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Evaluation of The Tetrolet Transformation in the Denoising of Images

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ABSTRACT -

It is noted that the provided solution is a local one, even though these adaptive algorithms can denoize the image and produce sustained image metrics. Therefore, to get around this issue and find a better solution, evolutionary computing technologies are employed. Recent years have seen the exchange of image-based information over a variety of wireless media. The wireless medium produces a lot of noise. As a result, the information contained in the photos is frequently contaminated and degraded. An picture must go through a process that involves cleaning the noise or otherwise removing it from the image in order to recover the information from such a noisy image. Denoising the image is the term used to describe this occurrence. In due time, a number of methods for image denoising are proposed. These traditional methods are frequently effective in removing noise from kinds such as Gaussian, salt, and pepper, among others. Some traditional methods for denoising have been offered, including spatial filtering and other transformation-based methods.

This thesis suggests a few changes to spatial filtering methods. In order to extract the best results that outperform the standard median filters, the modified filtering suggests the weighted median for conventional median filters, the dynamic window size in sliding windows, and occasionally fuzzy means. Similar to the conventional wavelet technique, the modified HAAR, often referred to as dynamic HAAR, is proposed, where the threshold is dynamically adjusted rather than having a constant value. Performance is assessed using picture metrics such as peak signal to noise ratio and structure similarity index in all methods to denoise the image, ranging from adaptive HAAR to evolutionary computing to simple modified filtering. MATLAB is used to conduct the simulation-based experiments.

I. INTRODUCTION

The Digital images are crucial for everyday uses like computer tomography, satellite television, and magnetic resonance imaging as well as for scientific and technological fields like remote sensing and geographic information systems. Noise typically taints data sets obtained by image sensors. The data of interest may be deteriorated by flawed equipment, issues with the data collection procedure, and intervening natural events. Additionally, compression and transmission problems might produce noise. As a result, denoising is frequently required and the initial action to be performed prior to picture data analysis. To make up for this kind of data corruption, an effective denoising approach must be used. Researchers find it difficult to eliminate noise from the noisy signal because doing so introduces artifacts and results in visual blurring. There are numerous strategies for reducing noise. Every strategy contains presumptions, benefits, and drawbacks. It is assumed that additive random noise, represented by a Gaussian distribution, is present in the majority of natural images. The denoising techniques can generally be divided into two categories: transform domain and spatial domain. Once more, the spatial domain techniques can be divided into linear and nonlinear denoising techniques. Because of its four fundamental characteristics, the wavelet transform outperforms other transform domain methods in image denoising. These include energy conservation through the use of an orthogonal transform, energy compaction—where there are many wavelet coefficients of small magnitude—and energy compaction.

II. LITERATURE REVIEW

Several wavelet-domain denoising techniques were devised as WT gained prominence during the past 20 years [21–24]. The WT domain was given more attention than the spatial and Fourier domains. The number of denoising papers has increased with the publication of Donoho's wavelet-based thresholding technique [27]. Despite the lack of novelty in Donoho's approach [26], his techniques did not necessitate the correlation or tracking of wavelet maxima and minima across several scales, as suggested by Mallat [28]. Because Donoho showed how to tackle a challenging problem in a straightforward manner, wavelet-based denoising approaches saw a resurgence in popularity. Various methods for calculating the parameters for wavelet coefficient thresholding were reported by researchers [29]. To reach the ideal threshold value, data adaptive thresholds were implemented. Subsequent research revealed that translation invariant techniques based on thresholding of an undecimated wavelet transform could yield significant gains in perceptual quality [27].

To lessen artifacts, these thresholding strategies were used to the non-orthogonal wavelet coefficients. Similar outcomes were also obtained using multiwavelets. It appeared that probabilistic models that made use of the wavelet coefficient's statistical characteristics performed better and gained popularity than thresholding methods. Bayesian denoising in the wavelet domain has received a lot of attention lately [30]. Additionally, Gaussian Scale Mixtures and Hidden Markov Models have gained popularity, and further research is being conducted in this field.

III. METHODOLOGY

Problem Statement : We read many research papers and books and found that even now in the world of image processing, the noise in images is a big problem. So we have applied filtering using many good effective techniques and we have tried to remove many types of noise in the image. For this, we have applied many different methods so that the quality of the image and the pixels are not affected and we have to remove the noise of the image so that the quality of the image is not affected.

