Color Image Enhancement with Noise Reduction by Virtual Histogram and Spatial Operation

Gurudev B. Sawarkar , Yogadhar Pandey
(M.Tech Scholar, Department Of Software Engineering, SIRT, Bhopal)
(Asst. Prof., Department Of CSE, SIRT, Bhopal)

ABSTRACT

This paper introduces a new hybrid image the concept of image fusion of filtered noisy images for impulse noise reduction and enhancement approach driven by both global and local processes on luminance and chrominance components of the image. The filtered images are fused to obtain a high quality image compared to individually denoised images. In-order to better appraise the noise cancellation behavior of our fusion technique from the point of view of human perception, an edge detection is performed using canny filter for the fused image. This approach, based on the parameter-controlled virtual histogram distribution method, can enhance simultaneously the overall contrast and the sharpness of an image. The approach also increases the visibility of specified portions or aspects of the image whilst better maintaining image color. The experimental results have shown the superiority of the proposed approach[1].

*KEYWORDS-***Noise reduction, Image processing, image enhancement, Control Intensity**, **histogram equalization.**

1.INTRODUCTION

Image enhancement, which transforms digital images to enhance the visual information within, is a primary operation for almost all vision and image processing tasks in several areas such as computer vision, biomedical image analysis, forensic video/image analysis, remote sensing and fault detection [2, 4]. For example, in forensic video/image analysis tasks, surveillance videos have quite different qualities compared with other videos such as the videos for high quality entertainment or TV broadcasting. High quality entertainment or broadcasting videos are produced under controlled lighting environment, whereas surveillance videos for monitoring outdoor scenes are acquired under greatly varied lighting conditions depending on the weather and time of the day. One of the common defects of surveillance videos is poor contrast resulting from reduced image brightness range. A routine examination of the histograms of the images from the videos reveals that some of the images contain relatively few levels of brightness, and some of the images have a type of histograms. In the type of histograms, a large span of the intensity range at one end is unused while the other end of the intensity scale is crowded with high frequency peaks [4], which is typically representative of improperly exposed images. The problem is how to approximate or reconstruct information that was lost because of the image having been captured under sub-optimal aperture or exposure conditions. Enhancement transformation to modify the contrast of an image within a display's dynamic range is, therefore, required in order to reveal full information contents in the videos, e.g., for forensic investigations.

1.1 BRIEF LITERATURE SURVEY

First of all, the basic strategies are briefly reviewed for image enhancement. Point-operation-based image enhancement includes contrast stretching, non-linear point transformation and histogram modeling [3, 4]. They are zero memory operations that remap a given input grey-level into an output grey-level, according to a global transformation [2, 4, 9]. Non-linear point transformations, which could be expressed as $\boldsymbol{G}(j,k)=[\boldsymbol{F}(j,k)]^p$ where $\boldsymbol{F}(j,k)$ represents the original image, $\boldsymbol{G}(j,k)$ represents the output image and p is the power law variable, have been shown to improve visual contrast in some cases whilst clearly impairing visual contrast in other cases,

In histogram modeling [10, 13, 17, 22, 24], the original image is scaled so that the histogram of the enhanced image is forced to be some desired form such as uniform, exponential, hyperbolic or logarithmic [18, 19]. These methods have the disadvantage of treating the image globally only. In order to differentiate between several areas of the image that may require different levels of contrast enhancement, an adaptive histogram modeling technique was proposed [16]. Images generated by the adaptive histogram modeling process, sometimes, is so harsh on the image visual appearance that an adaptive blurring of the window histogram was proposed prior to forming the cumulative histogram as a means of improving the image quality. Recently, some histogram based approaches, such as dynamic range separate histogram equalization (DRSHE)[6], brightness preserving dynamic histogram equalization (BPDHE)[7] and gain-controllable clipped histogram equalization (GC-CHE)[8] have been developed in order to overcome some drawbacks of histogram equalization methods.

