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INTELLIGENT COLOR CORRECTION FOR ENHANCEMENT (ICCE)

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ABSTRACT

In this research work a novel color correction algorithm for enhancing the color of digital images captured from low resolution cell 41phone cameras is proposed here. The procedure involves capturing images using various cell phones like Samsung, Nokia and Lenova having resolution of 2 mega pixels, 3 mega pixels and 5 mega pixels respectively. The scope of the work includes image acquisition using cell phones of various resolutions. The captured images are subjected to histogram analysis as an indication of preprocessing. The histogram equalization and clipping is done to increase the global contrast and reduce the dynamic range. Then Transportation Map Registration (TMR) filter is used for removing any artifacts present in the extracted images. Feed Forward Neural Network (FNN) trained with Back Propagation Algorithm (BPA) is used for efficient retrieval of the images based on its content. The coefficients of curvelet and wavelet transforms are used to estimate the Gaussian mixture model (GMM), Resolution Synthesis Color Correction (RSCC) and Generalized Gaussian mixture model (GGMM). The output of these color correction algorithms are being fused to get an optimized result. The performance of the proposed method to other existing color correction algorithms on cell phone camera (various resolution) images obtained from different sources are compared. The subjective and objective quality analysis is carried out to substantiate that the new color correction algorithm provides improved quality over the existing methods.

Keywords- Color correction, Enhancement, cell phone camera, resolution synthesis and Back Propagation Algorithm.

INTRODUCTION

Image enhancement is the process of adjusting the color values in an image so that, on the identified output device, the processed image gives a pleasant appearance. Color enhancement is very difficult as it depends on the quality of the captured image which may involve contrast enhancement, dynamic range compression and improving the color interpretation. The portability and multiple functionality features have made the cell phone cameras more popular. After thorough survey it is understood that the quality of the image from the existing cell phone cameras are very lower than the Digital Still Cameras (DSCs). All the colors in the original scene are not clearly visualized in the images captured from a cell phone camera. This causes a variance between original and observed colors leading to poor quality image. Consequently, these photos find a limited use for archiving, printing and sharing.

The low quality camera optics, image sensors and low cost for color processing are the factors influencing poor quality images. This causes poor contrast; incorrect exposure; color fringing and color imbalance or global color cast. The color artifacts in the acquired images from cell phone cameras affects the quality because it shows some observations such that it is not naturally present but occurs as a result of the investigative procedure.

LITERATURE SURVEY

A variety of algorithms have been proposed in the literature for dynamic range compression, exposure correction, and contrast enhancement in the luminance channel. Few applications use contrast stretching [15], [25], auto-level histogram equalization [30], [14], [15], [22], homomorphic filtering [29], and content-dependent exposure correction [5]. The unwanted global color casts in an image, arising due to changes in illuminant conditions, can potentially be corrected using color constancy processing [10].[12], [28].
An estimate obtained from the color constancy algorithm is used to transform the image colors to the relative standard illuminant. The technique proposed in [12] makes use of an Artificial Neural Networks (ANN) to obtain a two dimensional estimate of the chromaticity (hue and colorfulness) for ambient illumination. This is interpreted using a histogram. Correlation by Color [10] works by pre-computing the correlation matrix, in which the columns of the matrix characterize the possible distribution of image chromaticity under a set of proposed illuminants. Each column is used to estimate a measure of the likelihood that specifies the scene illuminant.

The contribution in [11] is about the color correction to yield better performance than color correlation and neural network methods. This method makes use of Support Vector Machine (SVM) based regression to estimate the illuminant chromaticity from histogram of the test image. Based on Land's human vision model for lightness and color perception [20], there is also an abundance of Retinex based image enhancement algorithms [16], [17], [23], including the popular algorithm known as Multi Scale Retinex with Color Restoration (MSRCR) [17]. MSRCR is a non-linear color correction algorithm whose goal is to improve the overall image quality by providing simultaneous color constancy and contrast enhancement in the luminance channel.

A hierarchical color correction algorithm for enhancing the color of digital images is discussed in [29]. First soft assignments are made for the images belonging to defective classes and then it is processed with an optimized algorithm. The hierarchical color correction is performed in three stages as indicated below.

In the first stage, global color attributes of the low quality input image are used in a GMM framework to perform a soft classification of the image into predefined global Image of ‘M’ classes.

In the second stage, the input image is processed with a non linear color correction algorithm that is designed for each of the ‘M’ global classes. This color correction algorithm used is Resolution Synthesis Color Correction (RSCC), applied for a spatially varying color correction determined by the local color attributes of the input image.

In the third stage, the outputs of the RSCC predictors are combined using the global classification of weights to yield the color corrected output image

In this research work, a new strategy for color enhancement of low quality cell phone camera images is proposed which is a training based method. The novelty of the proposed scheme is that it achieves color enhancement by recovering the Minimum Mean Squared Error (MMSE) estimate of a high quality reference image using Curvelet transform. The enhancement estimation is done using ANN. The low quality pictures from cell phone cameras with various resolutions are used for experimentation. A set of 38 reference images are used for training and remaining 13 images were taken for testing. However, the reference images considered for training and testing could be used in different applications. The proposed algorithm is based on non-linear color transformation that can be used to achieve color enhancement with precise functionality. The challenging task of the algorithm depends on the selection of the reference images from cell phone cameras for training and optimization of the algorithm parameters.

The color defects can arise either due to changes in illumination, or due to poor imaging hardware and image processing software in the cell phone camera. The proposed method draws inspiration from color by correlation [10] and Resolution Synthesis (RS) [2], [3]. Similar to the concept in [10], a training procedure is used to learn the parameters for the probability distribution of colors from a set of cell phone camera images displaying a particular type of global color distortion. The global color attributes of the test images are used to compute the feasibility of the observed colors in the image that are due to each of the global color distortions learned during training.

Based on the computed likelihoods, an optimal color transformation is determined for correcting the image. Unlike in [10], the color transformation is non-linear and spatially variant. Using a scheme similar to RS [2], [3], the color transformation at a pixel location is determined by the color of neighboring pixels in the local window. A pair of low quality images obtained from the cell phone camera sources and spatially registered reference images captured using a high quality digital still camera, to train our algorithm. The resulting pairs of images accurately represent the real world non-idealities typically found in real mobile camera pictures.

A comparison between GGMM [33] and RSCC is used for estimating the color corrected output pixel values, and demonstrated that a GGMM can provide better color estimation than a Gaussian mixture model (GMM). The paper is organized as follows from section 3 which deals with the methodology. In section 4, scope of the work is given. The section 5 includes the Results and Discussion while the concluding remarks are presented in section 6.

MATERIALS AND METHODS

i. Histogram Equalization

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. It can also be used on color images by applying the same method separately to the Red, Green and Blue components of the RGB color values of the image.

ii. Spatial Adaptive histogram Equalization

This technique is used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast.

iii. Shape preserving Equalization

Shape preserving Equalization for contrast enhancement is presented in this paper. Contrast enhancement is achieved by means of local histogram equalization algorithm which preserves the level-sets of the image.

iv. Histogram Clipping

The color value of a pixel has either been pushed to pure black (0, 0, 0) or pure white (255, 255, 255) in the RGB plane. When a large area of pixels is clipped, it contains no detail.

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v. TMR filter

The Adaptive Histogram Equalization applied on digital image leads to some visual artifacts. Then Transportation Map Registration (TMR) filter which computes the difference between original image and transformed image is calculated, and then a generic filtering method also called TMR filter which draws is used to regularize the transportation map so that artifacts are suppressed.

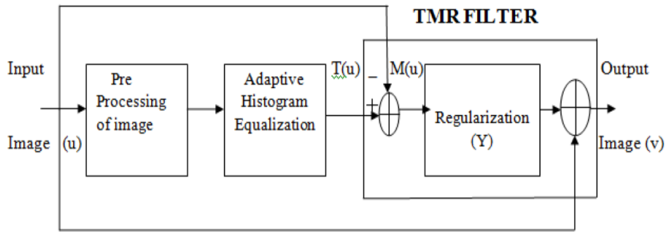


Figure 1. Block Diagram for TMR filter

The block diagram for TMR Filter is shown in Figure 1. The transportation map M (u) which is the difference between transformed image and original image is applied to TMR Filter. In this, weighted factor is computed, Regularization term is evaluated, finally stopping criterion is found out regularization process convergence. Then enhanced image will be obtained by combining the regularized image with original image (u).

