Slantlet Transform and Phase Congruency based Image Compression

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ABSTRACT
Image compression is an active area of research with a wide range of applications. Being able to represent an image with lesser number of coefficients, without affecting the image quality has been the prime aim of image compression. In this research, a new image compression technique has been proposed, based on Slantlet Transform and the principle of Phase Congruency. The compressed image quality has been assessed by computing the PSNR values and the compression ratios. Experimentation show highly promising results, in terms of the level of compression and the quality of the fused image.

General Terms
Image Processing, Image Compression.

Keywords
Image Compression, Slantlet Transform, Compression Ratio, Phase Congruency, Peak Signal to Noise Ratio

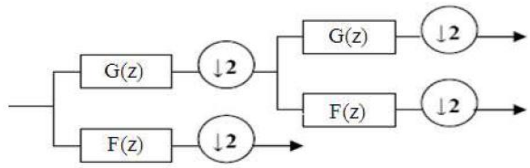
1. INTRODUCTION
Compressing images in the frequency domain has been proven to give better results, than trying to compress the image in the spatial domain [1]. The non-local property of Fourier basis [2] resulted in them being replaced by wavelet functions, which satisty certain mathematical requirements [3] that made them better suited or data representations. Wavelets were found to be highly efficient in approximating data with sharp discontinuities [4]. The Discrete Wavelet Transform (DWT) is carried out by iterating the filterbanks at each successive decomposition levels. However, for a fixed number of zero moments, it does not give an optimum basis with respect to time localization. The Slantlet transform was thus developed, which is an orthogonal DWT with two zero moments. It provides improved time localization than conventional DWT. Slantlet transform allows the design of filters of shorter length, at the same time satisfying the orthogonality and zero moments condition. Hence, it is a highly efficient tool for image compression [5].

Phase Congruency is a feature operator which is invariant to illumination and scale. It assumes an image to be highly rich in information and very little redundancy. This property makes sure that during compression no major information in the image is treated as redundancy and removed [6].

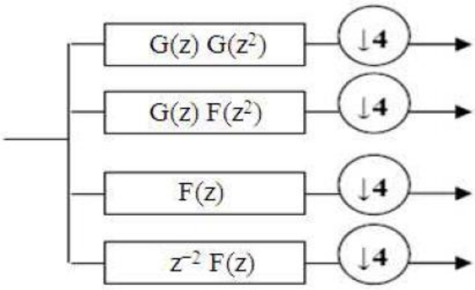
This paper combines Slantlet transform and the concept of Phase Congruency and proposes a new technique for image compression. When the proposed method is applied to the image as a whole, it results in a blocky appearance for the compressed image. This blocking occurs due to the fact that Slantlet transform assumes data to be piece-wise linear. In order to remove this blocking, the compression algorithm is carried out on image blocks of size 8x8. Even though every compression technique aims at maximizing compression, lossy compression techniques [7] also results in loss of information in the image. Hence, a trade-off must be obtained between the compression ratio and the quality of the compressed image. A good compression algorithm should aim to obtain a fairly good trade-off between the two. The compression ratio and the compressed image quality [8] are also dependent on the type of the input image. Experimental results show that the proposed method achieves very good levels of compression and at the same time does not compromise much on image quality, as the information loss is kept to the bare minimum.

2. SLANTLET TRANSFORM
Discrete Wavelet Transform (DWT) makes a tradeoff between the time-localization and smoothness properties of the basis functions, when it tries to achieve sparse representation of piecewise smooth signals. Even though iteration of the DWT filter bank gives us orthogonal basis with octave-band charateristics, for a fixed number of zero moments, the basis is not optimal with respect to time-localization.

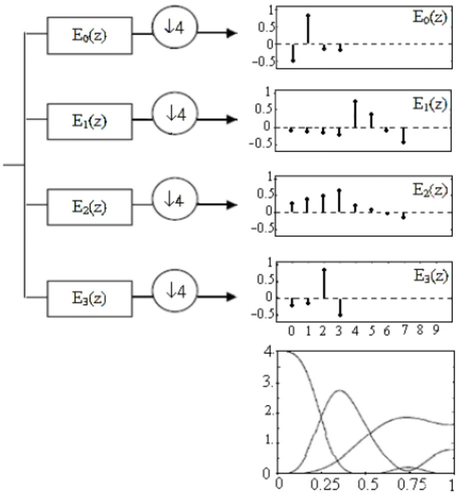
2.1 Slantlet Filterbank
The slantlet filterbank is an orthogonal filter bank for DWT, where the filters have shorter support than that of the conventional iterative filterbank tree. It retains the octave-band characteristic of the conventional DWT filterbank. Slantlet transform makes use of a special class of bases, which is constructed using Gram-Schmidt orthogonalization procedure [9]. Figure 1 and 2 shows the two-scale iterated DWT filterbank and its equivalent form respectively.



