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Weighted Denoising With Multi-Spectral Decomposition for Image Compression

[1,]Tamboli S. S. [2,]Dr. V. R. Udupi
[1,]*ADCET, Ashta*
[2,] *GIT, Belgaum*

ABSTRACT: *A modified approach to image compression is proposed in this paper. The objective of image compression based on multi spectral representation is developed. The denoising process of image coding is improvised so as to achieve higher processing accuracy with high PSNR value. A multi wavelet coding with a modified weighted filtration approach is proposed. The simulation observation evaluates the proposed approach and the comparative analysis of the proposed approach presents the improvement in coding efficiency.*

KEYWORD: *Image compression, Multi spectral coding, preprocessing, and denoising.*

I. INTRODUCTION

With the upcoming of new technologies the demand for new services and their usage is also increasing. New standards and architectures are coming up to achieve the objective of higher system performance. In various demanded services imaging applications are growing at a faster rate. For current demanded services new image coding approaches were proposed. These approaches are focused mainly to achieve better compression factor or higher accuracy. In the process of image coding the initial process is to remove the noise artifacts during the preprocessing operation. In Image coding inappropriate and coarse results may strongly deteriorate the relevance and the robustness of a computer vision application. The main challenge in noise removal is suppressing the corrupted information while preserving the integrity of fine image structures. Several and well-established techniques, such as median filtering are successfully used in gray scale imaging. Median filtering approach is particularly adapted for impulsive noise suppression. It has been shown that median filters present the advantage to remove noise without blurring edges since they are nonlinear operators of the class of rank filters and since their output is one of the original gray values [1] [2]. The extension of the concept of median filtering to color images is not trivial.

The main difficulty in defining a rank filter in color image is that there is no "natural" and unambiguous order in the data [3] [4]. During the last years, different methods were proposed to use median filters in color image processing [5] [6]. In vector filtering, the challenge is to detect and replace noisy pixels and preserve the relevant information. But it is recognized that in some image areas most of vector filters blur thin details and image edges [7] [8] even if many works such as Khriji and Gabbouj [9]. Generally impulse noise contaminates images during data acquisition by camera sensors and transmission in the communication channel. In [10] Chan and Nikolova proposed a two-phase algorithm. In the first phase of this algorithm, an adaptive median filter (AMF) is used to classify corrupted and uncorrupted pixels; in the second phase, specialized regularization method is applied to the noisy pixels to preserve the edges and noise suppression. The main drawback of this method is that the processing time is very high because it uses a very large window size of 39X39 in both phases to obtain the optimum output; in addition, more Complex circuitry is needed for their implementation. In [11] Srinivasan and Ebenezer proposed a sorting based algorithm in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel in contrast to AMF and other existing algorithms that use only median values for replacement of corrupted pixels. At higher noise densities this algorithm does not preserve edge and fine details satisfactorily. In this paper a novel robust estimation based filter is proposed to remove fixed value impulse noise effectively.

The proposed filter removes low to high density fixed value impulse noise with edge and detail preservation upto a noise density of 90%. Recently, nonlinear estimation techniques are gaining popularity for the problem of image denoising. The well-known Wiener filter for minimum mean-square error (MMSE) estimation is designed under the assumption of wide-sense stationary signal and noise (a random process is said to be stationary when its statistical characteristics are spatially invariant) [12]. For most of the natural images, the stationary condition is not satisfied. In the past, many of the noise removing filters were designed with the stationary assumption. These filters remove noise but tend to blur edges and fine details. This algorithm fails to remove impulse noise in high frequency regions such as edges in the image. To overcome the above mentioned difficulties a nonlinear estimation technique for the problem of image denoising has been developed based on robust statistics. Robust statistics addresses the problem of estimation when the idealized assumptions about a system are occasionally violated. The contaminating noise in an image is considered as a violation of the assumption of spatial coherence of the image intensities and is treated as an outlier random variable [12]. In [13] Kashyap and Eom developed a robust parameter estimation algorithm for the image model that contains a mixture of Gaussian and impulsive noise. In [12] a robust estimation based filter is proposed to remove low to medium density Gaussian noise with detail preservation. Though the techniques were developed for filtration of Gaussian or impulsive noise they are been developed for gray level images and are not suitable for color images. These approaches work on the method of denoising based on the current pixel or on the relevance surrounding pixels to make a decision.

