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New Roughness Entropy Fractal Dimension algorithm for denoising side scan sonar image

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ABSTRACT: This paper proposed a fractal-wavelet (FW) denoising method based on applying texture analysis technique to the fractal matching process. Roughness is a property to describe the structural texture. This paper applies the roughness entropy fractal dimension (REFD) algorithm to FW coding process, as the REFD FW algorithm. In this algorithm finding of each range subtree for the optimal matched domain subtree is done to minimize the differential of texture similarity measurements. These kinds of measurements would well capture the texture similarity. The REFD FW algorithm denoises a side-scan sonar image in such a way that the parts of noise-free image have to be approximated as well as possible whereas the noisy parts are rejected. The best possible minimal distance between the two REFD values of domain-range subtrees is used to determine which the best approximation is. The minimal similarity distance quantifies the degree of texture similarity between domain-range subtrees. The REFD FW algorithm have been applied to two side-scan sonar images, one is the wreck of M.V. Sea Angel which is taken by the Polaris, and the wreck of a sailing schooner from MSTL, in different configurations to investigate the corresponding quality of the images using two error criteria: mean square error (MSE) and the peak signal to noise ratio (PSNR). The experimental results indicate that the REFD is appropriate as the criteria of determining range domain matching in FW coder to well approximate the images. It is concluded that the REFD FW algorithm is adaptable in denoising side-scan sonar image and that the images are clearer visually.

KEYWORDS: acoustic noise, denoising, fractal, fractal-wavelet denoising, self-similarity, side-scan sonar image denoising, wavelet.

I.INTRODUCTION

Side-scan sonar has become an important tool for examining the ocean bottom in ocean geographic studies, inspecting objects on the sea bottom, and investigating hazard. Since there are large amount of acoustic noise everywhere in the underwater environment, sonar signal is easily polluted by the underwater noises and interfered from itself during the collection. The acoustic noise makes the sonar image deviate from the true situation, and degrades the accuracy of information extracted from sonar images. To eliminate or reduce noises from sonar images before using the images is very important and meaningful. Until

now denoising or noise reduction of sonar image is an old but also still a most commonly discussed topic in the literature.
The wavelet technique is one of the most powerful tools for noises reduction .The wavelet transform decomposes images into multi-resolution and multi frequency. The nature of inherently noisy sonar images suggests wavelet-based compression as an appropriate choice for denoising sonar image. Recently, the ability of fractal image coding to denoise image other than compression has been investigated. The idea of using the fractal image coding to denoise an image relies on the fact that the noise is not self-similar and would be eliminated during the fractal transformation. Fractal-wavelet (FW) schemes are inspired by applying the fractal image coding technique in the wavelet domain during the wavelet transformation.

Image denoising techniques are designed to suppress the noise while keeping as much as possible the important image features, such as the textures. A denoising method that is capable of reducing the noise and retaining texture information of an image is an essential part for many sonar applications. Side-scan signals collected from the seabed are primarily the reflections from many elements of the seabed and represent the texture the roughness information of the seabed. Inspired by the fractal model has been successfully applied to measure texture quantitatively and the roughness is one of the perceived properties to qualify image texture, the authors proposed a novel FD approach in their prepared paper to measure image roughness, namely, roughness entropy FD (REFD) algorithm. The REFD value describes the distribution of image roughnesses so that the feasible FD represented the texture features can be extracted from images. This paper proposes a novel texture-based coding algorithm based on the REFD, namely REFD FW algorithm, for denoising sonar image. The design of the new FW coding method used REFD algorithm to find a texture similar collage to approximate the original image is motivated by the observation that FD is an expression of the image in surface stability, and the texture information of image can be described by using REFD.

The REFD FW algorithm finds the smallest differential between the two REFD values of subtrees in higher and lower frequency subbands. The encoding is taken under an affine transformation defined by Jacquin's notation. The position of the best matched domain subtree and the affine transformation are stored in code book; and consequently the decoding of image is the reverse of encoding process according to the code book and results the denoised image. The REFD FW algorithm relies on the texture similarity so that the kernel algorithm works well in preserving the image texture information of the image after denoising.

