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# COLOR CORRECTION OF POOR QUALITY IMAGES BY USING CURVELET TRANSFORM

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***Abstract-***The highlights of this work assure and confront the usage of curvelet transform for color correction and contrast enhancement in various fields like engineering, defence, remote sensing and biomedical applications. The color of digital images is poor when captured from low resolution cell phone cameras. The procedure involves capturing images using various cell phones like Samsung and Nokia resolution of 2 and 3 mega pixels respectively. The extracted images are subjected to histogram analysis as a sign of preprocessing. The histogram equalization and clipping is done to increase the global contrast and reduce the dynamic range. Then Median filter is used for removing any artifacts present in the removed pictures. Nourish Forward Neural Network (FFNN) prepared with Radial Basis Function (RBF) is utilized for proficient recovery of the pictures in view of the coefficients of Curvelet change. The execution of the proposed strategy to other existing shading rectification calculations on mobile phone camera (different determination) pictures got from various sources are looked at utilizing exactness and review. The quality examination is completed to approve that the anticipated shading rectification calculation gives better quality results over the current strategies.

***Keywords***-Color adjustment, PDA camera, Radial Basis Function, accuracy and review

## I. Introduction

The strategy of picture upgrade is to direct the shading values in a picture so that, on the perceived yield contraption, the created picture gives a wonderful appearance. Shading improvement is greatly convoluted as it relies on upon the nature of the recorded picture which may select differentiation upgrade, dynamic range firmness and improve the color elucidation. The haulable nature and various performance features have made the cell phone cameras more popular. After thorough survey it is unstated that the quality of the image from the existing cell phone cameras are very lower than the Digital Still Cameras (DSCs). The entire colors in the unique panorama are not evidently envisaged in the images recorded from a digital phone camera. This causes an inconsistency between actual and experimental colors leading to deprived quality image. Therefore, these snapshots are bounded for limited usage like documentation, publishing and sharing.

The low class 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 exposes some observations such that it is not naturally present but occurs as a result of the investigative procedure.

## II. Literature Survey

A variety of algorithms have been anticipated in the writing for element go robustness, presentation remedy, and difference improvement in the luminance channel. Couple of uses utilize differentiate extending [15], [25], auto-level histogram adjustment [30], [14], [15], [22], homomorphic separating [29], and substance subordinate presentation rectification [5]. The undesirable worldwide shading throws in a picture, emerging because of changes in illuminant conditions, can conceivably be amended utilizing shading steadiness handling [10].[12], [28].

An estimation acquired from the shading unwavering quality calculation is utilized to change over the picture hues to the virtual normal illuminant. The system was proposed in [12] makes utilization (ANN) to acquire a two dimensional gauge of the chromaticity (shade and brilliance) for encompassing enlightenment. This is translated utilizing a histogram. Relationship by Color [10] works by pre-processing the connection grid, in which the sections of the network portray the conceivable conveyance of picture chromaticity under an arrangement of proposed illuminants. Every section is utilized to appraise a measure of the probability that indicates the scene illuminant.

The commitment in [11] is about the shading adjustment to yield preferred execution over shading connection and neural system techniques. This strategy makes utilization of Support Vector Machine (SVM) based relapse to appraise the illuminant chromaticity from histogram of the test picture. In view of Land's human vision demonstrate for softness and shading observation [20], there is additionally a wealth of Retinex based picture improvement calculations [16], [17], [23], including the famous calculation known as Multi Scale Retinex with Color Restoration (MSRCR) [17]. MSRCR is a non-direct shading rectification calculation whose objective is to

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enhance the general picture quality by giving synchronous shading consistency and differentiation upgrade in the luminance channel.

A progressive shading revision calculation for improving the shade of advanced pictures is discussed in [29]. First soft assignments are made for the images belonging to defective classes and then it is prepared with an improved calculation. The various leveled shading adjustment is performed in three phases as demonstrated beneath.

i) In the primary stage, worldwide shading properties of the low quality information picture are utilized as a part of a GMM system to play out a delicate arrangement of the picture into predefined worldwide Image of "M" classes.

ii)In the second stage, the information picture is prepared with a non straight shading amendment calculation that is intended for each of the "M" worldwide classes. This shading adjustment calculation utilized is Resolution Synthesis Color Correction (RSCC), connected for a spatially changing shading amendment controlled by the nearby shading characteristics of the info picture.

iii)In the third stage, the yields of the RSCC indicators are joined utilizing the worldwide arrangement of weights to yield the shading adjusted yield picture

In this examination work, another system for shading heightening of low quality PDA camera pictures is proposed which is dependent on 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 deformities can emerge either because of changes in enlightenment, or because of poor imaging equipment and picture handling programming in the PDA camera. The proposed strategy draws motivation from shading by connection [10] and Resolution Synthesis (RS) [2], [3]. Like the idea in [10], a preparation system is utilized to take in the parameters for the likelihood dissemination of hues from an arrangement of mobile phone camera pictures showing a specific sort of worldwide shading contortion. The worldwide shading qualities of the test pictures are utilized to register the possibility of the watched hues in the picture that are because of each of the worldwide shading bends learned amid preparing.

