Quality assessment on digital images using parallel non-linear de-blocking model

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Abstract:-To achieve a non-linear de-blocking on digital images, a framework called Parallel Non-linear De-Blocking (PN-DB) is developed in this paper. The PN-DN framework is developed to reduce the blocking artifacts and therefore to increase the image quality. In PN-DB framework, Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT) performs multi scale histogram representation on digital images. The ASDL changes the sampling matrix into sub-regions of digital images and improves the performance of the lossy-to-lossless image coding application. In the ASDL scheme, a Sinc interpolation filter with constant coefficient is adopted to interpolate both straight and perpendicular direction of the digital image aiming to minimize prediction errors during coding results. Finally, lossy and lossless digital image coding results of the PN-DB framework are shown to validate the advantage of the proposed structure. The performance of the proposed framework is evaluated using The Manuscripts and Archives Digital Images Database (MADID). Simulations conducted with MADID show the performance improvement in image quality by minimizing prediction error during coding results that further reduced the blocking artifacts in an extensive manner.

Keywords: Multimedia, Non-linear de-blocking, Artifacts, Adaptive Structures, Directional Lifting, Discrete Wavelet Transform, Sinc interpolation filter

1 Introduction

Computer is becoming more and more powerful with the rapid use of digital images. Besides, the latest growth of data intensive multimedia based applications has put many demands on the researchers to discover the way of using the images in the applications more effectively. Over the past years, various representation systems for quality assessment on digital images governed by mathematical and algorithmic framework have been proposed. However, the most common shortcomings of these methods are the lack of non-linear de-blocking of artifacts over multiple scales.

With the increasing use of digital images, the serious issue of encoding and decoding huge volume of images, the uncompressed encoded multimedia (i.e.,) graphics, audio and video images necessitate a significant storage capacity and transmission bandwidth. Many research works has been contributed towards improving the image quality. Quality Assessment of Deblocked Images (QA-DI) [1] presented a block sensitive index with the objective of reducing the noise ratio and there improving the image quality. On the other hand Images as Occlusions of Textures (IOT) [2] presented a flexible segmentation framework with aiming at improving the image quality for image processing applications using local histograms. The other method called, Minimum Description

Length (MDL) [3] was designed for multidimensional signal with aiming at improving the lossless image coding.

With the significant need in the improvement of image quality mushroom growth of quality assessment tools has been designed. Quality evaluations tools using Mechanical Band Meter (MBM) [4] was presented with the objective of improving the quality of images. Another tool using Scalable Video Coding (SVC) [5] approach was presented aiming at improving the coding efficiency using Structural Similarity Index (SSI).

In recent years, methods uses digital image database to reconstruct high-resolution digital images from its low-resolution (LR) counterpart that have achieved great success. In [6], a New Face Hallucination framework was presented using Local Pixel Structure to Global Image Super Resolution (LPS-GISR). In [7], Spatial Sparsity Induced Prediction (SSIP) method was designed to improve the prediction optimal decompositions involving images and video frames. A Maixmum Likelihood Method (MLM) was presented in [8] to improve image quality of both omni directional images and multi view feature matching. Two regularization strategies called, Landweber iteration and non expansive mappings was presented in [9] with the objective of reducing the image deblurring. Image resolution enhancement using Stationary Wavelet Transform (SWT) was presented in [10] with the objective of reducing the error rate.

In past few years, increasing interest in biometric evaluation systems security has resulted in the numerous and very diverse initiatives on this major field of research. Image quality assessment of fake biometric detection was presented in [11] which provided an improved image quality. An Internal Generative Mechanism (IGM) [12] was designed for image quality assessment (IQM) with the objective of improving the overall quality score. A novel method for lossless discrete color images was designed in [13] with the objective of improving the compressed ratio. A review of binary compressed imaging was presented in [14]. Image quality assessment based on visual codebook was presented in [15] using No Reference Image Quality Assessment (NRIQA) algorithm. A survey on subjective and objective quality of assessment of images was presented in [16].