The adaptive filtration is an emerging solution to the dynamic noise processing. However in the process of dynamic filtration proper denoising value is required to eliminate the noise effect. In this paper a modified filtration approach for image denoising is presented. A denoised sample is then processed to achieve best representation achieving both compression improvement and coding efficiency. To achieve the objective JPEG 2000 coding standard were presented. The coding in such architecture is developed using wavelet transformation. However the spectral representation of such coding is limited and finer resolution information are neglected. This assumption reduces the coding accuracy. In this paper a multi-spectral decomposition for image compression is proposed. Wavelet-based coding [14, 15] provides substantial improvements in picture quality at higher compression ratios. For better performance in compression, filters used in wavelet transforms should have the property of orthogonality, symmetry, short support and higher approximation order. Due to implementation constraints scalar wavelets do not satisfy all these properties simultaneously. Multiwavelets [16, 17] which are wavelets generated by finite set of scaling functions, have several advantages in comparison to scalar wavelets. One of the advantages is that a multiwavelet can possess the orthogonality and symmetry simultaneously [15, 18, 19] while except for the 'Haar' (scalar wavelet) cannot have these two properties simultaneously. Thus Multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. Multiwavelets can achieve better level of performance than scalar wavelets with scalar wavelets with similar computational complexity. With these approaches in this work a new image coding approach integrating modified denoising and multi spectral representation is proposed. The remaining section of the work is presented in 6 sections, where section 2 outlines the image coding system and its modeling approach. The conventional image coding approach is presented in this section. The proposed image coding methodology is presented in section 3. Section 4 presents the simulation observation obtained for the proposed approach and a conclusion is presented in section 5.

II. IMAGE CODING SYSTEM

The JPEG-2000 image compression architecture is the fundamental architecture consisting an encoder and decoder unit. The function of the encoder is to create a set of symbols from the given input data which is transmitted through a channel and then feed to decoder where we can reconstruct the image. There is a possibility that the reconstructed output image can the replica of the input image or the reconstructed image is distorted image due to channel interference. Figure 3.1 shows convention block diagram of a compression system.

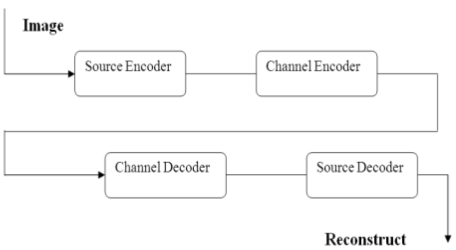


Figure 1: conventional Block Diagram of an Image compression system.

In the process of encoding the image is preprocessed for filtration and output is then processed using DWT. To perform the forward DWT the JPEG2000 system uses a one-dimensional (1-D) subband decomposition of a 1-D set of samples into low-pass and high-pass samples. Quantization refers to the process of approximating the continuous set of values in the image data with a finite (preferably small) set of values. After the data has been quantized into a finite set of values, it can be encoded using an Entropy Coder to give additional compression. An entropy coder encodes the given set of symbols with the minimum number of bits required to represent them using Huffman coding. The Huffman decoder block carries out decoding reading the unique code bits passed in place of the data bit. The dequantizer unit dequantizes the decoded data bits. Inverse transformation is the process of retriving back the image data from the obtained image values. The image data transformed and decomposed under encoding side is rearranged from higher level decomposition to lower level with the highest decomposed level been arranged at the top. There are several ways wavelet transforms can decompose a signal into various sub bands.The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal. . First, the low pass filter is applied for each row of data, thereby getting the low frequency components of the row. But since the low pass filter is a half band filter, the output data contains frequencies only in the first half of the original frequency range. Now, the high pass filter is applied for the same row of data, and similarly the high pass components are separated.