Order statistics filters exhibit better performance as compared to linear filters when restoring images corrupted by impulse noise. Impulse noises are short duration noises which degrade an image. They may occur during image acquisition, due to switching, sensor temperature. They may also occur due to interference in the channel and due to atmospheric disturbances during image transmission.

The goal of the filtering action is to cancel noise while preserving the integrity of edge and detail information. In this paper, we propose a novel technique for impulse noise reduction. In our technique, first an image in captured by a sensor. The image is filtered in parallel with five different smoothing filters. The denoised images obtained from five different filters are fused them to obtain a high quality image free from impulse noise.

Other classes of methods for image enhancement are approaches based on the Retinex theory [21, 23], spatial operations and pseudo-coloring. Spatial operations may suffer from enhancing excessively the noise in the image or conversely smoothing the image in areas that need to preserve sharp details [3] and these operations are also known to be time consuming. Pseudo-coloring methods artificially map the grey-scale image to a color image, with the disadvantage that extensive interactive trials are required to determine an acceptable mapping scheme [2].

1.2 NOISE REDUCTION FUSION TECHNIQUES

The process of combining two or more images into a single image while retaining the important features of each image is called image fusion. In this paper, the filtered images from five different smoothing algorithms are fused to obtain a high quality denoised image. Order-static filters are nonlinear filters whose response is based on the ordering (ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result. The best known filter in this category is

the median filter, which as the name implies, replaces the value of the pixel by the median of the intensity values in the neighborhood of that pixel defined in (3). The pixel with the median magnitude is used to replace the pixel in the signal studied.

MEDIANFILTER(x1,x2,..xN)=MEDIAN(x1,x2,..xN) (3)

The median filter is more robust with respect to the presence of noise.

In the **Vector median filter** (VMF) [1] for the ordering of the vectors in a particular kernel or mask a suitable distance

measure is chosen. The vector pixels in the window are ordered on the basis of the sum of the distances between each vector pixel and the other vector pixels in the window.

The sum of the distances is arranged in the ascending order and then the same ordering is associated with the vector pixels. The vector pixel with the smallest sum of distances is the vector median pixel. The vector median filter is represented as XVMF = *vectormedian* (window) (4) If δi is the sum of the distances of the ith vector pixel with all the other vectors in the kernel, then δi =*Nj* 1Δ(Xi, Xj) (5) where (1≤ i ≤ N) and Xi and Xj are the vectors, N=9. Δ(Xi, Xj) is the distance measure given by the *L*1 norm or the city block distance which is more suited to non correlated noise. The ordering may be illustrated as $\delta 1 \leq \delta 2 \leq \delta 3 \leq, ..., \leq \delta 9$ (6) and this implies the same ordering to the corresponding vector pixels i.e. $X(1) \leq X(2) \leq ..., \leq X(9)$ (7) where the subscripts are the ranks. Since the vector pixel with the smallest sum of distances is the vector median pixel, it will correspond to rank 1 of the ordered pixels, i.e., $XVMF = X(1)$ (8)

For **Basic Vector Directional Filter (BVDF) [5]**, Let W be the processing window of size n, and let xi, i=1,2,…n be the pixels in W. Let also the vector valued image function at pixel xi is denoted as fi. Let αi correspond to fi.

αi =*nj* 1A(fi, fj) where A(fi, fj) denotes the angle between fi and fj. An ordering of the αi,,sα(1) ≤ α(2) ≤ …….. ≤ α(m) ≤…… α(n) (9)

implies the same ordering to the corresponding fi‟sf(1)≤ f(2) ≤ …….. ≤ f(m)≤…… f(n) (10)

The first term in (10) constitutes the output of the BVDF BVDF [f1,f2,……fn] = f(1) (11)

The **Spatial median filter** (SMF) [2] is a uniform smoothing algorithm with the purpose of removing noise and fine points of image data while maintaining edges around larger shapes. The SMF is based on the spatial median quantile function which is a L1 norm metric that measures the difference between two vectors.

