International Journal of Research in Advent Technology (IJRAT)
Vol. 1, No. 3, October 2013, ISSN: 2321–9637

AN AUTOMATIC WAVELET BASED-NONLINEAR IMAGE ENHANCEMENT USING WDRC FOR AERIAL IMAGERY

Ch.Ravi kiran[1] S.Koteswararao[2]
[1,2]ECE Departement
[1]Final M.Tech Student
[2]Associate Professor
steevan2@gmail.com

ABSTRACT
Recently we proposed a wavelet-based dynamic range compression algorithm to improve the visual quality of digital images captured in the high dynamic range scenes with nonuniform lighting conditions. The fast image enhancement algorithm which provides dynamic range compression preserving the local contrast and tonal rendition is a very good candidate in aerial imagery applications such as image interpretation for defense and security tasks. This algorithm can further be applied to video streaming for aviation safety. In this project the latest version of the proposed algorithm which is able to enhance aerial images so that the enhanced images are better then direct human observation, is presented. The results obtained by applying the algorithm to numerous aerial images show strong robustness and high image quality.
Keyword:wdrc,

1.INTRODUCTION

Aerial images captured from aircrafts, spacecrafts, or satellites usually suffer from lack of clarity, since the atmosphere enclosing Earth has effects upon the images such as turbidity caused by haze, fog, clouds or heavy rain. The visibility of such aerial images may decrease drastically and Sometimes the conditions at which the images are taken may only lead to near zero visibility even for the human eyes. Even though human observers may not see much than smoke, there may exist useful information in those images taken under such poor conditions. Captured images are usually not the same as what we see in a real world scene, and are generally a poor rendition of it. High dynamic range of the real life scenes and the limited dynamic range of imaging devices results in images with locally poor contrast. Human Visual System (HVS) deals with the high dynamic range scenes by compressing the dynamic range and adapting locally to each part of the scene. There are some exceptions such as turbid (e.g. fog, heavy rain or snow) imaging conditions under which acquired images and the direct observation possess a close parity .The extreme narrow dynamic range of such scenes leads to extreme low contrast in the acquired images.[1]

2. DIGITAL IMAGE PROCESSING

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of Multidimensional Systems[4].

2.1 in particular, digital image processing is the only practical technology for:

- Classification

- Feature extraction
- Pattern recognition
- Projection
- Multi-scale signal analysis

2.2 Some techniques which are used in digital image processing include:

- Pixelization
- Linear filtering
- Principal components analysis
- Independent component analysis
- Hidden Markov models
- Anisotropic diffusion
- Partial differential equations
- Self-organizing maps
- Neural networks
- Wavelets

3. AERIAL IMAGERY

Aerial imagery can expose a great deal about soil and crop conditions. The "bird's eye" view an aerial image provides, combined with field knowledge, allows growers to observe issues that affect yield. Our imagery technology enhances the ability to be proactive and recognize a Problematic area, thus minimizing yield loss and limiting exposure to other areas of your field. Hemisphere GPS Imagery uses infrared technology to help you see the big picture to identify these everyday issues. Digital infrared sensors are very sensitive to subtle differences in plant health and growth rate. Anything that changes the appearance of leaves (such as curling, wilting, and defoliation) has an effect on the image. Computer enhancement makes these Variations within the canopy stand out, often indicating disease, water, weed, or fertility problems. Because of Hemisphere GPS technology, aerial imagery is over 30 times more detailed than any commercially available satellite imagery and is available in selected areas for the 2010 growing season. Images can be taken on a scheduled or as needed basis. Aerial images provide a snapshot of the crop condition.[7]

Fig 4.1 Areal image of the test the building

Whereas, digital aerial imagery should remain in the public domain and be archived to secure its availability for future scientific, legal, and historical purposes.

4. NON-LINEAR IMAGE ENHANCEMENT TECHNIQUE

We propose a non-linear image enhancement method, which allows selective enhancement based on the contrast sensitivity function of the human visual system. We also proposed An evaluation method for measuring the performance of the algorithm and for comparing it with existing approaches. The selective enhancement of the proposed approach is especially suitable for digital television applications to improve the perceived visual quality of the images when the source image contains less satisfactory amount of high frequencies due to various reasons, including interpolation that is used to convert standard definition sources into high-definition images. Non-linear processing can presumably generate new frequency components and thus it is attractive in some applications[8].