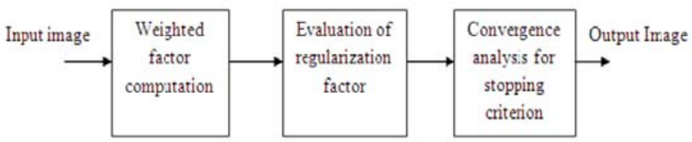


Figure 2. Flow diagram for Regularization of TMR filter

All the artifacts mentioned above are removed by regularizing the transportation map, which is defined as the image of the differences between the original image and the one after contrast or color modification. All these artifacts may be interpreted as spatial irregularities of this transportation map. In order to regularize this map without introducing blur in the final image, inspiration is taken from nonlocal methods that have been proposed for image de-noising and more precisely from the Yaroslavsky filter. The transportation map is filtered by averaging pixel values using weights that are computed on the original image, therefore adapting to the geometry of this initial image.

It will be shown that artifacts are progressively suppressed by iterating this filtering stage. The transportation map is calculated which gives the difference between original image and transformed one. 'Yu' is the operator, a weighted average with weights depending on the similarity of pixels in the original image u. The weights or filter coefficients to be found out for each and every pixel leaving the first pixel. From the second pixel onwards 8 neighborhoods of each pixel is taken. Where ||.|| stands for the Euclidean distance in Rn, where, $N(x) = x + N(0) \subset \Omega$ with N (0) a spatial neighborhood of 0, where σ is a tuning parameter C(x) of the method and is the normalization constant. Then add all the weights which are calculated for each and every pixel. Observations are made such that if applied to the image 'u', the Yaroslavsky filter coefficients are obtained. This is pictorially represented in Figure 2.

The regularization of the image T(u) given in Equation 1, referred to as transportation map regularization (TMR), is then defined as TMR

$$u\,(T(u)) := u + Yu\,M(u) \qquad (1)$$

This formulation can be divided in two terms as of image TMR as Equation 2.

$$u\,(T(u)) = Yu(T(u)) + u - Yu(u) \qquad (2)$$

T (u) is the original image which is filtered by 'Yu', a nonlocal operator, followed by the regularity of the image. This operation attenuates noise, compression and color proportion artifacts but also the details of the image T (u). The second operation is performed by adding the quantity details of TMR filter which can be considered as details of the original image

vi. Median filtering

The median filtering is a nonlinear digital filtering method popularly used to remove noise. A typical pre-processing step to improve the results of in the later stage focuses on the noise removal (for example, edge detection on an image). The median filter considers each pixel and its neighborhood pixels to decide whether or not it is representative of its surroundings. The neighboring pixel values are replaced with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood in numerical order and then replacing the pixel being considered with the middle pixel value.

vii. Feed Forward Neural Network (FNN)

The neural network used was the standard back propagation neural network as explained below. A few features were used to enhance the performance of the network such as the addition of logarithmic and exponential input and output neurons. In practice, any kind of neural network algorithm can be used to model a predictor, but back propagation was found to provide the best controllability in terms of rate of learning and generalization capabilities of the neural network [34].
A back propagation neural network was written in MATLAB for a single hidden layer. The inputs are assumed to be stored in a column wise matrix, and the outputs of the training set likewise in a column wise matrix. The number of nodes in the hidden layer is the same as the number of input layer nodes. The BPN performs updating operations taking the entire input matrix into consideration. The algorithm for back propagation is as follows:

Step1: Inputs and outputs are normalized as explained above. Total number of inputs to the network is given by $l = iO \times 3$ and number of outputs is given by $n = jO \times 3$, where iO and jO are the number of inputs and outputs. The number of hidden layer neurons m equals the number of input neurons i.e. m = l.

Step2: Let 'nTest' be the number of training sets. This means the size of the input matrix will be lxm and the size of the output matrix will be nxm.

Step3: The input and output pattern are stored in rows of the input and output matrices leaving two places for the augmented neurons. Every second row of the input and output matrix is given by computing the ln (loge) of the preceding row to give the logarithmic neuron. Every third row of both matrices is computed by the exponential of the original pattern.

Step4: Assign learning rate and momentum factor to some initial value.

Step5: Initialize the input layer – hidden layer weight matrix v (lxm) and the hidden layer – output layer weight matrix w (mxn) to some random values.

Step6: Let the thresholds given by delv and delw, both be zero matrices initially.

Step7: Variable 'iterate' is used to store the number of iterations that training is going to take place for.

Step8: Since the input neurons use a linear activation function, output of input layer 'Oi' is made equal to input to input layer 'Ii' for each pattern (stored as a column).

Step9: Input to the hidden layer is calculated by multiplying the output of the input layer with corresponding weight values. That is, $I_h = v' \times O_i$, where 'Ih' represents the input to the hidden layer and is a column matrix of length m.

Step10: Hidden layer outputs 'Oh' are calculated using the sigmoidal function as shown in Equation 2

$$O_O = \frac{1}{1+e^{-I_o}} \quad (2)$$

Step11: Target output 'To' (nx1) is calculated from the output matrix by taking the appropriate column.

Step12: Error is calculated in two steps. First, the part error ePart is calculated as in Equation 3

$$ePart = \sum (T_O - O_O)^2 \quad (3)$$

Final error is given in Equation 4 as root mean square (rms) value of ePart or

$$E_{RMS} = \frac{\sqrt{ePart}}{n} \quad (4)$$

Step13: Calculated output 'Y' (mxn) is given by $Y' = O_h \times d'$.

Where d is given by Equation 5

$$d = (T_O - O_O) \times O_O \times (1 - O_O) \quad (5)$$

Step14: 'delW' is updated using the formula given in Equation 6

$$delW = (momentum \times delw) + (learningRate \times Y) \quad (6)$$

Step15: The complete training set 'nSet' error is calculated as $e = w \times d$

Step16: 'X' is calculated as

$X = O_i \times dStart'$.

Where

$dStar = e \times O_h \times (1 - O_h)$.

Step17: Change in input layer weights is given by Equation 5

$$delv = (momentum \times delv) + (learningRate \times X) \quad (7)$$

the weights are adjusted as

$v = v + delv$ and $w = w + delw$.

Step18: Repeat steps 9 to 18 until the error rate is lesser than tolerance value. Save the weights and exit.

viii. Wavelet transform

Wavelet transform is used for decomposition and reconstruction of an image or signal which does have any information about its concrete structure. The coefficients are categorized into decomposition and approximations by using the scaling and wavelet functions. This algorithm reduces the length of signal after decomposition by a factor of ½ (half) each time, so that the computation is carried out at a faster rate. Two sets of filter banks comprising low pass and high pass filters are used. The structure for realization of the decomposition and reconstruction using wavelet transform is shown in Figure 3 and the flowchart for extracting the wavelet co-efficients is shown in Figure 4.

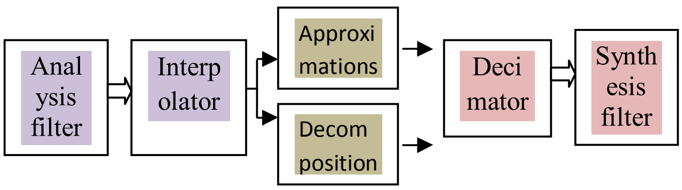


Figure 3. Wavelet transform decomposition and approximation

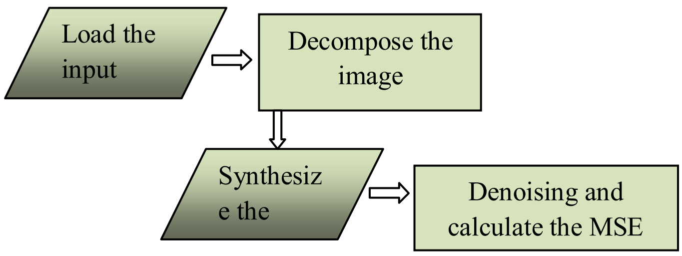


Figure 4. Flowchart for extraction of wavelet coefficients

ix. Curvelet transform

The discrete curvelet transform for a 256 × 256 image is performed as is shown in Figure 5(a). The discrete curvelet transform can be performed in three steps:

1) The 256 × 256 image is split up in three subbands.
2) The Basis subband consists of 256x256 image
3) Tiling is performed on band pass subbands Δ1 and Δ2.
4) Then the discrete Ridgelet transform is performed on each tile.