II. LITERATURE

Noise reduction for underwater acoustic signals has attracted considerable attention over the last few decades. Among the numerous techniques, wavelet soft-thresholding (STH) has been considered as one of the most effective noise reduction approaches, as it achieves near complete success in minimizing the mean-squared-error (MSE) and eliminating oscillations caused by noise. However, a limitation with STH is its preference towards lower frequency bands, which may cause distortions in the high frequency bands. Few previous research efforts have reported on the reduction of such frequency distortions. By introducing the time-scale filters (TSF), a novel technique for underwater noise reduction that improves the standard STH in reducing distortions in the joint time-frequency (TF) space is presented. TSF is an advanced noise reduction algorithm which utilizes the signal's time-scale (TS) support region. It provides smooth reconstructions in both time and frequency spaces. The noise reduction results for two typical underwater noise sources: the snapping shrimp sound and the rainfall sound is demonstrated. A TF distortion measurement as a criterion that compares the TF distributions of the denoised signal and the clean signal is introduced. For a signal-to-noise ratio (SNR) from 10 to 20 dB, the noise reduction results obtained using TSF have an average of 42.1% lower TF distortion than STH for the snapping shrimp noise, and a 23.3% lower TF distortion for the rainfall noise [15].

Fractal techniques for image compression have recently attracted a great deal of attention. A technique for image compression that is based on a very simple type of iterative fractal is implemented in [3]. An algorithm based on wavelet transform (quadrature mirror filter pyramid) is used to decompose an image into bands containing information from different scales (spatial frequencies) and orientations. The conditional probabilities between these different scale bands are then determined, and used as the basis for a predictive coder. The wavelet transform's various scale and orientation bands have a great deal of redundant, self-similar structure. This redundant structure is, however, in the form of multi-modal conditional probabilities, so that linear predictors perform poorly. The algorithm uses a simple histogram method to determine the multi modal conditional probabilities between scales. The resulting predictive coder is easily integrated into existing sub band coding schemes. Comparison of this fractal based scheme with the standard wavelet vector coder on **256 x 256** grey-level imagery shows up to a two-fold gain in coding efficiency with no loss in image quality, and up to a four-fold gain with small loss in image quality. Coding and decoding are implemented by small table lookups, making real-time application feasible [3].

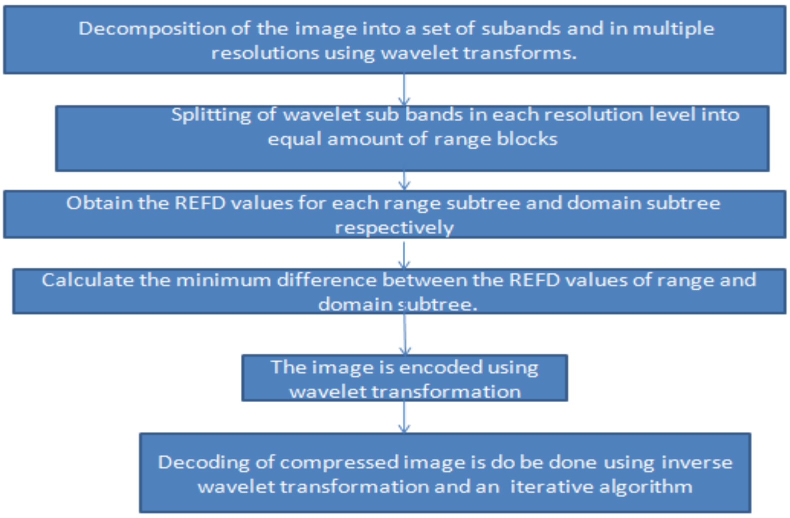
Fractal coding is a new method of image compression; however, the baseline fractal image coding is time consuming due to the best matching search between range blocks and numerous domain blocks. In order to improve the encoding speed, a fast fractal coding algorithm was proposed based on image dividing. An image was first divided into small regions before encoding and then each region was encoded quickly because of which the time of matching search has been reduced in a small image region. Such algorithm is also convenient for programming. Experiments on fractal compressing of standard images show that the proposed algorithm reduced the encoding time greatly while the quality of decoding image was reduced slightly. In comparison with the baseline fractal algorithm, this proposed algorithm can speed up the encoding process by about 1300 times [8].

