Fuzzy Wavelet and Contourlet Based Contrast Enhancement

Ehsan Nezhadarya, Mohammad B. Shamsollahi and Omid Sayadi

***Abstract*— This paper presents a fuzzy approach for contrast enhancement, based on two multi-scale transforms, namely wavelet and contourlet transforms. Separability and nondirectionality of conventional 2D wavelet transform, makes it unsuitable for sparsely representation of curve or line shaped image objects. On the other hand, the contourlet transform is a good alternative for this purpose. In this paper, coefficient enhancement, both in wavelet and contourlet spaces, is carried out by making use of simple fuzzy rules. These rules make the enhancement procedure more understandable and flexible. With this method, the knowledge and experience of the expert from the distribution of the coefficients can also be used in designing better enhancement functions. The proposed method is applied to both mentioned separable and nonseparable transforms. Implementation results demonstrate that this approach is very effective both in wavelet and contourlet spaces.**

I. INTRODUCTION

Since some features are hardly detectable by eye in an image, we usually try to enhance these features. Histogram equalization [1] is one of the most well-known methods for contrast enhancement. This technique makes use of global statistical information of the image and is not capable of diagnosing the local variations. These local variations are usually called "edge". Edge in the image is one of the most important features; one can use to construct the whole image. Therefore, enhancing the edges can result in enhancement of the entire image. These changes usually constitute the high frequency part of the image. So, one way for image contrast enhancement is to enhance or amplify the amplitudes of these high frequency features. Unsharp masking [2] is a simple Laplacian based contrast enhancement technique in this way. One important problem of using these high-pass filters is the enhancement of noise in noisy environments. Wavelet transform is one way to overcome this problem. The sparsity of this transform is more than Fourier transform and by simple thresholding, it is efficiently capable of removing or reducing white Gaussian noise from the signal. Different wavelet based contrast enhancement methods are proposed in the literature [3]. Because, conventional 2-D wavelets are produced by tensor product of 1-D wavelets, the wavelet transform can only identify pointwise discontinuities [4]. In other words, this transform is not capable of diagnosing the direction of any line-shaped edge in the image. In these cases, the sparsity reduces, when separable nondirectional transforms are used for image representation. Therefore, to properly represent this kind of directional discontinuities, non-separable directional transforms are needed. Recently introduced Contourlet transform [5] is one of these transforms, applicable for edge based contrast enhancement.

In this paper, we propose a new fuzzy method for image contrast enhancement by means of contourlet transform. The fuzzy approach is simple, more understandable and more flexible, than other enhancement procedures proposed up to now. The enhancement function is also applied to wavelet coefficients. Implementation results are also compared with each other and with histogram equalization method. In following sections, at first contourlet transform is studied in brief, and then the fuzzy rules used for enhancement is described. Finally, the methods are compared with each other.

E. Nezhadarya is with Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran. e_arya@ee.sharif.edu

M. B. Shamsollahi and Omid Sayadi are with the Department of Electrical Engineering, Sharif University of Technology, Azadi Ave., Tehran, Iran. mbshams@sharif.edu, osayadi@ee.sharif.edu

II. METHOD

A. The Contourlet Transform

The contourlet transform is a new geometrical image-based transform, which is recently introduced by Do and Vetterli [5]. In contourlet transform, the Laplacian pyramid [6] is first used to capture the point discontinuities, then it is followed by a directional filter bank to link point discontinuities into linear structures. The overall result is an image expansion using elementary images like contour segments, called contourlet transform, which is implemented by a pyramidal directional filter bank. The Laplacian pyramid (LP) is used to decompose an image into a number of radial subbands, and the directional filter banks (DFB) decomposes each LP detail sub-band into a number of directional subbands. The analysis part of this type of filter-bank is shown in "Fig. 1". Quincunx filter banks are the building blocks of the DFB. We used the fan filters designed by Phoong, Kim, Vaidyanathan, and Ansari [7] with support size of (23, 23) and (45, 45) for the Quincunx filter banks in the DFB stage.

