

Contourlet Based Lossy Image Coder with Edge Preserving

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Abstract: - In this paper we present a lossy image coder based in multiscale and directional contourlet transform which allows edge preserving in decompressed images. The preserving task is made by capture the edge points of an image using a robust and efficient edge detector known as Smallest Univalued Segment Assimilating Nucleus (SUSAN). The resulting edges coordinates are used as a priori knowledge of the positions of points which are mapped to the correspondent position in the transformed domain by exploit the contourlet parent-child relationship. The contourlet points are coded and finally the image is decompressed to measure the quality. The use of contourlet transform allows us to take advantage of the directional and multiscale representation of edges which is showed in the good edge preserving results obtained.

Key-Words: - Image compression, edge preserving, transform domain, contourlet, parent-child relation.

1 Introduction

Data compression plays an important role in technology because a lot of the information generated and used by human beings (e. g. images and video) is in digital format. The number of bytes required to represent multimedia data is big considering storage space and bandwidth for transmission. A way to handle this big amount of data is compression. The goal of data compression is to reduce the volume of necessary data to represent a certain quantity of information [1]. For the case of images, compression can be carried out with or without loss of information. In lossless methods the decompressed data are an exact copy of the originals, whereas in lossy methods, the decompressed data are an approximation of the originals, this paper are focused in this last type.

The Discrete Wavelet Transform (DWT) has been used to build a lot of efficient lossy image coders [2], [3], and is proved as a powerful tool for different tasks including signal analysis and image denoising. The DWT have the problem that can not adapt well to two directional information and dimensional singularities found in images such as lines or curves, which are very important features for early human image recognition [4]. A proposed solution to wavelet problem is to design multiscale and directional representation of images in order to capture the intrinsic image geometrical structures such as smooth contours.

By the other hand, it is well known that much information that offers images to humans is represented by features such as edges that contain high frequency energy. In digital image processing feature extraction is a key stage for the success of

subsequent stages such as object recognition. There are different industries (medical, textile, etc.) in which image compression preserving useful features of images are imperative [5], [6]. For these reasons it is important design lossy image coders that offers the advantage of saving storage space and additionally a way to save or to handle the important information for future tasks such as pattern recognition.

In this paper we show the methodology design to build a lossy image coder using as a base the contourlet transform allowing edge preserving. In section two, we present the model for the lossy coder, section three shows test and results obtained, finally, section four presents the conclusions.

2 Methodology

The main goal of the methodology proposed is to build an image coder with edge preserving using the contourlet transform. The stages of model shown in figure 1 are: a) Image selection and Edge detection, b) Contourlet transform, c) Selection of important coefficients (edges), d) Image compression with edge preserving, and e) Image decompression.

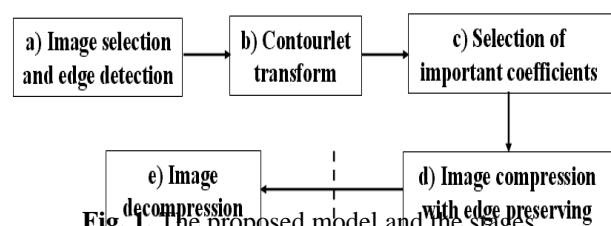


Fig. 1. The proposed model and the stages.

2.1 Image Selection and Edge Detection

At the first stage, we need to select the images to compress, for this purpose in figure 2 we shows six 256 x 256 images with different high frequency information (edges) used for this paper: *camman*, *apple*, *clown*, *lena*, *magnetic resonance*, and *f14*.

After image data base selection we apply a digital image processing task in order to find the image features, for this paper edges. Canny is one of the most algorithms used for edge detection, but it is known that Canny have some problems such as: corners are rounded, poor edge localization and connectivity, etc [7]. To avoid this problems, instead of Canny, we use an edge detector known as Smallest Univalued Segment Assimilating Nucleus (SUSAN) which is a more robust and effective method than Canny in the sense that it provides much better edge localization and connectivity.