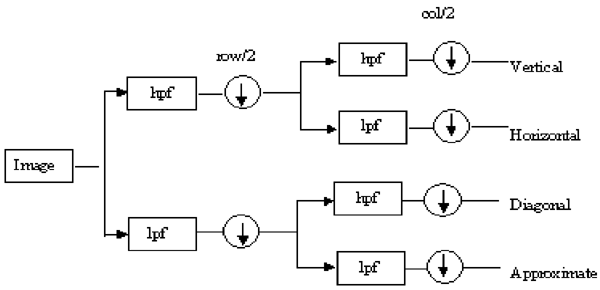


Figure 2 : Wavelet Decomposition of the image sample

To perform the forward DWT the JPEG2000 system uses a one-dimensional (1-D) subband decomposition of a 1-D set of samples into low-pass and high-pass samples. Low-pass samples represent a down-sampled, low-resolution version of the original set and High-pass samples represent a down-sampled residual version of the original set. The Huffman code is found to be more optimal since it results in the shortest average codeword length among all encoding techniques that assign a unique binary codeword to each pattern. In addition, Huffman codes possess the prefix-free property, i.e., no codeword is the prefix of a longer codeword. The first step in the encoding process is to identify the unique patterns in the test set. A codeword is then developed for each unique pattern using the Huffman code construction method. The obtained Huffman tree is then used to construct code words for the patterns of a data set. These code words are assigned to the data bits for compression. The rate of compression achieved is considerably high compared to other encoding techniques due to its variable length property. Typical image coder generally consist of this encoding process, however this method require extensive training of non adaptive entropy codes and has to maintain a codebook for encoding and decoding. System following Huffman coding generally shares the codebook under transmission and reception. These parameters make the coding system non efficient. An enhance coding proposed by Shapiro [1] over come these excessive codebook maintenance.

The inverse fast wavelet transform can be computed iteratively using digital filters. The figure below shows the required synthesis or reconstruction filter bank, which reverses the process of the analysis or decomposition filter bank of the forward process. At each iteration, four scale j approximation and detail sub images are up sampled and convolved with two one dimensional filters-one operating on the sub images columns and the other on its rows. Addition of the results yields the scale j +1 approximation, and the process is repeated until the original image is reconstructed. The filters used in the convolutions are a function of the wavelets employed in the forward transform.

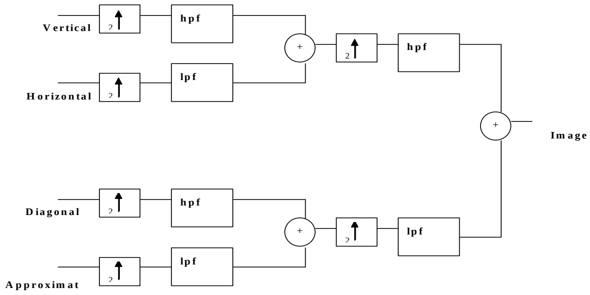


Figure 3: reconstruction unit for IDWT

The simplest of smoothing algorithms is the Mean Filter. Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e. reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in an image. The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbors, including itself. This has the effect of eliminating pixel values, which are unrepresentative of their surroundings. The mean value is defined by,

$$MnF(x_i) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Where, N – number of pixels

x_i – corresponding pixel value,

i= 1….. N

The mean filtration technique is observed to be lower in maintaining edges within the images. To improve this limitation a median filtration technique is developed. The median filter is a non-linear digital filtering technique, often used to remove noise from images or other signals. Median filtering is a common step in image processing. It is particularly useful to reduce speckle noise and salt and pepper noise. Its edge-preserving nature makes it useful in cases where edge blurring is undesirable. The idea is to calculate the median of neighbouring pixels' values. This can be done by repeating these steps for each pixel in the image. a) Store the neighbouring pixels in an array. The neighbouring pixels can be chosen by any kind of shape, for example a box or a cross. The array is called the window, and it should be odd sized.

b) Sort the window in numerical order

c) Pick the median from the window as the pixels value.

The process of this filtration is limited to the surrounding pixel only. This limitation of noise suppression and a finer representation is presented in the following section.

III. WEIGHTED MULTI-SPECTRAL (WMS) CODING

In a Spatial Median Filter the vectors are ranked by some criteria and the top ranking point is used to replace the center point. No consideration is made to determine if that center point is original data or not. The unfortunate drawback of these filters is the smoothing that occurs uniformly across the image. Across areas where there is no noise, original image data is removed unnecessarily. In the proposed weighted filtration approach, after the spatial depths between each point within the mask are computed, an attempt is made to use this information to first decide if the mask's center point is an uncorrupted point. If the determination is made that a point is not corrupted, then the point will not be changed.

The proposed modified filtration works as explained below,

[1]. Calculate the spatial depth of every point within the mask selected.

[2]. Sort these spatial depths in descending order.

[3]. The point with the largest spatial depth represents the Spatial Median of the set. In cases where noise is determined to exist, this representative point is used to replace the point currently located under the center of the mask.

[4]. The point with the smallest spatial depth will be considered the least similar point of the set.

[5]. By ranking these spatial depths in the set in descending order, a spatial order statistic of depth levels is created.

[6]. The largest depth measures, which represent the collection of uncorrupted points, are pushed to the front of the ordered set.