A new wavelet-based framework for analysing block based fractal compression schemes was introduced. Within this framework it is possible to draw upon insights from the well-established transform coder paradigm in order to address the issue of why fractal block coders work. Fractal block coders introduced by Jacquin and Haar wavelet subtree quantization schemes are shown in [13]. A generalization of the schemes to smooth wavelets with additional vanishing moments is examined. The performance of the generalized coder is comparable to the best results in the literature for a Jacquin-style coding scheme. The wavelet framework gives new insight into the convergence properties of fractal block coders, and it leads to develop an unconditionally convergent scheme with a fast decoding algorithm. The experiments with this new algorithm indicate that fractal coders derive much of their effectiveness from their ability to efficiently represent wavelet zero trees. Finally, the framework reveals some of the fundamental limitations of current fractal compression schemes [12].

In paper [11] the two implementations of fractal (Pure-fractal and Wavelet fractal image compression algorithms) which have been applied on the images in order to investigate the compression ratio and corresponding quality of the images using peak signal to noise ratio (PSNR) is shown. The threshold value for reducing the redundancy of domain blocks and range blocks, and then to search and match is setted in paper [11]. By this, one can largely reduce the computing time. In this paper it is tried to achieve the best threshold value at which one can achieve optimum encoding time.

III. METHODOLOGY

1) Decomposition of the image into a set of subands and in multiple resolutions using wavelet transforms.
2) Split wavelet sub bands in each resolution level into equal amount of range blocks
3) Obtain the REFD values for each range subtree and domain subtree respectively.
4) Calculate the minimum difference between the REFD values of range and domain subtree.
5) Now the image is encoded using wavelet transformation
6) Decoding of compressed image is to be done using inverse wavelet transformation and an iterative algorithm.



Flow chart

IV. WAVELET COMPRESSION

Wavelet Theory deals with both discrete and continuous cases. Continuous wavelet transform (CWT) is used in the analysis of sinusoidal time varying signals. CWT is difficult to implement and the information that has been picked up may overlap and result in redundancy. If the scales and translations are based on the power of two, the DWT is used in the analysis. DWT is more efficient and has the advantage of extracting non overlapping information about the signal. 2-D transform can be obtained by performing two 1-D transform. Signal is passed through low and high pass filters L & H, which is decimated by a factor of 2, each consisting of 1 level transform. In this way the image is spited into four sub-bands referred as LL, HL, LH & HH (Approximation, Horizontal Detail, Vertical Detail, and Diagonal Detail respectively). Further decomposition is achieved by acting upon four sub-bands. The inverse transform is obtained by up sampling all the four sub bands by a factor of 2 and then using reconstruction filter. Higher scales correspond to more stretched wavelet.

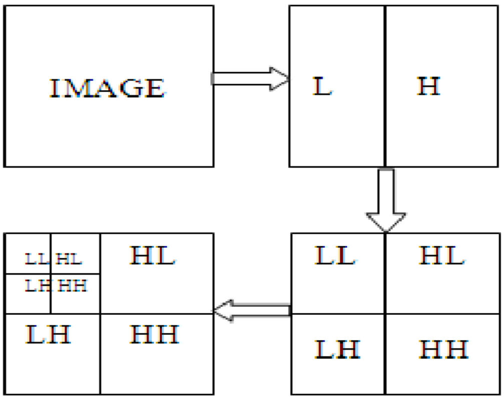


Fig 4.1: Two levels Wavelet Decomposition applied on an image.

WAVELET–FRACTAL IMAGE COMPRESSION ALGORITHM

The motivation for Wavelet-fractal image compression stems from the existence of self-similarities in the multi-resolution wavelet domain. Fractal image compression in the wavelet domain can be considered as the prediction of a set of wavelet coefficients in the higher frequency sub bands from those in the lower frequency Sub bands. Unlike Pure-fractal estimation, an additive constant is not required in wavelet domain fractal estimation, as the wavelet tree does not have a constant offset.

