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AN EFFICIENT EXEMPLAR BASED IMAGE INPAINTING USING MULTIDIRECTIONAL CONTOURLET TRANSFORM

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ABSTRACT

Problem statement: This paper proposes an exemplar based image inpainting using contourlet transform. It is a new multiscale and multidirectional image representation which effectively captures the edges and contours of images. Approach: The contourlet transform is an extension of wavelet transform in two dimensions, combines Laplacian Pyramid (LP) with a Directional Filter Bank (DFB). The Laplacian pyramid is used to capture the point discontinuities, and is then followed by a Directional Filter Bank to link point discontinuities into linear structures. The image inpainting, also known as image completion, is such a kind of art that modifies an image or video with the available information outside the region to be inpainted in an undetectable way by the ordinary observers. Results: The wavelet inpainting is the existing method in which problem of filling missing data of inpainting will occur. Compare to existing methods, contourlet transform is more effective one. The Contourlet transform has better performance in representing edges than wavelets, therefore well-suited for multi-scale edge enhancement.Conclusion: Experimental results indicate that the proposed algorithm can fill large inpainting regions with good visual quality, presenting results comparable to or better than other approaches for image inpainting.

Keywords: *Contourlet Transform, Laplacian Transform, Exemplar Based, Image Inpainting.*

1. INTRODUCTION

Digital image inpainting is a mechanism that aims to fill missing parts of a digital image, preferably using its own information in an routine way. The area with missing parts is called the inpainting region and it should be filled in such way that both structure (edges) and texture information of the image remain rational. Digital inpainting can be used in several applications, such as image restoration, object removal or to increase image resolution. The focus is on completing regions with missing information that has either been lost or erased intentionally. The concept of inpainting was fake by artists using their own information and abilities in order to fix or reconstruct damages in paintings or sculptures. Today the ability of digitalizing several types of visual information creates the need for techniques that also repair digital damage, as once was done with paintings. Digital inpainting is a more recent field of study that aims for the (preferably automatic) completion of an image area with some missing information, which could have been caused deliberately. Art repairers use their knowledge of the world and the abilities of the brain to complete missing parts of something this can either be a part of a structure or a gap in an image. This ability is described in neuropsychology as the connectivity principle (Kanizsa (1979), Rane (2002), Sarkar (1993)) and allows us to see the missing parts of an image and complete it in such way that one could think that nothing was ever missing. In proposed model, use the same approach with the least possible user interaction; only an inpainting area must be informed by the user, meaning that the selection of the data that will fill the image is done automatically. The region to be filled is analyzed by the algorithm, which selects blocks of dimension 3×3 or higher that best fit the gap, aiming to preserve the image structure and the existing textures. This last characteristic is especially important when filling large inpainting areas. The remainder of this paper is organized as follows. The next section presents some basic concepts and the state-of-the-art in the area of image inpainting. Section 3 provides a brief revision of the contourlet transform. Section 4 describes the proposed model, and some experimental results are illustrated in Section 5. Finally, the conclusions are drawn in Section 6.

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2. RELATED WORK

The fact that inpainting techniques have been very popular since the time of Renaissance artists, modern digital inpainting techniques were established only in recent times. The first steps have a strong user dependency and the inpainting area had to be filled manually with user selected patches (Criminisi (2004), Drori (2003), Do (2005)). In 2000 Bertalmio et al introduced the first aspects of digital inpainting, providing an efficient way to routinely fill the target area. The technique gathers the information to complete the inpainting region by applying a dispersal scheme based on partial differential equations (PDEs) over the boundary of the area to be filled. The core of this method is to transmit isophotes into the inpainting region, alternating with anisotropic diffusion for directional smoothing. More recently, Tschumperle and Deriche (2005) proposed a unified approach for image restoration, object removal and resolution improvement also based on PDEs. In the paper, the authors present a powerful mechanism for digital inpainting based on image regularization through vector fields. Although both methods presented good results for relatively simple regions, they failed to complete larger texturized regions. The need to fill larger inpainting regions provoked the development of techniques that propagate blocks of pixels per iteration instead of isolated pixels. The evolution of Bertalmio's (2003) work describes a mechanism that splits the image information in texture and structure, supported by the methods devised by (Meyer (2001), Vese(2003)). The structured part of the image is processed with an inpainting algorithm, and the texture is synthesized using Efros' method(1999). Criminisi et al. (2004) developed important work in digital inpainting with texture synthesis. In their work, the authors state that exemplar-based texture synthesis suffices in order to fill large inpainting regions. Criminisi's method estimates the gradient vector of the image and a confidence term in order to determine the block that should be processed first at each iteration, aiming to preserve both image structure and texture. The filling of the selected first-block is done with an exemplar-based texture synthesis method, where the pixels to fill the region must minimize the sum of squared errors between the two sets of pixels within an overlapping region. Drori et al. (2003) also proposed a fragment-based image completion algorithm. In their approach, a confidence map is used in the completion algorithm, which is performed in a coarse to fine fashion, using fragments of different sizes. Other inpainting methods such as those by Chen (2003) and Sun (2005) propagate the image texture in a semi-automatic way, where the user is needed to sketch in the image the structure that must be conserved. Then, the algorithm just fills the region with the appropriate textures. Such methods present very good results, but at the cost of user intervention.