[7]. The smallest depth measures, representing points with the largest spatial difference among others in the mask and possibly the most corrupted points, and they are pushed to the end of the list.

This prevents the smoothing by looking for the position of the center point in the spatial order statistic list.

For a given parameter ζ (where $1 \leq \zeta \leq$ masksize), which represents the estimated number of original points under a mask of points. As stated earlier, points with high spatial depths are at the beginning of the list. Pixels with low spatial depths appear at the end.

If center point ‘c’ $\leq \zeta$ then current pixel MSF (ζ , x_i) = r_c

elsif center point ‘c’ $> \zeta$ then current pixel MSF (ζ , x_i) = r_1

else if c =1 then, pixel canot be modified.

If the position of the center mask point appears within the first ζ bins of the spatial order statistic list, then the center point is not the best representative point of the mask, and it is still original data and should not be replaced.

Two things should be noted about the use of ζ in this approach. When ζ is 1, this is the equivalent to the conventional Median Filter. When ζ is equal to the size of the mask, the center point will always fall within the first ζ bins of the spatial order statistic and every point is determined to be original. This is the equivalent of performing no filtering at all, since all of the points are left unchanged. The algorithm to detect the least noisy point depends on a number of conditions. First, the uncorrupted points should outnumber, or be more similar, to the corrupted points. If two or more similar corrupted points happen in close proximity, then the algorithm will interpret the occurrence as original data and maintain the corrupted portions. While ζ is an estimation of the average number of uncorrupted points under a mask of points, the experimental testing made no attempt to measure the impulse noise composition of an image prior to executing the filter.

These filter outputs are then processed for multi spectral operation.

The conventional wavelet transform is a type of signal transform that is commonly used in image compression. A newer alternative to wavelet transform is the multiwavelet transform. Multiwavelets are very similar to wavelets but have some important differences. In particular, whereas wavelets have an associated scaling function $\Phi(t)$ and wavelet function $\Psi(t)$, multiwavelets have two or more scaling and wavelet functions. For notational convenience, the set of scaling functions can be written using the vector notation $\Phi(t) = [\Phi_1(t), \Phi_2(t)\ldots, \Phi_r(t)]^T$, where $\Phi(t)$ is called the multiscaling function. Likewise, the multiwavelet function is defined from the set of wavelet functions as $\Psi(t) = [\Psi_1(t), \Psi_2(t)\ldots, \Psi_r(t)]^T$ Called a scalar wavelet, or simply wavelet where r = 1, $\Psi(t)$. While in principle ‘r’ can be arbitrarily large, the multiwavelets studied to date are primarily for r = 2. The multiwavelet two-scale equations resemble those for scalar wavelets defined by;

$$\phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \phi(2t-k)$$

$$\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \phi(2t-k)$$

However, $\{H_k\}$ and $\{G_k\}$ are matrix filters, i.e., H_k and G_k are “r x r” matrices for each integer k. The matrix elements in these filters provide more degrees of freedom than a traditional scalar wavelet. These extra degrees of freedom can be used to incorporate useful properties into the multiwavelet filters, such as orthogonality, symmetry, and high order of approximation. The key idea is to figure out how to make the best use of these extra degrees of freedom.

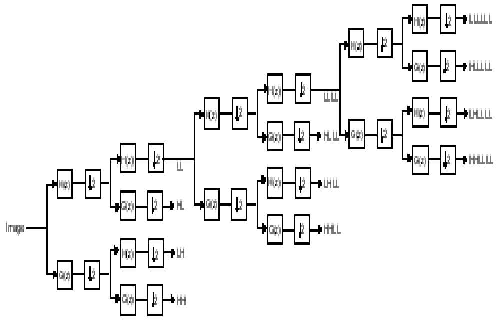


Figure4 : Pyramidal decomposition of multi spectral decomposition

For the processing of MRI image using multiwavelet, the typical approach is to process each of the rows in order, and process each column of the result. Nonseparable methods work in both image dimensions at the same time. While non-separable methods can offer benefits over separable methods, such as savings in computation.