In the **Modified Spatial Median Filter** (MSMF) [2], first calculate the spatial depth of every point within the mask and then sort these spatial depths in descending order. After the spatial depth of each point within the mask is computed, an attempt is made to use this information to first decide if the mask‟s center point is an uncorrupted point. If the determination is made that a point is not corrupted, then the point will not be changed. If the point is corrupted, then the point is replaced with the point with the largest spatial depth. We can prevent some of the smoothing by looking for the position of the center point in the spatial order statistic. Let us consider a parameter P (where 1≤ P ≤ N, where N represents numbers of points in the mask), which represents the estimated number of original points under a mask of points. If the position of the center mask point appears within the first P ranks of the spatial order statistic, then we can argue that while the center point is not the best representative point of the mask, it is likely to be original data and should not be replaced. The MSMF is defined by rc c ≤ PMSMF(T,x1,x2,……xN) =r1 c > P We generated five denoised images using the above smoothing algorithms. By fusing the best features of these five denoised images, a high quality image is obtained. The fusion of the filtered images is given by F = ζ Ri where i= 1,2,3,4,5 iR1 is the median filtered image, R2 vector median filtered image, R3 vector directional filtered image, R4 spatial median filtered image and R5 modified spatial median filtered image. ζ is the fidelity factor. The fusion criterion depends on the fidelity factor of the image. For a heavily noised image the fidelity factor ζ will be smaller compared to a lightly noised image and hence we fuse the images, each image contributes to the recovered image depending on its noise density. A lightly noised image contributes more compared to a heavily noised image. This helps to obtain a high quality fused image. We have taken fidelity factor ζ=0.2.

2. PROBLEM FORMULATION : NEED & SIGNIFICANCE OF PROPOSED RESEARCH WORK & OBJECTIVE

Local enhancement methods have been developed based on the gray-level distribution in the neighborhood of every pixel in a given image. A typical example of local enhancement methods is the adaptive histogram equalization (AHE), which has shown good results in medical imaging applications. However, AHE uses an enhancement kernel that is quite computationally expensive. Moreover, AHE may yield unsatisfactory outputs, e.g., images with noise artifacts and falsely enhanced shadows [1, 5].

Furthermore, all the aforementioned methodologies, except the pseudo-coloring, only deal with grey-scale image enhancement, i.e., they only use luminance component of a color image for color image enhancement.

With a especial interest in surveillance video/image processing, the proposed color image enhancement method is a fast adjustable hybrid approach controlled by a set of parameters in order to take the advantages of point operations and local information driven enhancement techniques, in making effective use of the entire range of available pixel-values for both color and luminance components of a color image.

The organization of this paper is as follows. Section II addresses the principles of the proposed image enhancement technique. Experimental results are presented in Section III. Final conclusions are drawn in Section IV.

3. PRINCIPLE OF THE PROPOSED METHOD

In surveillance videos/images, the luminance histogram of a typical natural scene that has been linearly quantized is, more often than not, highly skewed toward the darker levers; a majority of the pixels possess a luminance less than the average. In such images, details in the darker regions are often not perceptible. One means to enhance these types of images is a technique called histogram modification, where the original image is scaled so that the histogram of the enhanced image follows a desired distribution. Usually, a uniform distribution is used to create an image with equally distributed brightness levels over the entire brightness scale. While histogram equalization applies a transformation that yields a close-to-uniform histogram for the relative frequency of the brightness-levels in an image, it only enhances the contrast for brightness values close to histogram maxima, and decreases the contrast near histogram minima [2, 12, 15]. If the image analyst is interested in certain parts or features of an image and the brightness of the parts or features of the image is not close the histogram maxima or, even worse, near the histogram minima, which happens often in surveillance video/image analysis, histogram equalization is helpless in the required contrast enhancement task. A linear-like or no-linear brightness stretching is only effective for an image where the histogram is narrow [2, 9], which is, unfortunately, not often the case in practical video/image analysis.