Research Methodology : Nevertheless, the denoising techniques used in the aforementioned discussion are predicated on the assumption that the noise model is Gaussian, which is supported by the literature in this field. Because noise comes from a variety of sources and forms, this assumption might not always be accurate in practice. A perfect While a practical technique could not have the necessary knowledge about the noise model or variance of the noise, a denoising procedure necessitates prior knowledge about the noise. In order to compare the performance of various algorithms, the majority of them make the assumption that the noise and noise model have known variance. To assess the algorithms' performance, Gaussian noise with varying variance values is introduced to the natural photos. Not every researcher tests the performance of the system using a large value of variance algorithm when the signal strength and noise levels are similar. Likewise, there hasn't been any discussion of high density salt and pepper noise using a straightforward modified filtering technique. Due of its characteristics, such as sparsity, multiresolution, and multiscale nature, the WT is typically regarded as the most performance-suited option.

Research parameters and objectives:

In light of the literature review mentioned above and the research need, the suggested effort has the following goals.

A) To adaptively alter the spatial filters' structure. Put fuzzy logic into practice and evaluate each case's performance.

B) To incorporate the transformation technique's adaptive features.

C) To use evolutionary computing technologies to regulate transformation procedure parameters.

D) To evaluate the suggested technique's resilience using a watermarking program.

The approach used in this work to conduct the simulation-based experimentation consists of the following straightforward steps.

1) Transform the input picture (I) into one of the two predetermined sizes, 256 x 256 or 512 x 512 pixels.

2) Create a noise image (N) by adding a chosen noise type with varying densities.

3) Utilize the suggested denoising method to produce a denoised image (D).

4) Calculate the PSNR, SSIM, and other relevant image metrics for the I and D images.

5) Examine the suggested technique's performance using the calculated image metrics.

IV. EXPERIMENT AND RESULT

EVALUVATION OF THE TETROLET TRANSFORMATION IN THE DENOISING OF IMAGES

Wavelet Transformation based De-noising :

Wavelet transforms have been effectively demonstrated as effective methods for de noising because of their capacity for de-correlation, or the separation of valuable data from noise.

Figure 7.9 Block schematic of the Wavelet Transform de-noising process

The fundamental idea behind the noise reduction based Calculating the multi-scale wavelet decomposition of the corrupted image into wavelet coefficients and modifying the resulting wavelet coefficients are the steps involved in the wavelet transform. By applying a preset threshold to them in accordance with a shrinkage rule, the changed coefficients are produced.

The intended de noised image is subsequently obtained through reconstruction using these altered coefficients. Figure 7.9 shows a flow diagram that breaks down the major steps of the wavelet-based de noising process.

Tetrolet Transforms : The fundamental concept of Tetrolet, a novel adaptive algorithm, is straightforward but incredibly quick and efficient. Because the basis functions are not redundant, the method is specifically intended for sparse image approximation. The building is comparable to the concept of digital wedgelets [99], which takes into account Haar functions on wedge partitions. The image is divided into 4x4 blocks, and a tetromino partition tailored to the image geometry in each block is then determined. Four equal-sized squares are connected together along an edge with at least one additional square to form tetrominoes. Golomb first introduced tetrominoes, and the well-known computer gaming classic "Tetris" helped make them popular. Tetrolets, or Haar-type wavelets, are defined on these geometric shapes and constitute a local orthonormal basis. The absence of redundancy results in a filter bank that has been critically sampled, breaking down a picture into a sparse representation. An image approximation can be obtained by reconstructing the image using an appropriate shrinking approach applied to the tetrolet coefficients. The tetrolet transform is not limited to image processing, it should be noted.

On the other hand, the technique works incredibly well for compressing actual data arrays. The shapes known as tetrominoes serve as the supports for tetrolets, which are Haar-type wavelets. The As seen in Figure 7.10, tetrominoes are geometric shapes found in the well-known computer game "Tetris." Four squares of the same size are joined to create each tetromino. The following figure lists the five fundamental free tetrominoes, excluding rotations and reflections :

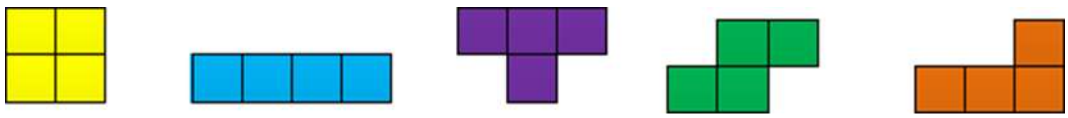


Figure-7.10 Five free tetrominoes

When transforming an image using the tetrolet transform

g = [g(x,y)] {N to x,y=1} …………………..(1)

We split a picture into 4 X 4 blocks using N = 2K, K ˛ N. Then, depending on the local structure in the block, any four free tetrominoes are used to cover each block, taking into account the tetrominoes' rotations and reflections.

