Texture Enhancement using Morphological Component Analysis

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Abstract- *Digital Image Segmentation is one of the major tasks in digital image processing. It is the process of subdividing a digital image into its constituent objects. This work proposes a new approach for segmentation, based on texture of the image. In this approach, the first step is to decompose the image into morphological components, according to different texture characteristics such as coarseness, contrast, directionality and line-likeness using Morphological Component Analysis (MCA). Then each morphological component is modified to enhance the texture characteristics and recombined to produce a texture enhanced image. We have evaluated the proposed approach using Brodatz and SIPI dataset. Experimental results show an enhanced image quality.*

Keywords- MCA, Segmentation, texture characteristics

I. INTRODUCTION

The purpose of this work is to establish a general purpose texture enhancement algorithm to improve the differentiability of texture with respect to texture features in order to obtain greater performance from any texture-based segmentation method. The texture features are 1) Coarseness: Coarseness basically relates to the distance in gray levels of spatial variations, which is implicitly related to the size of primitive elements forming the texture. It has a direct relationship to scale and repetition rates and most fundamental texture feature. The coarseness quantifies the number of edges in a local texture. 2) Contrast: Contrast measures distribution of gray levels that varies in an image and to what extent its distribution is biased to black or white. 3) Directionality: Directionality of an image is measured by the frequency distribution of oriented local edges against their directional angles. It is a global property over a region. This texture feature given by Tamura does not differentiate between orientations or patterns but measures the total degree of directionality in an image is given by Directionality. It is the most important feature given by Tamura about matrix to distinguish from another image that how much uniforms the region. 4) Line-Likeness: Line-Likeness in an image is average coincidence of direction of edges that co-occurred in the pairs of pixels separated by a distance along the edge direction in every pixel. Segmentation and classification plays a vital role in computer vision and pattern recognition and is widely applied to many areas such as industrial automation, bio-medical image processing and remote sensing. Over the last decade, several studies are developed to improve texture of the image for better segmentation performance. All these methods enhance the texture by representing all texture information using a single component.

II. LITERATURE SURVEY

Jianning Chi et al. discussed about the texture enhancement method was proposed which uses an image decomposition that allows different visual characteristics of textures. This method uses a modification of morphological component analysis (MCA) which allows texture to be separated into multiple morphological components each representing a different visual characteristic of texture. Then the methods propose procedures for modifying each texture component and recombining them to produce a texture-enhanced image [1]. Jerome Bobin et al, a new extraction/separation algorithm, MCA proved its efficiency. Then, exhibit a new advantageous way to tune the thresholds which we called MOM (Mean-of-Max). The MOM strategy differs from other heuristics in the sense that it is fast, accurate and adaptive. As it performs drastically faster than BP, MCA/MOM provides a practical alternative to this well-known sparse decomposition algorithm [2]. M. Joseph Prakash et al, This paper proposes a new segmentation method for noise removal, image enhancement and segmentation. The proposed algorithm offers the advantage of providing good quality segmentation [3]. X.H. Wang et al, A new methodology for denoising the image using stationary wavelet transforms (SWT). The testing result on sample microarray images has shown an enhanced image quality [4].

J. L. Starck et al, This method extend MCA to a multichannel MCA (MMCA) for analyzing multispectral data and present a range of examples to illustrate the result [5]. M. J. Fadili et al, This paper proposed a novel decomposition method-morphological component analysis (MCA)-based on sparse representation of signals. MCA assumes that each (mono channel) signal is the linear mixture of several layers, the so-called morphological components, that are morphologically distinct. The success of this method relies on two tenets: sparsity and morphological diversity [6]. Idrissi Sidi Yassine et al, The method described the texture feature analysis process based on the spectral histogram. After that a new algorithm for texture segmentation using this descriptor, statistics based on the spectral histogram, and mathematical morphology was described [7]. M. Joseph Prakesh et al, This paper described a novel technique of image segmentation for texture images based on six different texton patterns and morphological transforms [8].S.D. Pathak et al, The use of edge guidance for boundary delineation can also be extended to other applications in medical imaging where poor contrast in the images and the complexity in the anatomy limit the clinical usability of fully automatic edge-detection techniques [9]. Dorin Comaniciu et al, Discrete data is convergence of a recursive mean shift procedure to the nearest stationary points of the underlying density function and thus, it is used in detecting the modes of the density. The relation of the mean shift procedure to the Nadaraya -Watson estimator from kernel regression and the robust M-estimators of location is also established [10].

