Denoising Based Nonlinear Image Quality Enhancement on Digital Images

D. Ferlin Deva Shahila, S.H. Krishnaveni

Abstract— ***The use of computer is more powerful in digital images (DI). Enhancement of image quality (IQ) and the sharpness are the linked tasks to be performed. Besides, the latest growth of data intensive multimedia based applications put many demands on researchers to discover usage of the images in the applications. Over the past years, various representation systems for quality assessment on DI governed by mathematical and algorithmic framework have been proposed. However, the most common shortcomings of these methods are the lack of non-linear denoising artifacts over multiple scales. To accomplish non-linear noise eradication on DI, a Denoising based Nonlinear image quality Enhancement (DNIQE) is developed. DNIQE framework lessens the noise artifacts to enhance IQ. In DNIQE k, Adaptive Structures Directional Lifting (ASDL) with Discrete Wavelet Transform (DWT) presents multi scale histogram representation on DI. ASDL modifies sampling matrix into sub-regions of DI and enhance the performance of lossy-to-lossless image coding application. A Sinc interpolation filter with constant coefficient is considered in ASDL scheme to interpolate both straight and perpendicular direction of DI to lessen prediction errors in coding results. At last, lossy and lossless DI coding results of DNIQE framework is shown to validate the advantages of proposed structure. The proposed framework is estimated using Manuscripts and Archives digital images Database (MADID). The result analysis shows the performance improvement in IQ by enhancing PSNR during coding results which lessens noising artifacts in extensive manner.***

Keywords — **Multimedia, Non-linear denoising, Artifacts, Directional Lifting, Discrete Wavelet Transform, Sinc interpolation filter**

I. INTRODUCTION

With the increasing use of DI, the encoding and decoding huge volume of images issues, the uncompressed encoded multimedia requires a large storage capacity and transmission bandwidth. Many research works has been designed for improving the IQ. In [2], Dual Tree Complex Wavelet Transform (DTCWT) was presented to enhance better accuracy and smoothness accuracy than DWT and redundant than SWT. But, IQ was improved to the required level after denoising. Quality Assessment of Deblocked Images (QA-DI) [5] designed a block sensitive index for reducing the noise ratio results in improving the IQ. In [8], Images as Occlusions of Textures (IOT) presented a flexible segmentation framework to enhance IQ for image processing applications.

In [1], denoising and contrast enhancement of digital X-ray images (DCE-DI) was presented the patch-based filter is exploited to noise corrupting X-ray images. Filtered images are exploited as oracles to illustrate non parametric noise control maps utilized in multiscale contrast enhancement framework to increase trade-off among enhancement of visibility of anatomical structures and noise reduction. However, IQ was not enhanced. A twofold processing algorithm [3] is planned for minimizing the multiplicative speckle noise. The first fold is denoising technique used for minimizing the speckle and for increasing the object blurring. Second fold instigates to re-establish object boundaries and texture with adaptive wavelet fusion. However, the noise is not reduced in input image. In [4], an objective stereo IQA (OSIQA) model was designed using matrix decomposition and structure information distortion of the image for IQ. Though, the model needs additional enhancement in the noise removal.

Multi-exposure image fusion (MEF) [7] is exploited as efficient quality enhancement technique in consumer electronics to perceptual quality estimation of multi-exposure fused images. But, quality estimation of MEF images for other image fusion applications is lacking. It includes images united from multi-focus images in photography applications. To forecast gamut-mapping distortions, Color-image-difference (CID) metric is introduced in [6]. An algorithm is designed to enhance gamut mapping with CID metric as key function. Images include numerous visual artifacts addressed through many modifies presenting improved CID (iCID) metric. Variation models depends on Higher Order Derivatives (Variation-HOD) in [10] lessens curvature of each level lines in DI. An efficient minimization algorithm depends on graph cuts does not have precise relationship on gradient flow. To optimize huge class of transform-domain thresholding algorithms, PURE-LET was introduced in [9] for denoising images lessens the quality via mixed Poisson–Gaussian noise.