In order to meet the above particular practical demands and stringent requirements for forensic image/video analysis, biomedical image analysis and remote sensing, a new colour image enhancement method is proposed as follows. The proposed enhancement technique is driven by both global and local processes to achieve not only effective improvement of overall contrast but also the significant enhancement of details in identified features/areas of interest of a color image. The proposed method also aims at employing a much less time-consuming enhancement mechanism than those used by the existing methods.

Histograms are used to depict image statistics in an image interpreted visual format. With histogram, it is easy to determine certain types of problems in an image, such as if the image is properly exposed. Luminance histogram and component histogram both provide useful information about the lighting, contrast, dynamic range, and saturation effects relative to the individual color components [4]. Therefore, in the proposed method the histogram of the enhanced color image should not be saturated at one or both ends of the dynamic range or at least not bring new significant spikes at the tail ends in order not to introduce new poor exposure like defects in the image. In addition to a full use of the maximum possible dynamic range, color component and local information can, certainly, make a contribution to the contrast enhancement. Ideally, an effective image enhancement technique devised using color component and local information must not have or introduce very large spikes in the histogram of the enhanced image.

Therefore, the intention of the proposed method is to find a monotonic pixel brightness transformation $q=T(p)$ for a color image such that the desired output histogram can not only meet specific requirements but also be as uniform as possible over the whole output brightness scale [9] to fill in the full range of brightness values.

First of all, definitions and notations are presented for introduction of the proposed enhancement method.

Let $C = \{c = (c_1 c_2) \mid 1 < c_1 < M, 1 < c_2 < N\}$ denote the pixel coordinates of a color image, where M and N are the height and width of the image, respectively. At each pixel coordinate, c **e** C, multivariate value $\boldsymbol{x}_{RGB}(\mathbf{c}) = [x_R(\mathbf{c}), x_G(\mathbf{c}), x_B(\mathbf{c})]$ is used to represent the pixel in RGB (Red, Green, Blue) color space at the current position and multivariate value $\boldsymbol{x}_{YCCR}(\mathbf{c}) = [x_Y(\mathbf{c}), x_{CB}(\mathbf{c}), x_{CR}(\mathbf{c})]$ is used to represent pixel in YCBCR color space [2, 21]. For each RGB color channel, each individual histogram entry is defined, respectively, as

$$\boldsymbol{h}_R(i)=card\{\mathbf{c} \mid x_R(\mathbf{c})=i, ceC\}, \quad (1)$$
$$\boldsymbol{h}_G(i)=\text{card}\{\mathbf{c} \mid x_G(\mathbf{c})=i, ceC\}, \quad (2)$$
$$\boldsymbol{h}B(i)=\text{card}\{\mathbf{c} \mid x_B(\mathbf{c})=i, ceC\}, \quad (3)$$

where card{•} is the cardinality function, $0 < i < K$, and K is a scale for a component of the color image and, usually, 256.

Second, the color image is, some times, transformed from the RGB color space or another color space to the YCBCR color space necessarily in the proposed image enhancement [2, 21]. The luminance channel histogram of an image in the YCBCR color space is defined as

$$\boldsymbol{h}_Y(i)=\text{card}\{\mathbf{c} \mid x_Y(\mathbf{c}) = i, c \,\mathbf{e}\, C\}, \quad (4)$$

where all symbols are as defined in equations (1) to (3). The cumulative histogram for each RGB component and luminance component, Y, for the YC_BC_R colour space are defined by extending the definition of cumulative histogram from grey-scale image, respectively as

$$H_R(p) = i\,p, h_R(i), \; H_G(p) = 2\_.hG(i), \quad i=p_0$$

$$H_B(p) — 2\_, h_B(i) \quad i=p_0$$

and $H_Y(p) = 2\wedge h_Y(i). \quad i=p_0$

where the input brightness value is $[p0, p_k]$ and p e $[p0, pk]$. The cumulative histograms are monotonic no-decreasing functions with

$\mathbf{H}_R(K)= \mathbf{H}_G(K)= \mathbf{H}_B(K)= \quad \mathbf{H}_Y(K)=$ (14)
MN.