III. PROPOSED METHOD OF TEXTURE ENHANCEMENT

In the method presented herein, it is assumed that texture consist of several different components representing different visual characteristics. By modifying these components in different ways, distinct textures become more different in terms of the descriptors used to differentiate them.

The Morphological Components of different textures are then modified in different ways so that textures become more different with respect to these texture characteristics. Morphological Component Analysis (MCA) has proven successful in decomposing images into morphological distinct components.

A texture characteristic is broadly defined any property of a texture that can be quantified. Fig.1 shows a schematic of the proposed method to enhance textural differences by manipulating certain texture characteristics in certain ways.

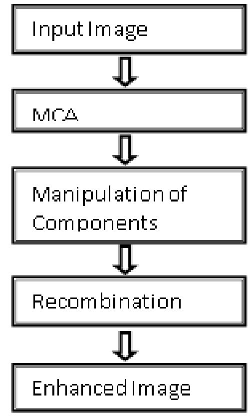


Fig.1 Architecture Diagram of proposed System

Intuitively, each step functions as follows:

1) The image is decomposed to several pairs of components where each pair consist of a component that strongly exhibits a particular texture characteristic and a component that weakly exhibits it, or exhibits opposite characteristics.

2) The components are manipulated to enhance the texture characteristics.

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.

1. Decomposition using MCA

1.1. Standard Cartoon + Texture Decomposition

Morphological component analysis (MCA) was proposed to seek components of the image x by solving the following:

$$\{s_1^{opt}, \dots, s_i^{opt}\} = arg \min_{\{s_{1,\dots,}s_i\}} \sum_{K=1}^{K} \parallel T_i s_i \parallel_1 + \lambda \parallel x - \sum_{i=1}^{i} s_i \parallel_2^2$$

----- (1)

where $s_1, \dots, s_i$ are image components, T_i , i = 1, 2, . . . , i are transformations employed by the i^{th} dictionary to represent the i^{th} component s_i as a "sparse" linear combination of a small number of basic elements. To minimize and seek two images s_c and s_t as the cartoon and texture components of the image x, the following equation is used:

$$\{s_c^{opt}, s_t^{opt}\} = arg \min_{\{s_c, s_t\}} ||T_c s_c \parallel_1 + ||T_t s_t||_1 + \lambda\, ||x - s_c - s_t||_2^2$$

----- (2)

where s_c and s_t are the cartoon and texture components, *x* is the image to be decomposed, T_c and T_t are transformations employed by dictionaries for representing cartoon and texture components respectively.

Algorithm 1. MCA algorithm

(1) Initialize N_{max}, number of iterations, and threshold $\delta = \lambda$. N_{max}, s=input image, s_c=s_t=0. T_c, T_t, R_c, R_t are the forward and inverse transforms for the dictionaries respectively.

(2) Perform N_{max} times:

- Update of S_c assuming S_t is fixed:

  - calculate the residual r= s-s_t-s_c.
  - calculate the transform T_c or S_c + r and obtain α_c=T_c (S_c+r).
  -soft threshold the coefficient $\boldsymbol{\alpha}_c$ with the **δ** threshold and obtain **α**c.
  -reconstruct st by S_c= $R_c\boldsymbol{\alpha}_c$.

- Update of S_t assuming S_c is fixed:

  - calculate the residual r = S-S_c-S_t.
  - calculate the transform T_t or S_t + r and obtain a_t=T_t(S_t+r).
  -soft threshold the coefficient a_t with the **δ** threshold and obtain $\boldsymbol{\alpha}_t$.
  -reconstruct S_t by S_t=$R_t\boldsymbol{\alpha}_t$

(3) Update the threshold by **δ= δ-** λ.