II. RELATED WORKS

Support Vector Regression (SVR) was used in [11] to minimize the distortion in images by Human Mean Opinion Score (HMOS). Stereoscopic IQ assessment (IQA) is presented in [12] to estimate qualities of 3D images which include similar opinion with human results. To offer quality estimation derived from properties of human visual system, the stereoscopic IQA algorithms describe 2D IQA algorithms on stereoscopic observations, disparity maps,

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and/or cyclopean images. Simple quality assessment for stereoscopic image was presented in [13] based on gradient magnitude similarity. The method [14] used normalized based pooling scheme to eliminate the prediction bias results in the improvement of quality prediction. However, IQ was not at required level.

With the significant need in the improvement of IQ mushroom growth of quality assessment tools has been designed. Quality evaluations tools using Mechanical Band Meter (MBM) [16] was presented with the objective of improving the quality of images. The other method called, Minimum Description Length (MDL) [15] for multidimensional signal was planned for improving the lossless image coding. However, the noise level was not reduced in the image. A multiscale denoising algorithm [17] is used in broad noise model. It outcomes in blind denoising algorithm for real JPEG images and scans of old photographs for enlargement of model is unidentified. A method is introduced for quality measurement of multi-exposure multi-focus image fusion [18] derived from estimation of major factors of fused IQ. Though, quality of images generated by joining many images is not completely aligned with each other.

In the few years, enhancing interest in biometric evaluation systems security resulted in numerous and various initiatives on this foremost field of research. In [20], IQA of fake biometric detection was introduced to offer improved IQ. In [19], Dictionary Pair Learning on the Grassmann-manifold (DPLG) algorithm was introduced and is learned by subspace partition technique on Grassmann manifold where refined dictionary pair is achieved by sub-dictionary pair merging. DPLG accomplish a sparse representation via programming every image patch with chosen sub-dictionary pair. However, learning three-dimensional numerous dictionaries for video denoising and find out combination of numerous denoising and multi-dimensional sparse coding techniques are not carried out.

We introduced a efficient non-linear noise removal on DI based on DNIQE Framework. The foremost contributions of the paper is below: (1) An ASDL based DWT for minimizing the noising artifacts and enhances the IQ using ADSL algorithm is designed; (2) Exact direction and exact direction decision are computing using distortion rate and predefined rate of bits for many DI using sampling matrix to improve the IQ; (3) Finally, Constant Coefficient-based Sin Interpolation Filter is demonstrated that emphasis on lessens noise level. The rest of paper is ordered as follows. Section 2 presents DNIQE Framework. The experimental results with parametric definitions are provided in Section 3 and discussed in Section 4, and, finally, conclusions are drawn in Section 5.

III. DESIGN OF DNIQE

In this section, the detailed structure of DNIQE framework is constructed. The DNIQE framework is split into three parts. The first part in DNIQE framework constructs an ASDL with DWT for minimizing the noising artifacts. The second part in DNIQE framework uses DBEP model with the objective of improving the performance of image coding application. Finally, the third part involves the design of Constant Coefficient-based Sin Interpolation Filter that minimizes the prediction error during coding results. The elaborate description of DNIQE framework is described as given below.

III. ASDL

ASDL is performed in DI in order to minimize the noising artifacts and to increase the IQ. Parallel Non-Linear artifacts are visible all over the DI in varying degrees of strength and the entire reconstructed DI uses the DNIQE framework. In DNIQE framework, ASDL with DWT executes multi scale histogram representation on DI.

The prevalent two-dimensional image using lifting method exploits neighboring pixels in horizontal or vertical direction for quality assessment. Though, if digital two-dimensional edges are not horizontal or vertical, the ASDL model aligns direction of wavelet transform to direction of edges. DNIQE framework unites DWT in the direction of edges for plan of executing directional lifting-based implementation.

In order to ensure direction other than horizontal and vertical attributes, the proposed DNIQE framework uses ASDL with DWT for minimizing the noising artifacts. This is attained by applying direction prediction into the prevalent lifting method, resulting in the ASDL based Discrete Wavelet Transform. Figure 1 portrays the block diagram of ASDL based DWT.

