $T^o_{s,i}$ and $T^o_{w,i}$ are the transformations used as dictionaries for decomposition of image with strong and weak textures of *i*-th characteristics,

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respectively. An Algorithm is proposed to compute the components $S_{s,i}$ and $S_{w,i}$as well as dictionaries $T_{s,i}$ and $T_{w,i}$ where $\mu_{s,i}$ and $\mu_{w,i}$ are the parameters of dictionaries. I_m is the maximum number of iterations for decomposition. The values for parameters of every dictionaries are listed in Table 1.

Table 1. Dictionaries and parameters for decomposing the image using MCA

Textures	Strong		Weak	
	Dictionary	**Parameters**	**Dictionary**	**Parameters**
Coarseness	Bilateral filter	[10, 5]	Wavelet thresholding	0.95
Contrast	Anisotropic shrink	0.95	Anisotropic Diffusion	0.95
Directionality	SWT thresholding	0.95	SWT thresholding	0.95
Line-likeness	Gradient	0.95	Gradient	0.95

III. MANIPULATION OF DECOMPOSED IMAGE COMPONENTS

For our MCA framework Human visual perceptual characteristics were selected since it describes how human beings perceive the texture. The following characteristics from Tamura descriptor [12] were selected as the basis of decomposition:

A. DICTIONARIES FOR COARSENESS:

Decomposing a texture into the coarse and the fine is to apply dictionaries regions with few strong texture edges and regions with many weak texture edges, respectively.

To extract Coarse component [1] Bilateral filtering is used as the dictionary since it can remove small-scale elements from the image.

$$\left(T_{s,1}\big(I(x)\big) = \frac{1}{K}\sum_{\P\in S} I(\P).e^{-\frac{1}{2}\left(\frac{\|\P-x\|}{\pm_d}\right)^2}.e^{-\frac{1}{2}\left(\frac{I(\P)-I(x)}{\pm_d}\right)^2} \right) \tag{2}$$

where x is center pixel in neighborhood of sample S,I(x) is intensity of center pixel, I(ξ) is intensity of neighborhood . $\sigma_d$and$\sigma_r$are the spatial and spectral bandwidths.|I(x)-I(ξ)| are preserved, while |I(x)-I(ξ)| ≈0 are removed. Coarse textures will be enhanced while fine textures will be suppressed.

The low coarse or fine component [1] need to remove strong edges.

$$T_{w,1}(I) = idwt(\cdot\,') \tag{3}$$

$$\cdot = dwt\,(I)$$

where dwt and idwt are forward and inverse discrete wavelet transform respectively.

B. DICTIONARIES FOR CONTRAST:

Contrast measures the variance of the grey scale intensities in a local area. Low and High Contrast are chosen as two dictionaries:

For the low-contrast component [1], we make use of anisotropic diffusion.

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$$T_{w,2}(I(x)) = I(x) + \frac{1}{S}\sum_{\P \in S} c(\nabla I(\P))\nabla I(\P)$$
$$c(\nabla I(\P)) = e^{-\left(\frac{\nabla I(\P)}{k}\right)^2} \tag{4}$$

Where I(x) is the pixel intensity of image I at x, S is the neighborhood centered at x, ξ denotes the neighboring pixels in S, |S| is the number of pixels in the neighborhood.

The high-contrast parts will be smoothed and reduced in contrast because in such regions the ad behaves as isotropic diffusion (Gaussian filtering).

For high contrast components [1], Anisotropic Shrink is used as a dictionary.

$$T_{s,2}(I(x)) = I(x) + \frac{1}{S}\sum_{\P \in S} c(\nabla I(\P))\nabla I(\P)$$
$$c(\nabla I(\P)) = 1 - e^{-\left(\frac{\nabla I(\P)}{k}\right)^2} \tag{5}$$

where |I(x)-I(ξ)| ≈0 are low contrast. The result is that the high- contrast components are retained.

C. DICTIONARIES FOR DIRECTIONALITY:

Directionality of texture measures the orientation of the local texture. Though the orientation of texture could be anywhere in the range from 0 to π, we decompose the texture into only the horizontal component and the vertical component because any orientation can be considered as combination of horizontal and vertical direction.