a)



b)



c)

Fig 1: a) Two-scale iterated filter bank b) Equivalent structure of the Two-scale iterated filterbank c) Two-scale filterbank structure using Slantlet

The slantlet filterbank is obtained from the equivalent form, where the filters are replaced and are no longer in product form. Giving up the product form gives extra degrees of freedom, which makes it possible to design filters of shorter length, while satisfying orthogonality and zero moment conditions [10]. The filterbank thus obtained are orthogonal, have zero moments and has an octave-band charateristic. Each filterbank has a scale dilation factor of two and provides a multi-resolution decomposition. The slantlet filters are piece-wise linear. Even though the slantlet filterbank does not have a tree structure, it can be efficiently implemented, so that its computational complexity is same as that of conventional DWT. The filter coefficients used in the slantlet filterbank for our experiments are as derived by Selesnick in [4].

3. PHASE CONGRUENCY

It has been traditionally a practice in image processing to think about features in terms of derivatives. This is because, features in images are mostly thought of as edges, which are points of discontinuities. As a result, gradient based operators are mostly used to detect the features in images. The gradient based feature estimation techniques, such as those developed by Sobel [11], Marr and Hildreth [12] and Canny [13, 14], face two major drawbacks. Firstly, the gradient operators are sensitive to illumination variations. i.e; they cannot be relied on, when working with images of varying lighting and contrast. The second shortcoming of gradient operators is that, localization of features depends on the scale of analysis. Hence, the localization becomes innacurate when analysed at varying scales. This leads to the need of a feature operator that is invariant to illumination and scale.

Phase congruency model of feature detection [6] assumes an image to be high in information and low in redundancy. Thus, instead of searching for points of sharp changes in intensity, this model searches for patterns, where the phase components of the Fourier transform of the image are in order (maximally in-phase). It is a frequency-based model and instead of spatial processing of data, it processes an image using the phase and amplitude components of the individual frequency components.

Consider a 1-D slice through an image. Such a signal *f(x)* can be reconstructed from its Fourier transform by:

$$f(x) = \int_{-\infty}^{\infty} a_{\omega} \cos(T\omega x + \phi_{\omega}) d\omega,$$

where for each frequency ω, a_{ω} is the amplitude of the cosine wave and $T\omega x + \phi_{\omega}$ is the phase offset of that wave. The term '***T***' is related to the size of the image window. The phase congruency model in the discrete form is expressed as:

$$f(x) = \sum_{n=0}^{\infty} \frac{1}{(2n+1)^{p}} [\sin(2n+1)x + \phi],$$

where, ***p*** gives the decay in the amplitude with frequency and ϕ is the phase offset.

Phase Congruency is the ratio of local energy to amplitude. $PC(x) = \frac{|E(x)|}{\sum_{n} A_n(x)}$, where, $A_n(x)$ is the amplitude and $E(x)$ is the local energy and $0 \le PC(x) \le 1$ [10].

4. PROPOSED IMAGE COMPRESSION TECHNIQUE

In [5] the authors have discussed an image compression technique using Slantlet transform. This proposed technique de-correlates the input image information by transforming the image into the frequency domain using Slantlet transform. The proposed algorithm makes use of the concept of phase congruency, to determine the amount of redundant information that needs to be removed from the input image. The threshold provided by the user determines the amount of trade-off obtained between the compression ratio and the visual quality of the compressed image. The algorithm is applied on 8x8 blocks of the input image, in order to remove the blocking appearance, which occurs when the algorithm is applied to the image as a whole. This blocking is due to the fact that, when Slantlet transform is applied to an image, it is done on each column of the image separately. Hence, here the image is not decorrelated as a whole. Each column is separately taken, converted to the transform domain and then the thresholding applied based on the phase congruency map. This leads to vertical blocking appearance in the compressed image. This effect is reduced by applying the algorithm to *mxm* blocks of the input image. The following steps are carried out on each *mxm* block of the input image.

4.1 Decomposition of the input image using Slantlet Transform

Slantlet transform is applied to each column of the input image. The slantlet filter coefficients used in this experimentation is obtained from [4].

Let *I(x,y)* be the input block to be compressed. The slantlet transform of each column of the block is carried out, resulting in a corresponding coefficient block in the transform domain, denoted as $T_I(u,v)$. Let the transform domain coefficients of the transformed block be represented as $C(u,v)_{TI}$.

4.2 Phase Congruency map for the decomposed image

The next step in the proposed compression technique is to create the phase congruency map for the transformed image block, $T_I(u,v)$. Each transform domain coefficient will thus have a phase congruency value corresponding to the position of the coefficient in the transformed image. Let the phase congruency map for the transformed image block be denoted as PC_{TI} and each phase congruency value be represented as $PC(u,v)_{TI}$.