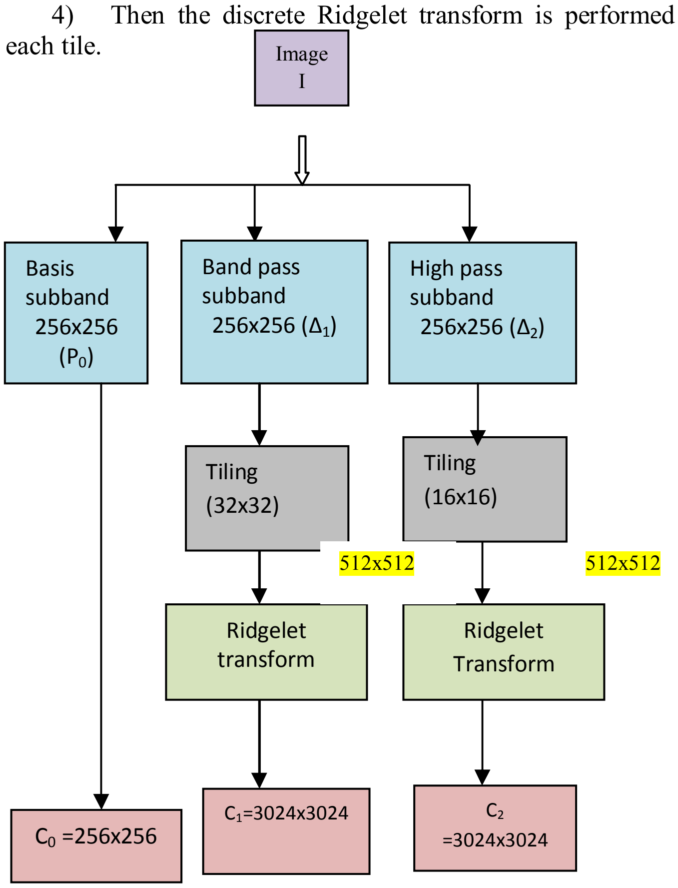


Figure 5(a). Flowchart for Curvelet transform

x. Performance analysis using Resolution Synthesis Color Correction (RSCC) and Gaussian mixture model (GMM)

a. Resolution Synthesis Color Correction (RSCC)

The RSCC algorithm extracts the color feature vector from a neighborhood around the current pixel and performs its soft classification into a number of local color subclasses. An affine color transform associated with each subclass is next applied to the current pixel, and then the outputs of the RSCC color transforms are combined to compute the final color corrected image.

b. Gaussian Mixture Model (GMM)

Gaussian mixture models are often used for data clustering. Clusters are assigned by selecting the component that maximizes the posterior probability. Like k-means clustering, Gaussian mixture modeling uses an iterative algorithm that converges to a local optimum. Gaussian mixture modeling may be more appropriate than k-means clustering when clusters have different sizes and correlation within them. Clustering using Gaussian mixture models is sometimes considered a soft clustering method. The posterior probabilities for each point indicate that each data point has some probability of belonging to each cluster. The flowchart is shown in Figure 5(b).

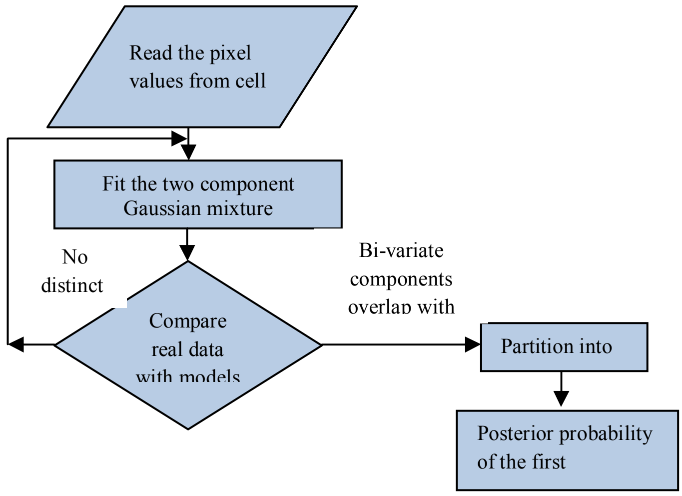


Figure 5(b). Flowchart for Gaussian Mixture Model

SCOPE OF THE WORK

The images obtained from the cell phone camera in Samsung mobile phone, Lenova mobile and from Nokia mobile are termed as class1 and class 2 respectively. Totally 102 images were collected out of which it is split into two parts for training and testing. In the training phase the images are preprocessed to remove noise; features are extracted using various transforms and ANN algorithms. Finally the output of the classifier indicates the efficiency of enhancement. The method is illustrated in Figure 6(a) and 6(b)

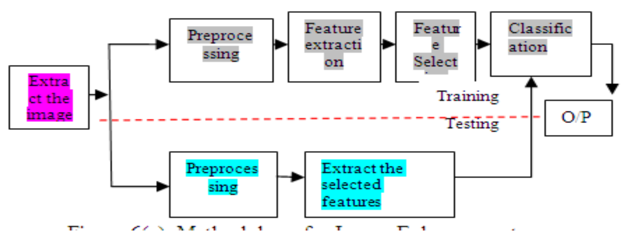


Figure 6(a). Methodology for Image Enhancement

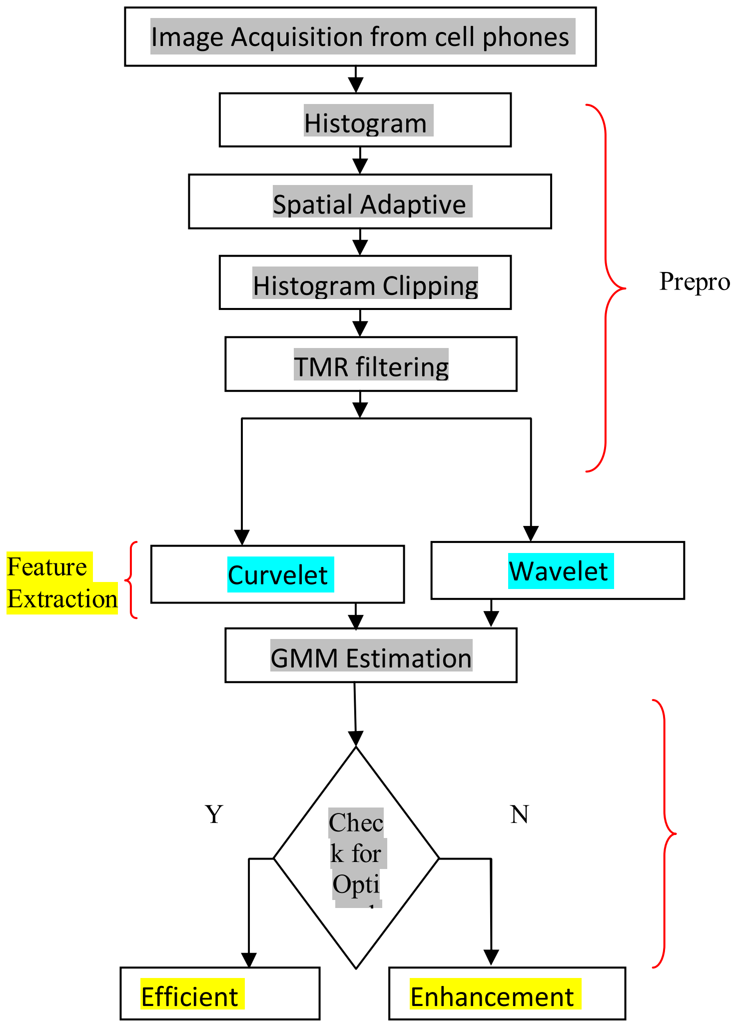


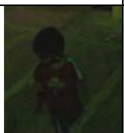
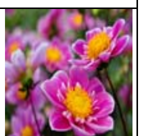
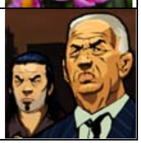
Figure 6(b). Flowchart for Image enhancement

RESULTS AND DISCUSSION

i. *Acquisition of Original Images*

The input images are gathered using three types of mobile cameras of the brand Samsung, Nokia and Lenova and categorized as class1 (low resolution) and class2 (medium resolution) respectively. The resolution of the cameras is also corresponding to 3 types and also identified as low and medium respectively. The images collected are shown in Table 1.

Table 1. Sample images

S.No	Category	Resolution Type	Samsung	Nokia	Lenova
1.	Class 1	Low resolution			
2.	Class 2	Medium resolution			

ii. *Preprocessing*

The images are preprocessed to remove noise using Median and TMR filters. Prior to this Histogram Equalization and spatial adaptive histogram equalization followed by histogram clipping is done.

iii. *Histogram Equalization*

This method is done to enhance the contrast of the images. If the dynamic range of the histogram is high then the quality of the image captured is good. If the spread out of the frequent intensity values are large then the dynamic range is high. A good quality image has high dynamic range. The intensity values ranges from minimum to a maximum of 0 to 255.