Recently, the wavelet transform has been widely used in the medical image processing. Mallat (1989) introduced a fast discrete wavelet transform algorithm that is the method of choice in many applications. Laine and Song (1992a, b) and Laine et al. (1994) use this algorithm to develop the micro calcifications in mammograms. Fu et al. (2000a, b) used a wavelet-based histogram equalization to enhance sonogram images. The wavelet transform is a type of multi-scale analysis that decomposes input signal into high frequency detail and low frequency approximation components at various resolutions. To enhance features, the selected detail wavelet coefficients are multiplied by an adaptive gain value. The image is then enhanced by reconstructing the processed wavelet coefficients. In our opinion, the wavelet transform may be not the best choice for the contrast enhancement of a retinal image. This observation is based on the fact that wavelets are blind to the smoothness along the edges commonly found in images. In other words, wavelet can not provide a 'sparse' representation for such an image because of the intrinsic limitation of wavelet. Some new transforms have been introduced to take advantage of this property. The Curvelet (Cande`s and Donoho, 1999) and Contourlet (Do and Vetterli, 2005) transforms are examples of two new transforms with a similar structure, which are developed to sparse represent natural images. Both of these geometrical transforms offer the two important features of an anisotropy scaling law and directionality and therefore are good choice for edge enhancement. Do and Vetterli (2005) utilized a double filter banks structure to develop the Contourlet transform and used it for some nonlinear approximation and de-noising experiments and obtained some hopeful results. In this work, a new approach for retinal image contrast enhancement that is based on Contourlet transform is proposed. The main reason for the choice of Contourlet is based on its better performance of representing edges and textures of natural images, i.e. better representation of lesions and blood vessels of a retinal image. We compare this approach with other contrast enhancement methods: Histogram Equalization (HE), the Local Normalization (LN)

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(Joes et al., 2004), Linear Unsharp Masking (LUM) and the wavelet-based contrast enhancement in addition to the proposed Contourlet transform method. The experimental results show encouraging improvement and achieve better visual results and outperformed the previous methods the region with the appropriate textures. Such methods present very good results.

3. A REVISION OF CONTOURLET TRANSFORM

The contourlet transform is an extension of wavelet transform in two dimensions, which has been introduced by Minh Do and Martin Vetterli (Duncan, et al., 2006) the contourlet transform combines Laplacian Pyramid (LP) with a Directional Filter Bank (DFB). The Laplacian pyramid is first used to capture the point discontinuities, and is then followed by a directional filter bank to link point discontinuities into linear structures. The Laplacian Pyramid (LP) is used to decompose an image into a number of radial subbands and the Directional Filter Banks (DFB) decompose each LP detail subband into any power of two's number of directional subbands. Fig. 1shows an example frequency partition of the contourlet transform where the three scales are divided into four, eight and eight directional subbands from coarse to fine scale, respectively. The contourlet coefficient can be represented in a quad-tree structure. Each coefficient in the coarsest level has four children in the next higher subband and each of the children has four children in the next higher subband and a quad -tree will emerge