5. PROPOSED ENHANCEMENT METHOD

5.1 Basic Strategy

The basic strategy of the proposed approach shares the same principle of the methods That is, assuming that the input image is denoted by I, then the enhanced image O is obtained by the following processing

$$O = I + NL(HP(I)) \qquad \text{……..(5.1)}$$

where $HP(\,)$ stands for high-pass filtering and $NL(\,)$ is a nonlinear operator. As will become clear in subsequent sections, the non-linear processing includes a scale step and a clipping step. The $HP(\,)$ step is based on a set of Gabor filters.

The performance of a perceptual image enhancement algorithm is typically judged through a subjective test. In most current work in the literature, such as this subjective test is simplified to simply showing an enhancement image along with the original to a viewer. While a viewer may report that a blurry image is indeed enhanced, this approach does not allow systematic comparison between tow competing methods[7]

5.2 Automatic image enhancement

5.2.1 Digital data compression

Many image file formats use data compression to reduce file size and save storage space. Digital compression of images may take place in the camera, or can be done in the computer with the image editor. When images are stored in JPEG format, compression has already taken place. Both cameras and computer programs allow the user to set the level of compression. Some compression algorithms, such as those used in PNG file format, are lossless, which means no information is lost when the file **is saved.** By contrast, the JPEG file format uses a lossy compression algorithm by which the greater the compression, the more information is lost, ultimately reducing image quality or detail that cannot be restored. JPEG uses knowledge of the way the human brain and eyes perceive color to make this loss of detail less noticeable.[12]

5.3 Layers

Another feature common to many graphics applications is that of Layers, which are analogous to sheets of transparent acetate (each containing separate elements that make up a combined picture), stacked on top of each other, each capable of being individually positioned, altered and blended with the layers below, without affecting any of the elements on the other layers. This is a fundamental workflow which has become the norm for the majority of programs on the market today, and enables maximum flexibility for the user while maintaining non-destructive editing principles and ease of use.[13]

5.4 Histogram

Image editors have provisions to create an image histogram of the image being edited. The histogram plots the number of pixels in the image (vertical axis) with a particular brightness value (horizontal axis). Algorithms in the digital editor allow the user to visually adjust the brightness value of each pixel and to dynamically display the results as adjustments are made. Improvements in picture brightness and contrast can thus be obtained.[15]

5.5 Noise reduction

Image editors may feature a number of algorithms which can add or remove noise in an image. JPEG artifacts can be removed; dust and scratches can be removed and an image can be de-speckled. Noise reduction merely estimates the state of the scene without the noise and is not a substitute for obtaining a "cleaner" image. Excessive noise reduction leads to a loss of detail, and its application is hence subject to a trade-off between the undesirability of the noise itself and that of the reduction artifacts.Noise tends to invade images when pictures are taken in low light settings. A new picture can be Given an 'antiquated' effect by adding uniform monochrome noise[9].

5.6 Removal of unwanted elements

Most image editors can be used to remove unwanted branches, etc, using a "clone" tool. Removing these distracting elements draws focus to the subject, improving overall composition. Introduced in Photoshop CS5, the "Content-Aware Fill" could be used to select an object (unwanted branches) and remove it out of the picture by simply pressing "Delete" on the keyboard, without destroying the image. The same feature is available for GIMP in form of the plug-in "Resynthesizer" developed by Paul Harrison.[16]

5.7 slicing of images

A more recent tool in digital image editing software is the image slicer. Parts of images for graphical user interfaces or web pages are easily sliced, labeled and saved separately from whole images so the parts can be handled individually by the display medium. This is useful to allow dynamic swapping via interactivity or animating parts of an image in the final presentation.

6. Wavelets

Wavelet is a waveform of effectively limited duration that has an average value of zero. The Wavelet transform is a transform of this type. It provides the time-frequency representation. (There are other transforms which give this information too, such as short time Fourier transform, Wigner distributions, etc.) Often times a particular spectral component occurring at any instant can be of particular interest. In these cases it may be very beneficial to know the time intervals these particular spectral components occur. For example, in EEGs, the latency of an event-related potential is of particular interest (Event-related potential is the response of the brain to a specific stimulus like flash-light, the latency of this response is the amount of time elapsed between the onset of the stimulus and the response). Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. How wavelet transform works is completely a different fun story, and should be explained after short time Fourier Transform (STFT) . The WT was developed as an alternative to the STFT. The STFT will be explained in great detail in the second part of this tutorial. It suffices at this time to say that the WT was developed to overcome some resolution related problems of the STFT, as explained in Part II. To make a real long story short, we pass the time-domain signal from various highpass and low pass filters, which filters out either high frequency or low frequency portions of the signal. This procedure is repeated, every time some portion of the signal corresponding to some frequencies being removed from the signal. Assuming that we have taken the lowpass portion, we now have 3 sets of data, each corresponding to the same signal at frequencies 0-250 Hz, 250-500 Hz, 500-1000 Hz..Then we take the lowpass portion again and pass it through low and high pass filters; we now have 4 sets of signals corresponding to 0-125 Hz, 125-250 Hz,250-500 Hz, and 500.