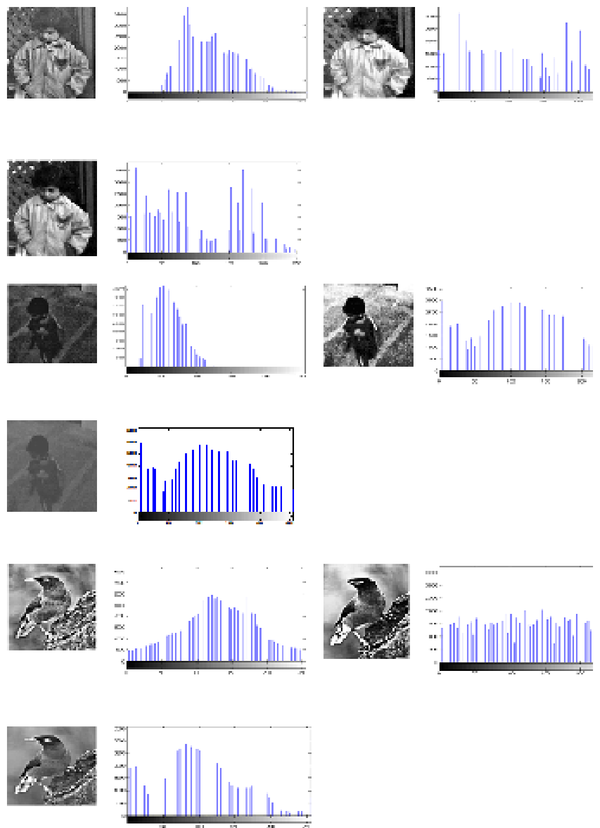


Figure 7. Outputs for Histogram Equalization

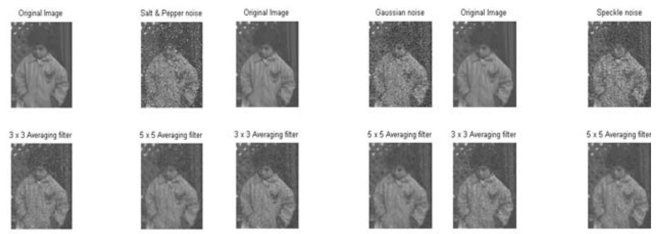
iv. *Spatial adaptive histogram*

This method computes many histograms, corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image.

v. *Noise removal*

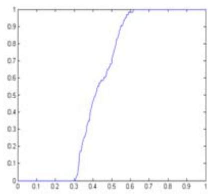
Linear filtering is for removal of certain types of noise. Certain filters, such as averaging or Gaussian filters, are appropriate for this purpose. For example, an averaging filter is useful for removing grain noise from a photograph. Because each pixel gets set to the average of the pixels in its neighborhood, local variations caused by grain are reduced.

Median filtering is similar to an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

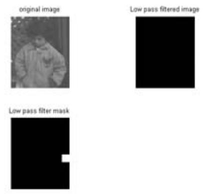


(a). Noise Removal

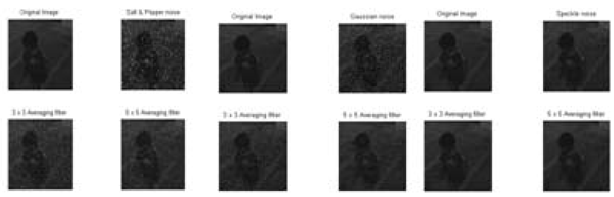
(b). Bit plane Slicing



(c). Adaptive histogram

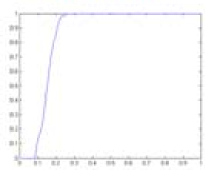


(d). Low pass filter

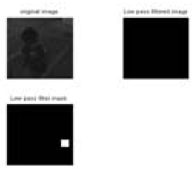


(e). Noise Removal

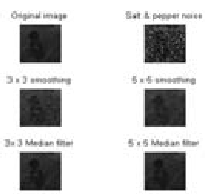
(f).Bit plane Slicing



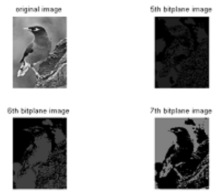
(g). Adaptive histogram



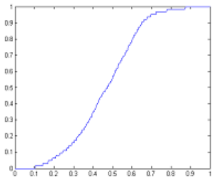
(h). Low pass filter



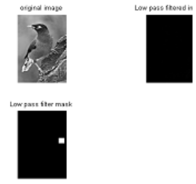
(i). Image Smoothing



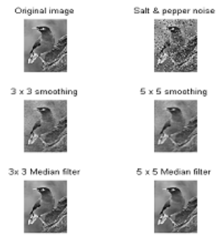
(k). Bit plane Slicing



(l). Adaptive histogram



(m). Low pass filter



(n). Image Smoothing

Figure 8. Spatial adaptive histogram

vi. Feature Extraction using Curvelet transform

The features are the basic information present in the image. They are well defined pixel representation which gets repeated in various directions. The main feature focused here is the color of the image. Curvelet transform is used to extract the co-efficients from the images so that the entropy can be computed. Feature extraction is carried out as a part of Hierarchical Color correction as shown in Figure 9(a). The white balance and auto contrast of image is adjusted for which the results are shown in Figure 9 (b) and (c) respectively. The quality of the processed image is verified using Histogram analysis. Finally the noise removal is carried out using Iterated TMR filter.

Figure 9(a). Hierarchical Color correction

Figure 9(b). White Balance Image

Figure 9(c). Auto contrast Image

(a). Original Image

(b). Histogram Equalization

(c). Spatial Histogram Equalization

(d). Adaptive Histogram Equalization

(e). Histogram Clipping

Figure 10. Histogram Analysis

Histogram equalization is used to adjust the image to make it easier so as to analyze or improve visual quality. The Figure 10(a) to (e) states that the contrast of the image is enhanced after histogram equalization.

vii. TMR Filtering

TMR filter is only applied to pixels for which the convergence map is greater than the threshold value. In all experiments, the convergence threshold ‘θ’ is maintained to be ‘1’. The outputs after TMR filtering are shown in Figure 11(a) to (f) respectively.

(a). Zoom before Iterated TMR

(b). Zoom after Iterated TMR

(c). Before TMR Filtering

(d). After TMR Filtering

(e). After Adaptive TMR Filtering

(f). Enhanced Image

Figure 11. Output for TMR filtering

viii. Wavelet Transform

The image transforms are widely used in image filtering, data description, etc. Nowadays the wavelet theorems make up very popular methods of image processing, denoising and compression. Considering that the Haar functions are the simplest wavelets, these forms are used in many methods of discrete image transforms and processing. The image transform theory is a well known area characterized by a precise mathematical background, but in many cases some transforms have particular properties which are not still investigated. This paper for the first time presents graphic dependences between parts of Haar and wavelets spectra. It also presents a method of image analysis by means of the wavelets–Haar spectrum. Some properties of the Haar and wavelets spectrum were investigated. The extraction of image features immediately from spectral coefficients distribution was shown. In this paper it is presented that two–dimensional both, the Haar and wavelets functions products man be treated as extractors of particular image features. Furthermore, it is also shown that some coefficients from both spectra are proportional, which simplify slightly computations and analyses.

A wavelet is a wave like oscillation with amplitude that begins at zero, increases, and then decreases back to zero. Big objects are examined at low resolutions which are the base for multi-resolution processing. The concept of Image pyramid is used in wavelet transform. The base of the pyramid has the highest resolution and the apex of the pyramid has the lowest resolution. The full pyramid has J+1 resolution levels from $2^J \times 2^J$ to $2^0 \times 2^0$. The level J – 1 approximation is used to create approximation pyramids and level J prediction residual is used to create prediction residual pyramids. This concept is used in wavelet transform. The block diagram for producing image pyramids is shown in Figure 12.