The wavelet coefficients [ψa,ψh,ψv,ψd] □ψ (approximation, horizontal, vertical, diagonal) of the input image I.

$$T_{s,3}(I) = iswt(\cdot\,')$$
$$\cdot \; = swt(I)$$
$$\cdot\,(x,y)' = \begin{cases} \cdot\,(x,y), if \left|\cdot_h(x,y)\right| > \bar{}_h \\ 0, otherwise \end{cases} \tag{6}$$

where swt(·) and iswt(·) are forward and inverse stationary wavelet transform respectively, the wavelet coefficients [$_{a,h,v,d}$] □(approximation, horizontal, vertical, diagonal) of the input image *I* are filtered with the soft thresholding method

To decompose the texture into horizontal and vertical components [1], we apply the wavelet thresholding based on the stationary wavelet transform (SWT) [13] since it can preserve more details in the high frequency sub-bands so that more small texture edges can be retained. As shown as (6) and (7), coefficients in different sub-bands are preserved to different extents so that the texture is decomposed into components representing different directions:

$$T_{w,3}(I) = iswt(\cdot\,')$$
$$\cdot \; = swt(I)$$
$$\cdot\,(x,y)' = \begin{cases} \cdot\,(x,y), if \left|\cdot_v(x,y)\right| > \bar{}_v \\ 0, otherwise \end{cases} \tag{7}$$

Applying the wavelet thresholding based on the stationary wavelet transform (swt) it can preserve more details in the high frequency sub-bands so that more small texture edges can be retained.

D. DICTIONARIES FOR LINE-LIKENESS:

The decomposition based on line-likeness [1] requires two dictionaries corresponding to textures with very similar, and very different direction in every local region, respectively. We propose two transformations based on image gradients as dictionaries Ts,4 and Tw,4 to represent these two types of textures:

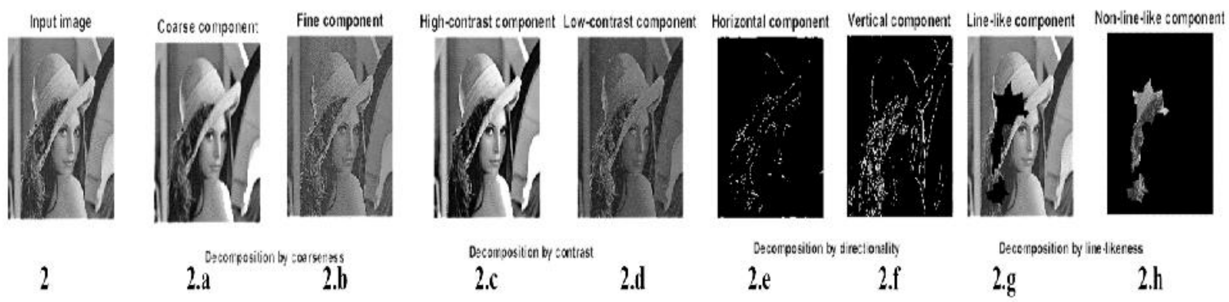
$$T_{s,4}(I(x,y)) = \begin{cases} I(x,y), if d(x,y) < \text{¢}_{simi} \\ I(x,y).(1-d(x,y)), otherwise \end{cases}$$

$$d(x,y) = std(g(\text{¶})), \text{¶} \in N \qquad (8)$$

Where d (x, y) measures the standard deviation std(・) of the gradient magnitudes g (ξ) in the neighborhood n.

To separate the texture into components having similar but not identical direction, the pixel gradients g (ξ) are quantized.By applying the transformation $T_{s,4}$to the image, the line-like regions where the standard deviation d is lower than the threshold $\delta_{simi}$are preserved while the non-line like regions where the standard deviation of gradients are larger than the threshold are removed. Conversely, the transformation $Tw_{,4}$preserves regions where the standard deviation of gradients is large.