7. Algorithm

The proposed enhancement algorithm consists of three stages: the first and the third stage are applied in the spatial domain and the second one in the discrete wavelet domain.

7.1 Histogram Adjustment

Our motivation in making an histogram adjustment for minimizing the illumination effect is based on some assumptions about image formation and human vision behavior. The sensor signal $S(x, y)$ incident upon an imaging system can be approximated as the product[8],[26]

$$S(x,y) = L(x,y)R(x,y), \quad (1)$$

where $R(x, y)$ is the reflectance and $L(x, y)$ is the illuminance at each point (x, y). In lightness algorithms, assuming that the sensors and filters used in artificial visual systems possess the same nonlinear property as human photoreceptors, i.e.,logarithmic responses to physical intensities incident on the their photoreceptors [8], Equation 1 can be decomposed into
a sum of two components by using the transformation

$$I(x,y) = \log(S(x,y)):$$

$$I(x,y) = \log(L(x,y)) + \log(R(x,y)), \quad (2)$$

where $I(x,y)$ is the intensity of the image at pixel location (x,y).Equation 2 implies that illumination has an effect on the image histogram as a linear shift. This shift, intrinsically, is not same in different spectral bands.

Another assumption of the lightness algorithms is the grayworld assumption stating that *the average surface reflectance of each scene in each wavelength band is the same: gray* [8].

From an image processing stance, this assumption indicates that images of natural scenes should contain pixels having almost equal average gray levels in each spectral band.

7.2 Wavelet Based Dynamic Range Compression And Contrast Enhancement

Dynamic Range Compression

Dynamic range compression and the local contrast enhancement in WDRC are performed on the luminance channel. For input color images, the intensity image $I(x,y)$ can
be obtained with the following equation:

$$I(x, y) = \max[I_i (x, y)], i Î \{R,G,B\}. \quad (3)$$

The enhancement algorithm is applied on this intensity image.The luminance values are decomposed using orthonormal wavelet transform as shown in (4):

$$I(x,y) = \sum_{k,l \in z} a_{J,k,l} \Phi_{J,k,l}(x,y) + \sum_{j \geq J} \sum_{k,l \in z} d^h{}_{j,k,l} \Psi^h{}_{j,k,l}(x,y) + \sum_{j \geq J} \sum_{k,l \in z} d^v{}_{j,k,l} \Psi^v{}_{j,k,l}(x,y) + \sum_{j \geq J} \sum_{k,l \in z} d^d{}_{j,k,l} \Psi^d{}_{j,k,l}(x,y) \quad (4)$$

where aJ,k,l are the approximation coefficients at scale J with corresponding scaling functions FJ,k,l (x, y) , and d j,k,l are the detail coefficients at each scale with corresponding wavelet functions Y*j*,*k*,*l* (*x*, *y*) . A raised hyperbolic sinefunction given by Equation 5 maps the normalized range [0,1] of *aJ*,*k*,*l* to the same range, and is used for compressing the dynamic range represented by the coefficients. The compressed coefficients at level *J* can be obtained by

$$\overline{a}_{J,k,l} = \left[\frac{\sinh(4.6248 a'_{J,k,l} - 2.3124) + 5}{10} \right]^r \quad (5)$$

where *a* ¢ *J*,*k*,*l* are normalized coefficients given by

$$a'_{J,k,l} = \frac{1}{255} \frac{a_{J,k,l}}{2^J}, \quad (6)$$

and, *r* is the curvature parameter which adjusts the shape of the hyperbolic sine function. Applying the mapping operator to the coefficients and taking the inverse wavelet transform would result in a compressed dynamic range with a significant loss of contrast. Thus, a center/surround procedure that preserves/enhances the local contrast is applied to those mapped coefficients.