In this paper, we proposed a simple yet effective non-linear de-blocking on digital images based on Parallel Non-Linear based De-Blocking framework. The main contributions of this paper are as follows: (1) An ASDL based Discrete Wavelet Transform aiming at reducing the blocking artifacts and therefore improve the image quality using ADSL algorithm is constructed; (2) Optimal direction and optimal direction decision are computing using distortion rate and predefined rate of bits for several digital images using sampling matrix to improve the image quality; (3) Finally, Constant Coefficient-based Sinc Interpolation Filter is demonstrated that emphasis on minimizing the prediction errors.

The rest of the paper is organized as follows. Section 2 discusses the related work. Section 3 presents Parallel Non-linear De-Blocking (PN-DB) framework. The experimental results and analysis are provided in Section 4, and, finally, conclusions are drawn in Section 5.

2 Related Researches

During the past decades, Most of the researches have been developed for improving the image quality assessment. For example, yadong Wu et al. presented a method called Perceptual Image Quality Assessment (PIQM) based on Total Variation (TV) with the objective of improving the image quality assessment measures in [17]. Shanshan Wang et al. developed a Simple quality assessment for stereoscopic image that based on gradient magnitude similarity in [18]. Jiheng Wang et al. designed a novel method [19] that used normalized based pooling scheme to eliminate the prediction bias leading to significant improvement of quality prediction. Yuming Fang et al. employed a Support Vector Regression (SVR) [20] to reduce the distortion in images using Human Mean Opinion Score (HMOS).

Guo-Cheng Yang et al. introduced a novel exposure fusion method based on the nonsubsampled contourlet transform (NSCT) [21] to remove the motion objects in dynamic scenes. Hiroko Furuya et al. investigate the performance of the Wiener filter in the frequency domain [22] for image restoration which results in improved image quality. Roumen Kountchev et al. designed a non-linear still image representation method [23] based on Inverse Difference Pyramid (IDP) with Neural Networks (NN) for better visual image quality. Hieu V. Dang et al. introduced a logo data hiding method [24] for colour images to maximize the quality of watermarked image. Xu Hong presented a novel method [25] for compressed sensing MRI (CS-MRI) based on discrete shearlet transform for improving the quality of reconstructed image and preserving more information about texture and edge.

In addition, most of the researches have been developed for removing block artifacts in images. For example, Reza Pourreza-Shahri et al. designed an optimization method [26] to reduce blocking artifacts in JPEG images by means of utilizing the image gradient information. Kawaldeep Singh Randhawa et al. introduced a new post-processing algorithm [27] based on signal adaptive filtering for removing the blocking artifact in JPEG compressed images. Simon Tongbram et al. presented a de-blocking algorithm [28] in DCT domain that significantly reduces block artifacts while preserving edge and texture information as much as possible. An Adaptive post filtering algorithm was designed in [29] to remove coding artifacts in block-based DCT compressed medical images. An image compression technique with DCT and quantization method [30] reducing the blocking artifacts in reconstruction.

3 Design of Parallel Non-linear De-Blocking (PN-DB)

In this section, the detailed structure of Parallel Non-linear De-Blocking (PN-DB) framework is constructed. The PN-DB framework is split into three parts. The first part in PN-DB framework constructs an Adaptive Structures Directional Lifting with Discrete Wavelet Transform aiming at minimizing the blocking artifacts. The second part in PN-DB framework uses Direction Aligned Optimal Decision model with the objective of improving the performance of image coding application. Finally, the design of Constant Coefficient-based Sinc Interpolation Filter is designed to minimize the prediction error during coding results. The elaborate description of PN-DB framework is described as given below.