Fig. 2 Decomposition by Image into different components using Dictionaries



The above figure shows the Decomposed Coarse components 2. is the original image 2.a and 2.b, Contrast components 2.c and 2.d, Directionality components 2.e and 2.f, Line-like components 2.g and 2.h. The textures decomposed are Coarse, Fine, High-contrast, Low-contrast, Horizontal, Vertical, Line-like and Non-line-like components. Each dictionary is different to extract the exact required textures from the input image.

IV. MANIPULATION OF TEXTURES

The Decomposed components from section-III are manipulated to enhance each different textures by applying filters and transformations as shown in below Table-2

Table 2. Filters and parameters for manipulating the decomposed image using MCA

Textures	Strong		Weak	
	Filter	**Parameters**	**Filters**	**Parameters**
Coarseness	NL-means filter	Window 4x4	Stick filter	5
Contrast	Laplacian and Median filter	Window 5x5	Power-law transformation	[0.35 0.85]
Directionality	SWT enhancing	1.5	SWT enhancing	1.5
Line-likeness	Adaptive histogram equalization	0.9	Power-law transformation	2

A. MANIPULATION OF DECOMPOSED COARSE COMPONENT:

To enhance the coarse component, the NL-means filter works well because weak edges are further suppressed,

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enhancing texture coarseness.

For the enhancement of the fine component, the number of edges because the coarseness is defined as the number of edges in a neighborhood. The sticks filter [11] with stick length 5 was applied to transform the component because of its success in line and boundary detection. Most edges, even weak ones, can be detected and enhanced by sticks filter. Therefore, the fineness of the fine-texture component will be increased.

B. MANIPULATION OF DECOMPOSED CONTRAST COMPONENT:

To enhance the high-contrast component $s_{s,2}$, we propose to use Laplacian filtering and median filtering together to increase the contrast as follows :

$$Ss,2 = Ss,2 + m \quad (|\nabla 2(Ss,2)|)(9)$$

To enhance the Fine component, in neighborhood, the sum of pixel values along the line is calculated. The segment with the largest sum is selected and the sticks image value at the center pixel is the maximum of the sums. This step is repeated for all the pixels in the image. In the output image, fine lines are increased.

Laplacian filter is a linear filter. In this filter a window or mask with some values works with values of image pixels in the neighborhood.

Median filter replaces the value of a pixel by median of the gray levels in the neighborhood of that pixel. The median filter runs through the image pixel by pixel, replacing each pixel with the median of neighboring pixels.

For Low contrast a Power law Transformation is applied. This technique detects two edge points, strong and weak using two threshold values T1 and T2 such that T1<T2. If the pixel values greater than T2 then the edge values are strong and if pixel values are in between T1 and T2 then these are called weak edge pixels.

C. MANIPULATION OF DECOMPOSED DIRECTIONALITY COMPONENT:

The SWT was used because it can represent textures of different directions in different sub-bands [13]. Since the wavelet coefficients in one sub-band represent intensity variation in a specific direction, they are independent of the coefficients in other sub-bands. The horizontal morphological component $s_{s,3}$was manipulated as:

$$S'_{s,3} = is \quad (w'_{s,3,h}, w'_{s,3,a}, w'_{s,3,v}, w'_{s,3,d}) \tag{9}$$

Where iswt(.) is the inverse stationary wavelet transform and w are the horizontal, approximate, vertical and diagonal coefficients .

The Stationary Wavelet Transform is used because it can represent textures of different directions in different sub-bands.Since the wavelet coefficients in one sub-band represent intensity variation in a specific direction, they are independent of the coefficients in other sub-bands.

For the vertical morphological component, the vertical wavelet coefficients are amplified and the horizontal wavelet coefficients are set to zero.

$$W'_{s,3,v} = a.w_{s,3,v} \tag{10}$$
$$W'_{s,3,h} = 0$$
$$W'_{s,3,d} = w_{s,3,d}$$

D. MANIPULATION OF DECOMPOSED LINE-LIKENESS COMPONENT:

Adaptive histogram equalization [7] improves by transforming each pixel with a transformation function derived from a neighborhood region.

