Morphological Component Analysis for Textural Enhancement

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Abstract: **In practice, image segmentation can be performed in many areas like medical and satellite communications to detect objects and regions in the image.The texture enhancement methods representing all texture information using a single image component. In previous texture enhancement methods reduce noise or artifacts in the image to highlight the textures with the help of filters which reduces the quality of the image. In this project propose a new texture enhancement method using Morphological Component Analysis which uses image decomposition that allows different visual characteristics of textures to be represented by separate components. This method is intended to be a preprocessing step to the use of texture based segmentation algorithms. It uses the modification of Morphological Component Analysis which allows textures to be separated into multiple components each representing different visual characteristics of texture. It select four such texture characteristics and propose a new dictionaries to extract these components using Morphological Component Analysis (MCA). This method produces superior results compared to comparator methods for all segmentation algorithms tested. It results the clusters of local texture features of each distinct image texture to mutually diverge within the multidimensional feature space to a vastly superior degree competes the comparator enhancement methods. The motivation for this project is to extract the greater performance from any texture based segmentation method by establishing a general purpose texture enhancement algorithm.**

Index Terms**—Texture, enhancement, segmentation, morphological component analysis, non-linear transform**

I. INTRODUCTION

Some early texture enhancement methods reduce noise or artifacts in the image to highlight the textures indirectly, for example, the median filter [1] and the Weiner filter . However, these conventional filters remove the textures in addition to removing noise because of their low pass-filter-like qualities. Discontinuity-preserving filters were developed to mitigate this issue to a certain extent, for example, the non-local means filter Which can smooth the noise and artifacts in the image while preserving image detail as much as possible. Wavelet-based methods, e.g. VISU Shrink, Bayes Shrink[5] , SURE Shrink [3], were proposed to remove noise by shrinking coefficients in high-frequency sub-bands not exceeding certain thresholds, while preserving the image textures which are represented by coefficients in high-frequency sub-bands that exceed these thresholds. Other methods enhance the textures in the image directly. Unsharp masking (UM) was proposed to improve the visual appearance of an image by emphasizing its high frequency contents [7]. However, the high pass-filter-like nature of UM causes enhancement of noise and artifacts in the image as well. The same is true of histogram equalization methods. Therefore, some non-linear methods have been proposed to enhance the textures. Hong et al. [11] proposed a texture enhancement algorithm that can improve the clarity of ridge and valley structures of fingerprint textures based on the estimated local ridge orientation and frequency. Coherence-enhancing anisotropic diffusion is based on the modifications of partial differential equations (PDEs) which can preserve strong discontinuities at edges while removing artifacts from smooth regions. Shock filtering is a transformation of anisotropic diffusion which smooth's along the coherent texture flow orientations, and reduces diffusivity at non-coherent structures which enhances textural detail [4]. All of the above methods enhance or reduces the "textural" components and "non-textural" components of the image to the same extent, thus, the quantitative difference between texture descriptors for different textures is not much altered. This occurs because all of the different textures in an image are treated as a single "texture" component alongside other non-texture components which results in any transformation to texture being applied to all textures uniformly. In the method presented herein, it is assumed that textures 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 between them. Morphological component analysis (MCA) has proven successful in decomposing images into morphologically distinct components, e.g., a smooth component, an oscillating component and noise component [3]. By filtering out the noise component and recombining the smooth component and the oscillating component, the image variations due to noise is reduced [5]. However, these works only decompose images according to the "cartoon+texture+noise" model [3] or otherwise express texture using only a single morphological component. In this paper, we first select some textural characteristics based on human visual perception. Then, a novel form of MCA is used to decompose textures into *multiple* morphological components according to these characteristics by introducing several dictionaries. The morphological components of different textures are then modified in different ways so that textures become more different with respect to these textural characteristics.

II. RELATED WORK

A. Bauds, B. Coll, and J.-M. Morel was proposed "[1]A non-local algorithm for image denoising," in Proc. IEEE Comput. In 2005. In this propose a new measure, the method noise is to analyze and compare the performance of digital image denoising methods. Here first compute and analyze this method noise for a wide class of denoising algorithms, we call the local smoothing filters. Then, we propose a new algorithm is the nonlocal means (NL-means), which is based on a nonlocal averaging of all pixels in the image. Finally, we present some experiments comparing the NL-means algorithm and the local smoothing filters.