3.1 Adaptive Structures Directional Lifting

The Adaptive Structures Directional Lifting is performed in digital images in order to reduce the blocking artifacts and to increase the image quality. Parallel Non-Linear artifacts are visible all over the digital image in varying degrees of strength, and all the reconstructed digital images uses the PN-DB framework. In PN-DB framework, Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT) performs multi scale histogram representation on digital images.

The prevalent two-dimensional image using lifting method employs neighboring pixels in either horizontal or vertical direction for quality assessment. However, if the digital two-dimensional edges are neither horizontal nor vertical, the proposed ASDL model aligns the direction of wavelet transform to the direction of the edges. The proposed PN-DB framework integrates the DWT in the direction of the edges with the idea of performing directional lifting-based implementation.

In order to ensure direction other than horizontal and vertical attributes, the proposed PN-DB framework uses Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT), aiming at reducing the blocking artifacts. This is attained by applying direction prediction into the prevalent lifting method, resulting in the Adaptive Structures Directional Lifting (ASDL) based Discrete Wavelet Transform. The block diagram of

ASDL based Discrete Wavelet Transform is shown in below figure.

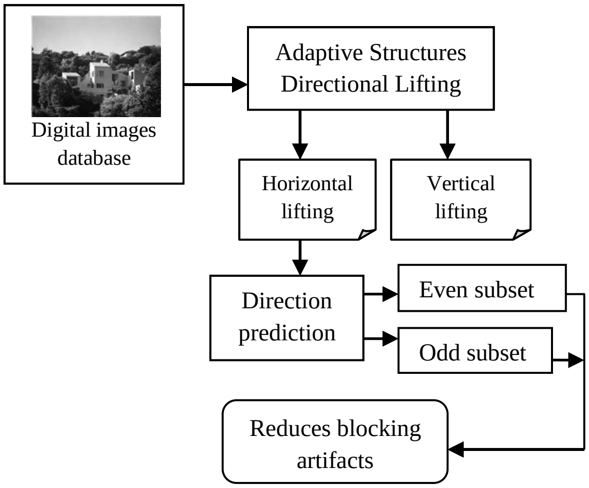

Fig.1 Block diagram of ASDL based Discrete Wavelet Transform

As shown in the fig.1, input digital image is obtained from Manuscripts and Archives Digital Images Database (MADID). In addition to horizontal and vertical lifting, the Adaptive Structures Directional Lifting performs the direction prediction based on the even and odd subset on two-dimensional image, aiming at reducing the blocking artifacts.

The ASDL based DWT involves separate directional (i.e. horizontal or vertical) lifting. Let a digital image '$DI_i = DI_1, DI_2, \ldots, DI_n$' be represented as a two-dimensional image '$a(i,j)$' that is split into even subset '$a_e(i,j)$' and odd subset '$a_o(i,j)$'. Therefore the mathematical formulation of even subset and odd subset is as given below.

$$a_e(i,j) = a(2i,j) \quad (1)$$

$$a_o(i,j) = a(2i+1,j) \quad (2)$$

From (1) and (2), the two-dimensional image '$a(i,j)$' is split into even subset 'a_e' and odd subset 'a_o'. In order to predict the odd subset '$a_o(i,j)$' in a two-dimensional image, the neighbouring event subset '$a_e(i,j)$' is used which is formulated as given below.

$$Predict\left(a_o(i,j)\right) = \sum_k a_e(2i,j) \quad (3)$$

However, in the predict step '$Predict$', the odd subset '$Predict$' is predicted from the neighbouring even subset '$a_e(2i,j)$' with an optimal direction. Subsequently, the predict operator is performed on the basis of an aligned optimal direction in ASDL based DWT and referred to as Direction Aligned Optimal Predict (DAOP). The DAOP function is mathematically formulated as given below.

$$DAOP\left(a_e(i,j)\right) = \sum_k AOD_{2i+1 \rightarrow 2i+k} * \left(a_o\,(i+k,j)\right) \quad (4)$$

From (4), the Direction Aligned Optimal Predict function '$DAOP$' is evaluated on the basis of aligned optimal direction 'AOD'. This is in turn performed through the odd subset 'a_o' that is predicted from neighbouring even subset 'a_e' with an optimal direction flowing from '$2i+1$' to '$2i+k$'. The block diagram of ASDL algorithm is described as follows.