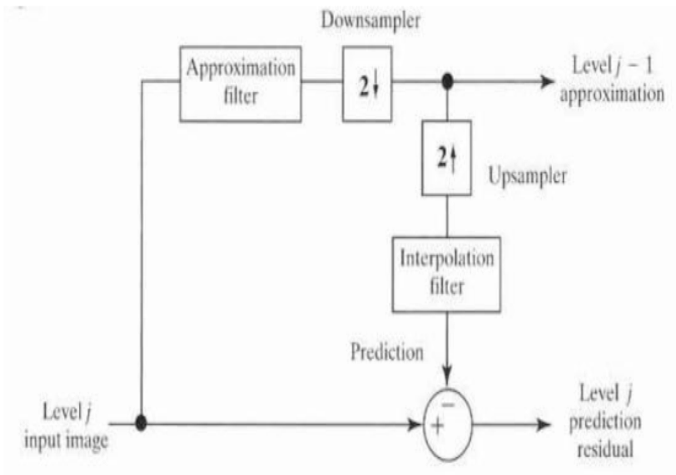


Figure 12. Block diagram for Image Pyramids

The original image is synthesized and Decomposed for denoising, plotting the histogram, compression and obtaining the related statistics. This is done with the help of wavelet toolbox in MATLAB. This is shown in Figure 13 (a) to (h)

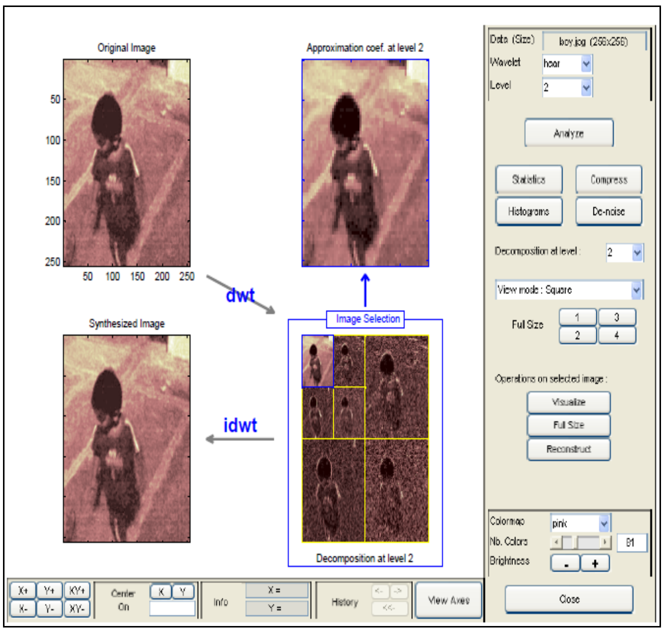


Figure 13(a). Square mode Synthesized and Decomposed Image

The Wavelet transform uses Haar wavelet for decomposing the original image. Figure shows the histogram plot for the original image before the wavelet transform is applied. The various features like mean, median, standard deviation, mode, maximum and minimum intensity are extracted.