(4) If **δ>** λ, return to step2, Else, finish

1.1. Decomposition by multiple texture characteristics

The traditional MCA method by loosening the restrictions of dictionaries and seeking optimal parameters for those selected dictionaries, so that the image can be decomposed into different components corresponding to k textural characteristics described for solving the following k optimization problems using:

$$\{s_{s,n}^{opt}, s_{w,n}^{opt},\} = arg \min_{\{s_{s,n}, s_{w,n}\}} \parallel T_{s,n}s_{s,n} \parallel_1 + \parallel T_{w,n}s_{w,n} \parallel_1 + \parallel I - s_{s,n} - s_{w,n} \parallel_2^2$$

----- (3)

where $s_{s,n}$ and $s_{w,n}$ are the components having strong and weak aspects of the n th texture characteristic, n = 1, 2, . . . , *i*, e.g. a “coarse” component and a “non-coarse” component. $T_{s,n}$ and $T_{w,n}$ are dictionaries for $S_{s,n}$ and $S_{w,n}$ respectively, and I is the original image.

Algorithm 2. Algorithm for Minimizing Equation

(1) Initialize N_{max}, number of iterations, and threshold $\delta = \lambda$. N_{max}, s=input image, s_c=s_t=0. T_c, T_t, R_c, R_t are the forward and inverse transforms for the dictionaries respectively. Initialize the number of iterations N_{max}, the parameters $\mu_{s,n}$ and $\mu_{w,n}$ of the dictionaries $T_{s,n}$ and $T_{w,n}$, $\delta = \lambda$. N_{max}, threshold for stopping decomposition, and Φ is a threshold for updating parameters of dictionaries. $S_{s,n}$ = $S_{w,n}$ = 0.

(2) Perform L_{max} times:

- Update of $s_{s,n}$ assuming $s_{w,n}$ is fixed:

  - calculate the residual r = I – $s_{s,n}$ – $s_{w,n}$.
  - calculate the transformation $T_{s,n}$ of $s_{s,n}$ + r and obtain $\boldsymbol{\alpha}_{s,n}$=$T_{s,n}$ ($s_{s,n}$+r).
  - calculate d = $\left\|s'_{s,n} - s_{s,n}\right\|$
  - **if** d>Φ , update $T_{s,n}$ by updating $\mu_{s,n}$ with $\mu_{s,n}$ - $\frac{\mu_{s,n}}{N_{max}}$ **else** $\mu_{s,n}$ keep the same values.
  - update $s_{s,n}$ with $s'_{s,n}$.

- Update of $s_{w,n}$ assuming $s_{s,n}$ is fixed:

  - calculate the residual r = I – $s_{s,n}$ – $s_{w,n}$.
  - calculate the transformation $T_{w,n}$ of $s_{w,n}$ + r and obtain $\boldsymbol{\alpha}_{s,n}$=$T_{s,n}$ ($s_{w,n}$+r).
  - calculate d = $\left\|s'_{w,n} - s_{w,n}\right\|$
  - **if** d>Φ , update $T_{w,n}$ by updating $\mu_{w,n}$ with $\mu_{w,n}$ - $\frac{\mu_{w,n}}{N_{max}}$ **else** $\mu_{s,n}$ keep the same values.
  - update $s_{w,n}$ with $s'_{w,n}$.

(3) Update the threshold by **δ= δ-** λ.

(4) **If δ>** λ, return to step2, **Else**, finish

The dictionaries used in this method have adjustable parameters so that the performance of decomposition can be more consistent for different images than the traditional MCA. To allow for the additional optimization of dictionary parameters we use following equation:

$$\{s_{s,n}^{opt}, s_{w,n}^{opt}, T_{s,n}^{opt}, T_{w,n}^{opt}\} = \arg \min_{\{s_{s,}s_{w,i}, T_{s,i}, T_{w,i}\}} ||\,T_{s,n}s_{s,n}||_1 + \left|\left|T_{w,n}s_{w,n}\right|\right| + ||I - s_{s,n} - s_{w,n}||_2^2$$