The four indices in each tetromino subset Iz are mapped to a distinct order {0, 1, 2, 3} by using a bijective mapping L. These four tetrominoes, which make up the adaptive basis, are represented as {I0, I1, I2, I3}. Krommweh [93] constructed the following discrete basis functions for each tetromino subset Iz based on these definitions:

$$\phi_{I_v}[x',y'] := \begin{cases} 1/2, & (x',y') \in I_v \\ 0, & otherwise \end{cases}$$

$$\psi^{l}_{I_v}[x',y'] := \begin{cases} \in [l, L(x',y')], & (x',y') \in I_v \\ 0, & otherwise \end{cases}$$

……….(2)

Representation of Tetrolets : We first need some definitions and notations before we can describe the concept of the tetrolet transform. We limit our thoughts to two-dimensional square data sets for simplicity's sake.

Let I = {(i, j): i, j = 0. . . N −1} ⊂ Z^2

Be the digital image's index set a=(a[i,j]) $_{(i,j)\in I}$ withN = 2^J,J ∈ N.

We identify an index's 4-neighborhood. (i, j) ∈ I by

N_4(i,j):={(i−1, j), (i+1, j),(i, j−1), (i, j +1)}.

An index located at the image's vertex has two neighbors, while an index at the boundary has three. We employ a one-dimensional index set J (I) for our study by taking the bijective

Mapping J:I→ {0, 1, . .. ,N^2−1} with J((i, j)):= jN +i.

A set E={I_0. . . I_r}, r∈N, of subsets I_z⊂I is a disjoint partition of I if I_z ∩ Iμ =∅for z ≠μand U^r=0 I_z = I.

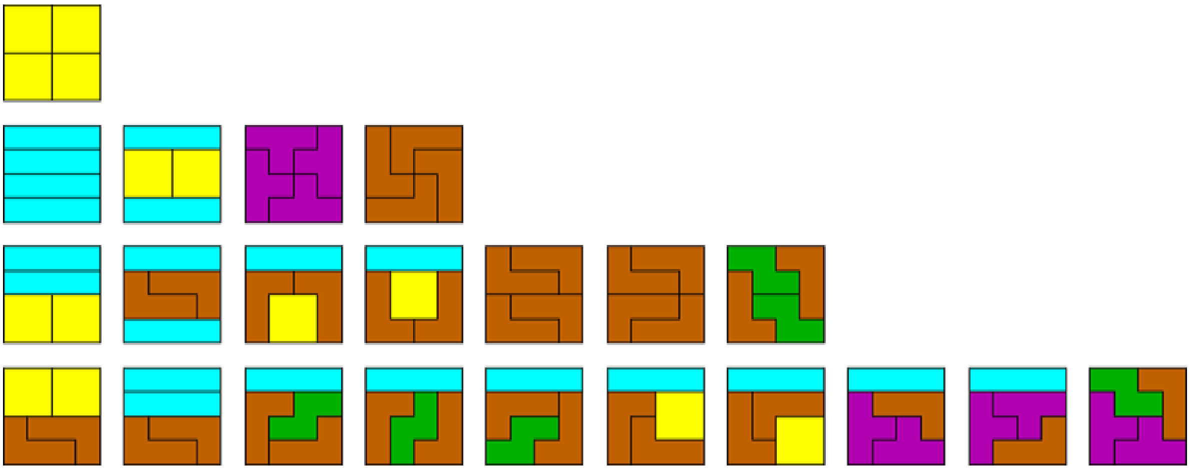


Figure 7.11: Fundamental tetrominoes for a 4X4 tile

Implementation :

A modified form of HWT called AHWT is the transformation type taken into consideration in this work. The algorithm operates independently on every block of the image and is local. Comparing it to other Haar wavelet transform-based techniques, it performs comparably (achieves up to 2 dB greater PSNR). The suggested approach is ideally suited for effective hardware implementation due to the local character of the algorithm and the ease of the Haar wavelet transform computations.