SUSAN use a predetermined window centred on each pixel in the image, applying a locally acting set of rules to give an edge response. This response is then processed to give as output a set of edges. In summary SUSAN performs the following three steps at each image pixel to obtain the edge map [8]:

1. Place a circular mask (sometimes known as windows or kernels) around the pixel in question (the nucleus circle in figure 3). The radius of the mask is defined by the user, for this work we use a 37 pixels mask (see figure3).

0	0	1	1	1	0	0
0	1	1	1	1	1	0
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	1	1	1	1	1	0
0	0	1	1	1	0	0

Fig. 3. SUSAN circular mask and it nucleus.

2. Calculate the number of pixels within the circular mask which have similar brightness to the nucleus, these is made with equation 1.

$$c(\vec{r}, \vec{r}_0) = e^{-\left(\frac{I(\vec{r}) - I(\vec{r}_0)}{t}\right)^6} \tag{1}$$

Where \vec{r}_0 is the position of the nucleus in a 2D image, \vec{r} is the position of any other point within the mask, $I(\vec{r})$ is the brightness of any pixel, t is defined by user and determines the maximum contrast of features which will be detected and also the minimum amount of noise which will be ignored, and c is the output of the comparison. This comparison is done for each pixel within the mask,

and running total n times of the outputs (c) is made.

3. Subtract the USAN size from the geometric threshold to produce an edge strength image as it is shown in equation 2.

$$R(\vec{r}_0) = \begin{cases} g - n(\vec{r}_0) & \text{if } n(\vec{r}_0) < g \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Where g is the geometric threshold which is set to $3n_{\max} / 4$, where $n_{\max} = 37$, is the maximum value which n can take. $R(\vec{r}_0)$ is the initial edge response.

We do not consider the final two steps proposed at the original SUSAN algorithm because we only need and edge map and not edge directions and thinning. Figure 4 shows the six edge map images obtained with SUSAN. As a result of edge detection we obtain an edge map (points), the details of the number of points obtained for each image and the thresholds used are shown in table 1.

Table 1. Points and thresholds for the edge maps.

Image	Edge points	Threshold
Camman	2725	90
Apple	5744	9
Clown	4205	70
Lena	4234	60
MR	4766	60
F14	1568	80

2.2 Contourlet Transform

The contourlet transform has been introduced by Do and Vetterli in 2002, allows a multiscale and directional decomposition of an image using a combination of a modified laplacian pyramid and a Directional Filter Bank (DFB), the Discrete Contourlet Transform is also called as Pyramidal Directional Filter Bank (PDFB) [9].

Contourlets not only posses the main features of wavelets, but also offers a high degree of directionality and anisotropy.

The PDFB allows for different number of directions at each scale/resolution to nearly achieve critical sampling. The DFB is designed to capture high frequency components (representing directionality), the laplacian pyramid allows subband decomposition to avoid leaking of low frequencies into several directional subbands, and thus directional information can be captured efficiently [10]. In resume the process to compute the contourlet transform is:

1. Determine the number of pyramidal and directional decompositions, for the images of this paper we use two pyramidal decompositions with four and eight directions respectively.

2. Select and design the filters to compute the decompositions, in this work the ladder filters known as PKVA [11] were used for both pyramidal and directional decompositions, but any other wavelet filter such as Haar can be used.

3. Compute the pyramidal decomposition of an image, as a result two images were obtained, one is the result of a low band approximation (half resolution of the original) and a band pass image (details of the image) which have a resolution equals to the size of the original image.

4. Directional decomposition. For this stage we use the band pass image, the process is made by means of a two dimensional filter bank that decomposes an image into any arbitrary power of twos number of directions. Then quincunx polyphase decomposition is made, as a result we obtain two subband images which are used for posterior directional decompositions until we reach the final decomposition number correspond to the pyramid (scale) analyzed.