They are generally more difficult to implement. Computing Discrete Multi-wavelet Transform, scalar wavelet transform can be written as follows:

$$\begin{pmatrix} H_o & H_1 & H_2 & H_3 & 0 & \cdots & 0 \\ G_o & G_1 & G_2 & G_3 & 0 & \cdots & 0 \\ 0 & 0 & H_0 & H_1 & H_2 & H_3 & \\ 0 & 0 & G_0 & G_1 & G_2 & G_3 & \end{pmatrix} \quad (1)$$

Figure 5: Filter coefficient for the Multi spectral decomposition

Where H_i and Gi are low and high pass filter impulse responses, are 2-by-2 matrices which can be written asfollows:

$$\begin{pmatrix} H_o & H_o & H_1 & H_1 & \ldots & \ldots & \ldots & \ldots & \ldots \\ H_o & H_o & H_1 & H_1 & \ldots & \ldots & \ldots & \ldots & \ldots \\ G_o & G_o & G_1 & G_1 & \ldots & \ldots & \ldots & \ldots & \ldots \\ G_o & G_o & G_1 & G_1 & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & 0 & H_o & H_o & H_1 & H_1 & \ldots \\ 0 & 0 & 0 & 0 & H_o & H_o & H_1 & H_1 & \ldots \\ 0 & 0 & 0 & 0 & G_o & G_o & G_1 & G_1 & \ldots \\ 0 & 0 & 0 & 0 & G_o & G_o & G_1 & G_1 & \ldots \end{pmatrix}$$

Figure 6: Filtration process in Multi spectral coding

By examining the transform matrices of the scalar wavelet and multi-wavelets, it is observed that in multi-wavelets transform domain there are first and second low-pass coefficients followed by first and second high pass filter coefficients rather than one lowpass coefficient followed by one high pass coefficient. Therefore, if we separate these four coefficients, there are four sub bands in the transform domain. Since multi-wavelet decompositions produce two low-pass sub bands and two high pass sub bands in each dimension, the organization and statistics of multiwavelet sub band differ from the scalar wavelet case.

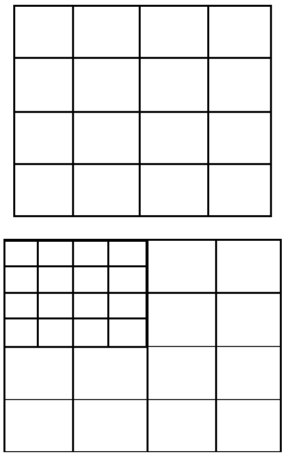


Figure7 : Conventional iteration of multiwavelet decomposition.

During a single level of decomposition using a scalar wavelet transform, the 2- D image data is replaced by four blocks corresponding to the sub bands representing either low pass or high pass in both dimensions. These sub bands are illustrated in Fig. 6. The sub band labels indicate how the sub band data were generated. For example, the data in sub band LH was obtained from high pass filtering of the rows and then low pass filtering of the columns.

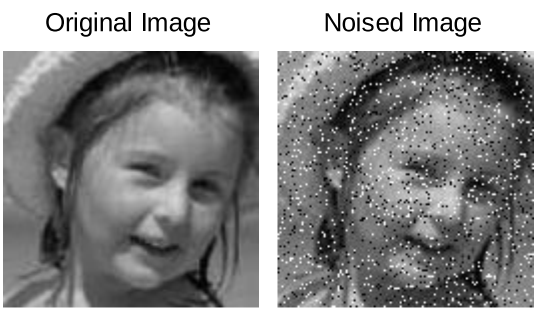
The multi-wavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Since multiple iteration over the low pass data is desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. The multi-wavelet decomposition sub bands are shown in Fig.7. For multi-wavelets the L and H have subscripts denoting the channel to which the data corresponds. For example, the sub band labeled L_1H_2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. This shows how a single level of decomposition is done. In practice, there is more than one decomposition performed on the processing image. Successive iterations are performed on the low pass coefficients from the pervious stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original signal energy, this iteration process yields better energy compaction. After a certain number of iterations, the benefits gained in energy compaction becomes rather negligible compared to the extra computational effort. Usually five levels of decomposition are used. A single level of decomposition with a symmetric-antisymmetric multi-wavelet is roughly equivalent to two levels of wavelet decomposition. Thus a 3–level multiwavelet decomposition effectively corresponds to 6-level scalar wavelet decomposition. The scalar wavelet transform gives a single quarter-sized sub band from the original larger sub band. The multi-level decomposition is performed in the same way. The multi-wavelet decomposition iterates on the low pass coefficients from the pervious decomposition. In the case of the scalar wavelets, the low pass quarter image is a single sub band. But when the multi-wavelet transform is used, the quarter image of low pass coefficients is actually a 2 x 2 block of sub bands (the LL_j sub bands in Fig. 6. Due to the nature of the preprocessing and symmetric extension method, data in these different sub bands becomes intermixed during iteration of the multiwavelet transform. The intermixing of the multiwavelet low pass sub bands leads to suboptimal results. Consider the multi-wavelets transform coefficients resulting from single-level decomposition. It can be readily observed that the 2 x 2 "low pass" block (upper left corner) actually contains one low pass sub band and three band pass sub bands. The L_1L_1 sub band resembles a smaller version of the original image, which is a typical characteristic of a true low pass sub band. In contrast, the L_1L_2, L_2L_1, and L_2L_2 sub bands seem to process characteristics more like those of high sub bands. Also only L_1L_1 sub band contains coefficients with a large DC value and a relatively uniform distribution. The L_1, L_1, H_1 and H_2 sub bands, measured along the vertical direction.