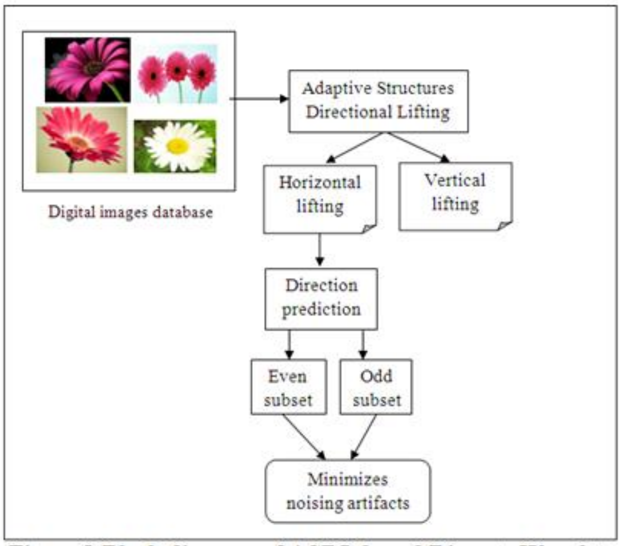

Figure 1 Block diagram of ASDL based Discrete Wavelet Transform

The input DI is attained from MADID. Besides horizontal and vertical lifting, the ASDL functions the direction prediction derived from even and odd subset on two-dimensional image for minimizing the noising artifacts.

The ASDL based DWT includes the separate directional (i.e. horizontal or vertical) lifting. Assume a DI is represented as '$I_i = I_1, I_2, \ldots, I_n$' and the two-dimensional image is denoted as '$d(i,j)$'. The two dimensional image is split into even subset '$d_{es}(i,j)$' and odd subset '$d_{os}(i,j)$'. The mathematical formulation of even subset and odd subset is as given by,

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$$d_{es}(i,j) = d(2i,j) \tag{1}$$

$$d_{os}(i,j) = d(2i+1,j) \tag{2}$$

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

$$Predict\left(d_{os}(i,j)\right) = \sum_k d_{es}(2i,j) \tag{3}$$

But, in predict step '$Predict$', the odd subset '$Predict$' is forecasted from neighbouring even subset '$d_{es}(2i,j)$' with optimal direction. The predict operator is performed on the basis of an aligned optimal direction in ASDL based DWT and referred to as Direction Based Exact Prediction (DBEP). The DBEP function is mathematically formulated as given below.

$$DBEP\left(d_{es}(i,j)\right) = \sum_k AOD_{2i+1\rightarrow 2i+k} * (d_{os}(i+k,j)) \tag{4}$$

From (4), the Direction Based Exact Predict function '$DBEP$' is evaluated on the basis of aligned optimal direction 'AOD'. This is executed through odd subset 'd_{os}' which is forecasted from neighbouring even subset 'd_{es}' with optimal direction flowing from '$2i+1$' to '$2i+k$'. Figure 2 shows the block diagram of ASDL algorithm.

Input: Digital image '$I_i = I_1, I_2, \ldots, I_n$', two-dimensional image '$d(i,j)$',
Output: Minimizes Denoised artifacts
Step 1: Begin Step 2: For all Digital image 'I_i' Step 3: For all two-dimensional image '$d(i,j)$' Step 4: Calculate even subset using (1) Step 5: Calculate odd subset using (2) Step 6: Execute predict function using (3) Step 7: Execute DBEP function using (4) Step 8: End for Step 9: End for Step 10: End

Figure 2 ASDL algorithm

The above figure shows the ASDL algorithm minimizes the denoising artifacts. For all digital two-dimensional images with horizontal and vertical lifting, the ASDL algorithm based on DWT executes even and odd subset based on the adjacent pixels. The resultant value is applied to the predict function to predict with an optimal direction. Finally, DBEP function is executed on exact direction for minimizing the noising artifacts.