4.3 Removing the redundant CWT coefficients

The phase congruency map acts as the basis for removing the redundant Slantlet coefficients. The compression algorithm chooses only those slantlet coefficients from the transformed image block, which has edge strength greater than a threshold T_{SH}. The edge strength is represented by the normalized phase congruency value from the phase congruency map. The decision rule can be expressed as:

$$\begin{aligned} C^C(u,v)_{TI} &= C(u,v)_{TI}, \quad if \quad PC(u,v)_{TI} > T_{SH} \\ &= 0, \quad\quad\quad\quad if \quad PC(u,v)_{TI} < T_{SH} \end{aligned}$$

where, $C^C(u,v)_{TI}$ are the slantlet coefficients of the compressed image.

4.4 Obtaining the final compressed image block

To get the compressed image block, the inverse slantlet transform of the coefficients thus selected is taken. The final result is expressed as:

$$F_{IC}(x,y) = IST(C^C(u,v)$$

where, $F_{IC}(x,y)$ is the final compressed image block. It can be observed that the number of slantlet coefficients that were used to reconstruct back the compressed image block is much lesser than the actual number of slantlet coefficients that was used to represent the input image block.

When the above steps are carried out on all the *mxm* blocks of the input image, we get the resultant compressed image. Experimental results also prove that this technique helps to achieve a high compression ratio, without trade-off in visual quality of the image.

5. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed slantlet transform and phase congruency based compression technique was applied on a set of grayscale images of size 512 x 512 of various categories such as standard test images, natural images, user created images and medical images. The compression ratio and PSNR values are computed to determine the degree of compression achieved and the amount of information loss respectively. Experimental results pertaining to six images of various categories are discussed here. The block size chosen for experimentation was 8x8, in order to avoid blocking in the compressed image. Figure 2 shows the input images used and Figure 3 shows the output images of the compression technique. It can be observed that the visual quality of the image has not degraded due to this technique.