IV. SIMULATION RESULT

This section represents the performance evaluation of the proposed approach. For the evaluation of the proposed system different images were tested as shown below. To test the accuracy of the developed approach, a color image with mean distortion is applied. To estimate the quality of a reconstructed image, the Root-Mean-Squared Error between the original and the reconstructed image is computed. The Root-Mean-Squared Error (RMSE) for an original image I and reconstructed image R defined by,

$$RMSE(I,R) = \sqrt{\frac{1}{I_w \times I_h} \sum_{i=0}^{Iw} \sum_{j=0}^{Ih} \left\| I(i,j) - R(i,j) \right\|^2}$$

To test the operation performance for developed system the PSNR for the system is evaluated under different medium distortion level. The coding robustness is evaluated over the level of distortion introduced at different level bit coding. To evaluate the process.



(a) (b)

(b) (d)

(e)

Figure 8: (a) Original sample, (b) Noised sample attacked with salt & pepper Noise at ρ =0.4, (c) filtered output after performing denoising using mean filtration, (d) Filtered output after performing median filtration, (e) Obtained result after filtration with proposed weighted filtration

The observation illustrates that the obtained visualization of the filtered result using weighted filtration is comparatively more accurate than the conventional filtration approach.

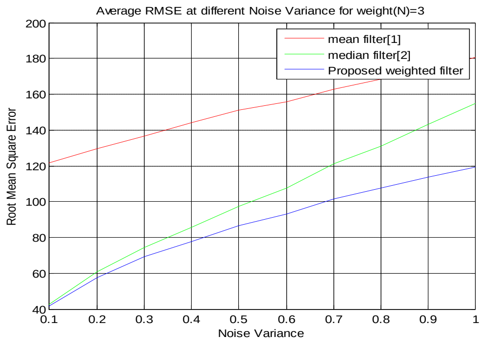


Figure 9: Average RMSE observation over variant Noise variance

Figure illustrates the obtained comparative analysis of the proposed weighted filtration approach over the conventional filtration technique. It is observed that the RMSE value for the proposed approach is decreased to about 40 units as comparative to the conventional approach.

(a) (b)

(c)

Figure 10: (a) filtered output using weighted filtration at N=2, (b) filtered output using weighted filtration at N=3, (c) filtered output using weighted filtration at N=4

It is observed that the obtained filtration is improved with the block size increment. At N=4 the obtained filtration is comparatively accurate.

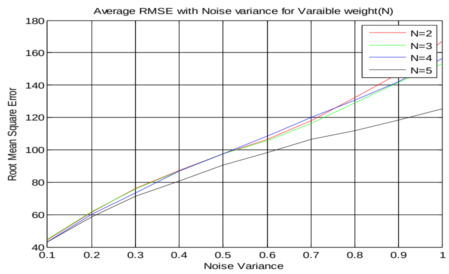


Figure 11: comparative average RMSE with the variation in noise level.

Figure shows the obtained comparative analysis after performing a block size variation. It could be observed that the RMSE value get minimized with the increase in the block size; at N=5 the obtained observation is minimum, hence an optimal N=5 value is chosen for the coding. A Similar observation is carried out over different samples and a comparative result for the developed method is as summarized in table 1.

Table 1: Observation for the obtained RMSE at different Noise variation

Noise Variance	Mean filter [1]	Median Filter [2]	Proposed weighted filter
0.1	125.5	67.23	43.5
0.2	123.5	67.1	43.11
0.3	121.4	66.4	42.23
0.4	120.1	65.7	41.71
0.5	119.2	65.4	41.4
0.6	117.9	64.32	40.3
0.7	116.2	62.8	39.6
0.8	114.5	61.44	38.3
0.9	113.3	60.7	37.2
1.0	110.3	60.33	36.1

The obtained observation illustrates an improvement of about 40 units in the obtained RMSE observation.