5. Steps 3 and 4 are repeated until the number of pyramidal and directional decompositions is reach. The multiscale and directional decomposition advantage offered by contourlet is used in order to obtain good edge image representation. In order to design the edge preserving coder we follow the next steps:

1. Compute the pyramidal and directional subbands (as we explain above) using the original images (figure 2) and the images obtained from edge detection (figure 4).

2. Copy the information resulting from the lowband of the original images to the lowband information obtained in pyramidal and directional subbands with edge images, with this we obtain the final contourlet decomposition as it is shown in figure 5.

The upper band images of figure 5 (larger rectangles finer subbands) are the results of a pyramidal decomposition and eight DFB decomposition, each vertical subband have a size of 128 x 64, and each horizontal subband have a size of 64 x 128.

The middle band images represent a pyramidal decomposition and four DFB each with a size of 64 x 64.

The lower band image is the low band pass and has a size of 64 x 64.

The sum of all coefficients obtained by the contourlet transform is: $(128 \times 64 \times 4) + (64 \times 64 \times 4) + (128 \times 128 \times 4) + (64 \times 64) = 32768 + 32768 + 16384 + 4096 = 86016$ coefficients, that represent an expansion of almost a third part of the coefficients of the original images (65536), this is because contourlet is a redundant (expansive) transform.

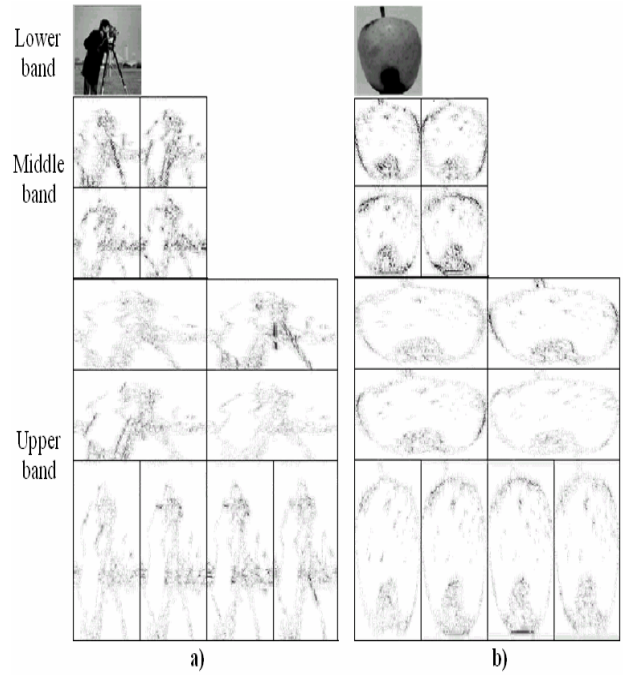


Fig. 5. Contourlet transform. a) *Camman* image with two pyramidal decompositions and four and eight directions respectively, b) *Apple* image with the same decomposition of a.

2.3 Selection of Important Coefficients

As we explain in section 2.2 after the contourlet transform we obtain redundant information of the original image, in order to avoid redundancy we select only those coefficients pertaining to coordinates obtained in the edge map (section 2.1), for this, we need to find the same edges but now in the contourlet domain.

In order to select only those coefficients that represent edges in contourlet transform we need to map the positions of the edges (coordinates) of the original domain to the contourlet domain. Similar to the wavelet domain in which we have a parent-child relationship we find that relationship in the contourlet domain. We use the scheme proposed by Do [10] which is shown in figure 6. Remember, contourlet coefficients can have their four children in two separate directional subbands.

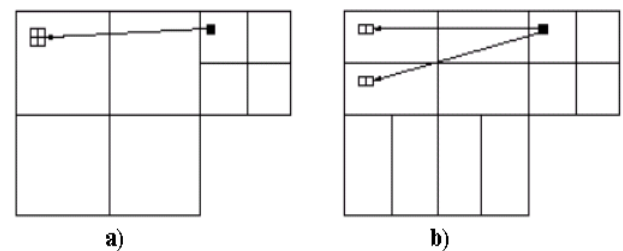


Fig. 6. Contourlet parent-child relation. a) Childs at the same subband, b) Children spread over two subbands [10].