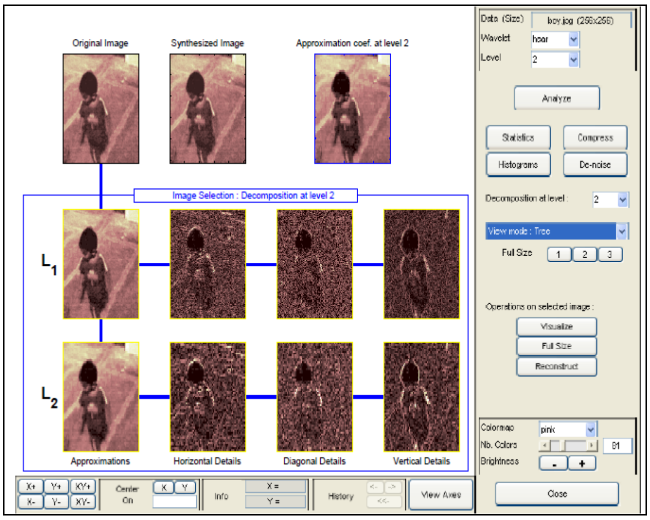


Figure 13(b). Tree mode Decomposed Image

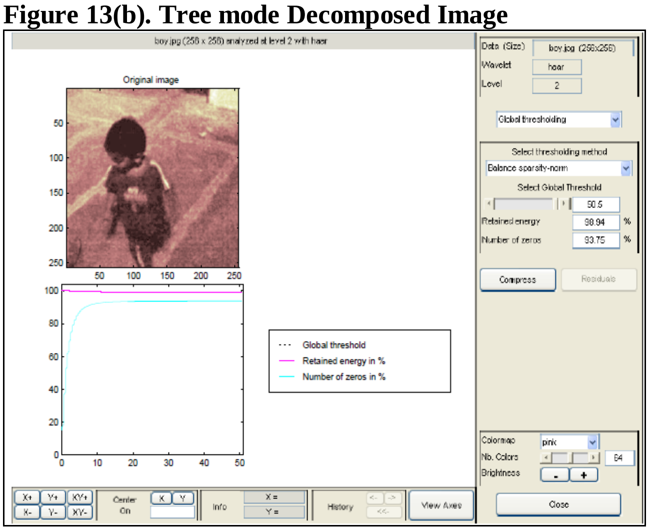


Figure 13(c). Global thresholding for Compression

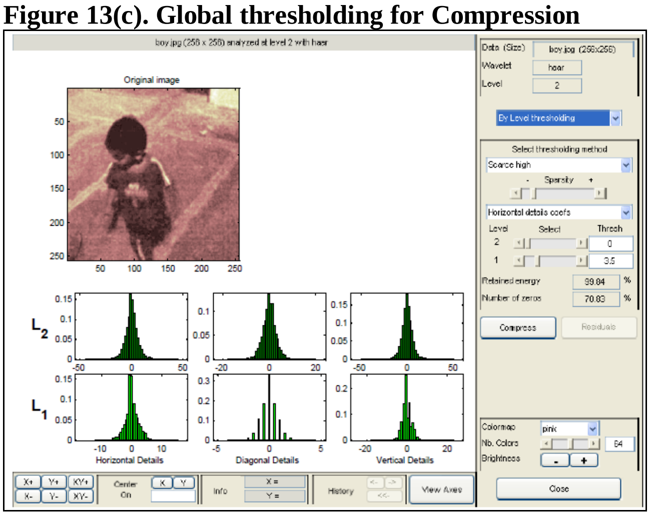


Figure 13(d). By level thresholding for Compression

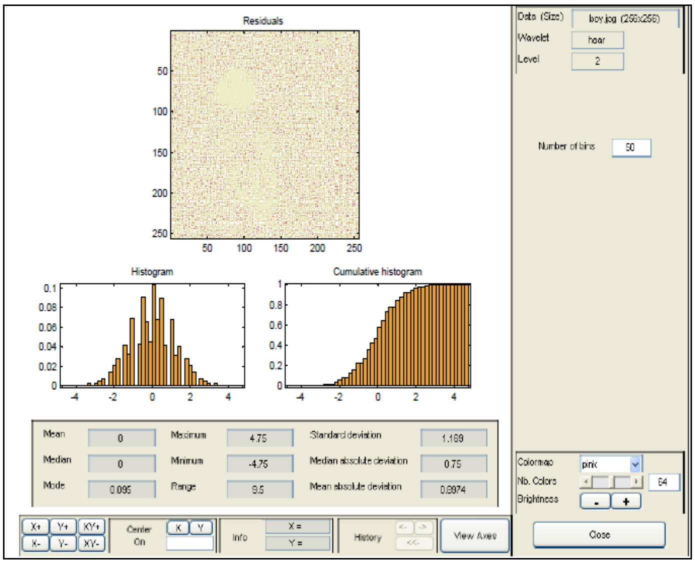


Figure 13(e). Residuals from Wavelet Transform

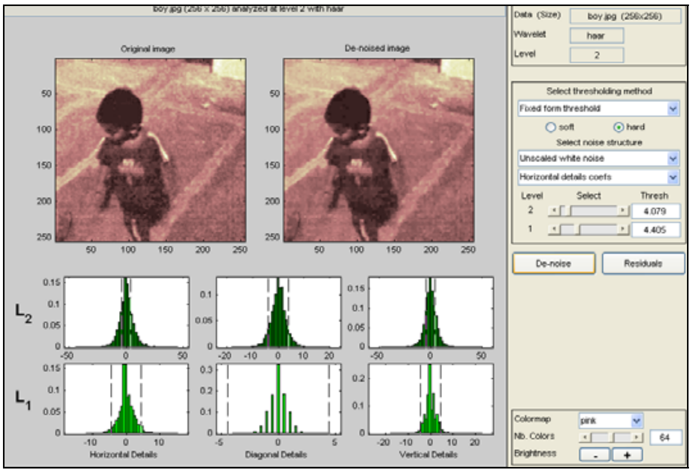


Figure 13(f). Image Denoising

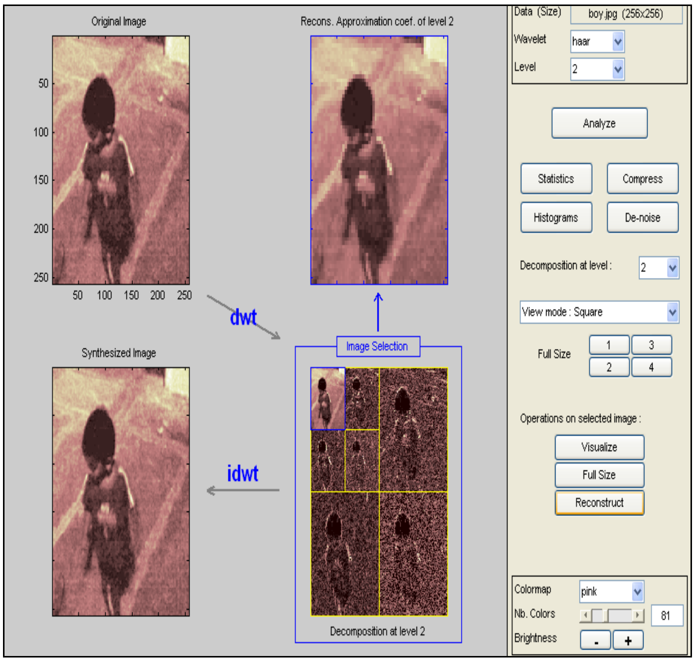


Figure 13(g). Image Reconstruction for two level decomposition

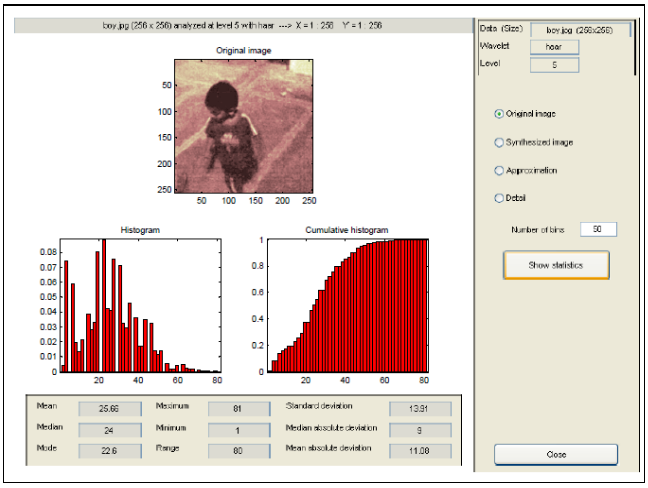


Figure 13(h). Histogram and Statistical feature extraction for original Image

Similarly Figure shows the histogram plot for the synthesized image using Haar wavelet. The various features like mean, median, standard deviation, mode, maximum and minimum intensity are extracted. From Figure 1 and 2 it is inferred that there the statistical features remain unaltered after the synthesis has taken place.

In the analysis part the image is split up as approximations and details. The approximation, or scaling, coefficients are the low pass representation of the signal and the details are the wavelet coefficients. At each subsequent level, the approximation coefficients are divided into a coarser approximation (low pass) and high pass (detail) part. This is depticted in Figure

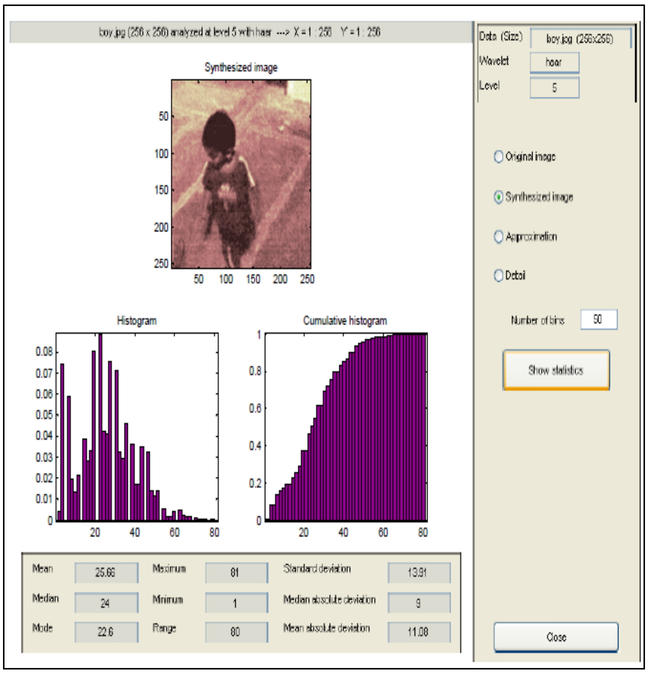


Figure 13(i). Output for Synthesized Image with five levels

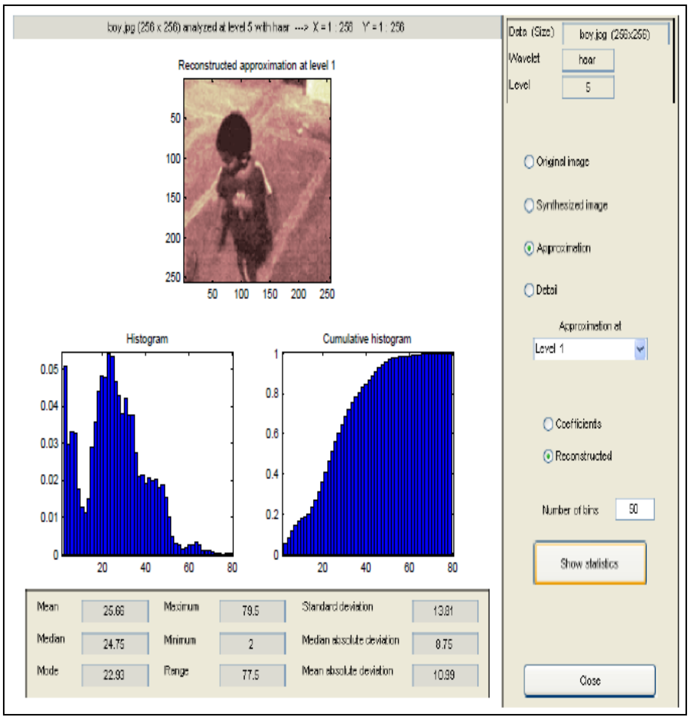


Figure 13(j). Output for Approximations of a Reconstructed Image with five levels