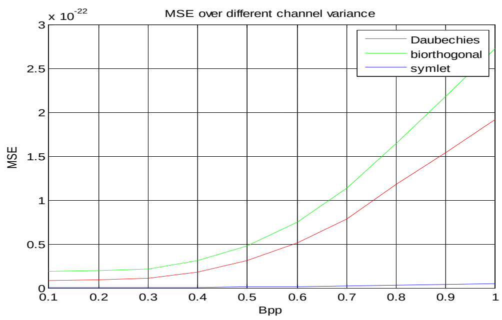


Figure 12: comparative analysis of different wavelet transformations at variable bpp.

Figure illustrates the comparatively analysis of multiple wavelet feasibility for developed method. It is observed that with the usage of symlet transformation the obtained MSE is lower.

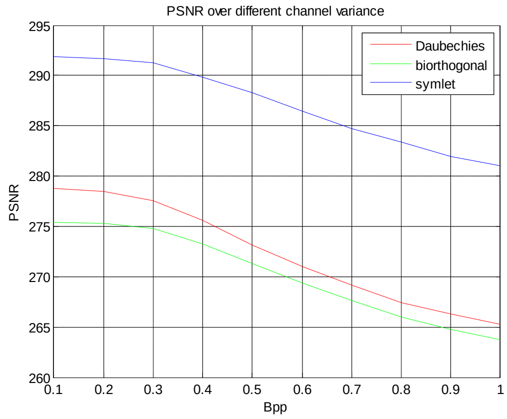


Figure 13: PSNR for different Bpp

The obtained PSNR value for different Bpp is developed. It is seen that higher bpp symlet transformation results in higher PSNR than the other transformation technique.

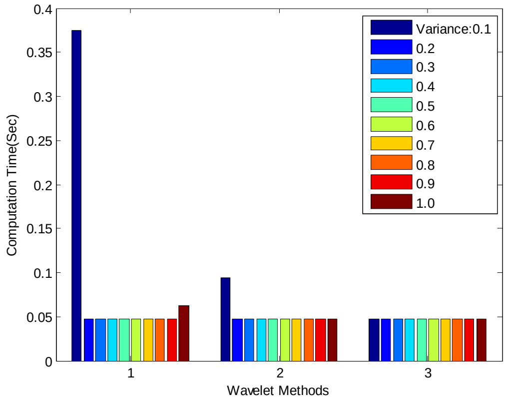
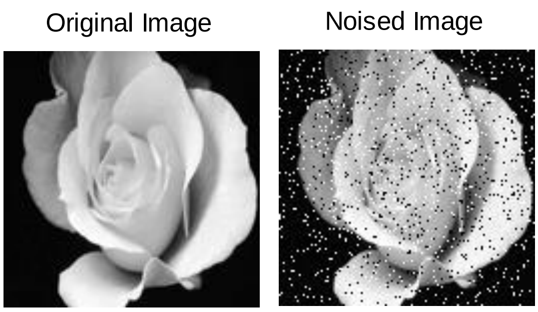


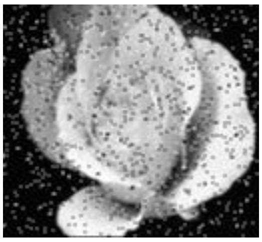
Figure 14: The computational time for the developed approach at different variance level

It is observed that the developed approach takes more time is computation due to higher noise value, whereas this time is reduced using symlet transformation.
A similar observation is carried out for other samples and the obtained observation is as shown,



(a) (b)

Mean filtered



(c)

Median Filtered

(d)

weighted filter

(e)

Figure 15: (a) Original Rose sample, (b) Noised sample attacked with salt & pepper Noise at ρ =0.4, (c) filtered output after performing denoising using mean filtration, (d) Filtered output after performing median filtration, (e) Obtained result after filtration with proposed weighted filtration