Input: Digital image '$DI_i = DI_1, DI_2, \ldots, DI_n$', two-dimensional image '$a(i,j)$',
Output: Reduced block artifacts
Step 1: Begin Step 2: For each Digital image 'DI_i' Step 3: For each two-dimensional image '$a(i,j)$' Step 4: Measure even subset using (1) Step 5: Measure odd subset using (2) Step 6: Perform predict function using (3) Step 7: Perform DAOP function using (4) Step 8: End for Step 9: End for Step 10: End

Fig .2 ASDL algorithms

Fig.2 shows the ASDL algorithm aiming at reducing the blocking artifacts. For each digital two-dimensional image, in addition to horizontal and vertical lifting, the ASDL algorithm based on Discrete Wavelet Transform performs even and odd subset based on the neighbouring pixels. The resultant value is applied to the predict function to predict with an optimal direction. Finally, Direction Aligned Optimal Predict function is performed on aligned optimal direction aiming at reducing the blocking artifacts.

3.2 Design of Direction Aligned Optimal Decision

The ASDL changes the sampling matrix into sub-regions of digital images and improves the performance of the lossy-to-lossless image coding application. For the image coding application, the Direction Aligned Optimal Decision is presented in the proposed framework, PN-DB. The decision regarding optimal direction is performed based on the high pass subband. The result of Direction Aligned Optimal Predict function '$DAOP$' function is provided as the input to the sampling matrix. The block diagram of Direction Aligned Optimal Decision model is illustrated in following figure.

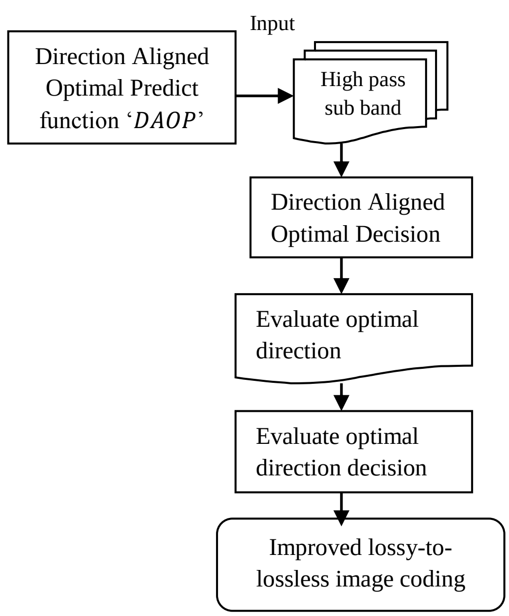

Fig.3 Block diagram of Direction Aligned Optimal Decision model

As shown in the fig.3, the result of Direction Aligned Optimal Predict function '$DAOP$' is applied as input to the high pass subband with aimed at improving the lossy-to-lossless image coding. To achieve this, a direction aligned optimal decision is made by evaluating the optimal direction. Accordingly, the optimal direction decision is made on the basis of the distortion and predefined rate of bits.

Let us consider the sampling matrix '$Mat_s, where\ s = (0, 1, 2, 3, 4, 5, 6)$'. Then, the high pass subband components are defined as 'HH_s'. The Direction Aligned Optimal Decision '$Dir\ (i, j)$' is selected in such a way that it improves the performance of the lossy-to-lossless image coding application of '$HH_s\ (i, j)$'. Then, the optimal direction is mathematically formulated and as given below.