7.3 Local Contrast Enhancement

The local contrast enhancement which employs a center/surround approach is carried out as follows The surrounding intensity information related to each coefficient is obtained by filtering the normalized approximation coefficients with a Gaussian kernel.

$$G(x,y) = \kappa \exp\left(-\frac{x^2 + y^2}{\sigma^2} \right), \quad (7)$$

where s is the surround space constant, and k is determined under the constraint that

$$\sum_x \sum_y G(x,y) = 1. \quad (8)$$

Local average image representing the surround is obtained by 2D convolution of (7) with image *A* ¢, the elements of which are the normalized approximation coefficients *a* ¢ *J*,*k*,*l* and given by (6) :

$$A_f(x,y) = A'(x,y) * G(x,y) = \sum_{x'=0}^{M-1}\sum_{y'=0}^{N-1} A'(x',y')G(x-x',y-y') \quad (9)$$

The contrast enhanced coefficients matrix *Anew* which will replace the original approximation coefficients *aJ,k,l* is given by

$$A_{new} = \begin{cases} 255\overline{A}^{R}2^{J} & for \;\; R \leq 1 \\ 255\overline{A}^{\left(\frac{1}{R}\right)}2^{J} & for \; R > 1 \end{cases} \quad (10)$$

where, *R* is the centre/surround ratio given by $R = (A'/A_f)^d$. *d* is the enhancement strength constant with a default value of 1; *A* is the matrix whose elements are the output of the hyperbolic sine function in (5).

A linear combination of three kernels with three different scales, combined-scale-Gaussian (*Gc*), is used for improved rendition is given by

$$G_c(x,y) = \sum_{k=1}^{3} W_k \kappa_k \exp\left(-\frac{x^2+y^2}{\sigma_k^2}\right), \quad W_k = \frac{1}{3}, k = 1,\ldots,3. \quad (11)$$

7.4 Detail Coefficient Modification

The detail coefficients are modified using the ratio between the enhanced and original approximation coefficients. This ratio is applied as an adaptive gain mask such as:

$$D_{new}^{h} = \frac{A_{new}}{A} D^{h}; \;\; D_{new}^{v} = \frac{A_{new}}{A} D^{v}; \;\; D_{new}^{d} = \frac{A_{new}}{A} D^{d}, \quad (12)$$

where *A* and *Anew* are the original and the enhanced approximation coefficient matrices at level 1; Dh , Dv , Dd are the detail coefficient matrices for horizontal, vertical and diagonal details at the same level, and Dnew h , Dnew v , Dnew d are the corresponding modified matrices, respectively. If the wavelet decomposition is carried out for more than one level, this procedure is repeated for each level.

7.5 Color Restoration

A linear color restoration process is used to obtain the final color image in our previous work .For WDRC with color restoration a non-linear approach is employed. The RGB values of the enhanced color image (,) , I x y enh i along with the CR factor are given as:

$$I_{enh,i} = \alpha_i I_{enh}, \alpha_i = \left(I_i(x,y)/\max\left(I_i(x,y)\right)\right)^{\beta} \quad (13)$$

where *Ii*(*x*, *y*)is the RGB values of the input color image at the corresponding pixel location and *Ienh* (*x*, *y*) is the resulting enhanced intensity image derived from the inverse wavelet transform of the modified coefficients. Here _ is the non-linear gain factor corresponding. This factor has a canonical value and increases the color saturation resulting in more appealing color rendition. Since the coefficients are normalized during the
enhancement process, the enhanced intensity image obtained by the inverse transform of enhanced coefficients, along with the enhanced color image given by (15) span almost only the lower half of the full range of the histogram. For the final display domain output *enh i I* , 's in (15) are stretched to represent the full dynamic range. Histogram clipping from the upper tail of histograms in each channel give the best results in
converting the output to display domain.