B. Contrast Enhancement Method

The complete algorithm for edge based contrast enhancement is as follows:

1) Carry out the transform to get a complete representation of data in transform domain.
2) Shrink transform coefficients within the finer scales to partially remove noise.
3) Emphasize features through an enhancement function.
4) Perform the inverse transform and reconstruct the image.

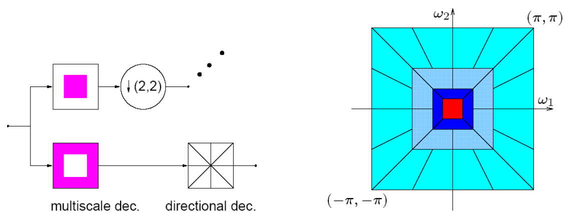

Fig. 1. (left) Laplacian Pyramid is used for multi-scale decomposition and DFB is used for directional decomposition of each detail sub-band, (right) Respective frequency plane decomposition.

Linear enhancement functions tend only to emphasize strong edges, which can lead to inefficient usage of the dynamic range available on a display screen. Therefore, usually non-linear functions are used for enhancement, in which lower coefficient magnitudes are amplified with a higher gain than larger magnitudes. In other words, low contrast area is enhanced more than high contrast area. In addition, an anti-symmetric and monotonic function must be used for enhancement [2]. This knowledge of enhancement procedure leads to following rules:

Rule 1. If the coefficient is small, then make it very small.
Rule 2. If the coefficient is normal, then make it large.
Rule 3. If the coefficient is large, then make it very large.

The first rule is used for denoising purpose. This is the coefficient shrinkage based on for example Donoho's thresholding or shrinking procedures, namely Visushrink, Riskshrink or Sureshrink. Rules 2, 3 are used for proper enhancement or coefficient amplification due to available dynamic range. Depending on desired denoising level and enhancement gain, different weights can be assigned to each rule. For example, if the noise power is low, then we can ignore Rule 1. Besides, if a high enhancement gain is not necessary, we can reduce the weight assigned to Rule 2. Ordinarily, all weights are put to 1. Instead of changing weights, we can make use of different suitable membership functions, to properly enhance the desired features in the image. But almost some special choices for membership functions lead to successful contrast enhancement. A collection of some of these membership functions used for premises and conclusions are shown in "Fig. 2". Membership function types and their associated parameters are also given in Table 1. In this table, Gauss, Gauss2 and Sigm functions are defined as follows:

- Gauss or Gaussian function:

$$f(x,\sigma,c) = \exp\left(\frac{(x-c)^2}{2\sigma^2}\right) \quad (1)$$

- Gauss2 function is constructed from two Gauss membership functions as its right and left side curves.
- Sigm or Sigmoid function:

$$f(x,a,c) = \frac{1}{1+\exp(-a(x-c))} \quad (2)$$

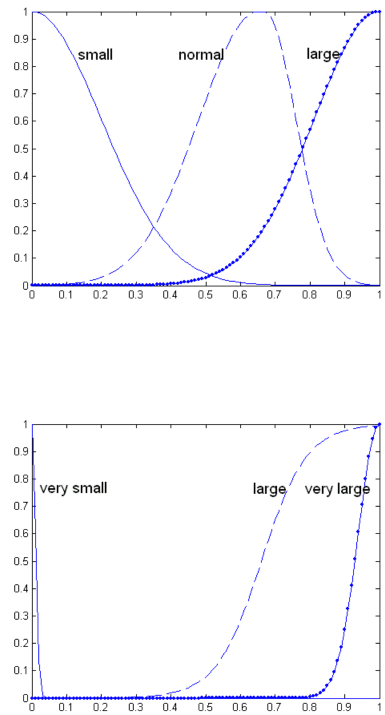

Fig. 2. Membership functions used for fuzzy enhancement model, (up) MFs of premises, (down) MFs of conclusions.