$$Dir\ (i, j) = \mathrm{Min}_s\big(\ HH_s\ (i, j)\big) \quad (5)$$

With the objective of improving the performance of the lossy-to-lossless image coding application, the proposed framework PN-DB does not assigns the direction information of the pixels but the block information of the digital image in the form of sampling matrix 'Mat_s' is divided by the quad tree decomposition. The quad tree 'T' is constructed by applying the quad tree decomposition to the sampling matrix 'Mat_s'. The process of decomposition is performed until the defined block size is reached. Let us consider a subtree 'Sub_T', with distortion 'Dis_{Sub}' with predefined rate of bits '$Rate_{Sub}$' respectively. Then, the optimal direction decision is expressed as given below.

$$Sub'_T = Min\ [Sub_T(Dis_{Sub} +\ Rate_{Sub})\ (6)$$

$$Dis_{Sub} = HH_\alpha\, s(i, j) \quad (7)$$

$$Rate_{Sub} = rcoeff(\alpha) +\ rcod(\alpha) \quad (8)$$

From (6), (7) and (8), 'α' represents a node in sampling matrix of subtree 'Sub_T', whereas '$rcoeff$' and '$rcod$' is defined as rate of coefficient and coding side information of node 'α' respectively. In this way, the performance of the lossy-to-lossless image coding application is improved in a significant manner using

Direction Aligned Optimal Decision. Fig.4 shows the Direction Aligned Optimal Decision (DAOD) algorithm.

Input: Sampling matrix 'Mat_s', quad tree 'T', subtree 'Sub_T', Distortion 'Dis_{Sub}' Predefined bit rate '$Rate_{Sub}$', rate of coefficient '$rcoeff$', node 'α', coding side information '$rcod$', block size 'n'
Output: Improvised image coding results
Step 1: Begin Step 2: For each sampling matrix 'Mat_s' Step 3: Repeat Step 4: Perform Direction Aligned Optimal Decision using (5) Step 5: Perform optimal direction decision using (6) Step 6: Until (block size is reached) Step 7: End for Step 8: End

Fig. 4 Direction Aligned Optimal Decision (DAOD) algorithm

As shown in the fig.4, the Direction Aligned Optimal Decision (DAOD) algorithm performs two important steps to attain improvised image coding results. For each sampling matrix, the first step is to perform the Direction Aligned Optimal Decision function based on the high pass subband components. The second step is to obtain the optimal direction decision using the distortion rate of the subtree and predefined bit rate. These two steps are performed until a predefined block size is reached resulting in the improved image coding results.

3.3 Design of Constant Coefficient-based Sinc Interpolation Filter

In the ASDL scheme, a Constant Coefficient-based Sinc Interpolation Filter is applied in PN-DB framework to interpolate both straight and perpendicular direction of the digital image by minimizing prediction errors during coding results. With the objective of reducing the prediction errors during coding results, Constant Coefficient-based Sinc Interpolation Filter is applied for each individual image.

Since the straight and perpendicular direction can be approximated as linear edges, it assumes that the neighboring pixels are highly correlated with the pixel between them. Therefore, in order to identify the best direction, a direction error 'Dir_e' between the odd subset and the weighted functions of even subset is used as the distortion measure for estimating the direction. Then, the direction error 'Dir_e' is mathematically formulated as given below.

$$Dir_e(O) = a_o(i,j) - [Sub'_T(a_e)] \quad (9)$$

$$Dir_e(E) = a_e(i,j) - [Sub'_T(a_o)] \quad (10)$$

From (9) and (10), the direction error for odd subset '$Dir_e(O)$' and even subset '$Dir_e(E)$' is formulated aiming at reducing the prediction errors in a significant manner. Finally, lossy and lossless digital image coding results of the PN-DB framework are shown to validate the advantage of the proposed structure.

4 Experimental Results and Analysis

Parallel Non-linear De-Blocking (PN-DB) framework is developed in MATLAB platform. The PN-DB framework uses the Manuscripts and Archives Digital Images Database (MADID) that includes digital images in the form of photographs, posters, drawings, text documents, and other images obtained from the research collections of Manuscripts and Archives, Yale University Library. The MADID includes manuscript group number followed by collection name that includes a title, image number, original material, copyright holder, description, manuscript group name, manuscript box number, folder number, folder name, file name and so on.