In table 2 we present the number of points selected in each contourlet subband for each image used (black dots showed in figure 5) and the total points obtained to compute the compression factor. Observe that for lower subband the points selected are the entire subband and not only the edge points, it is necessary in order to obtain good image reconstruction.

Table 2. Edge points selected in each image subband.

Image	Upper band	Middle band	Lower band	Total points
Camman	2725	1362	4096	8183
Apple	5744	2872	4096	12712
Clown	4205	1932	4096	10233
Lena	4234	2117	4096	10447
MR	4766	2383	4096	11245
F14	1568	784	4096	6448

2.4 Image Compression with Edge Preserving

After the selection of important information the image compression stage is made using the points selected in section 2.3. The selection process can be viewed as a quantization stage in which the coefficients that not pertain to edge points in the middle and upper subbands are ignored or zeroed. The stored file contains information about the size of the original image, the level decomposition used (pyramidal and directional) and the coefficients selected. Then the size of a compressed image is determined as the sum of all coefficients selected plus two bytes that represent image size, plus one byte to represent decomposition level, plus one byte to store information of the filter used. For example the original images have 65536 bytes, and the apple compressed size is: 12708 + 2 + 1 + 1 = 12712 bytes. The compression factor obtained for each image is presented in the first column of table 3. It is important to remark that the purpose of this research work is to show the methodology for edge preserving image compression with contourlets and not to improve the compression factor which can be made with and additional stage of entropy coding.

2.5 Image Decompression

After image compression the decompression stage is made, it is the inverse process of the compression. Here we obtain the size of the image, the decomposition level, the filters used and the contourlet coefficients and then we compute the inverse contourlet transform with respective pyramidal and directional levels. In figure 7, we show the six decompressed images.

From the decompressed images, differences in the textures are observed but the edges looks good. In order to give a measure of the image errors several measures were computed and presented in section 3.

3 Results and Discussion

When a lossy image compression coder is made, it is important to measure two important factors: a) the compression factor (*CF*) that is a measure obtained dividing the size of the original image by the size of the compressed domain and, b) the difference between the original image (*I*) and the decompressed image (*I'*) in order to determine the quality of the reconstructed image. For the quality we use four measures: Mean Square Error (*MSE* eq. 3), Peak Signal to Noise Ratio (*PSNR* eq. 4) and the norm2 (*N₂*) and Frobenius norm (*F*) in equation 5.

$$MSE = \frac{1}{MN} \sum_{y=1}^M \sum_{x=1}^N [I(x, y) - I'(x, y)]^2 \tag{3}$$

$$PSNR = 10 * \log_{10}(255 / \text{sqrt}(MSE)) \tag{4}$$

$$N_2, F = \frac{\|I - I'\|_{2,F}}{\|I\|_{2,F}} \tag{5}$$

Table 3 shows the error measures obtained for the decompressed images, the columns information are: the name of the image, the *CF*, the *MSE*, the *PSNR*, *F* and *N₂*.

Table 3. Decompressed images error measures.

Image	CF	MSE	PSNR	F	N2
Camman	8:1	321.344379	23.061097	0.133946	0.042001
Apple	5.15:1	242.835908	24.277675	0.124477	0.043120
Clown	6.6:1	547.284031	20.748676	0.171962	0.046187
Lena	6.27:1	432.588129	21.770058	0.185507	0.043058
MR	5.9:1	334.878596	22.881930	0.207408	0.046898
F14	10.1:1	322.744238	23.042219	0.079317	0.030800

With the errors measures showed in table 3 we can give several comments: first, remember that the first goal of this work is the edge preserving lossy image compression and not to improve the compression rate obtained, Second, the compression factor of this tests were determined by the edge points obtained in the selection process, this factor can be defined by a bit rate that users need and adding a phase using SPITH or EZW. Third the most important thing in this

method is the edge preserving image compression, only focus on the detailed features is need and this improvement is attributed to the edge management in contourlet transform so that the objective error measures can be bad but the edge preserving is good. Fourth, even with the comment that error measures can not show the goodness of the compressor, that measures are so close to other algorithms at the same compression rate. Fifth, the methodology can be improved by finding a way to compute the best contourlet subband decomposition and improving the stage of detection and mapping the important information. Finally, in order to observe the good edge reconstruction in figure 8 we show a zoom of the decompressed images for *apple* of a section in the upper left and for *camman* a section of the middle left (arm). Observe that for example, the textures present artifacts (because we spent few bits in textures) but the edges are well preserved and sometimes enhanced.