The term adaptive HWT refers to a novel image compression technique that is suggested in [103] and is similar to the adaptive nature of the HWT. We call it the "Tetrolet transform." The transformation's creation is also quite straightforward

consistently efficient over time. Images are often separated into 2x2 blocks for a 2D HWT. Applying HWT to produce two different kinds of four coefficients comes next.

Less storage is needed because the entire image does not need to be kept. It is comparable to denoising based on the translation invariant wavelet with the redundant coefficients transform. Better Edge Preservation is observed when the suggested method is added to the above, since picture structures are taken into consideration during de-noising.

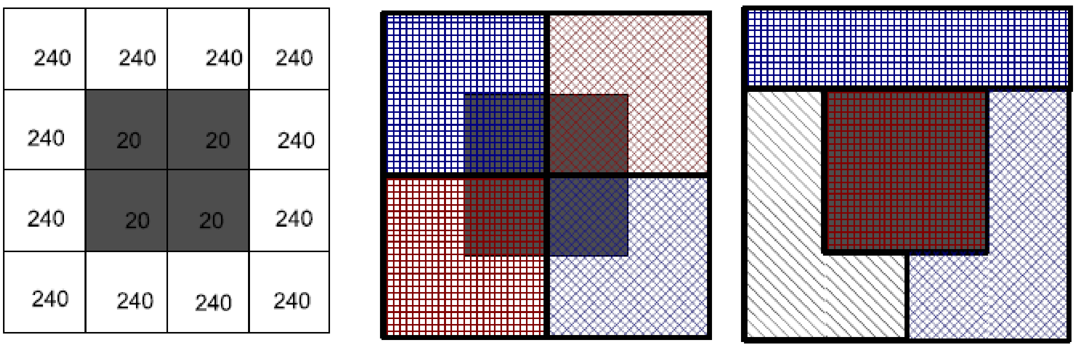
The Haar wavelet transform is among the most basic wavelet transforms. The following are the definitions of the scaling and wavelet functions for the Haar wavelet transform :

Φ (t) = 1 for $0<t<1$; 0 otherwise

Φ (t) = 1 for $0 < t < 0.5$;

Φ (t)= -1 for $0.5<t < 1$; 0 otherwise

Examine Figure 4.6 to comprehend the AHWT. It displays an illustration of a 4x4 block with a white backdrop and a dark core. Pixel values range from 0 to 255, where 255 represents pure white and 0 represents total black.



(a) Block (b) HWT partition (c) AHWT partition

Figure 7.12: Representation of HWT and AHWT

370	370	110	-110
370	370	110	-110
110	110	-110	110
-110	-110	110	-110

480	40	0	0
480	480	0	0
0	0	0	0
0	0	0	0

Figure 7.12 (b) displays the AHWT coefficients, while Figure 7.12 (a) displays the resulting Ha ar coefficients. In the case of the AHWT coefficient, it is evident that the energy is at high contraction; however, in the case of the HWT, it is dispersed over all coefficients. Better de-noising results are obtained thanks to this energy contraction feature.

Result : There are two situations in the simulation-based experimentation. While instance 2 refers to the implementation and performance analysis based on the number of coefficients, case 1 refers to the implementation and comparison examination.

Case-1 :

(a) HWT

(b) AHWT thresholding

Figure 7.13 Displays the Lena image processed for noise reduction using HWT and the proposed technique.

It is evident that the AHWT approach yields the best image. Using the HWT approach yields the second-best image. Usually, the AHWT is up to 2 dB louder than alternative techniques. The test image is denoised using several techniques and contaminated with white noise for additional analysis.

TABLE 7.2 : Effectiveness of AHWT

Transformation	**HWT(dB)**	**AHWT(dB)**
9	27.56	33.46
13	29.63	25.47
19	32.42	30.12
24	31.45	33.43
31	34.47	28.46

Case-2 :

In a second scenario, the number of coefficients used to determine the optimal method for image de-noising is used to evaluate the AHWT's performance. On the line, the "Lena" image is taken into consideration once more, but this time it has a resolution of 256 px X 256 px, which is readily validated in the Mat lab.

Figure 7.14: Input image Lena

(a) (b)

(c) (d)

Figure 7.15 De-noised images with various coefficients are output (a), (b), (c), and (d).