----- (4)

where $T_{s,n}^{opt}$ and $T_{w,n}^{opt}$ are the transformations or local spatial filters used as dictionaries for components corresponding to strong and weak aspects of n^{th} characteristic, respectively, whose parameters have been optimized. Algorithm 2 is proposed to solve the optimization problem in to seek components $s_{s,n}$ and $s_{w,n}$ as well as the parameters of dictionaries $T_{s,n}$ and $T_{w,n}$. Algorithm 2, $\mu_{s,n}$ and $\mu_{w,n}$ are the parameter sets of the dictionaries $T_{s,n}$ and $T_{w,n}$ respectively. N_{max} is the maximum number of iterations for decomposition. The parameters in $\mu_{s,n}$ and $\mu_{w,n}$ are decreased uniformly over each iteration.

1.2. Manipulation of the image components

After decomposing the image into pairs of strong and weak texture characteristic components, these components are manipulated to enhance the texture characteristics they are meant to capture. In general using the following equations:

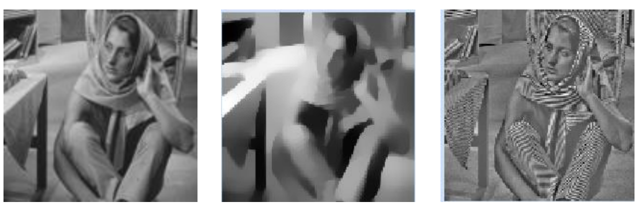
$$s'_{s,n} = f_{s,n}\left(s_{s,n}\right) \qquad \text{----- (5)}$$

$$s'_{w,n} = f_{w,n}\left(s_{w,n}\right) \qquad \text{----- (6)}$$

where $s_{s,n}$ and $s_{w,n}$ are the components respectively exhibiting strong and weak aspects of the n^{th} texture characteristic, n = 1, 2, . . . , i, $s'_{s,n}$ and $s'_{w,n}$ are the manipulated strong and weak characteristic components, and $f_{s,n}$ and $f_{w,n}$ are the manipulation functions used to enhance the texture components $s_{s,n}$ and $s_{w,n}$ respectively.

1.3. Re-combination of the manipulated components

After manipulating every component to enhance its own properties, the components are re-combined into a final texture-enhanced image I'.



(a) Input Image (b)Cartoon Image (c) Texture Image

Fig.2 MCA Decomposition of Cartoon+Texture

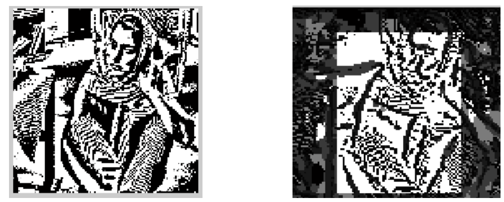
1. Texture manipulation

The input image is decomposed into $s_{s.n}$ and $s_{w,n}$ according to four specific texture characteristics, where n = 1, 2, 3, 4 represent coarseness, contrast, directionality and line-likeness respectively. By modifying each of the individual texture components and recombining them, the textures can be manipulated to be more different with respect to the specific characteristics represented by the modified components. Various manipulations are applied to transform the components.

2.1 Manipulations for coarseness-decomposed components

To enhance the coarse component, $s_{s,1}$, we found that the NL-means (Non-Local means) filter works well because weak edges are further suppressed, enhancing texture coarseness.

For the enhancement of the fine component, $s_{w,1}$, we need to increase the number of edges because the coarseness is defined as the number of edges in a neighborhood. The sticks filter 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.