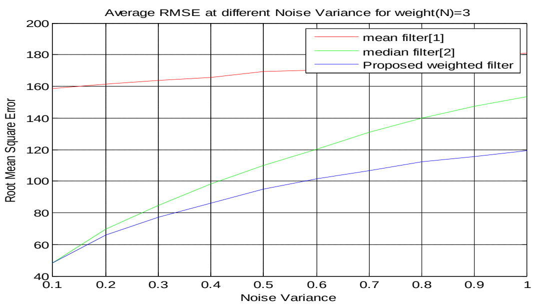


Figure 16: Average RMSE observation over variant Noise variance for the rose sample

weighted-Filtered at N=2

(a)

weighted-Filtered at N=3

(b)

weighted-Filtered at N=4

(c)

Figure 17: (a) filtered output using weighted filtration at N=2, (b) filtered output using weighted filtration at N=3, (c) filtered output using weighted filtration at N=4

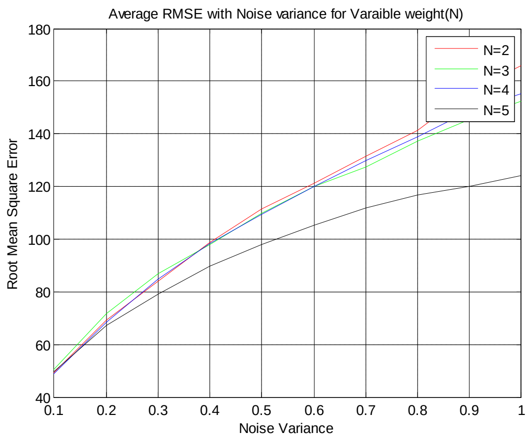


Figure 18: comparative average RMSE with the variation in noise level.

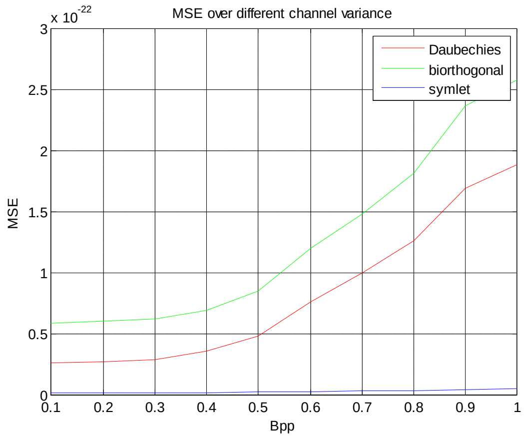


Figure 19: comparative analysis of different wavelet transformations at variable bpp

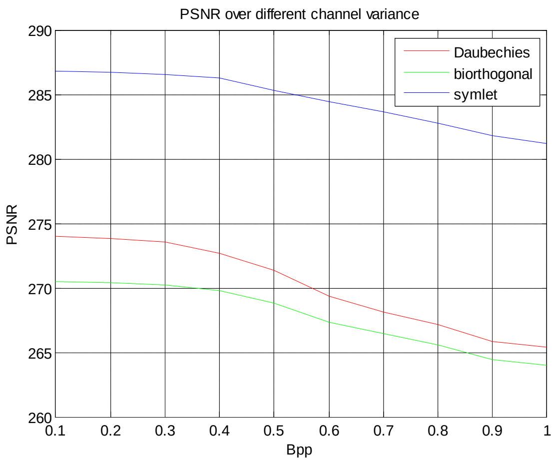


Figure 20: PSNR for different Bpp

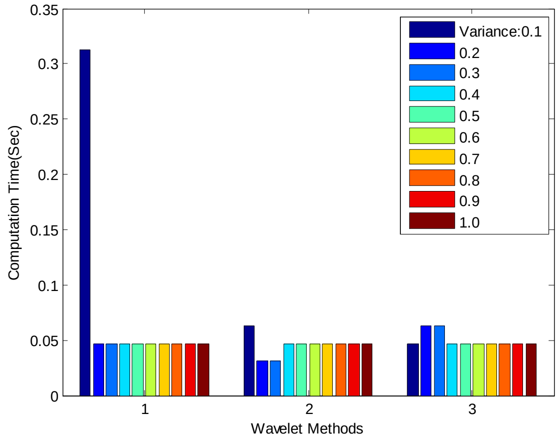


Figure 21: The computational time for the developed approach at different variance level

V. CONCLUSION

The image coding system proposed performance generally depends on weight value offered. Very-low-frequency content (ordinary images)usuallygives better performancefor images withscalarwavelet. However multiwavelets appear to excel at preserving high frequency content. In particular, multiwavelets capture the sharp edges and geometric patterns better that occur in images. With the incorporation of the proposed new coding approach of weighted multispectral coding an improvement of PSNR is achieved. This development leads to a new proposal in image coding architecture.

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