This MADID was obtained from Manuscripts and Archives, Yale University Library. By using digital images from MADID database, the defined testing method results are compared with existing method. The PN-DB framework is compared with the existing Quality Assessment of Deblocked Images (QA-DI) [1] and Images as Occlusions of Textures (IOT) [2] methods. The experiment is conducted on factors such as blocking artifacts, lossy-to-lossless image coding and prediction errors with respect to different digital images.

The Blocking Artifacts gains significant improvement in the separation between blocking noise, image features and effective reduction of image blurring. The proposed PN-DB framework measures the blocking artifacts by obtaining the sum of the even and odd subset and subtracting it with the actual digital image size. The framework PN-DB yields better performance in terms of both objective and subjective views than the existing QA-DI and IOT. The mathematical formulation of evaluating the blocking artifacts is as given below.

$$BA = Digital\ image\ size - [a_e(i,j) + a_o(i,j)] \quad (11)$$

From (11), the blocking artifacts 'BA' is measured (in terms of percentage) using the even subset 'a_e' and odd subset 'a_o' respectively. The image coding results is measured by summing the distortion rate with the predefined rate of bits for each digital image. The mathematical formulation of image coding results is measured as given below.

$$IC = (Dis_{Sub} + Rate_{Sub}) \quad (12)$$

From (12), the image coding result 'IC' is obtained using the distortion rate 'Dis_{Sub}' and predefined rate of bits for each digital images '$Rate_{Sub}$' respectively. Lower the image coding results more efficient the method is said to be. It is measured in terms of bits per pixel (bpp).

The prediction error measures the expected squared distance between what the predictor predicts for a specific value and what the true value is. The mathematical formulation for prediction error is measured as given below.

$$Prediction_e = (Actual_e - Dir_e)^2 \quad (13)$$

From (13), the prediction error '$Prediction_e$' is obtained using the true value '($Actual_e$' and predictor prediction rate for a specific value 'Dir_e' respectively.

4.1 Impact of blocking artifacts

The table 1 represents the blocking artifacts obtained using MATLAB simulator and comparison is made with two other methods, namely QA-DI [1] and IOT [2].

Table 1. Tabulation for blocking artifacts

Digital image size (MB)	Blocking artifacts (MB)		
	PN-DB	QA-DI	IOT
512	95	135	149
605	105	145	160
628	125	165	180
739	149	189	204
812	140	180	185
934	152	192	209
985	165	205	215

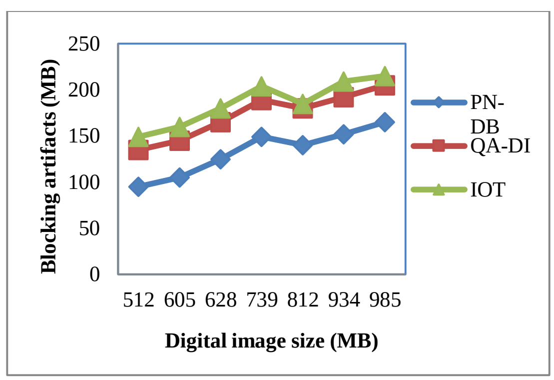

Fig.5 Measure of blocking artifacts

Fig.5 shows the measure of blocking artifacts using PN-DB framework, QA-DI [1] and IOT [2] respectively. As shown in the figure, the proposed PN-DB framework provides lower blocking artifacts when compared to QA-DI [1] method and IOT [2] method. This is because of the application of Adaptive Structures Directional Lifting in PN-DB framework. The Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT) evaluates the direction prediction based on the even subset and odd subset present in digital images in an efficient manner. By applying Direction Aligned Optimal Predict (DAOP) function to the even and odd subset, the blocking artefact is reduced by 31.16% as compared to QA-DI and 41.44% as compared to IOT respectively.