III. DESIGN OF DBEP MODEL

ASDL modify the sampling matrix into sub-regions of DI and enhances the performance of lossy-to-lossless image coding application. For the image coding application, the DBEP is designed in DNIQE. The prediction in exact direction is executed based on the high pass subband. The result of DBEP '$DBEP$' function is presented as the input to the sampling matrix. Figure 3 demonstrates block diagram of DBEP model.

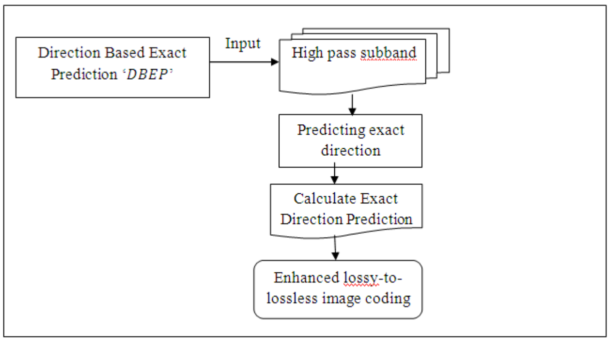

Figure 3 Block diagram of DBEP model

From figure 3, the result of DBEP function '$DBEP$' is used as input to the high pass subband for enhancing the lossy-to-lossless image coding. To attain this, DBED is created by choosing the exact direction. Consequently, the exact direction prediction is created because of the distortion and predefined rate of bits.

Let us consider the sampling matrix 'S_m, where $m = (0,1,2,3,4,5,6)$'. Next, high pass subband components are signified as 'HP_s'. DBEP '$D\ (i,j)$' is elect to enhance results of lossy-to-lossless image coding application of '$HP_s\ (i,j)$'. Then, the exact direction is mathematically designed and as given below.

$$D\ (i,j) = \mathrm{Min}_s\left(HP_s\ (i,j)\right) \tag{5}$$

With intention of enhancing the performance of lossy-to-lossless image coding application, the proposed DNIQE does not allocates direction information of pixels but block information of DI in form of sampling matrix 'S_m' is divided via quad tree decomposition. Quad tree 'T' is build via the quad tree decomposition to sampling matrix 'S_m'. The process of decomposition is performed until the defined block size is reached. Let us consider a subtree 'S_T', with distortion 'Dis_S' with predefined rate of bits 'R_S' respectively. Then, the exact direction prediction is expressed as given below.

$$S_T' = Min\ [S_T(Dis_S + R_S)] \tag{6}$$

$$Dis_S = HH_\alpha\, s(i,j) \tag{7}$$

$$R_S = rcoeff(\alpha) + rcod(\alpha) \tag{8}$$

From (6), (7) and (8), 'α' symbolizes a node in sampling matrix of subtree 'S_T', whereas '$rcoeff$' and '$rcod$' is described as rate of coefficient and coding side information of node 'α'. The performance of lossy-to-lossless image coding application is enhanced using Direction Aligned Optimal Decision. Figure 4 shows the Direction Based Exact Decision (DBED) algorithm.

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Input: Sampling matrix 'S_m', quad tree 'T', subtree 'S_T', Distortion 'Dis_S' Predefined bit rate 'R_S', rate of coefficient '$rcoeff$', node 'α', coding side information '$rcod$', block size 'n'
Output: Improvised image coding results
Step 1: Begin Step 2: For all sampling matrix 'S_m' Step 3: Repeat Step 4: Find Exact Direction using (5) Step 5: Execute exact direction prediction using (6) Step 6: Until (block size is attained) Step 7: End for Step 8: End

Figure 4 DBEP Algorithm

As shown in the figure, the DBEP algorithm performs two important steps to attain improvised image coding results. For each sampling matrix, the first step is to perform the DBEP function derived from the high pass subband components. The second step is to obtain the exact direction prediction by the distortion rate of the subtree and predefined bit rate. These two steps are performed until a predefined noise size is attained in the enhanced image coding results.

III. DESIGN OF CONSTANT COEFFICIENT-BASED SIN INTERPOLATION FILTER

In ASDL scheme, a Constant Coefficient-based Sin Interpolation Filter is exploited in DNIQE framework to interrupt both straight and perpendicular direction of DI via lessen prediction errors in coding results. For minimizing the prediction errors during coding results, Constant Coefficient-based Sin Interpolation Filter is applied for each individual image.