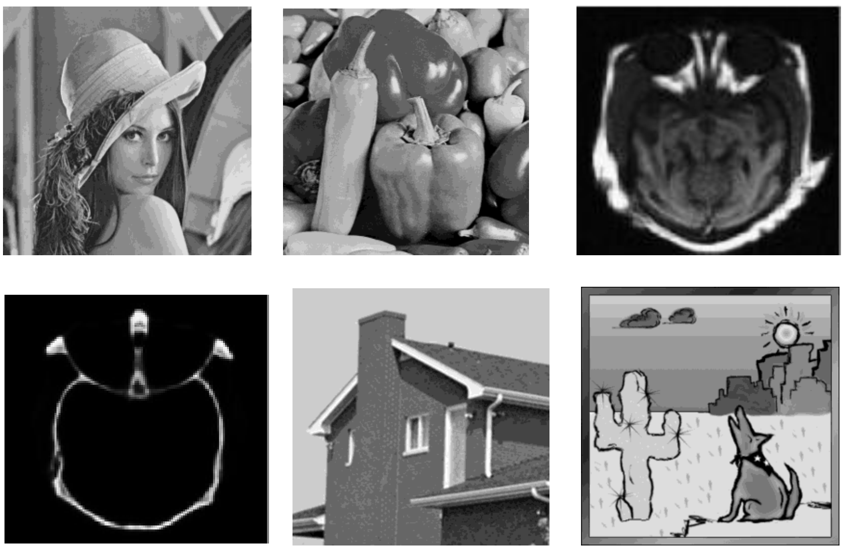


Fig 2: Input Images

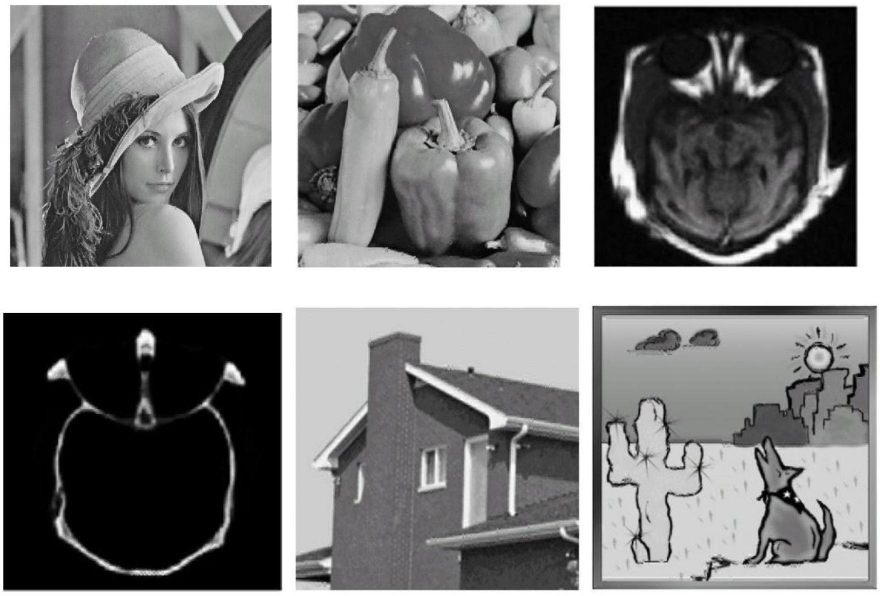


Fig 3: Compressed Images for Threshold value = 0.01

For analyzing the performance of the proposed technique PSNR and Compression ratio have been chosen as the metrics. In each case the number of slantlet coefficients required to represent the image and the number of coefficients required to represent the same image, after the proposed compression technique have been used for analysis. Table 1, 2 and 3 shows the details regarding the number of coefficients in slantlet transform, the resultant coefficients after the proposed compression technique, compression ratio and PSNR, for threshold values 0.01, 0.02 and 0.05 respectively.

Table 1: Metrics for threshold = 0.01

	Lena	Peppers	Natural	User Created	CT	MRI
Slantlet Coeff.	262144	262144	262144	262144	262144	262144
Slantlet + PC Coeff.	124799	117056	132913	122162	83017	164380
Compression Ratio	0.4761	0.4465	0.5070	0.4660	0.3167	0.6271
PSNR	35.4073	32.3783	35.3883	25.8093	36.6704	38.6929

Table 2: Metrics for threshold = 0.02

	Lena	Peppers	Natural	User Created	CT	MRI
Slantlet Coeff.	262144	262144	262144	262144	262144	262144
Slantlet + PC Coeff.	101455	93498	105476	112397	75958	128637
Compression Ratio	0.3870	0.3567	0.4024	0.4288	0.2898	0.4907
PSNR	33.7531	31.0610	33.5880	25.3619	35.8602	35.1202

Table 3: Metrics for threshold = 0.05

	Lena	Peppers	Natural	User Created	CT	MRI
Slantlet Coeff.	262144	262144	262144	262144	262144	262144
Slantlet + PC Coeff.	53113	52206	47108	59414	58942	72815
Compression Ratio	0.2026	0.1992	0.1797	0.2266	0.2248	0.2778
PSNR	30.9935	28.9968	31.0197	24.0074	33.7495	32.0403

From the results thus obtained, graphs are plotted for the percentage of compression and PSNR values.

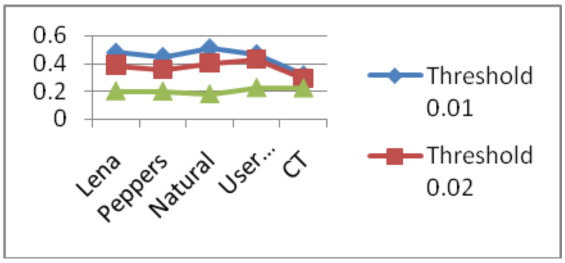


Fig 4: Graph of Compression ratios for various thresholds

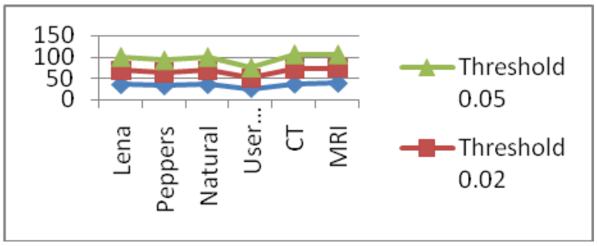


Fig 5: Graph of PSNR values for the images for various thresholds

It can be observed from figures 4 and 5 that as the threshold value for the phase congruency map increases, the degree of compression also increase. However, the visual quality does not change which is also reflected by the PSNR value. In the experiments conducted, three different threshold values have been chosen as 0.01, 0.02 and 0.05. From Figures 4 and 5, it is evident that for a threshold of 0.05, the number of slantlet coefficients required to represent the compressed image is drastically reduced. However, the PSNR values for the same threshold do not have a drastic fall, and it remains very well close to that of thresholds 0.01 and 0.02. Hence this proposed method is superior to most other conventional compression techniques in terms of visual quality and compression ratio.

6. CONCLUSION

This work infers that Slantlet transform replaces conventional DWT with filters having shorter support, thereby removing the iterative behaviour of DWT and introduces different filters for different decomposition levels. It retains the octave-band characteristic of the conventional DWT filterbank. In this paper, a new compression technique based on slantlet transform and phase congruency has been proposed. The phase congruency map generated from the slantlet coefficients of each input image has been used as the decision rule to find out the coefficients that has to be removed for removing the redundancy in the image. Exhaustive experiments conducted on grayscale images exhibit promising results. The experimental analysis of the results thus obtained shows that using the proposed method, a high degree of compression can be achieved.

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