A. Chambolle, was proposed "Partial differential equations and image processing", in 1994. Here first recall the undeniable way of the theory of multiscale analysis of images and try at the same times to see how it can be applied later to the problem of color image processing. After stating the theorems that follow from this theory, we discuss some examples of PDEs and show results.

J. Weickert, was proposed "Coherence-enhancing diffusion filtering",in Apr. 1999. Shock filters are based in the idea to apply locally either dilation or an erosion process, depending on whether the pixel belongs to the influence zone of a maximum or a minimum. They create a sharp shock between two influence zones and produce piecewise constant segmentations. In this paper we design specific shock filters for the enhancement of coherent low-like structures. They are based on the idea to combine shock filtering with the robust orientation estimation using the structure tensor. Experiments with grayscale and color images deduce that these novel filters may outperform previous shock filters as well as coherence-enhancing diffusion filters.

X. H. Wang, R. S. H. Istepanian, and Y. H. Song, was proposed "Microarray image enhancement by denoising using stationary wavelet transform, in Dec. 2003. Microarray imaging is considered as significant tool for large scale analysis of gene expression. The performance of the gene expression depends on the experiment itself and further image processing. We know that the noises entered during the experiment will adversely affect the accuracy of the gene expression. How to overcome the effect of the noise constitutes a challenging problem in microarray analysis. Generally statistical methods are used to estimate the noises while the microarray images are being processed. Here we present a new approach to deal with the noise inherent in the microarray image processing procedure. Firstly denoise the image noises before further image processing using stationary wavelet transform (SWT). The time invariant characteristic of SWT is useful in image denoising. The evaluation results on sample microarray images have given an enhanced image quality. The results gives superior performance than common discrete wavelet transform .It is widely used adaptive Wiener filter in this procedure.

M. Zibulevsky and B. A. Pearlmutter, was proposed "Blind source separation by sparse decomposition in a signal dictionary. in Apr. 2001. The blind source separation problem is to extract the underlying source signals from a set of linear mixtures, where the mixing matrix is unknown. This problem is common in acoustics, radio, medical signal and image processing, hyper spectral imaging, and other areas. Here we suggest a two stage separation process: a priori selection of a possibly over complete signal dictionary (for instance, a wavelet frame or a learned dictionary) in which the sources are assumed to be sparsely represent able, followed by unmixing the sources by exploiting the their sparse represent ability. Here consider the general case of more sources than mixtures, but also derive a more efficient algorithm in the case of a non over complete dictionary and an equal numbers of sources and mixtures. The experiments with artificial signals and musical sounds gives significantly better separation than other known techniques.

III. EXISTING SYSTEM

The results of segmentation by various segmentation algorithms of an example synthetic image after texture enhancement by VISU Shrink (VISU), unsharp masking

(UM), shock filtering (SHK), coherence enhancing diffusion (CDF), "cartoon+texture" MCA filtering (MCA-CT), the "texture characteristic" MCA filtering without manipulation (MCA-NM) and the proposed method (proposed). The VISU and MCA-CT filter preserve the significant textures well but degrade the weak textures because processes them as noise. The shock filter can enhance the texture edges well but it breaks some smooth regions. The coherence-enhancing diffusion changes the shapes of the textures a lot by merging the small smooth regions close to each other. The unship masking can enhance the texture, especially the local contrast of the texture very well, but it Creates unwanted edge effects at

The same time. Moreover, all these methods process the textures as a single "texture" component; all the different textures in the image are enhanced to the same extent. Table I shows the average performance of our method and comparator texture enhancement methods in combination with various the transformation and segmentation of an example real-world image after texture enhancement by the same methods. Use of the proposed method prior to segmentation results in higher segmentation accuracy than other enhancement methods for every segmentation algorithm. Table II shows the average performance of our method and comparator texture enhancement methods in combination with various segmentation algorithms over 150 images.