4.2 Impact of image coding results

The image coding results involved while obtaining the lossless image is presented in table 2 with respect to 7 digital images obtained from MADID database with image number differing from 45188 to 45261. For different image number, the image coding results also differ in a significant manner.

Table 2. Tabulation for image coding results

Image number	Lossless (bpp)		
	PN-DB	QA-DI	IOT
45188	4.35	5.13	6.55
45189	7.16	8.34	10.44
45202	10.35	11.53	13.63
45205	14.23	15.41	17.51
45208	18.32	19.50	21.60
45215	21.39	22.57	24.67
45261	24.75	25.93	27.03

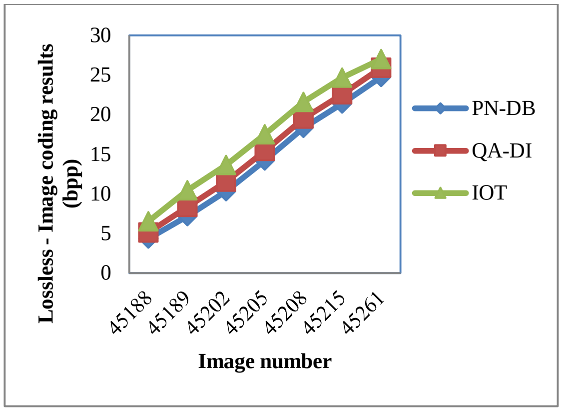

Fig.6 Measure of image coding results

To ascertain the performance of the image coding results, comparison is made with two other existing works Quality Assessment of Deblocked Images (QA-DI) [1] and Images as Occlusions of Textures (IOT) [2]. In fig.6, the number of images with image number varied between 45188 and 45261. From the figure it is illustrative that the image coding results is lowered or decreased using the proposed PN-DB framework when compared to the two other existing works. This is because with the application of Direction Aligned Optimal Decision model, the PN-DB decides the optimal direction based on the high pass subband and therefore improves the image coding results by 10.11% when compared to QA-DI [1] method. Furthermore, by obtaining the optimal direction decision for each digital image, that does not assigns the direction information to the pixels but the block information of the digital image and therefore improves the image coding results by 27.65% than when compared to IOT [2] method.

4.3 Impact of prediction errors

The comparison of prediction errors is presented in table 3 with respect to different image numbers. Depending on the images, the prediction error either increases or decreases but found to be reducing using the proposed PN-DB framework.

Table 3. Tabulation for prediction error

Image number	Prediction error (dB)		
	PN-DB	QA-DI	IOT
45188	7.48	10.32	13.15
45189	10.23	12.14	15.19
45202	17.39	18.14	25.89
45205	22.36	27.14	32.15
45208	29.36	32.15	38.39
45215	25.76	28.93	31.32
45261	21.35	26.14	29.15