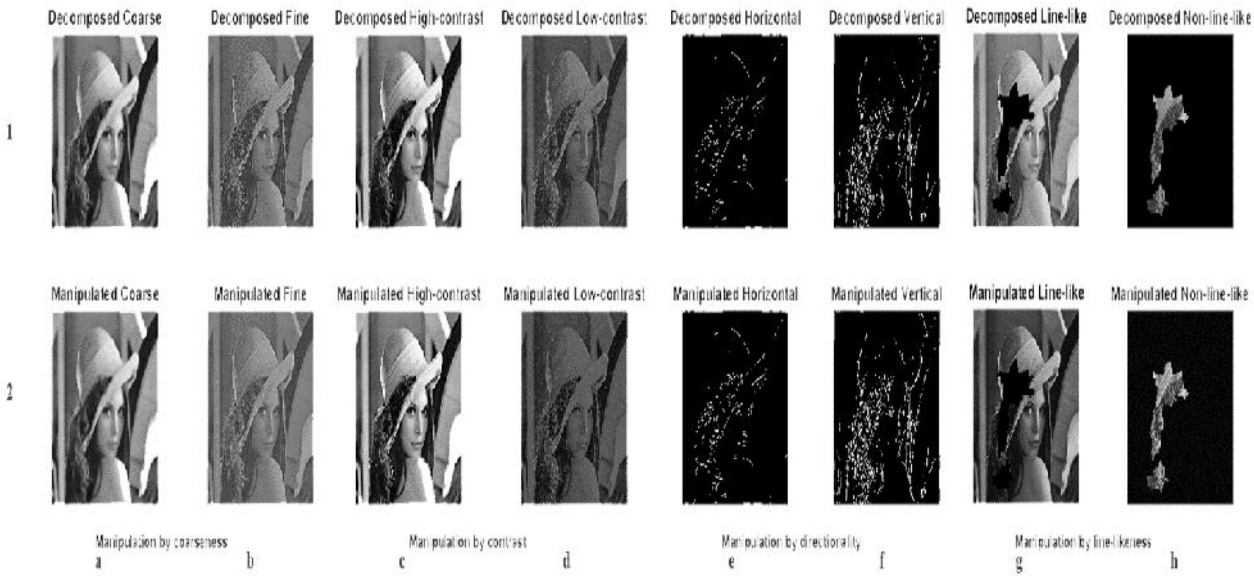
Adaptive histogram equalization enhances the line-like component because it increases the intensity contrast, making the line or boundary between different pixels, while decreasing the intensity contrast between two texture elements with very similar intensities, and removing very weak edges.

$$S'_{w,4} = S^{\gamma}_{w,4}(10)$$

Where $S^{\gamma}_{w,4}$ is the non-like component with γ=2

For the non-line-like component, power-law transform where non-like component boundaries and the local contrast are suppressed and the line-likeness of the non-line-like component will be further decreased.

Fig. 3 Manipulation of Decomposed Textures



The above figure shows the manipulated Coarse components 2.a and 2.b, Contrast components 2.c and 2.d, Directionality components 2.e and 2.f, Line-like components 2.g and 2.h.

V. RECOMBINATION OF MANIPULATED COMPONENTS

After manipulating every component to enhance its own properties, the components are re-combined into a final texture enhanced image. The Manipulated Components Coarse, Contrast, Directionality and Line-likeness are Recombined (added) to obtain the Enhanced Image.

a b

Fig. 4. a. Original Image   b. Enhanced Image

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The Proposed method is applied to real world images and synthetic images to enhance the different textures more precisely. The other Test image results are as shown in the figure-5