TABLE I
Average Segmenting Accuracy Over 150 Synthetic Texture Images For Various Combinations Of Texture Enhancement Methods

S.No	Different Segmentation Methods	Original	UM	VISU	MCA-CT	SHK	MCA -NM	MCA-CCL	MCA-CONDL
1	Thresholding	90.76%	82.75%	94.15%	85.35%	82.97%	92.64%	93.20%	90.55%
2	K-Means	91.52%	83.45%	92.24%	90.14%	83.754%	93.27%	80.28%	82.45%
3	Mean shift	84.54%	84.91%	91.75%	92.06%	84.81%	91.80%	89.71%	88.60%
4	GMM	94.78%	83.44%	90.48%	91.25%	91.77%	94.38%	92.24%	93.89%

TABLE II
Average Segmenting Accuracy Over 50 Real World Images For Various Combinations Of Texture Enhancement Methods

S.No	Different Segmentation Methods	Original	UM	VISU	MCA-CT	SHK	MCA -NM	MCA-CCL	MCA-CONDL
1	Thresholding	78.76%	85.75%	78.65%	85.35%	88.12%	91.16%	85.43%	83.66%
2	K-Means	85.52%	92.90%	80.76%	90.14%	87.54%	90.35%	82.98%	82.53%
3	Mean shift	91.54%	94.65%	94.68%	92.06%	90.78%	95.77%	89.46%	87.15%
4	GMM	88.78%	91.86%	89.48%	91.25%	91.25%	92.43%	85.05%	88.83%

IV. TEXTURE

While the word texture is commonly used in computer vision, it has no precise scientific definition that is widely accepted. However, it has been proposed that texture can be distinguished by relatively small scale structures which are distributed uncertainly relative to the object. It is apparent that these characteristics are variances in medical images. The question is whether the texture-based handling of images can be experimented more effectively than shape boundary-based handling when they appear simultaneously. The problem with using texture is that aliasing problems in texture mapping are usually highly visible. By definition texture usually manifests some kind of coherence or periodicity. The aliasing effect occurs as the periodicity in the texture approaches the pixel resolution. Therefore, the use of an anti-aliasing method is mandatory with texture mapping.

V. TEXTURE BASED SEGMENTATION

Image segmentation is a process of dividing an image into its constituent homogeneous regions to extract data from the attributes of the image. As a result, a good segmentation should result in regions in which the image elements should have uniform properties in terms of brightness, colour or texture etc. Though the image is to be portioned into regions, the considerable changes within the regions should be observable visually. The measurement of quality of segmentation is that the elements of the same region should be similar and should have clear difference between elements of the other regions. The image segmentation process can be divided into various category based on the parameter selected for segmentation like pixel intensity, homogeneity, discontinuity, cluster data, topology etc. Each approach has its own advantages and disadvantages. The result obtained using one way may not be the same as compared with other approach This selection of an appropriate approach to a segmentation problem can be a difficult dilemma. Generally the segmentation can be semi-interactive or fully automatic. The algorithms developed for segmentation between the categories. The major difficulty of ill-posed nature of segmentation it is rigid to obtain single answer for segmentation of given image as the interpretation varies from individual approaches. Generally manual interaction to segment the image may be error-prone .while the fully automated way can give error output (for example in case of watershed segmentation)and also interactive methods can be active and time consuming. Therefore a single approach to segment all variety of images may be practical unachievable. The prior information on the image can give better results and gives user the choice to decide proper method to segment the image.

This work was inspired by a challenging problem in image analysis: How to perform segmentation of images with texture characteristics in addition to objects' shape-boundary characteristics. This problem is suited for medical images and it is perhaps non coincidental that auto-segmentation of such images is still at its infancy given that most algorithms for medical image segmentation are based on object's shape-boundary characteristics. Texture-based medical images include mammograms, 2.3 ultrasonic liver images, and X-Ray lung images. Moreover, shape boundary-based image analysation usually implies assumption that the local intensities are uniform in pixel belonging to the same object which is typically not the case in gray scale.