In light of the processed probabilities, an ideal shading change is resolved for rectifying the picture. Dissimilar to in [10], the shading change is non-straight and spatially variation. Utilizing a plan like RS [2], [3], the shading change at a pixel area is dictated by the shade of neighboring pixels in the nearby window. A couple of low quality pictures got from the wireless camera sources and spatially enlisted reference pictures caught utilizing a top notch advanced still camera, to prepare our calculation. The subsequent sets of pictures precisely speak to this present reality non-idealities ordinarily found in genuine portable camera pictures. An examination between GGMM [33] and RSCC is utilized for evaluating the shading amended yield pixel values, and showed that a GGMM can give preferable shading estimation over a Gaussian blend display (GMM). The paper is sorted out as takes after from segment 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.

## III. Objective Of The Work

The objective of this work is Color redress and Contrast upgrade. This is accomplished utilizing histogram evening out and curvelet change. The worldwide differentiation of the pictures is expanded utilizing histogram evening out and the shading revision is carried out to increase the quality of the pics. Our main algorithm is also validated by collecting the input images from various brands of cell phones. The scope of this work is shown in Figure 1.

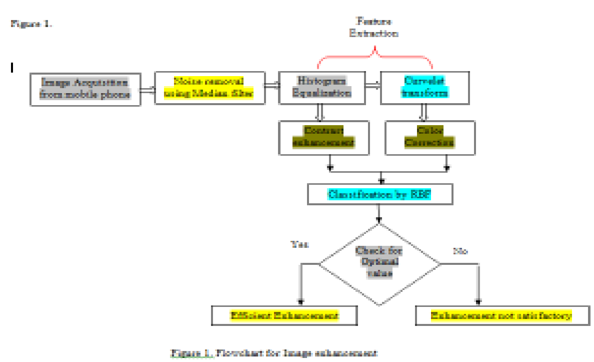



Figure 1. Flowchart for Image enhancement

## IV. Materials And Methods

The two major technical aspects of this work include histogram equalization and color correction. For color correction curvelet transform is used. The color enhancement is done using histogram equalization. The quality assessment or estimation is done using Artificial Neural Networks (ANN).

### IV.I Histogram Equalization

This technique ordinarily expands the worldwide differentiation of many pictures, especially when the usable information of the picture is spoken to by close difference values. Through this alteration, the forces can be better conveyed on the histogram. This considers territories of lower neighborhood complexity to pick up a higher differentiation. Histogram evening out fulfills this by viably spreading out the most incessant power values. It can likewise be utilized on shading pictures by applying a similar technique independently to the Red (R), Green (G) and Blue (B) parts of the Red (R), Green (G) and Blue (B) components of the RGB color image.

### IV.II Curvelet transform for color correction and Enhancement

The discrete curvelet transform for a 256 × 256 image is performed.

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

### IV.III Artificial Neural Networks (ANN)

Warren McCulloch and Walter Pitts (1943) made a computational model for neural systems in light of science and calculations called limit rationale. This model made ready for neural system research to part into two unmistakable methodologies. One approach concentrated on natural procedures in the cerebrum and the other concentrated on the usage of neural systems to fake comprehension.

In the late 1940s master Donald Hebb made a theory of learning in light of the portion of neural adaptability that is at present known as Hebbian learning. Hebbian learning is thought to be a "run of the mill" unsupervised learning principle and its later assortments were early models for entire arrangement potentiation. Experts began applying these thoughts to computational models in 1948 with Turing's B-sort machines.

Farley and Wesley A. Clark (1954) at initially utilized computational machines, then called "number crunchers," to duplicate a Hebbian create at MIT. Other neural structure computational machines were made by Rochester, Holland, Habit, and Duda

Straight to the point Rosenblatt (1958) made the perceptron, a calculation for example acknowledgment in light of a two-layer PC learning system utilizing basic expansion and subtraction. With numerical documentation, Rosenblatt additionally portrayed equipment not in the essential perceptron, for example, the restrictive OR circuit, a circuit whose intelligent figuring couldn't be dealt with until after the BPA was made by Paul Werbos (1975).

Neural structure get some information about stagnated after the era of machine learning research by Marvin Minsky and Seymour Papert (1969), who found two key issues with the computational machines that dealt with neural systems. The first was that solitary layer neural systems were unequipped for setting up the restrictive or circuit. The second basic issue was that PCs didn't have enough prepare essentialness to adequately deal with the long run time required by extensive neural systems. Neural structure get some information about hindered until PCs completed more recognizable arranging power. Another key drive that came later was the backpropagation calculation which successfully tackled the elite or issue (Werbos 1975).