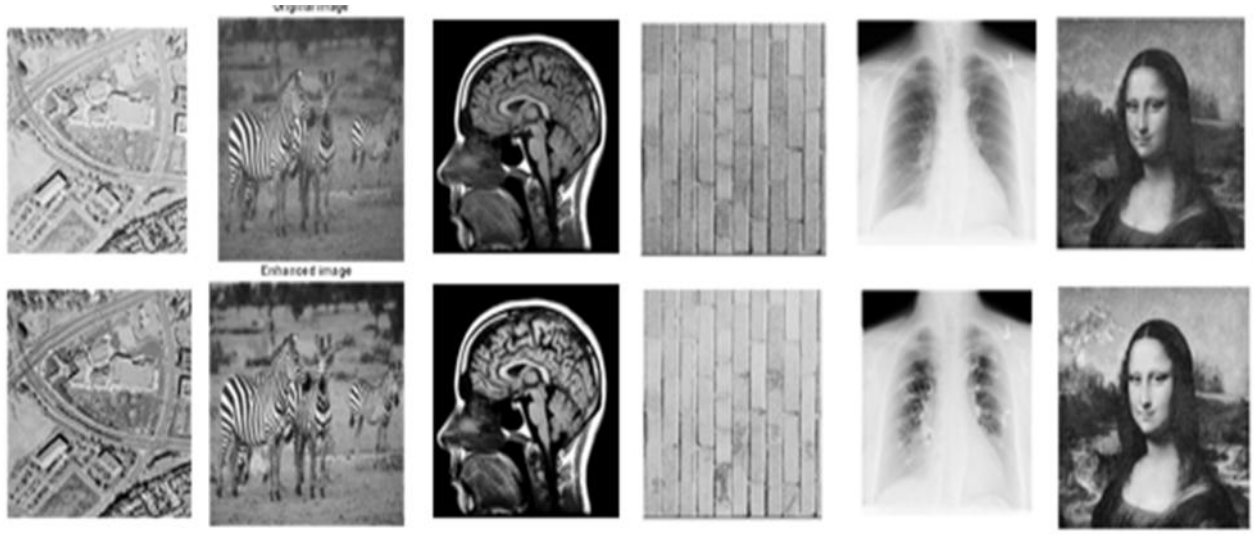

Fig 5. Other test image results: first row indicates the original images, second row indicates the enhanced images

VI. EXPERIMENTS AND ANALYSIS

The proposed method is tested and evaluated on synthetic textural images and real-world images containing different textures. The synthetic images are synthesized by combining textures from the Berkeley Segmentation database [3] and the SIPI texture database [4].

The performance of the proposed method is measured by comparing the results from different texture-based segmentation methods applied to the textures modified by different methods. The following texture-enhanced methods are used as comparators:

1) Unsharp masking [8] (UM) which enhances texture by emphasizing its high frequency contents;

2) Shock filtering [14] (SHK), which smooths along the coherent texture flow orientations and reduces diffusivity at non-coherent structures, which enhances texture details.

The comparator methods were selected to measure the performance of the manipulation of the texture components proposed in this paper, we also use the MCA with proposed dictionaries but no manipulation of the components prior to recombination (MCA-NM) as another comparator to demonstrate the manipulations are central to the success our method. Image segmentation tests were carried out as follows:

Textures were extracted from the 15×15 neighborhood of every pixel of each original test image, and each enhanced test image from different enhancement method tocreate feature maps, they were segmented using mean-shift segmentation method and theaccuracy of test images was computed by using the metric:

$$C = S(x,y)-I(x,y)/N \qquad (11)$$

where S denotes the segmented image, I represents the Original image,and N is the total number of the pixels in the image.

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The segmentation accuracy of the test images before and after enhancement was compared to evaluate the effect of different texture enhancement methods on segmentation accuracy.