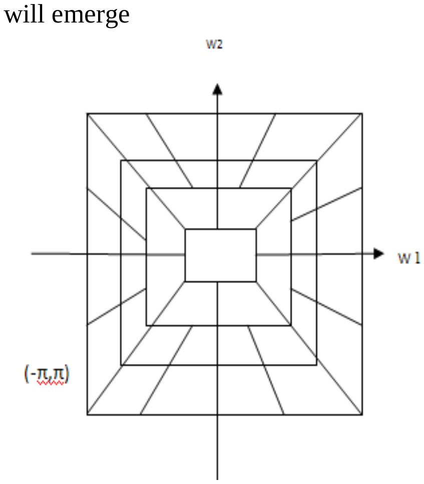

Figure 1: An Example of Frequency Partition By Contourlet Transforms

4. PROPOSED MODEL

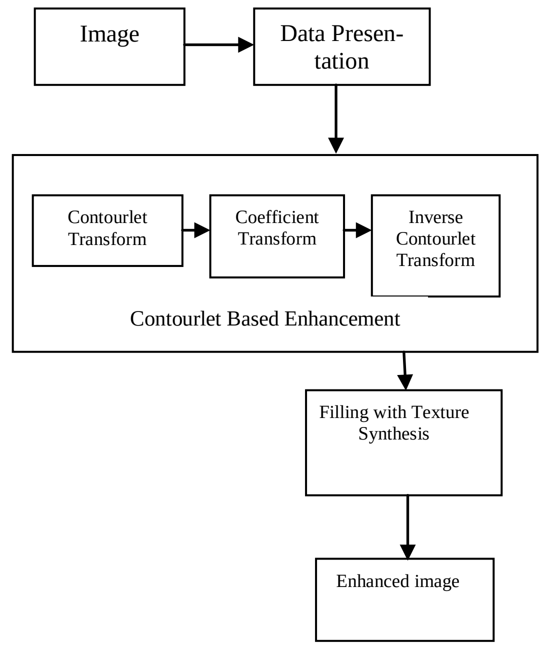

Figure 2: Block Diagram of Proposed Model

Fig 2 shows the Block diagram of proposed model. This section presents our model for digital inpainting in the contourlet method. Most of our test images are taken from a standard image source.

4.1. Data Presentation

With an automatic inpainting model, the only thing that the user must do is to define the inpainting region. This region is specified as a binary mask (inpainting mask), where the positions representing pixels that must be inpainted have value 1, and those that must be preserved have value 0. The information of the input image within the inpainting region is "erased" (all the pixels in such a region are set to zero), and the resulting image is submitted to a contourlet based enhancement. In general, this "erasure" process creates artificial edges on the border of the inpainting region, generating non-zero coefficients in detail wavelet images. The extension of these artificial edges depends on the support of the chosen wavelet basis:

Smaller support wavelets present a more local spread, while larger support wavelets produce a wider spread of edge information. To minimize this undesired spreading of artificial edges, we choose the Haar basis because of its very small support (only two pixels). The decomposition is made in 1 level only, providing us with an image with approximately half of the original resolution. Thus, the area of the inpainting region is reduced,

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and less iteration steps are needed. Once the image is to be in contourlet, set the coefficient values. The next step is contourlet based enhancement.

4.2. Contourlet Based Enhancement

The contourlet based enhancement is used to reconstruct the enhanced image from the modified contourlet coefficient is as follows

4.2.1. Contourlet Transform and Counter Coefficient

Fig 3(a) shows the flow graph of contourlet transform. It consists of two steps: the subbands decomposition and the directional transform. A Laplacian pyramid (LP) is first used to capture point discontinuities, then followed by a Directional Filter Bank (DFB) to link point discontinuity into linear structure. The overall result is an image expansion using basic elements like contour segments, and is thus named the Contourlet. Fig. 3(b) shows an example of the frequency decomposition achieved by the DFB. It depicts the Contourlet coefficients of one retinal image using three LP levels and eight directions at the finest level. Quincunx filter banks are the building blocks of the DFB.

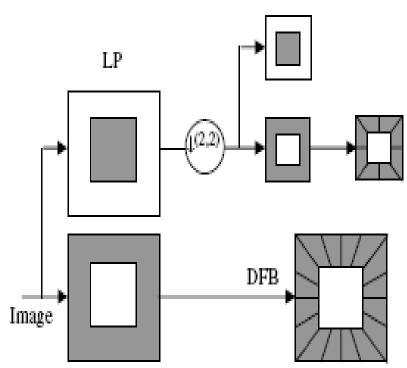

Figure 3(a): A Flow Graph of Contourlet Transforms

In Fig 3(a) it shows a flow graph of contourlet transform. The Image is first decomposed into subbands through Laplacian Pyramid and then each band pass detail image is analyzed by the directional filter banks.

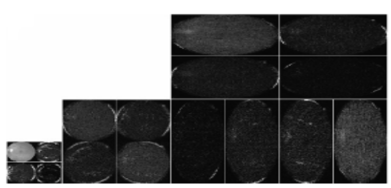

Figure 3(b): Examples of Contourlet Transform.

In Fig 3(b) Examples of the Contourlet transform of a image. For clear visualization, it is only decomposed into three pyramidal levels, which are the decomposed into four and eight directional subbands. Small coefficients are shown in black while large coefficients are shown in white.