Since straight and perpendicular direction estimated as linear edges, it considers neighboring pixels are extremely correlated with pixel among them. To detect precise direction, a direction error 'DE' among odd subset and weighted functions of even subset is exploited as distortion measure to estimate the direction. Then, the direction error 'DE' is formalized as below.

$$DE(O) = d_{os}(i,j) - [S_T'(d_{es})] \quad (9)$$

$$DE(E) = d_{es}(i,j) - [S_T'(d_{os})] \quad (10)$$

From (9) and (10), the direction error for odd subset ' DE (' and even subset ' DE (' is planned for minimizing the prediction errors in essential way. Finally, lossy and lossless DI coding results of DNIQE verify the merits of proposed structure.

IV. EXPERIMENTAL SETTINGS

DNIQE framework is developed in MATLAB platform. DNIQE framework exploits MADID which include DI in the shape of photographs, posters, drawings, text documents, and another images acquired from research groups of Manuscripts and Archives, Yale University Library. MADID consist of manuscript group number followed by collection name 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. Through the DI from MADID database, the described testing method results are estimated with existing method. DNIQE framework is evaluated with DCE-DI [1] and Dual Tree Complex Thresholding Wavelet Transform and Wiener filter (DTCWT-WF) [2]. Experiment is performed on factors namely noise removal rate, PSNR, false positive rate (FPR) and prediction accuracy (PA) with dissimilar DI. DNIQE yields better performance than the existing DCE-DI and DTCWT-WF.

Noise removal is imperative in medical imaging applications to improve and recover fine details which may be hidden in data. Noise level in background of photo image is estimated and eradicates noise from that image using DNIQE framework. Noise of DNIQE framework is evaluated in decibel (dB).

$$Noise\ Removal\ Rate = 10\log_{10}(Input\ image\ signal - Noise) \quad (11)$$

The difference of input image signal and noise is calculated with logarithmic form to calculate the noise removal rate. IQ is feature of an image which estimates perceived image degradation. IQ describes quality enhancement on photo image after eradication of noise artifacts and IQ is measured in pixel rate.

From table 1, Peak Signal Noise Ratio (PSNR) value using DNIQE method is estimated. The digital data image size used in this experiment ranges from 10 MB to 70 MB. PSNR is evaluated in decibel (dB) which describes noise error rate based on image size. PSNR is acquired via mean squared error (MSE). Given a DI DI as input, with an image size of $a * b$, then the MSE using DNIQE is

$$MSE = \frac{1}{a\,b} \sum_{a=1}^{m-1} \sum_{b=1}^{m-1} (DI(a,b) - DI'(a,b)^2) \quad (12)$$

After that, PSNR using DNIQE method is ratio of greater possible pixel value of DI with that of mean squared error is acquired as below

$$PSNR = 10 * log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (13)$$

Where MAX represents the maximum possible pixel value and MSE represents mean square error. False Positive Error (FPE) represents incorrectly predicted artifacts on DI.

$$False\ Positive\ Rate = \frac{Incorrectly\ predicted\ artifacts\ on\ Image}{Number\ of\ Images} \quad (14)$$

FPR denoted in percentage (%).

IV. RESULTS ANALYSIS OF DNIQE

Proposed DNIQE is evaluated with DCE-DI [1] and DTCWT-WF [2].

IV.1.1 *Impact of PSNR*

Table 1 portrays PSNR acquired using MATLAB simulator and evaluated with (DCE-DI) [1] and (DTCWT-WF) [2]. The effectiveness of the proposed DNIQE method extensive experimental analysis is reported in table 1.