(a)Coarse (b) Fine

Fig.3 Manipulate Coarse and Fine Component

2.2 Manipulations for contrast-decomposed components

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:

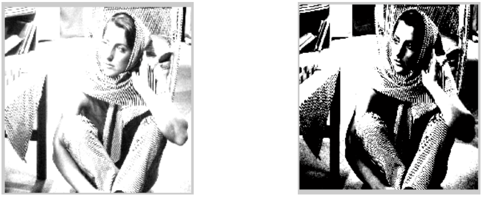
$$s'_{s,2} = s_{s,2} + medfilt\,(|\nabla^2\ (s_{s,2})|) \qquad \text{----- (7)}$$

where $|\nabla^2(\cdot)|$ is a 5 × 5 Laplacian filter, and medfilt($\cdot$) is a 3 × 3 median filter. The magnitude of the Laplacian is high in areas where intensity change is strongly non-linear. These magnitudes are then tempered by the median filter and added back into the original texture increasing the contrast of already high-contrast neighborhoods. For the low-contrast component $s_{w,2}$, we need to decrease local intensity diversity for the already low-contrast regions. We propose a piece-wise power-law transformation with two thresholds T_1 and T_2 as:

$$s'_{w,2}(n) = \begin{cases} \left(\frac{s_{w,2}(n)}{T_1}\right)^{\gamma_1} . T_{1,} & if\ s_{w,2}\,(n) < T_1 \\ \left(\frac{s_{w.2}(n)-T_1}{T_2-T_1}\right)^{\gamma_1} . (T_2 - T_1) + T_1, & if\ T_1 \le s_{w,2}(n) < T_2 \\ \left(\frac{s_{w,2}(n)-T_2}{1-T_2}\right)^{\gamma_2} . (1 - T_2) + T_2, & if\, s_{w,2}(n) \ge T_2 \end{cases}$$

----- (8)

where $\gamma_1 > 1$ and $0 < \gamma_2 < 1$, T_1= 0.35 and T_2= 0.85 this compresses the intensities of the darkest and brightest pixels, which reduces overall contrast.



(a) High Coantrast (b)Low Contrast

Fig.4 Manipulate High and Low Contrast Component

2.3 Manipulations for directionality-decomposed components

Intuitively, directionality is enhanced by making the horizontal component more horizontal and the vertical component more vertical. The SWT (Stationary Wavelet Transform) was 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. The horizontal morphological component $s_{s,3}$ was manipulated as:

$$s'_{s,3} = iswt\left(w'_{s,3,h}, w'_{s,3,v}, w'_{s,3,d}\right) \quad \text{----- (9)}$$

where iswt (·) is the inverse SWT transform, $w_{s,3,h}$, $w_{s,3,v}$ and $w_{s,3,d}$ are the horizontal, vertical and diagonal SWT coefficients of the horizontal morphological Component $s_{s,3}$ are:

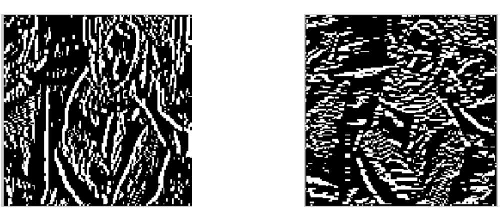
$$\left[w_{s,3,h}, w_{s,3,v}, w_{s,3,d}\right] = swt\left(s_{s,3}\right) \quad \text{----- (10)}$$

where swt (·) denotes the forward SWT transform, and the coefficients are manipulated as :

$$w'_{s,3,h} = a \cdot w_{s,3,h}$$
$$w'_{s,3,v} = 0$$
$$w'_{s,3,d} = w_{s,3,d} \quad \text{-----}$$

(11)

where a is the amplifying coefficient. For the vertical morphological component $\alpha_{w,3}$, we amplified the vertical wavelet coefficients $\omega_{w,3,v}$ and set the horizontal wavelet coefficients $\omega_{w,3,h}$ to zero.



(a)Directionality (b)Non-Directionality

Fig.5 Manipulate Directional and Non-Directional Component

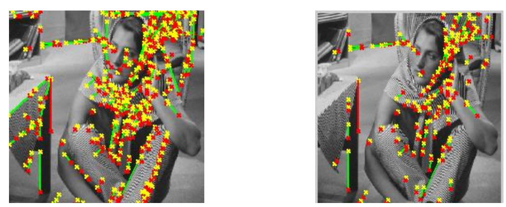
2.4 Manipulations for line-likeness-decomposed components

We make use of adaptive histogram equalization to enhance the line-like component because it increases the intensity contrast, making the line or boundary between different primitives more obvious, while decreasing the intensity contrast between two texture elements with very similar intensities, and removing very weak edges. In the experiment, we set the filtering window size as 8 × 8 and the contrast enhancement limit as 0.01.