The parallel disseminated handling of the mid-1980s got to be distinctly well known under the name connectionism. The course book by David E. Rumelhart and James McClelland (1986) gave a full composition of the utilization of connectionism in PCs to recreate neural procedures.

### 4.3.1. Outspread Basis Function arrange (RBFN)

It is a specific kind of neural system. In this , a non-direct classifier is utilized. The RBFN approach is more sharp than the MLP. A RBFN presents strategy by measuring the information's closeness to cases from the course of action set. Each RBFN neuron stores an "illustrate", which is only a solitary of the cases from the course of action set. When we need to orchestrate another information, every neuron figures the Euclidean segment between the information and its model. All around, if the data all the more nearly takes after the 'class A' models than the class B models, it is named class A.

### 4.3.2. The Input Vector

The information vector is the n-dimensional vector that you are trying to depict. The whole information vector is appeared to each of the RBF neurons.

### 4.3.3. The RBF Neurons

Each RBF neuron stores a "show" vector which is only a solitary of the vectors from the course of action set. Each RBF neuron considers the information vector to its model, and yields a propelling power in the locale of 0 and 1 which is a measure of closeness. On the off chance that the information is relative to the model, then the yield of that RBF neuron will be 1. As the parcel between the information and model develops, the reaction tumbles off exponentially towards 0. The state of the RBF neuron's reaction is a ringer bend, as depicted in the structure building design. The neuron's reaction respect is in like way called its "presentation" respect. The model vector is in like way regularly called the neuron's "inside", since it's the inspiration at the purpose of joining of the toll twist.

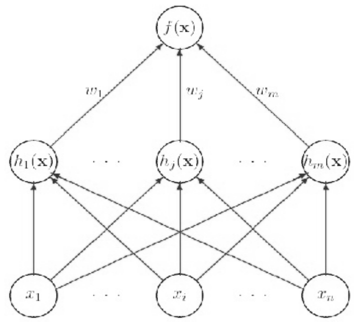



Figure 2. Structure of FFNN trained with Radial Basis Function Network

### 4.3.4. The Output Nodes

The yield of the system includes a blueprint of focus focuses, one for each portrayal that we are trying to total. Each yield focus methodology a kind of score for the related request. Ordinarily, a depiction choice is made by designating the dedication to the class with the most raised score. The score is set up by taking a weighted whole of the initiation values from each RBF neuron. By weighted whole we induce that a yield focus relates a weight a rousing power with each of the RBF neurons, and duplicates the neuron's presentation by this weight before adding it to the aggregate reaction. Since each yield focus point is figuring the score for a substitute class, each yield focus has its own particular blueprint of weights. The yield focus point will more often than not give a positive weight to the RBF neurons that have a place with its class, and a negative weight to the others.

### 4.3.5. RBF Neuron Activation Function

Each RBF neuron figures a measure of the comparability between the information and its model vector (taken from the course of action set). Input vectors which are more like the model give back an outcome more like 1. There are diverse conceivable decisions of comparability capacities, however the most prominent depends on the Gaussian. The various algorithms and methods used for achieving the objective is elaborated in the above mentioned section.

## V. Results And Discussion

This section exhibits the results obtained for the various stages in implementing this research work. MATLAB is used for developing the code for Curvelet transform and Radial Basis function. These outputs obtained are clearly discussed as various sub-divisions of this section.

### V.I Acquisition of Original Images

The input images are gathered using two types of mobile cameras of the brand Samsung and Nokia which are denoted as Category 1 (low resolution) and Category 2 (very low resolution) respectively. The resolution of the cameras is equivalent to 2 types and also identified as low and very low respectively. The images gathered are shown in Table 1.

Table1:Images Gathered with different resolutions

| Images from Samsung (Category 1)(Low Resolution) | Images from Nokia ( Category 2)(Very Low Resoultion) |
|---|---|
|  |  |

### V.II Preprocessing

The images are preprocessed to remove clamor utilizing Median channel. Middle separating is like an averaging channel, in that each yield pixel is set to a normal of the pixel values in the area of the relating input pixel. Be that as it may, with middle separating, the estimation of a yield 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.

### V.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. The results are interpreted in Figure 3(a) and (b) for both the images.