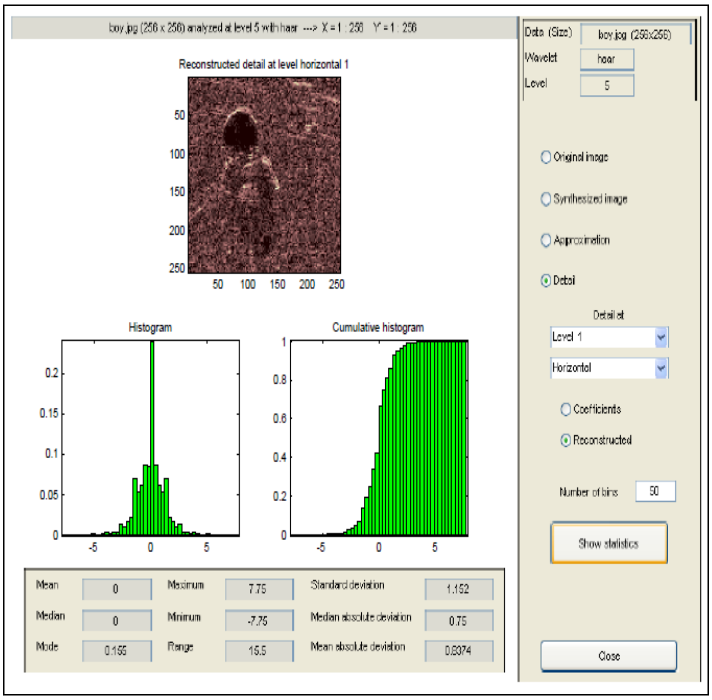


Figure 13(l). Output for Details - Reconstructed Image with five levels

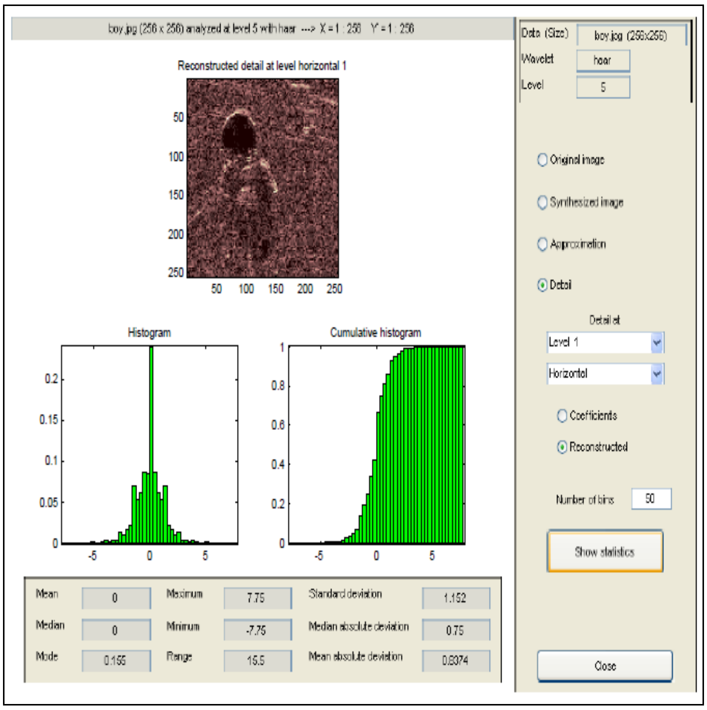


Figure 13(k). Output for Details of a Reconstructed Image with five levels

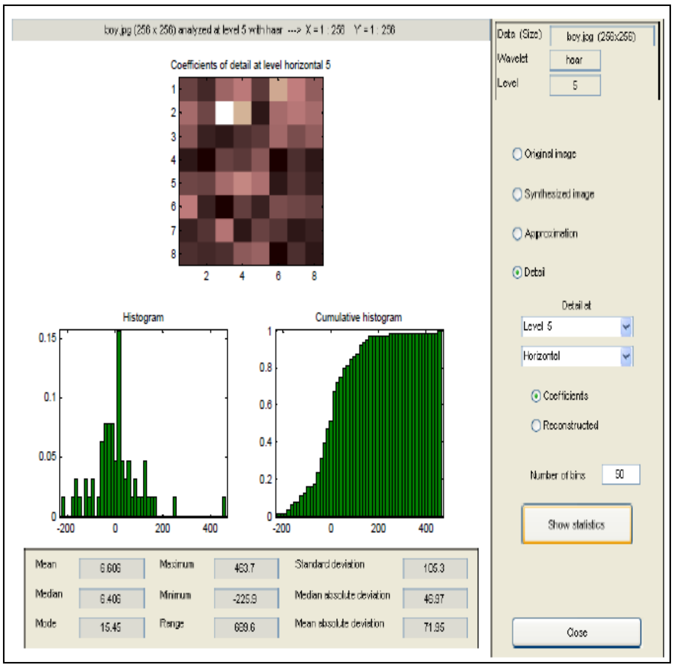


Figure 13(m) . Output for Details of a Reconstructed Image with five levels corresponding to level 5

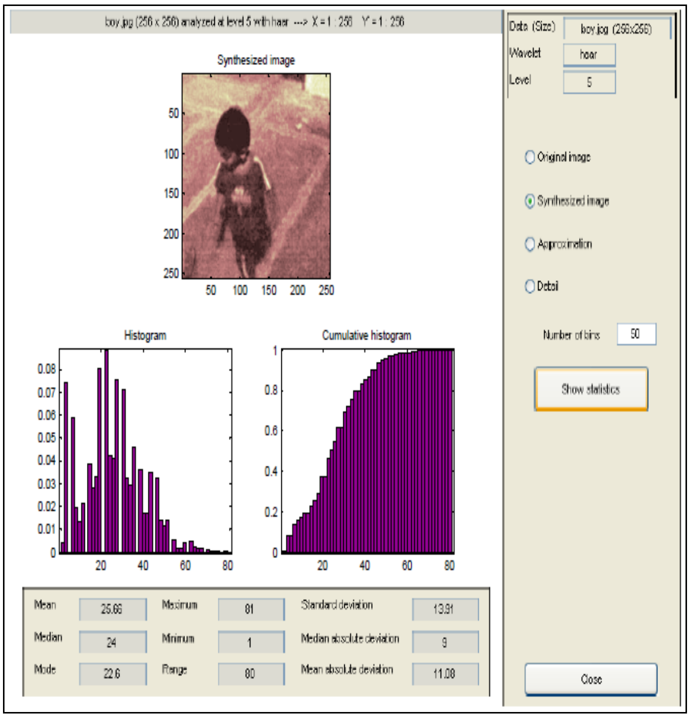


Figure 13(n). Output for the synthesized Image with five levels corresponding to level 5

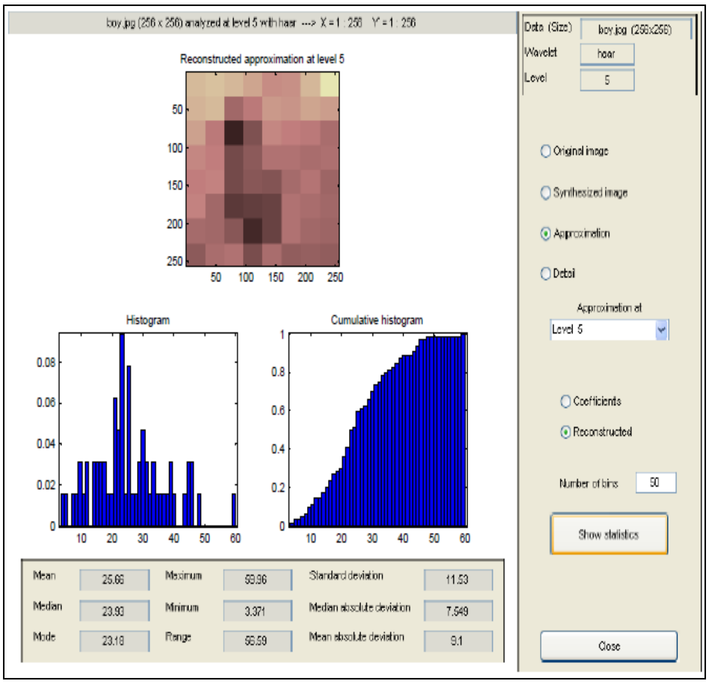


Figure 13(o). Output for the reconstructed Image with five levels corresponding to level 5

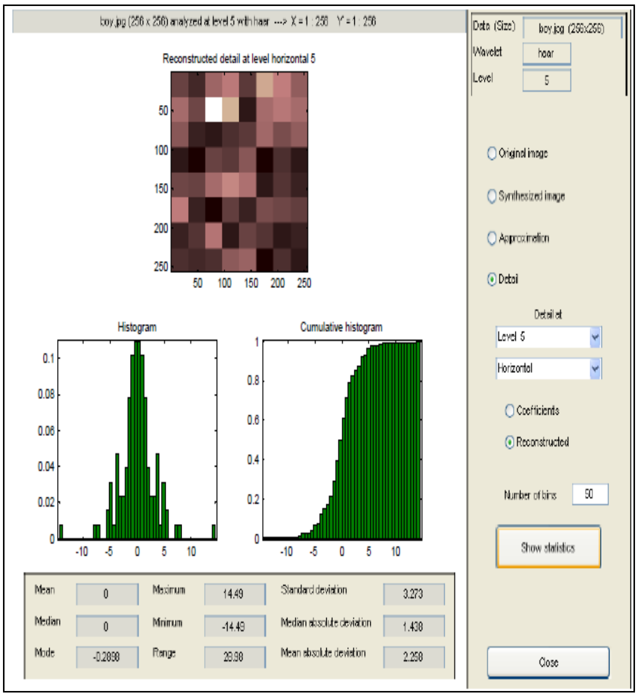


Figure 13(p). Output for Details of a Reconstructed Image with five levels corresponding to level 5

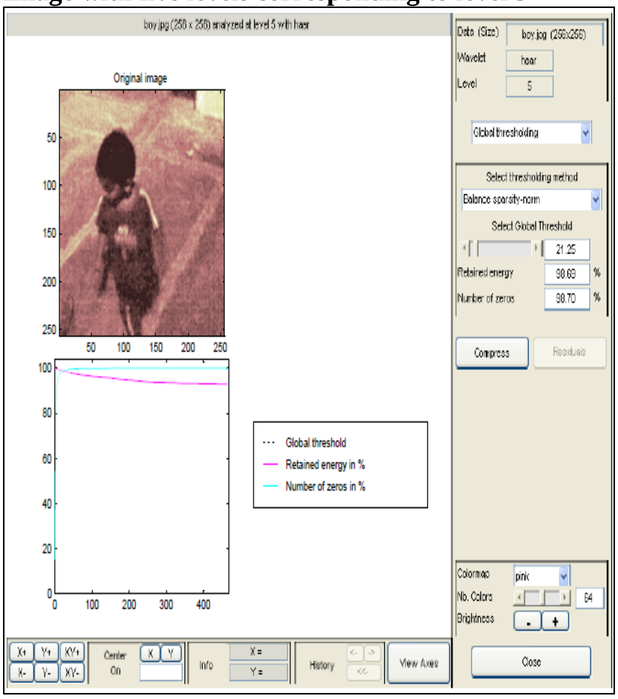


Figure 13(q). Output for Details of a Reconstructed Image with five levels corresponding to level 5