Down sampling of domain tree, matches the size of a domain tree with that of a range tree. The scale factor is then multiplied with each wavelet coefficient of domain tree to reach its correspondence in range tree. Dl denote the domain tree, which has its coarsest coefficients in decomposition level *l*, and let *Rl-1* denote the range tree, which has its coarsest coefficients in decomposition level *l*-1. The contractive transformation (T) from domain tree D_1 to range tree *Rl-1*, is given by T(D_i)= α * S. D_i where S denotes sub sampling and α is the scaling factor. Let x= (x_1, x_2, x_3, x_4,...... x_n) be the ordered set of coefficients of a range tree and y= (y_1, y_2, y_3, y_4,...... y_n) the ordered set of coefficients of a down sampled domain tree.

Then, the mean squared error is given by Equation

$$\text{MSE} = ||R_{i-1} - T(D_i)||^2 = \textstyle\sum_i^n (xi - \alpha * yi) \qquad (1)$$

And the optimal α is obtained by Equation

$$(\textstyle\sum_i^n xi * yi)/\sum_i^n l \qquad (2)$$

ROUGHNESS ENTROPY FRACTAL DIMENSION METHOD

The REFD is created based on the notion of allometric relation between the roughness node number and the path length of the structured roughness cluster in an image, in which the image roughness is defined as a pixel standing out among its neighbourhood. The REFD algorithm is described as follows. First, the image roughness is extracted by using the small neighbourhood algorithm. The roughness extraction takes the maximum and minimum among the surrounded pixels as the thresholds. When the value of target pixel is greater than the maximum or is less than the minimum, the target pixel is referred to as an image roughness. The REFD algorithm groups the contiguous image roughnesses into a structured roughness cluster based on 2-connectivity rule, in which the structured cluster is called a compound. The FD of a compound is derived according to the structure which was quantified by using Horton-Strahler order scheme [18]. The fractal dimension of a compound is obtained as follows:

$$D = \log(R_n)/\log(R_L)$$

(3)

where R_n is the ratio of the numbers of roughness nodes between adjacent levels, R_L is the ratio of the average path lengths between adjacent levels. Shannon's entropy was introduced to integrate the FDs of compounds into the FD of image in order to preserving the significances of compounds in the image. The FD of image fE is obtained by the following equation:

$$fE = -\sum_{i=1}^{n} P_i \left(\log P_i\right) fD_i$$

(4)

where fD_i is the FD of ith set of compound obtained by D. The derived FD summarized the complexity of image roughnesses as a single numerical value.

THE REFD FRACTAL- WAVELET DENOISING SCHEME

The FW algorithm does down sampling of domain tree so that the domain tree is as the same size as the range tree. Multiply the scale factor with each wavelet coefficient of domain tree to reach its correspondent range tree. Then search the domain trees to find the best matched domain subtree for a given range subtree. Range subtree is approximated by affine grayscale transformations of domain subtrees, in which the by product of such approximation is some variance reduction. Most of the variances are the noises. A detailed description of the down sampling of domain tree and scaling factor can be found in [19].

The REFD FW algorithm estimate the domain-range matching based on the relative degree of texture similarity. As shown in Fig. 1, the range subtrees are split by using a quadtree partitioning scheme into n levels of decomposition. Each level includes one low-frequency subband and three high-frequency subbands of different directions.