For the non-line-like component, $s_{w,4}$, apply the power law transform with $\gamma > 1$ in:

$$s'_{w,4} = s_{w,4}^{\gamma} \quad \text{----- (12)}$$

where $s_{w,4}$ is the non-line-like component. In our experiments we used $\gamma = 1.5$. Therefore, boundaries and the local contrast are suppressed and the line-likeness component. After re-combination of these manipulated components $s_{s,n}$ and $s_{w,n}$, the textures in the resulting image are more different with respect to the chosen texture characteristics.



(a)Line-Like (b)Non-Line-Like

Fig.6 Manipulate Line-Like and Non-Line-Like Component

2. *Texture manipulation*

Recombination is the reverse process of decomposition. After re-combination of these manipulated components $s'_{s,n}$ and $s'_{w,n}$ as in following Equation:

$$I' = \frac{1}{i}\sum_{n=1}^{i}\left(s'_{s,n} + s'_{w,n}\right) \quad \text{----- (13)}$$

where $s'_{s,n}$ and $s'_{w,n}$ are calculated as the manipulated strong and weak characteristic components respectively, and i is the total number of characteristics used for image decomposition. Decomposition of image into different texture characteristics was done in order to manipulate the image. By doing such manipulations, weak edges are removed and pixel intensities are improved with high clarity.

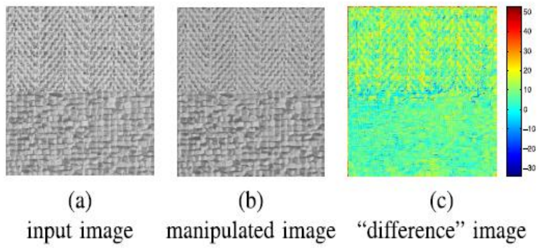


Fig.7 Recombine the Manipulated Image

After completing these steps, final enhanced image is obtained from these decomposed blocks by recombination. Recombination is the final stage that regains the input image as an enhanced image.

(a) Input Image (b) Enhanced Image

Fig.8 Enhanced Image

IV. EXPERIMENTAL RESULTS

The experiments are conducted on the texture and real world image database, which contains 82 textures and 10 real world images. Description of the datasets used in the proposed system is given in the Table 1.

Table.1 Dataset

Database	Brodatz, SIPI
Number of textures and real world	82 textures and 10 real world
Format	.tiff and .png
Size	256×256 pixels

The Peak Signal to Noise Ratio (PSNR) is the most commonly used as a measure of quality of reconstruction. It is the ratio between maximum power of a signal (image) and the power of corrupting noise that affects its representation. The PSNR of the image is evaluated using formula:

$$PSNR = 10 * \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad \text{----- (14)}$$

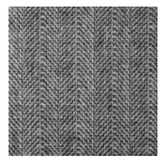
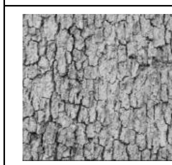
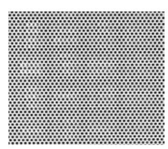
$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad \text{----- (15)}$$

where,

PSNR → Peak Signal to Noise Ratio

MSE → Mean Square Error

Table.2 Performance of proposed approach

INPUT IMAGE	**MSE**	**PSNR**
	1.8028	44.9721
	3.9684	42.1486
	0.73188	48.8871
	1.8061	45.5633
	3.2465	43.0167

V. CONCLUSION

In this paper, a novel system for Morphological Component Analysis (MCA) is used to decompose textures into multiple morphological components according to texture characteristics: coarseness, contrast, directionality and line-likeliness. We have evaluated the proposed approach using Brodatz and SIPI dataset. Experimental results show an enhanced image quality. For performance evaluation we have calculated MSE and PSNR of original input image and enhanced output image. We found that PSNR of output image is greater than 30.

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