The enhancement function obtained from these rules and membership functions is shown in "Fig. 3". In this function it is assumed that the coefficients larger than $t = .8$ of the maximum coefficient, are linearly amplified but they saturate at the end. This saturation can be efficient in proper dynamic range usage.

The other important advantage of the proposed method is its ability and flexibility for denoising. When the noise power is low, we can decrease the σ value related to the premise part of Gauss membership function in Rule 1 and vice versa. The value of this parameter can be proportional to any threshold, obtained from a denoising algorithm.

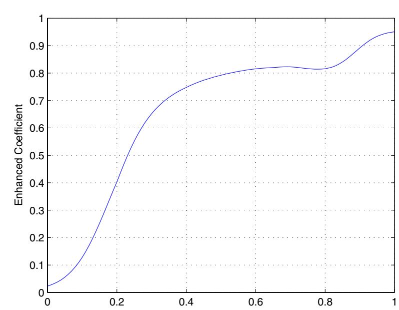

Fig. 3. The fuzzy enhancement function obtained from MFs of Fig. 2 and Rules 1, 2, 3.

TABLE I
TYPES OF MEMBERSHIP FUNCTIONS AND THE VALUES OF THEIR RELATED ENHANCEMENT PARAMETERS

Premise	Small	Guass	$\sigma = .2,\ c = 0$
	Normal	Gauss2	$\sigma_1 = .17,\ c_1 = .65,$ $\sigma_2 = .09,\ c_2 = .67$
	Large	Gauss	$\sigma = .188,\ c = 1$
Conclusion	Very Small	Guass	$\sigma = .01,\ c = 0$
	Large	Sigm	$a = 15.4,\ c = .66$
	Very Large	Sigm	$a = .06,\ c = 1$

This function is continuous and monotonic but not anti-symmetric. To make an odd enhancement function, we can use function "sign" after applying the enhancement to the absolute values of the coefficients. Thus, if we denote the nonlinear fuzzy-based function by $g(x)$ and the maximum absolute value of the coefficients of scale j by M_j then enhancement function can be obtained as follows:

$$G_{j,k}(x) = g(|\frac{x}{M_j}|) \cdot sign(x) \cdot M_{j,k} \tag{3}$$

In which k is index of the direction of transform atoms, and x is the contourlet coefficient. When wavelet transform is used for enhancement, there are only three directions, namely HH, HL and LH. Therefore, separate enhancement functions will be obtained for different scales and directions. In contourlet transform the number of directions in each scale is arbitrary. If l_j level DFB is used in each scale of contourlet transform, then the number of directions in that scale will be 2^{l_j}, or $0 \leq k \leq 2^{l_j} - 1$. In our experiments, we implemented separate enhancement functions due to (2), to different scales and directions of contourlet coefficients. Note that the enhancement function is only applied to the detail coefficients. Approximate coefficients are remained unchanged.

III. EXPERIMENTAL RESULTS

The experimental results of such an implementation are shown in "Fig. 4 and 5". In "Fig. 4", we have used the specified enhancement function with the same parameters for contrast enhancement of "coins" image in both wavelet and contourlet spaces. In "Fig. 5", the same procedure is applied to brain magnetic resonance image. We used Symmlet 4 for wavelet based contrast enhancement, due to its more denoising power. To implement contourlet transform, we used Quincunx filter bank with PKVA filters [7] for directional filter bank (DFB) and biorthogonal Daubechies 7-9 wavelet transform for Laplacian Pyramid (LP). For contourlet transform, we used 5 LP levels and 64 directions in the finest level.