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Table 1 Tabulation for PSNR

Image Size (MB)	Peak Signal Noise Ratio (dB)		
	DCE-DI	DTCWT-WF	DNIQE Method
10	15.21	10.23	17.45
20	17.36	13.25	19.65
30	19.45	15.32	23.45
40	21.36	18.26	25.31
50	25.21	21.36	28.96
60	27.38	24.96	31.06
70	31.87	29.63	34.65

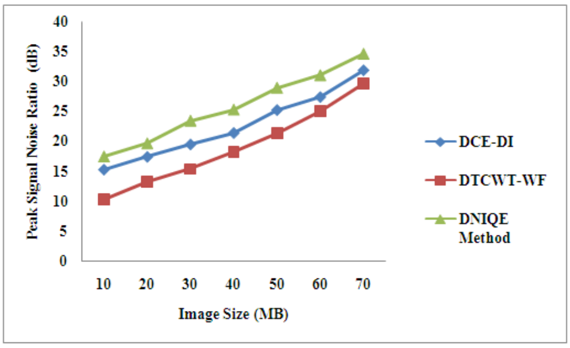

Figure 5 Measure of PSNR

Figure 5 describes the PSNR value of DNIQE method is estimated with DCE-DI [1] and DTCWT-WF [2]. The simulator MATLAB is used to experiment the factors and determine the result values with table and graph values. The performances are presented for different image sizes with the peak signal noise ratio. From the results, increase in the values of image sizes results in the increase in PSNR value, though the increase observed is not linear because of the image size. By applying DBEP function to the even and odd subset, the PSNR level is reduced by 12.85% compared to DCE-DI and 28.12% compared to DTCWT-WF respectively.

IV. IMPACT OF FALSE POSITIVE RATE

Table 2 portrays FPR acquired using MATLAB simulator and compared with DCE-DI [1] and DTCWT-WF [2]. The analysis of the proposed DNIQE method is reported in table 2.

Table 2 Tabulation for False Positive Rate

Number of Image (Number)	False Positive Rate (%)		
	DCE-DI	DTCWT-WF	DNIQE Method
10	11.26	15.61	8.34
20	15.36	19.34	11.25
30	19.01	24.96	13.68
40	23.85	27.54	14.63
50	25.69	30.01	17.32
60	28.12	34.59	21.63
70	32.63	38.69	24.96

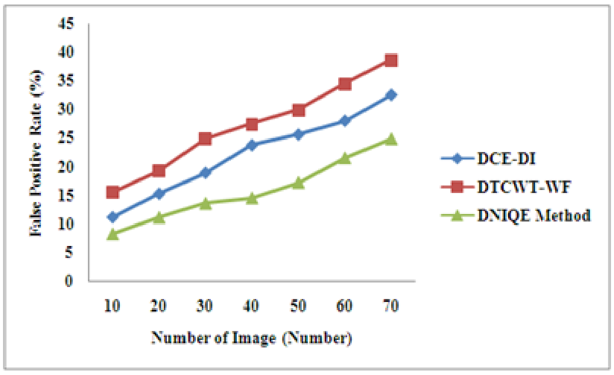

Figure 6 Measure of False Positive Rate

To verify the FPR results of DNIQE is estimated with two other existing works the DCE-DI [1] and DTCWT-WF [2] with number of images ranges between 10 and 70. From figure, the FPR is minimized using DNIQE framework as evaluated to two existing works. This is because with the application of DBEDmodel, the DNIQE predicts the exact direction based on the high pass subband and therefore lessens the FPR results by 40.40% and 74.04% as compared to [1] method and [2] method.

IV. IMPACT OF NOISE REMOVAL RATE

Table 3 portrays noise removal rate acquired using MATLAB simulator and compared with two DCE-DI [1] and DTCWT-WF [2]. The noise removal rate of the proposed DNIQE method extensive experimental analysis is reported in table 3.