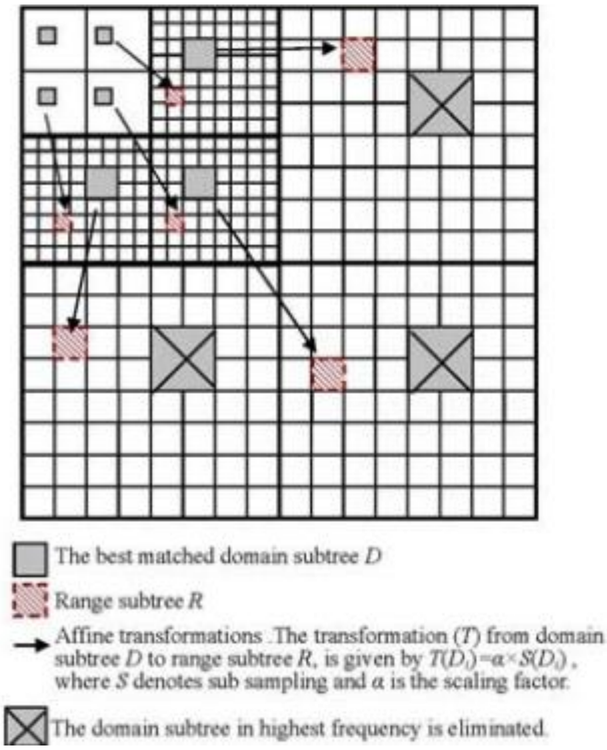


Fig. 4.2: The REFD FW algorithm finds each range subtree for its optimal matched domain subtree. The approximation of a range subtree through a contracted domain subtree is done in the wavelet domain.

The affine transformation in matching domain subtree with the corresponding range subtree is an integration of REFD method and [11]. The encoded parameters include the position of the domain tree and the scaling factor.

The REFD FW algorithm is described as follows:

1. First the wavelet will decompose the image into a set of subbands in the LL, LH, HL, and HH direction respectively in multiple resolutions. An example is illustrated in the (1) and (2) of Fig. 2.
2. Split wavelet subbands in each resolution level into equal amount of range blocks. Domain blocks in resolution 1 are not used. Domain blocks are down sampled in the same size of range block in the higher frequency band with one level less. An example is illustrated in the (3) and (4) of Fig. 2.
3. Obtain the REFD values fE^R and fE^D by using (4) for each range subtree and domain subtree respectively.
4. Then, calculate the $\sum \min(fE_i^R\text{-}fE_j^D)$ for each range subtree and domain subtree. The jth domain subtree results the minimal value of $\sum \min(fE_i^R\text{-}fE_j^D)$ is referred as the best match for the ith range subtree.
5. To encode the image, the position of the best matched domain subtree for the current range block (i.e. transformed domain subtree) and the scaling factor are stored in code book. For restricting the experimental conditions, the rotation and flipping have not been implemented in this experiment

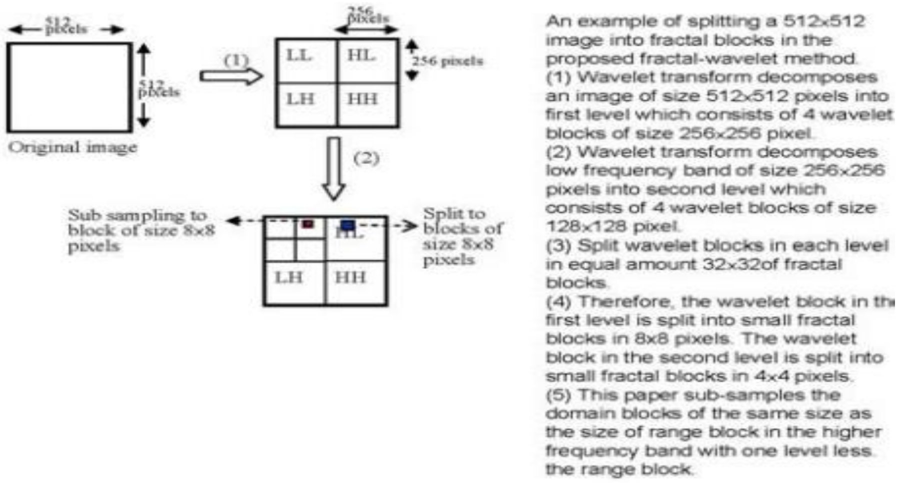


Fig. 4.3: From the high frequency subbands towards low frequency subbands, subband are split into range blocks of sizes 8x8 and 4x4, and the down-sampled domain blocks with the same block size of 8x8 and 4x4 are matching the range blocks in the subbands with one level less.

6. To decode the compressed image, iterate the domain subtrees with the scaling factor to the destination. Then, inverse the wavelet transformation to get the approximation. The decompression process is based on an iterative simple algorithm. It is started with a random initial image and this paper used 10 iterations, the decoded image is obtained.