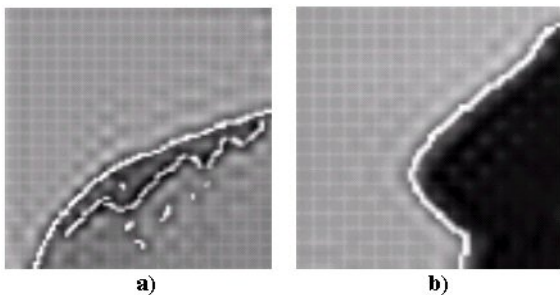


Fig. 8. Decompressed images zoom. a) *Apple* image zoom of the upper left, b) *Camman* zoom of the arm.

4 Conclusions and Further works

In this paper we have introduced the contourlet transform as a tool to model the image edges with multiscale and directional analysis. The contourlet transform is used as a base to build a lossy image compression coder that allows edge information preserving. The edge map was obtained with a robust algorithm known as Smallest Univalent Segment Assimilating Nucleus (SUSAN) which performs better than Canny. After edge detection a process of mapping (quantization) is made in order to detect the edge points in transformed domain and those points are preserved in image coding. Contourlet transform allows multidirectional representation of edges and permits solving the problem of classical wavelet in which is difficult to find two-dimensional singularities. From results shown, we can conclude that the importance of this method is not in the measure of the original and reconstructed image error, but in the good reconstruction of the edges.

As a future work we propose to design a method to compute the optimal pyramidal and directional decomposition to compress an image and test the system using another multidirectional and multiscale transform for example the bandelets, edgelets, etc. Another work can be to find an automatic unsupervised method embedded in the compression coder to obtain the important information to preserve in order to obtain success in pattern recognition tasks.

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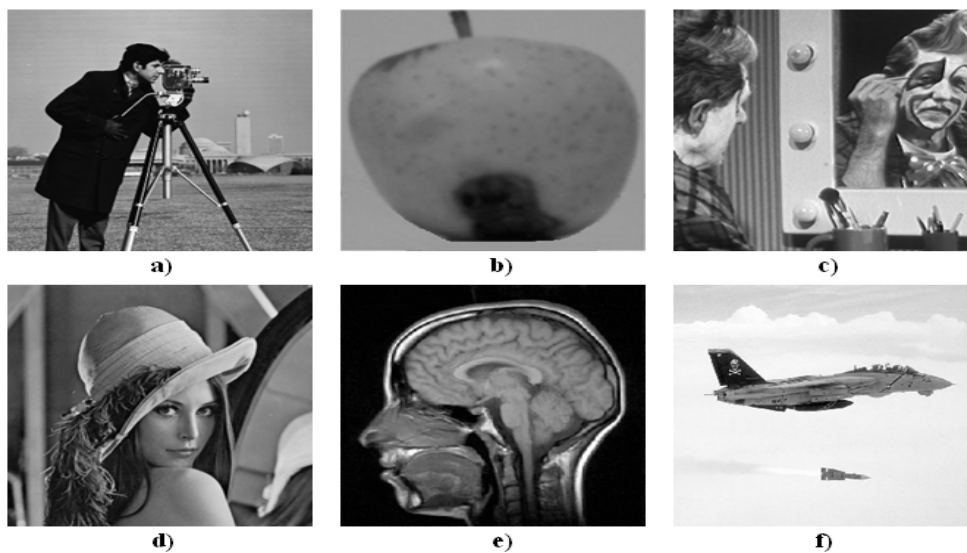


Fig. 2. Image data base. a) Camman, b) Apple, c) Clown, d) Lena, e) Magnetic resonance (MR) and f) F14.