8.RESULTS

WDRC Approximation image

Fig 1 shows that WDRC approximation image

WDRC Reconstructed Spatial Domain image

Fig2.shows the WDRC Reconstructed Spatial Domain image

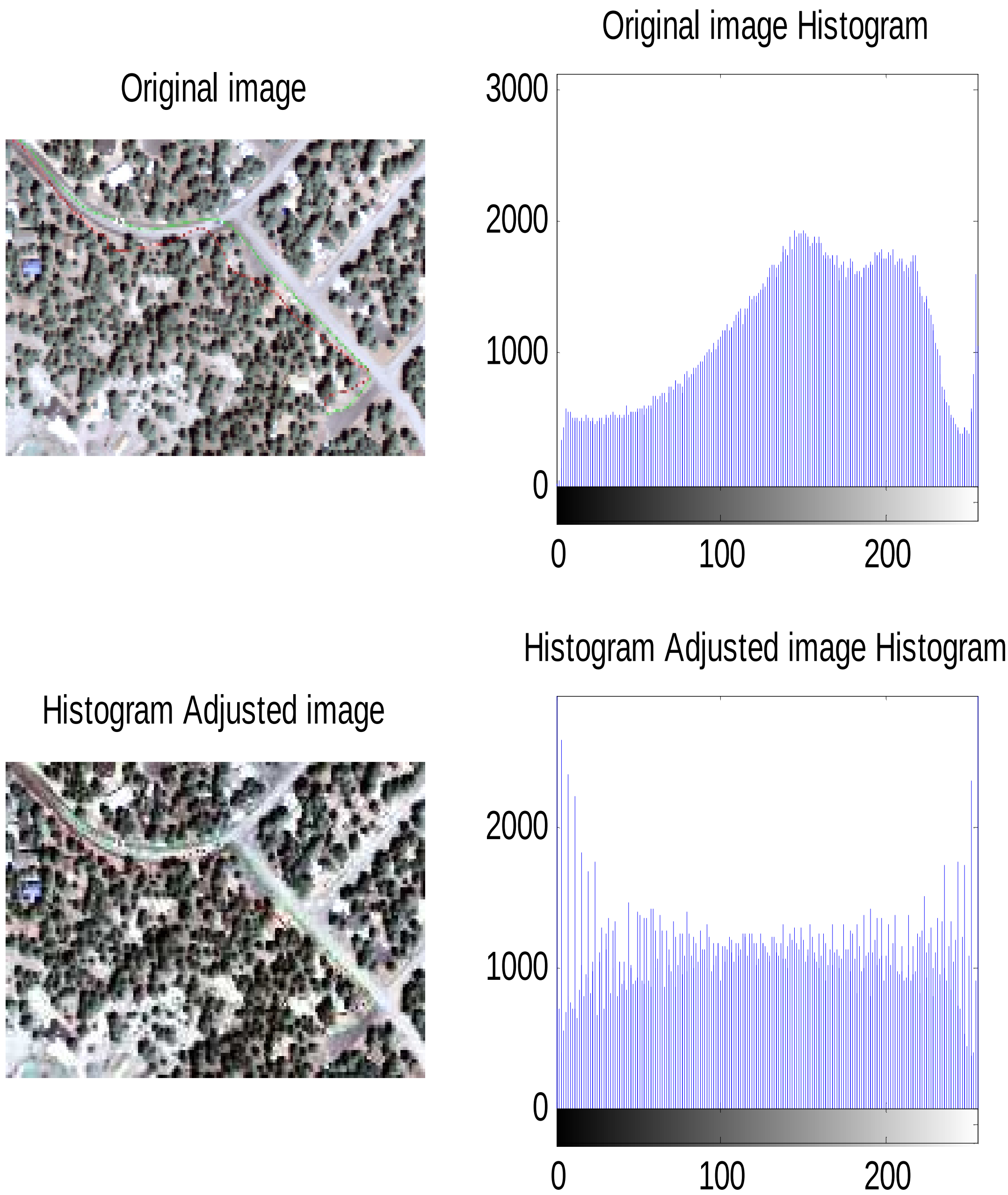
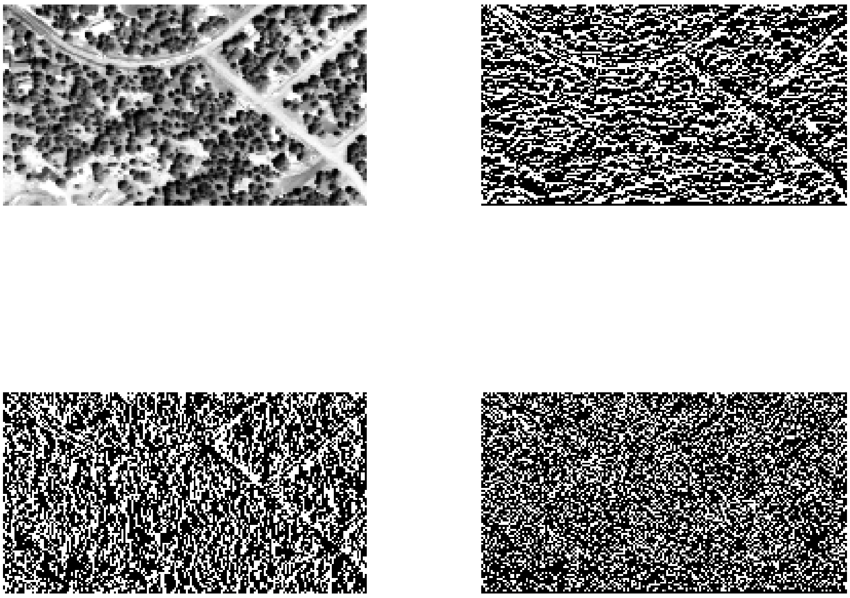