VI. MORPHOLOGICAL COMPONENT ANALYSIS

Mathematical morphology is a branch of image processing that has been successfully used to provide tools for representing, describing, and analyzing shapes in images. In addition to providing useful tools for extracting image components, morphological algorithms have been used for pre- or post processing the images containing shapes of interest. The basic principle of mathematical morphology is the extraction of geometrical and topological information from an unknown set (an image) through transformations using another, well-defined, set known as structuring element. In morphological image processing, the design of SEs, their shape and size, is crucial to the success of the morphological operations that use them. The two fundamental morphological operations upon which all other operations and algorithms are built: dilation and erosion. Dilation is a morphological operation whose effect is to “grow” or “thicken” objects in a binary image. The extent and direction of this thickening are controlled by the size and shape of the structuring element. Erosion is a morphological operation whose effect is to “shrink” or “thin” objects in a binary image. The direction and extent of this thinning is controlled by the shape and size of the structuring element.

VII. CONCLUSION

A novelty 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 transformation 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.

REFERENCES

[1]A. Buades, B. Coll, and J.-M. Morel, “A non-local algorithm for image denoising,” in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, vol. 2. Jun. 2005, pp. 60–65.

[2] J. Bobin,Y. Moudden, J.-L. Starck, and M. Elad,“Multichannel morphological component analysis,” in *Proc. SPARS*, 2005, pp. 103–106.

[3] J. Bobin, J.-L. Starck, J. M. Fadili, Y. Moudden, and D. L. Donoho, “Morphological component analysis: An adaptive thresholding strategy,” *IEEE Trans. Image Process.*, vol. 16, no. 11, pp. 2675–2681, Nov. 2007.

[4] A. Chambolle, “Partial differential equations and image processing,”in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, vol. 1. Nov. 1994,pp. 16–20.

[5] H. A. Chipman, E. D. Kolaczyk, and R. E. McCulloch, “Adaptive Bayesian wavelet shrinkage,” *J. Amer. Statist. Assoc.*, vol. 92, no. 440, pp. 1413–1421, Dec. 1997.

[6] D. Comaniciu and P. Meer, “Mean shift: A robust approach toward feature space analysis,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 5, pp. 603–619, May 2002.

[7] D. L. Donoho and J. M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage,” *Biometrika*, vol. 81, no. 3, pp. 425–455, 1994.

[8] D. L. Donoho and I. M. Johnstone, “Adapting to unknown smoothness via wavelet shrinkage,” *J. Amer. Statist. Assoc.*, vol. 90, no. 432, pp. 1200–1224, 1995.

[9] M. J. Fadili, J.-L. Starck, J. Bobin, and Y. Moudden, “Image decomposition and separation using sparse representations: An overview,” *Proc.IEEE*, vol. 98, no. 6, pp. 983–994, Jun. 2010.

[10] R. Gribonval and M. Nielsen, “Sparse representations in unions of bases,” *IEEE Trans. Inf. Theory*, vol. 49, no. 12, pp. 3320–3325, Dec. 2003.

[11] L. Hong, Y. Wan, and A. Jain, “Fingerprint image enhancement: Algorithm and performance evaluation,”

IEEE Trans. Pattern Anal. Mach.Intell., vol. 20, no. 8, pp. 777–789, Aug. 1998.

[12] T. Huang, G. Yang, and G. Tang, "A fast two-dimensional median filtering algorithm," *IEEE Trans. Acoust., Speech, Signal Process.*,vol. 27, no. 1, pp. 13–18, Feb. 1979.

[13] P. C. Mahalanobis, "On the generalized distance in statistics," in *Proc.Nat. Inst. Sci. (Calcutta)*, vol. 2. 1936, pp. 49–55

[14] H. Tamura, S. Mori, and T. Yamawaki, "Textural features corresponding to visual perception," *IEEE Trans. Syst., Man, Cybern.*, vol. 8, no. 6,pp. 460–473, Jun. 1978.

[15] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proc. 6th Int. Conf. Comput. Vis.*, Jan. 1998,pp. 839–846.

[16] X. H. Wang, R. S. H. Istepanian, and Y. H. Song, "Microarray image enhancement by denoising using stationary wavelet transform," *IEEE Trans. Nanobiosci.*, vol. 2, no. 4, pp. 184–189, Dec. 2003.

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