Table 3 Tabulation for Noise Removal Rate

Number of Images (Number)	Noise Removal Rate (%)		
	DCE-DI	DTCWT-WF	DNIQE Method
10	65.59	70.22	79.01
20	68.36	74.38	81.32
30	71.63	76.98	83.65
40	73.89	79.56	85.12
50	75.32	82.14	87.36
60	79.87	84.26	89.23
70	82.46	86.32	91.45

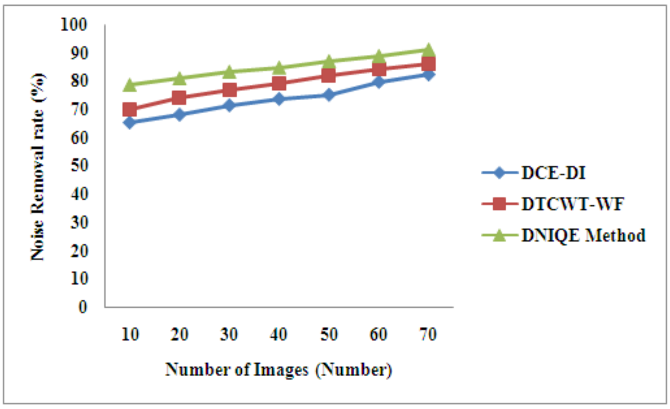

Figure 7 Measure of Noise Removal Rate

In figure 7, we represent the noise represent rate attained using 70 different DI extracted from MADID database using MATLAB. From figure 7, the superior noise removal rate is achieved using DNIQE framework as compared to existing DCE-DI [1] and DTCWT-WF [2]. At the same time, the noise removal rate obtained is directly proportional to the number of images. This in turn increases the noise removal rate during coding results using DNIQE framework by 13.51% compared to DCE-DI and 7.31% compared to DTCWT-WF.

IV. IMPACT OF PREDICTION ACCURACY

Table 4 signifies the PA obtained using MATLAB simulator and evaluated with existing (DCE-DI) [1] and (DTCWT-WF) [2]. The PA of the proposed DNIQE method extensive experimental analysis is reported in table 4.

Table 4 Tabulation for Prediction Accuracy

Number of Images (Number)	Prediction Accuracy (%)		
	DCE-DI	DTCWT-WF	DNIQE Method
10	65	70	84
20	68	73	86
30	72	76	88
40	75	79	91
50	77	81	92
60	81	84	94
70	83	87	96

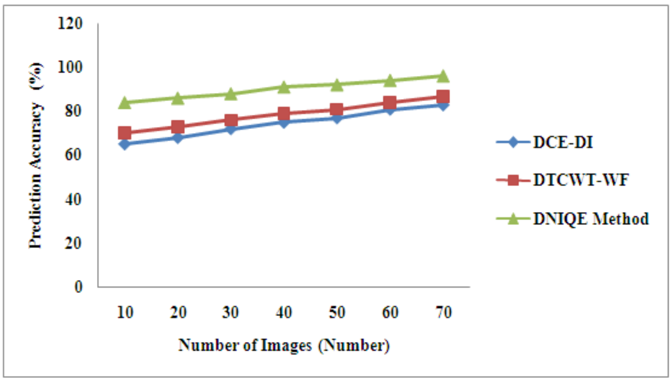

Figure 8 Measure of Prediction Accuracy

Figure 8 represent the PA attained using 70 diverse DI extorted from MADID database using MATLAB. From figure, the value of PA using DNIQE framework is superior as evaluated with DCE-DI [1] and DTCWT-WF [2]. PA obtained is directly proportional to the images as different image has varied image size. This in turn increases the PA during coding results using DNIQE framework by 17.57% compared to DCE-DI and 12.93% compared to DTCWT-WF.

V. CONCLUSION

In this work, a DNIQE is presented to enhance the performance of the lossy-to-lossless image coding application with DI given as input and noise removal during coding performances. The objective of DNIQE is used to minimize the noising artifacts for increasing the IQ using the DI extracted from MADID database. To do this, we first designed an ASDL with DWT that measures the blocking artifacts and the IQ based on the ASDL algorithm for MADID DI. Then, based on this measure, we proposed a DBEP model for increasing the image coding applications and therefore decreasing the FPR in an extensive manner. In addition DBEP model measures the DBED 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 DI that also reduced prediction error during the coding results evaluated to existing methods. Results depicts that DNIQE offers improvement of PA by 15.25% and PSNR value by 20.48% compared to DCE-DI and DTCWT-WF respectively.

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