Fig .3. a)original image b)original image histogram c)histogram adjustment d)histogram adjusted image



Original Image

Enhanced Image

8. CONCLUSION

In this project application of the WDRC algorithm in aerial imagery is presented. The results obtained from large variety of aerial images show strong robustness, high image quality, and improved visibility indicating promise for aerial imagery during poor visibility flight conditions. This algorithm can further be applied to real time video streaming and the enhanced video can be projected to the pilot's heads-up display for aviation safety.

9.REFERENCES

[1] D. J. Jobson, Z. Rahman, G. A. Woodell, G.D.Hines, "A Comparison of Visual Statistics for the Image Enhancement of FORESITE Aerial Images with Those of Major Image Classes," Visual Information Processing XV, Proc. SPIE 6246, (2006)
[2] S. M. Pizer, J. B. Zimmerman, and E. Staab, "Adaptive grey level assignment in CT scan display," Journal of Computer Assistant Tomography, vol. 8, pp. 300-305 ,(1984).
[3] J. B. Zimmerman, S. B. Cousins, K. M. Hartzell, M. E. Frisse, and M. G. Kahn, "A psychophysical comparison of two methods for adaptive histogram equalization," Journal of Digital Imaging, vol. 2, pp. 82-91 (1989).
[4] S. M. Pizer and E. P. Amburn, "Adaptive histogram equalization and its variations," Computer Vision, Graphics, and Image Processing, vol. 39, pp. 355-368, (1987).
[5] K. Rehm and W. J. Dallas, "Artifact suppression in digital chest radiographs enhanced with adaptive histogram equalization," SPIE: Medical Imaging III, (1989).
[6] Y. Jin, L. M. Fayad, and A. F. Laine, "Contrast enhancement by multiscale adaptive histogram equalization," *Proc. SPIE,* vol. 4478, pp. 206-213, (2001).
[7] E. Land and J. McCann, "Lightness and Retinex theory," Journal of the Optical Society of America, vol. 61, pp. 1-11, (1971).
[8] A. Hurlbert, "Formal Connections Between Lightness Algorithms", Journal of the Optical Society of America, vol. 3, No 10 pp. 1684-1693,(1986).
[9] E. Land, "An alternative technique for the computation of the designator in the Retinex theory of color vision," Proc. of the National.
[10] J. McCann, "Lessons learned from mondrians applied to real images and color gamuts," Proc. IS&T/SID Seventh Color Imaging Conference, pp. 1-8, (1999).
[11] R. Sobol, "Improving the Retinex algorithm for rendering wide dynamic range photographs," Proc. SPIE 4662, pp. 341–348, (2002).
[12] A. Rizzi, C. Gatta, and D. Marini, "From Retinex to ACE: Issues in developing a new algorithm for unsupervised color equalization," Journal of Electronic Imaging, vol. 13, pp. 75-84, (2004).
[13] D. J. Jobson, Z. Rahman and G.A. Woodell, "Properties and performance of a center/surround retinex," IEEE Transactions onImage Processing: Special Issue on Color Processing, No. 6, pp. 451-462, (1997).
[14] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Multiscale retinex forcolor image enhancement," Proc. IEEE International. Conference. on I Processing, (1996).
[15] D. J. Jobson, Z. Rahman, and G. A. Woodell, "A multi-scale retinex for bridging the gap between color images and the human observation of scenes," IEEE Transactions on Image Processing, Vol. 6, pp. 965-976, (1997).
[16] Z. Rahman, D. J. Jobson, and G. A. Woodell, "Retinex Processing for Automatic Image Enhancement", Journal of Electronic Imaging, January (2004).