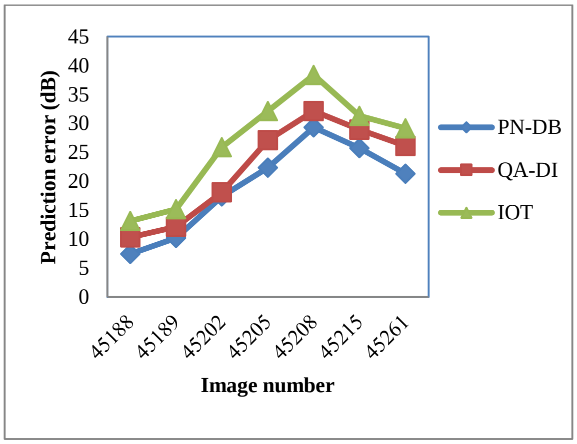

Fig.7 Measure of prediction error

In fig. 7, we depict the prediction error attained using 7 different digital images extracted from MADID database for experimental purposes using MATLAB. From the figure, the value of prediction error achieved using the proposed PN-DB framework is higher when compared to two other existing methods QA-IT [1] and IOT [2]. At the same time, the prediction error rate obtained is not directly proportional to the images as different image possess varied image sizes. Though the prediction error increases rapidly for different digital images, comparatively, by applying PN-DB framework, the PSNR rate is observed to be better when compared to all the other methods. This is because of the application of Constant Coefficient-based Sinc Interpolation Filter that interpolates both straight and perpendicular direction of the digital image. This in turn minimizes the prediction error during coding results using PN-DB framework by 18.04% when compared to QA-IT [1]. At the same time, the direction error 'Dir_e' between the odd subset and the weighted functions of even subset is applied for each digital image to measure the value of distortion that reduces the prediction error in PN-DB framework by 43.64% when compared to IOT [2].

4.4 Impact of image quality

The impact of image quality for PN-DB framework is elaborated in table 4 and comparison made with two other methods QA-DI and IOT respectively. We consider the method with 7 images with varying sizes in the range of 512MB to 985MB for experimental purpose using MATLAB.

Table 4. Tabulation for image quality

Methods	Image quality (%)
PN-DB	71.39
QA-DI	62.14
IOT	59.13

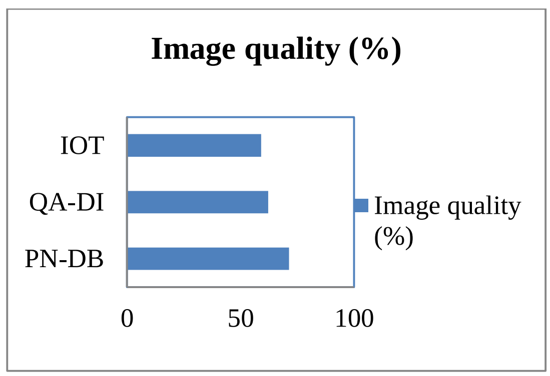

Fig. 8 Measure of image quality

Table 4 and fig. 8 shows the measure of image quality with respect to seven images obtained from MADID database and comparison is made with the two existing methods QA-DI [1] and IOT [2] respectively. From the figure it is evident that the image quality rate is improved using the proposed PN-DB framework when compared to two other methods [1] [2]. This is because of the application of ASDL and Direction Aligned Optimal Decision (DAOD) algorithm that obtain the optimal direction decision using the distortion rate of the subtree and predefined bit rate. This in turn improves the image quality rate in PN-DB framework by 12.95% when compared to QA-DI [1]. Furthermore, Direction Aligned Optimal Predict function is performed on aligned optimal direction that in turn improves the image quality rate using PN-DB framework by 4.84% when compared to IOT [2].

5 Conclusion

In this work, an effective framework called Parallel Non-linear De-Blocking (PN-DB) is presented. The framework improves the performance of the lossy-to-lossless image coding application with digital images given as input and prediction errors during coding results. The goal of Parallel Non-linear De-Blocking is to reduce the blocking artifacts and therefore to improve the image quality using the digital images extracted from MADID database which significantly contribute to the relevance. To do this, we first designed an Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT) that measures the blocking artifacts and the image quality based on the ASDL algorithm for MADID digital images. Then, based on this measure, we proposed a Direction Aligned Optimal Decision model for improving the image coding applications and therefore reducing the prediction error in an extensive manner. In addition Direction Aligned Optimal Decision model measures the Direction Aligned Optimal Predict function that is applied as input to the high pass subband and therefore ensures imaging coding results for both lossy and lossless applications. Through the simulations carried out using MATLAB, we observed that the digital images that also reduced prediction error during the coding results compared to existing methods. The results show that PN-DB framework offers better performance with an improvement of image quality by 8.90% and reduces the blocking artifacts by 36.30% when compared to state of the art works.

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