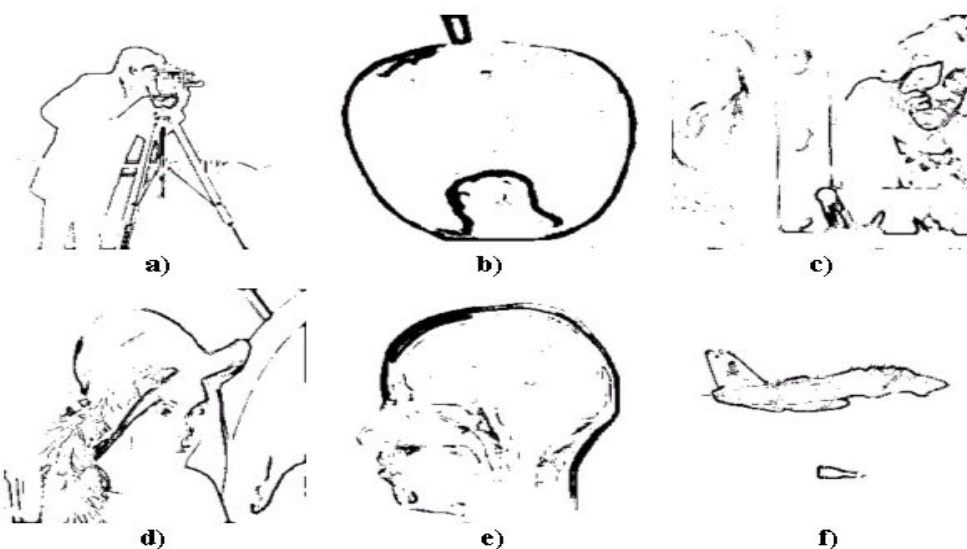


Fig. 4. Edge maps. a) Camman, b) Apple, c) Clown, d) Lena, e) MR and f) F14.

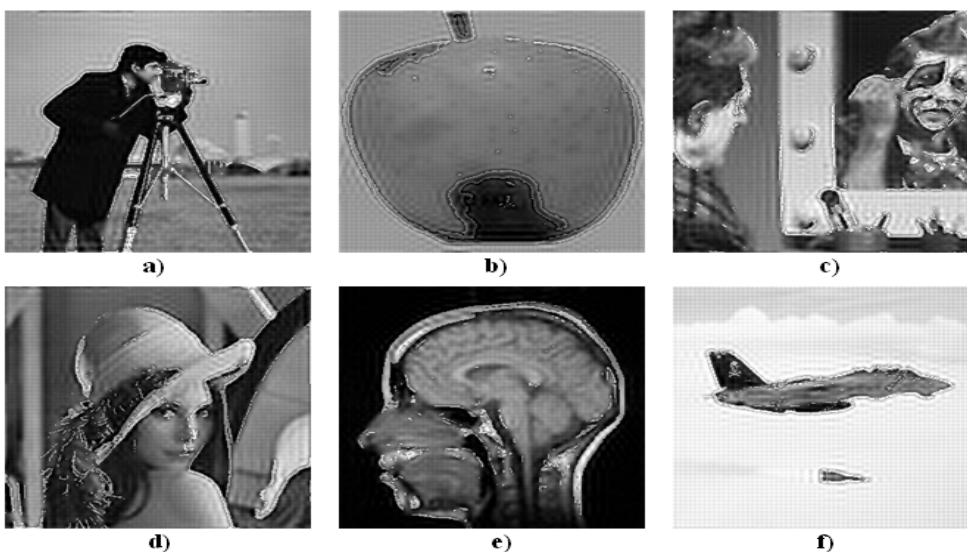


Fig. 7. Decompressed images. a) Camman, b) Apple, c) Clown, d) Lena, e) MR and f) F14.