V. RESULT AND CONCLUSION

This paper adopts two well-defined error criteria, the mean square error (MSE) and the peak signal to noise ratio (PSNR), of the visual quality to judge the denoising image. MSE is expressed as

$$MSE = \frac{1}{N \times M} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \left(B(x,y) - A(x,y) \right)^2$$

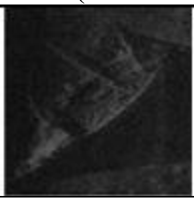
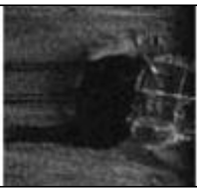
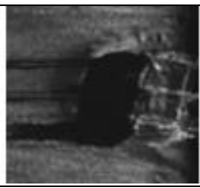
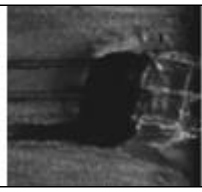
where A(x,y) and B(x,y) are the gray value expression of the original image A and the decoded image B. The images are of the same size N x M .The PSNR commonly is used to measure the difference of two images. In general, if the PSNR is large enough, there could be no visually perceptible differences between the reconstructed and original images. A small PSNR would suggest that the images are unrelated. The PSNR is defined in terms of the MSE as:

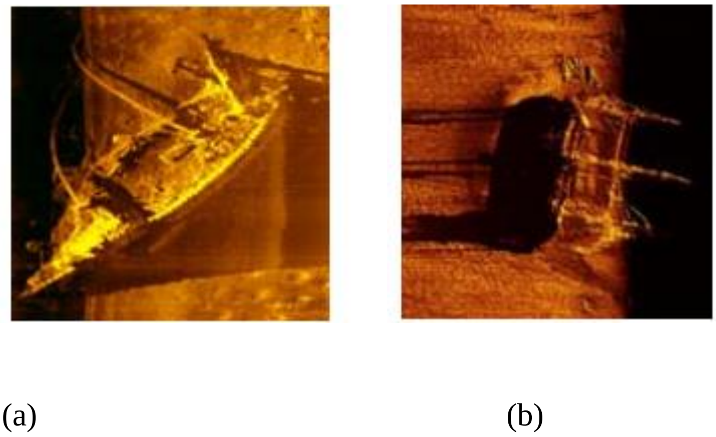
$$PSNR = 10 \log_{10} \frac{I_{\max}^2}{MSE}$$

Where max I max is the highest intensity pixel in the image. A classical comparison analysis based on emulated noisy image: it is build by taking a good quality image as the original, adding Gaussian white noise of a given variance σ to the original image, and then approximating the original image from the noisy one by the denoising method. Therefore i have taken two side-scan sonar images, one is the wreck of M.V. Sea Angel taken by the Polaris, and the other is a wreck of a sailing schooner provided as an open data by Marine Sonic Technology, to be the experimental objects. Enlarge them to size 2048×2048-pixel and then transform them to 8-bit gray images. Add Gaussian white noise (with zero mean and variance σ = 0.01) to the enlarged gray image as the noisy image.

This paper employs the REFD FW algorithm and a slightly modified generic FW scheme from to reduce noises of the noisy gray images. Table 1 demonstrated the results of two different FW schemes. The REFD FW denoising method uses image artificially distorted with well defined white Gaussian noise to achieve objective test results. The performance of the REFD FW algorithm was assessed based on two well-known criteria: the MSE and the PSNR of the images after denoising. Results obtained by using the REFD FW were compared with a generic FW Compression algorithm introduced by M.R.N. Avanaki et al.

Table 1. : The MSE and PSNR values of the REFD FW denoising and the generic FW scheme

	Guassian noise added(σ = 0.01)	Denoised using REFD FW algorithm	Denoised using generic FW scheme
Wreck of a sailing schooner			
MSE	810.21	56.65	1900.10
PSNR (dB)	15.32	25.56	13.32
Wreck of M.V. Sea Angel			
MSE	3200.51	210.56	3300.74
PSNR (dB)	10.54	19.75	11.42



(a) (b)

Fig 5.1 Original side-scan sonar images: (a) Wreck of a sailing schooner, (b) Wreck of M.V. Sea Angel

The results show that the REFD FW algorithm denoises images in an efficient and successful way. The results conclude that the REFD FW algorithm based on the texture similarity is an adaptive algorithm in denoising image for side-scan sonar

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