Histogram equalization is a statistical method and can not work well when there are high intensity distributions in the image. When the frequency of lower greyscale values is much more than the frequency of higher greyscale values, then HE will not act properly. This phenomenon is clearly shown in MR image enhancement. Localizing the

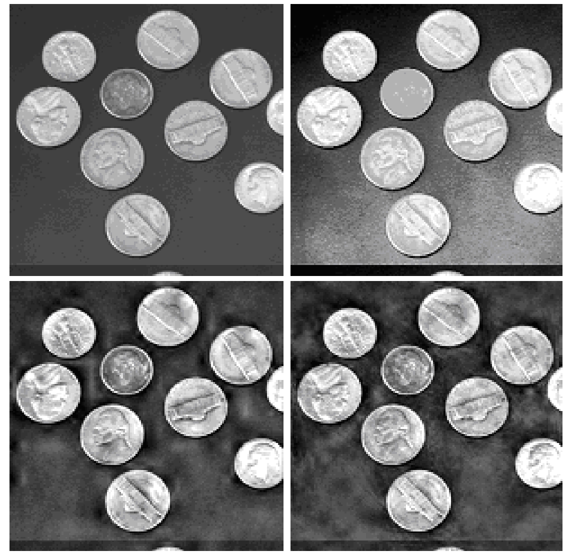

Fig. 4. Contrast enhancement using different methods (from left to right and top to bottom): coins image, histogram equalization, wavelet based fuzzy contrast enhancement and contourlet based fuzzy enhancement.

histogram equalization may lead to better results. Wavelet based methods are usually artefact free and because of denoising capability of wavelet transform, are mostly used for contrast enhancement in noisy environments. In comparison between wavelet and contourlet based contrast enhancements, two parameters must be considered: smoothness and detail enhancement. Wavelet is better, when a smooth image is desired after enhancement. Contourlet transform enhances some structures much better, but with some artefacts in the output image.

IV. CONCLUSIONS

In this paper we proposed a new method for image contrast enhancement based on fuzzy logic. Three general fuzzy rules, both for denoising and contrast enhancement, were suggested. The proposed fuzzy approach is more understandable and flexible. With a little change in each rule weight, it is possible to get the desired enhancement function. Also the threshold based denoising is simply done by changing the standard deviation of the Gauss membership function used for small coefficients. We applied the fuzzy model to both wavelet and contourlet transforms, as respectively nondirectional separable and directional non-separable transforms, to enhance the image contrast. The results were also compared with each other and with histogram equalization method. HE is not a proper choice because of its highly global statistical nature. Wavelet transform has powerful abilities to enhance image contrast, as well as denoising. To better enhance the line or curve shaped edges, contourlet transform is proposed. This transform is better in enhancement but weaker in denoising. Usually some artifacts are generated after contrast

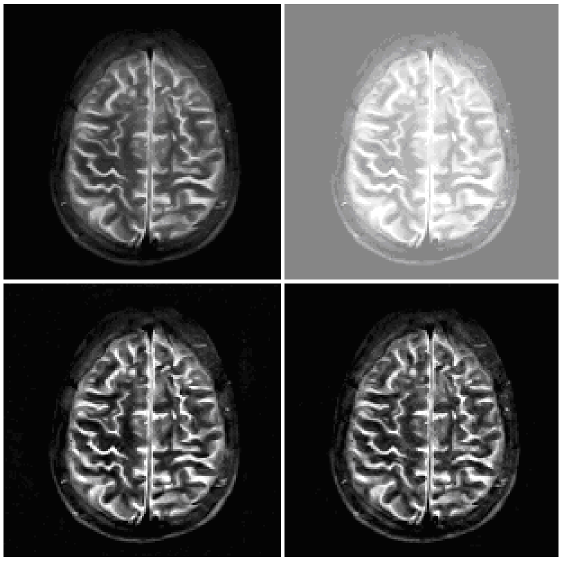

Fig. 5. Contrast enhancement using different methods (from left to right and top to bottom): brain MR image, histogram equalization, wavelet based fuzzy contrast enhancement and contourlet based fuzzy enhancement.

enhancement by contourlet transform. In general, it is not fair to compare these two transforms with one enhancement function. This is because of different statistical natures of the respective transform coefficients. For a perfect comparison, an expert must judge for each image, each enhancement functions and transforms, especially in biomedical field.

V. ACKNOWLEDGMENTS

This work is supported by Iran Telecommunication Research Center (ITRC).

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