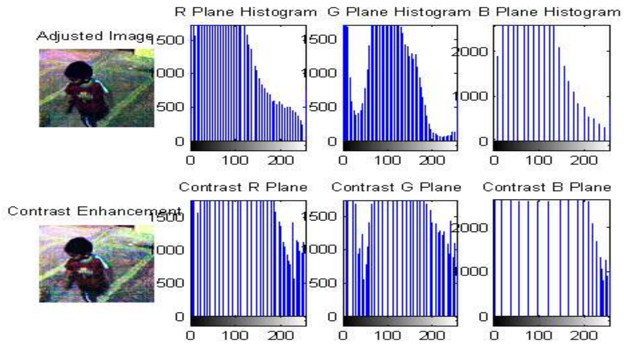



Figure 3(a). Contrast Enhancement – Histogram Equalization

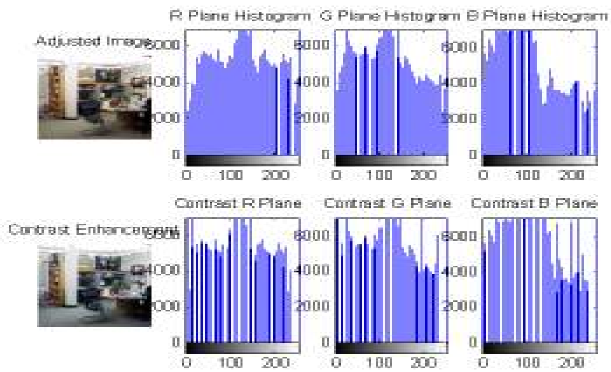



Figure 3(b). Contrast Enhancement – Histogram Equalization

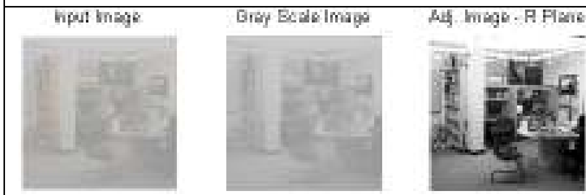
### V.IV Feature Extraction using Curvelet transform

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 4(e) to (k).

| (e).Input Image - Rack | (f).Color Corrected | (g).Contrast Enhanced |
|---|---|---|


**h). Output for Grayscale conversion – boy image**


**i)Intensity adjustment in RGB plane-boy image- Intermediate Results -Image 1: boy.jpg for Color Correction**




**(j). Output for Grayscale conversion – Rack image**


**(k). Intensity adjustment in RGB plane- Intermediate Results -Image 1: rack.jpg for Color Correction**

Figure 4. Results for Color corrected Images

### V.V Classification by FFNN using RBF

The efficiency of the enhancement is estimated using Artificial neural networks (ANN). The results for training the ANN are presented in Figure 5(a) to (c).Feed ward (FF) architecture trained with RBF.

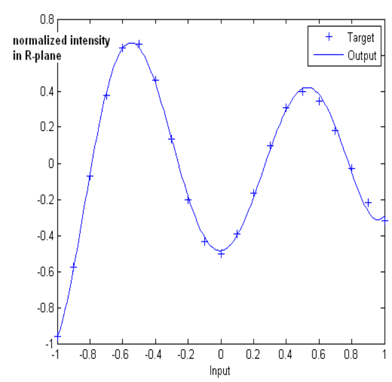
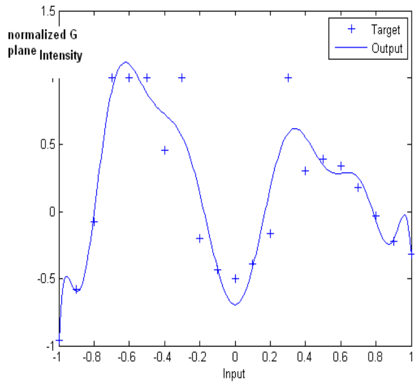
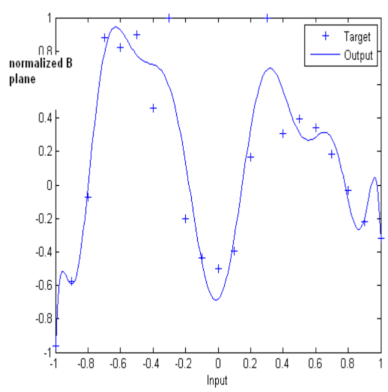



Figure 5(a). Classification by FF Architecture using RBF in R-plane




5(b). Classification by FF Architecture using RBF in G-plane




5(c). Classification by FF Architecture using RBF in B-plane

Table 3 ANN Parameters

| S.No | Performance measure | Value |
|---|---|---|
| 1. | Root mean squared error | 0.0035 |
| 2. | Learning rate | 0.9 |
| 3. | Momentum | 0.85 |
| 4. | No. of nodes in input layer | 4 |
| 5. | No. of nodes in hidden layer | 3 |
| 6. | No. of nodes in output layer | 1 |
| 7. | Activation function in hidden layer | Linear |
| 8. | Activation function in output layer | Sigmoid |
| 9. | No. of iterations | 420 |

The training parameters are tabulated in Table 3.

## VI. 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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