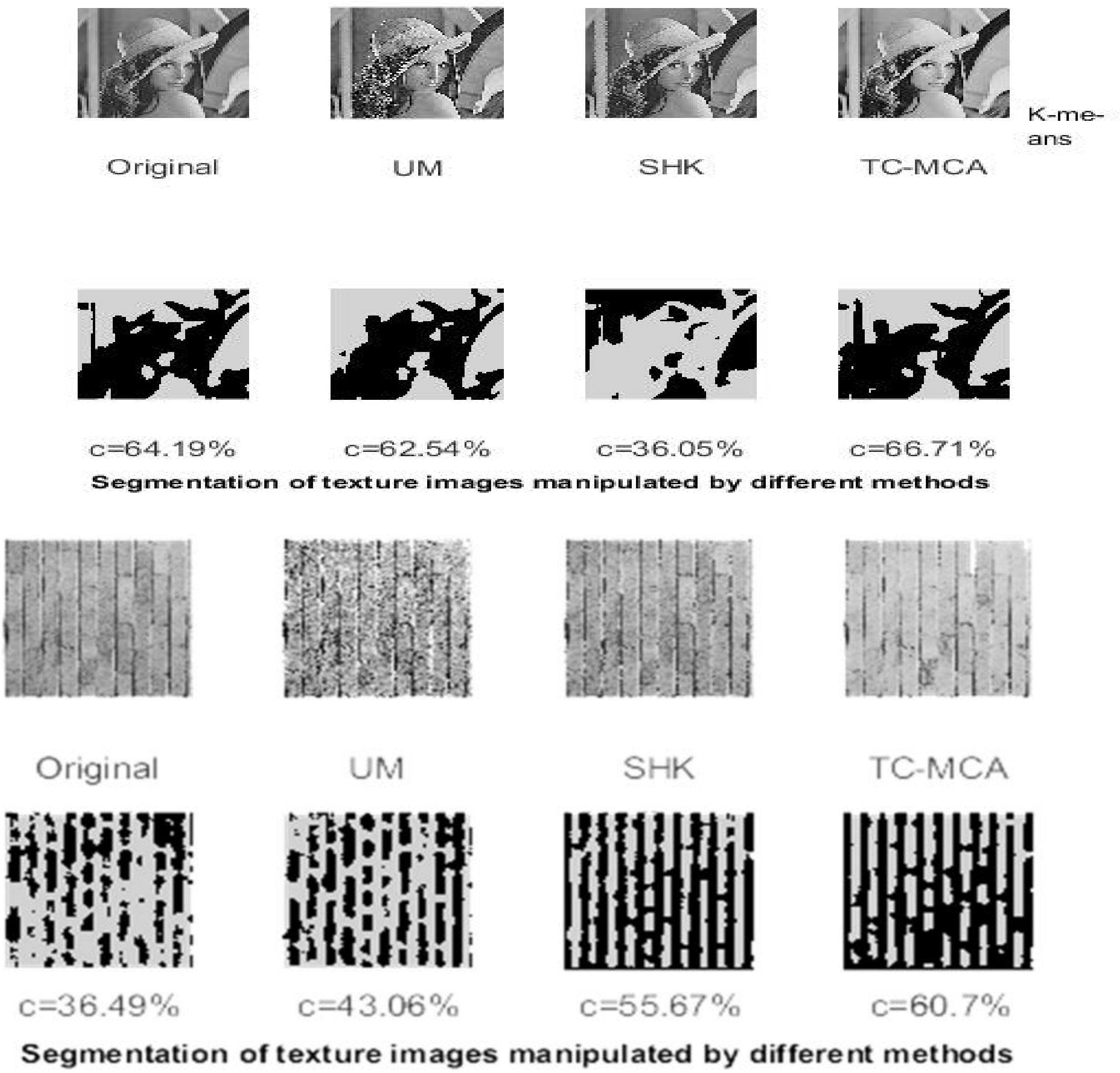

Fig. 5. Comparison of Proposed method with previous methods

After texture enhancement by unsharp masking (UM), shock filtering (SHK), and the proposed method (proposed). The shock filter can enhance the texture edges well but it breaks some smooth regions. The unsharp masking can enhance the texture, especially the local contrast very well, but it creates unwanted edge effects at the same time. Moreover, all these methods process the image as a single "texture" component, all the different textures in the image are enhanced to the same extent. Conversely, the proposed method can enhance different textures to different extents because it separates the textures into components representing different visual characteristics and modifies them in different ways. As a result, the proposed texture enhancement method results in higher segmentation accuracy than other enhancement methods.

VII. Conclusion

We proposed to decompose the texture image using the MCA method according to different texture characteristics: coarseness, contrast, directionality, and line-likeness. For every morphological component, we proposed transformations to enhance the characteristic captured by that component. The experimental results showed that the proposed texture enhancement method successfully enhanced the difference between textures with respect to the chosen texture characteristics while better preserving their visual appearance compared to other methods which led to improved texture-based segmentation results.

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