4.3. Algorithm with Contour Based Enhancement

Contourlet transform is well-adapted to represent images containing edges it is a good candidate for microstructure enhancement in images as well as edge enhancement in natural images. Contourlet coefficients can be modified via a nonlinear function yα. Taking noise into consideration, we introduce explicitly a noise standard deviation σ in the equation

$$y_\alpha(x,\sigma) = 1 \; if \; x < \alpha\sigma$$

$$y_\alpha(x,\sigma) = \frac{x-\alpha\sigma}{\alpha\sigma} \cdot \left(\frac{t}{\alpha\sigma}\right)^q + \frac{2\alpha\sigma - x}{\alpha-\sigma} \text{ if } \sigma \le x < 2\alpha\sigma$$

$$y_{\alpha(x,\alpha)} = \left(\frac{t}{x}\right)^q \quad \text{if } 2\,\sigma\alpha \le x < t$$

$$y_{\alpha(x,\sigma)} = \left(\frac{t}{x}\right)^s \quad \text{if } x \ge t \qquad (1)$$

Here, t determines the degree of nonlinearity and s introduces a dynamic range compression. Using a nonzero s will enhance the faintest edges and soften the strongest edges. α is a normalization parameter. The t parameter is the value under which coefficients are amplified. This value depends obviously on the pixel values. We can derive the t value from the data. Two options are possible:

t = Ftσ, where σ is standard noise deviation and Ft is an additional parameter which is independent of the Contourlet coefficient values, and therefore much easier for a user to set. For instance, using α = 3 and Ft = 10 amplifies all coefficients between 3 and 30.

t = lMα, with l < 1, where Mα is the maximum Contourlet coefficient of the relative band. In this case, choosing for instance α= 3 and l = 0.5, we amplify all coefficients with an absolute value between 3σ and half the maximum absolute value of the band.

The first choice allows the user to describe the coefficients to be amplified as a function of their signal to noise ratio, while the second one gives an easy and general way to fix t independently of the range of the pixel values.

4.4. Filling with Texture Synthesis

As the filling process takes place, the data that is copied into the inpainting region becomes less

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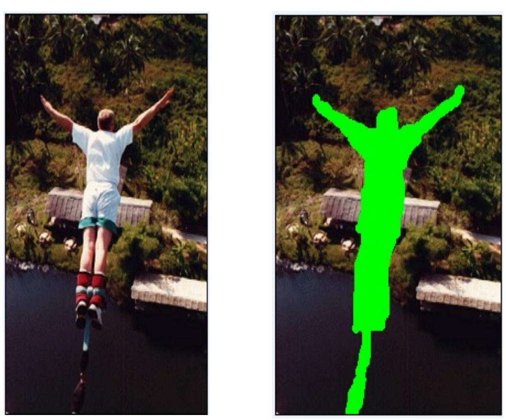
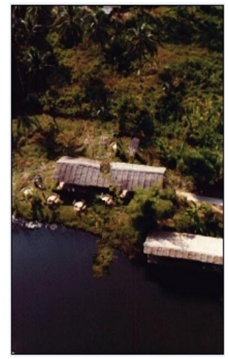
trustworthy than the original data, and the priority determination must be adjusted by inserting a confidence term. First the centre of the block is filled then another block is selected to complete. Such a block is selected for reducing the error between the coefficients. The blocks to be filled are fixed for the same texture (such a size is selected based on the scale of the texture pattern).

5. EXPERIMENTAL RESULTS

The experimental result is obtained using the proposed system, as well as the other methods for image combination of Laplacian Pyramid (LP) with a Directional Filter Bank (DFB). First the original image is taken then the target region in the original image is blanked out, finally the blanked out image is filled using algorithm. In order to better appreciate the results obtained with our proposed algorithm used many approaches for our contrast enhancement experiments. Reconstructing the enhanced image from the modified contourlet coefficients. Noise must be taken into consideration and not be amplified in enhancing edges. It is very advantageous there is no block effect at final stage. The method that performs well as compared with previous techniques designed for the restoration of small scratches. At instances in proposed method larger objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency.



(a)Original Imag (b)The Target Region has been Blanked Out



(c)Filled Image

Figure 5: The Resultant Image of ContourletTransform

Table 1 Comparision Of Various Inpainting Methods

Inpainting methods	MSE Values		
	10~pixels	20~pixels	40~pixels
Bertalmio Method	2601.75	4044.31	5913.22
Criminisi Method	1973.71	2967.99	4722.87
Our method	1751.24	2357.88	3089.27

6. CONCLUSION

Contourlet possess the most important properties of directionally and anisotropy which wavelet do not possess, so contourlet performs well is image inpainting. The Contourlet enhancement functions also take an account of image noise. As in wavelet transform there is an estimation problem with does not take care about continuity of the structure. As evidenced by the experiments with the Contourlet transform, there is better preservation of contours than with other methods. The Contourlet can detect the contours and edges quite adequately. With the exemplar-based texture synthesis, the proposed image restoration method can restore some structure features and composite textures both for large and thick or long and thin blackened regions without blurring. Careful research about the relationship between image statistical properties and the parameters of enhancement function should be applied in the future and then plan to work on methods to restore complex structures like corner, curve etc.

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