The comparable denoised image is displayed in Figure 7.15 (a), where the number of coefficients is first made proportionate to the image's resolution of 256 (22.51dB). As seen in Figure 7.15 (b), (c), and (d), the corresponding coefficient count is also increased for the inquiry from 1024 (25.92dB) through 4096 (30.01dB) and 8192 (31.8dB).

The visual implication and accompanying PSNR make it clear that the denoising algorithm's performance is significantly impacted by the number of coefficients. The quality of the denoised image improves with the number of coefficients. Table 7.3 makes it clear that, under the same circumstances, the Adaptive Haar Wavelet Transform performs better than both the standard HWT and the suggested spatial domain filtering technique.

TABLE 7.3 : Comparing the effectiveness of de-noising in the spatial and transform domains

Transformation %	Modified median filter(db)	HWT(dB)	AHWT(dB)
11	19.263	29.15	32.16
17	14.236	17.48	30.15
23	11.159	14.46	25.48

Reversibility	Irrevocable	Reversible
Execution with elevated Variance noise	Slow and impoverished	Enhanced performance

Conclusion : For picture de-noising, a novel algorithm based on the so-called AHWT (a modified variant of the HWT) was effectively put into practice. Its performance was demonstrated to be on par with or better than HWT's. It has also been demonstrated to have the benefit of being easy to deploy.

Only zero-mean additive white Gaussian noise was taken into consideration in this work for validation, while there are other kinds of noise that might taint a genuine image in real life. The moving average, Wiener, and Wavelet techniques were used to denoize the white noise-corrupted signal, and the outcomes were examined. Similarly, the moving average, Wiener2 filter, and Wavelet techniques were used to denoize the well-known Lena image that had been tainted by AWGN. Ultimately, it is determined that the suggested method is computationally straightforward from the perspective of both software and hardware implementation.

V. CONCLUSION AND FUTURE WORK

Summary : De noising photographs entails eliminating noise and returning the image to its initial state. The phenomena of de noising both color and grayscale images is carried out, and this thesis presents the findings related to the application of the procedure/technique used. A categorised reference to the necessity of de-noising and the kinds of noise that taint photographs and corrupt their information was given by the first review on image de-noising. A brief overview of the approach is also included, along with a discussion and presentation of the technique's performance measures for an effective evaluation.

The overall goal of the thesis is to improve the quality of recovered photos by incorporating adaptability into the traditional technique in a number of ways. When median filters employ adjustable window size, better denoising quality is seen on the line. Similarly, the accompanying fuzzy-based determination also demonstrated a novel denoising technique, as opposed to the traditional computation of the median eight elements in the window size of (4 X 4). Usually, this spatial image mitigation for denoising entails using a number of statistical and logical.

Adopting many statistical and logical interpretations inside a window that moves through the image size is usually required for this spatial mitigation of the image for denoising. Better results were obtained, nevertheless, when the threshold was chosen using a transformation technique with an adaptive flavor, as was the case with Tetrolets.

The computational process is carried out with minimal complexity by the evolutionary computing tools. Additionally, this method produced better results in both color and grayscale photos where Particle Swarm Optimization (PSO) was used to denoize the image. In order to effectively achieve denoising, the method usually employs PSO to adaptively regulate the wavelet transform's threshold and scaling factor. Afterwards, as a case study, the Evolutionary Computing Tool-based denoising is used to the watermarking application to assess its performance.

While methodically removing the noise that has an unpredictable influence on the watermark image, the PSO-based effective watermarking also proved to be resilient. This method was successful, and the findings show that it effectively isolated the watermarking image from various sounds that may have attacked the host image and rendered it impervious to attacks. Robustness is implemented by effectively and adaptively controlling the watermark injection and extraction processes. The work described in this thesis suggests that adaptive control of the denoising approach is more productive and efficient.

Future Work: The ideal scope of future work would involve developing a prototype using FPGA and expanding the work on 2D (both greyscale and color images) to 3D video and online video. Wide cost effectiveness is included here. It is difficult to verify suggested algorithms for real-time applications and implement them on FPGA (Field Programmable Gate Array) hardware such as Spartan 1. In order to accomplish the de-noising in this work, certain initial images that are shared by the transmitter and receiver sections are needed for training. This implies that the transmitter should be known to the receiver. This has drawbacks of its own, such as the fact that it's frequently not possible for transmitters and receivers to share common knowledge. Therefore, a potential area for future research would be to build and execute a de-noising system without any prior information transfer or reference between the transmitter and receiver.

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