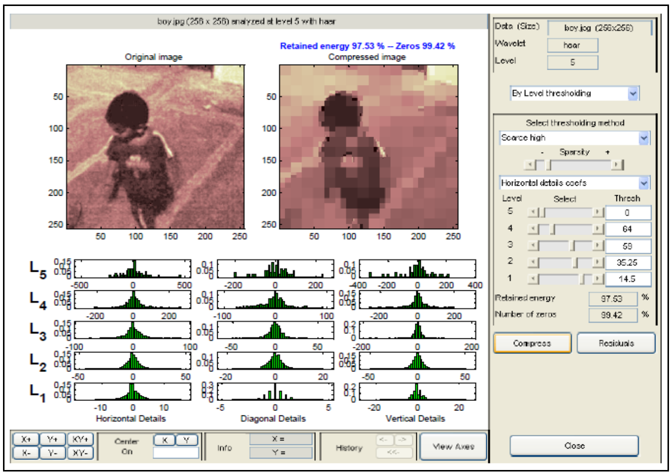


Figure 13(r). Output for Details of a Reconstructed Image with five levels

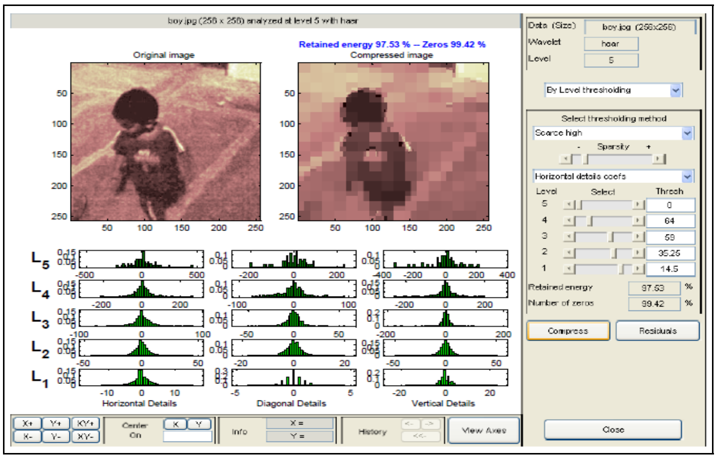


Figure 13(s). Output for Details of a Reconstructed Image with five levels corresponding to level 5

Table 2. Performance Evaluation for Noise removal by filtering

S. No	Evaluation Parameter	Transformed image	Image after Median filter	Image after TMR filter
1.	MSE	4321.826	12392.56	352.56
2.	PSNR (dB)	32.145	29.326	25.345
3.	Variance	70.23	55.892	27.4772
4.	SD	8.383	7.476	5.241

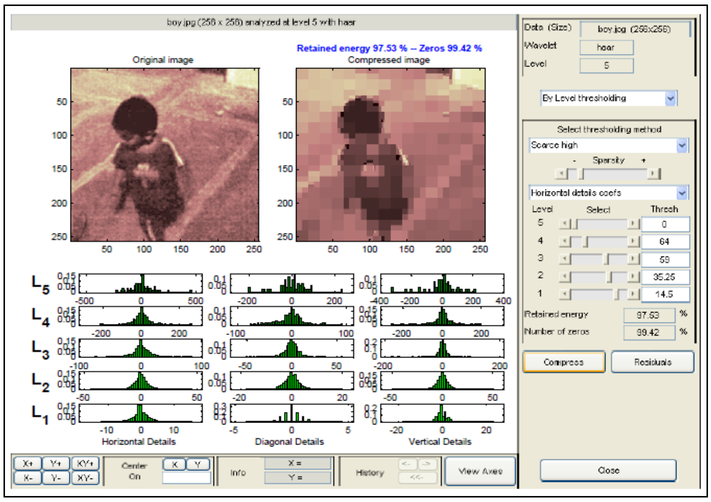


Figure 13(t). Output for Details of a Reconstructed Image with five levels corresponding to level 5

PERFORMANCE ANALYSIS

It is defined as feedback obtained after the execution of an algorithm so as to facilitate an objective feedback from the performers trying to get a positive change in performance. When performing an analysis, a long term approach would ensure that the performance improvement initiative would fulfill the objectives. The various performance measures used are Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), variance and Standard Deviation (SD).

i. *Mean Squared Error (MSE)*

It is defined as the squared value of the mean of the actual and target values whose expression is given in Equation 8

$$MSE=1/n\sum(\hat{U}_i-U_i)^2 \quad (8)$$

$\hat{U}_i$ and U_i is the target values and actual values respectively.

ii. *Peak Signal to Noise Ratio (PSNR)*

It is defined as the ratio of the peak value of the signal content to the noise and is denoted in Equation 9.

$$PSNR=20\log_{10}(Max_I/\sqrt{MSE}) \quad (9)$$

iii. *Variance*

The measure of the variability is called as variance. It is denoted by Equation 10

$$\sigma=[1/N\sum(x_i-\mu)^2] \quad (10)$$

iv. *Standard Deviation (SD)*

It denotes the measure of the spread out of the values. It is defined as the square root of the variance and denoted by 'σ' as in Equation 11

$$\sigma=\sqrt{[1/N\sum(x_i-\mu)^2]} \quad (11)$$

The Table 2 denotes the efficiency of the various types of filters used for noise removal. The values of various parameters clearly indicate that TMR performs effective filtering. Similarly Table 3 shows the RSCC values for the images from three types of cell phones having various resolutions.

Table 3. Performance Evaluation for Image Enhancement

Cell phone camera	Unprocessed cell phone image	FOR PROCESSED CELL PHONE IMAGES				
		Auto color	White balance	MSRCR	RSCC WITH GMM	RSCC WITH GGMM
Nokia	5.3849	7.5757	7.3739	5.7863	5.2234	5.823
Samsung	5.1492	7.7689	7.2378	5.7452	5.3411	5.746
Lenova	5.2387	7.6123	7.1769	5.6124	5.1221	5.621

v. Enhancement Estimation using ANN

The efficiency of the enhancement is estimated using Artificial neural networks (ANN). The results for training the ANN is presented in Figure 14. The feed forward architecture trained with Back Propagation Algorithm (BPA). The input-output pair used for training the ANN is given in the Table 4.

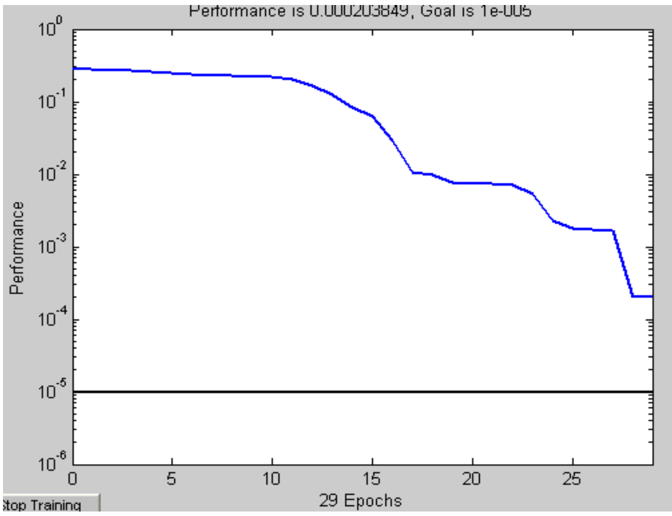


Figure 14. Performance Characteristics of ANN

Table 4 Sample Feature Set for Training the ANN

Input Features				Outputs	
Color feature 1	Color feature 2	Color feature 3	Color feature 4	Target values	Actual values
117.8264	66.4858	0.398749	98.22894	0.25	0.3833
117.8264	66.4858	0.398749	98.22894		
37.01038	11.50215	0.581454	42.52672	0.75	0.75
37.01038	11.50215	0.581454	42.52672		
105.9786	82.29505	0.121947	80.17065	1	0.9332
105.9786	82.29505	0.121947	80.17065		

Table 5 ANN Parameters

S.No	Performance measure	Value
1.	Root mean squared error	0.000203849
2.	Learning rate	0.9
3.	Momentum	0.8
4.	No. of nodes in input layer	7
5.	No. of nodes in hidden layer	4
6.	No. of nodes in output layer	1
7.	Activation function	Sigmoid
8.	No. of iterations	60

The following steps were followed to implement BPA for enhancement estimation and the network parameters are given in Table 5.

- Selection of Training data set
- Selection of ANN parameters (Input neurons, hidden layers, hidden neurons, initial weights, bias, learning rate, momentum factor, iterations, tolerance, learning algorithm etc)
- Selection of appropriate architecture
- Validation of the ANN estimator
-

CONCLUSION

An efficient method to enhance the quality of the images acquired from various cell phone cameras is discussed here. It is inferred from the broad analysis that the curvelet transform is capable of performing efficient enhancement as compared with wavelet transform. The subjective and objective quality analysis carried out denotes that the new color correction algorithm provides improved quality over the existing methods. Thus efficient enhancement estimation is implemented.

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