Based on above definitions, the proposed enhancement method is described as follows.

Prominent image events, such as objects or a scene such as edges and contours, originated from local changes in intensity or colour, are highly important for visual perception and interpretation of images. It is thus naturally that the enhancement of edges has been an important task in image processing.

Compared with the original image, an enhanced image with good contrast will have a higher intensity of the edges. Since a histogram of an image contains no information about the spatial arrangement of pixels in the image, luminance histogram and component histogram do not provide any information about the spatial distribution of the actual colours in the image. Since we are only interested in how to enhance the edge intensity without regard to its orientation, a linear differential operator, which is a local geometric information based operator, widely known as the Laplacian,

$$V^2\mathbf{x}(c_1,c_2) = \quad + d^2\mathbf{x}(c_1,c_2) \quad d^2\mathbf{x}(c_1,c_2)$$
$$dc^2 \quad dc^2 \quad vc_2$$

order to enhance edge related area in color images.

In color images, the scale of brightness is 256 represented by 8-bit for most of images, whereas a true RGB color space has distinct 2^{24} colors, with each color component pixel represented by 8-bit. Therefore, the edge information is not only described by their luminance but also conveyed by their color. In order to use information fully from both of brightness and color perception, the Laplacian operation is applied to each of the RGB channels, respectively.

Let

$LRGB(c) =| \wedge^2 xR(c) |+| V^2x_G(c) |+| V^2x_B(c) |.$ (10)

Based on (10), we can define

$S_{La}p=\{ c|L_{RGB}(c) > Tla, \quad c \ \mathbf{6} \ C \}$ “, where threshold T_{la} e [1, 10] , and the default threshold T_{la} is set to 3. (11)

Hence, SL_{ap} is a set of pixel coordinates of an image, i.e., S_{Lap} *a C* . Each of the pixels with their coordinates in

The left side of Equation (17) is the corresponding uniform probability distribution function. The desired pixel brightness histogram transformation *T* is defined as

the set *SLap* has a sum of absolute value of output of the pixel processed with a Laplace operator V (10) and the sum value is greater than T_{la}. We define

$h_{Yv}(p)=\text{card}\{c| x_Y(\mathbf{c})=p, \text{ce } S_{Lap}\},$ (12)

where the input brightness value are $[p_0, p_k]$ and p e $[p_0, pk]$. *hYv(pi)* can be treated as a special density function depended on the local feature of every pixel and the frequency of the brightness value of the pixels.

If a histogram for an input colour image is $h_Y(p)$ and the input brightness value is *[p0, pk]*, *H*, *H1* and H_2, are defined as follows: p_k

$H = V\ hY(i)$ (13)

pki

$H_1 = w\ '1\ h_{Yw}(i)$
$i^= pk_{10}$

and

$$H_2 — v\ /h_{Yv}(i) \quad (15)$$
pk, $i=p_0$

where *pk1* and *pk10* are in the range of *[p0, pk]*; $h_{Yw}(p)= h(p)$ *ifp* is in the range of *(pk10, pk1]*, otherwise $h_{Yw}(p)=0$; *w* is a parameter with the default value of 2; *v* is a parameter with the default value set to 1. Here, *H1(p)* is designed to suit special enhancement requirements for the image interpretation.

Using c — as a normalisation
$H + H_1 + H_2$
coefficient, a new virtual distribution function is defined as

$$\sum_{i=p0}^{p} \wedge h_0(i) - c_n\Big(\sum_{i=p_0}^{p} \wedge h_Y(i) + w \sum_{i=p_{k\,10}}^{p} \wedge h_{Yw}(i) + v \sum_{i=p_0}^{p} \wedge h_{Yv}(i)\Big) \quad (16)$$

If *M* and *N* are the height and the width of an image, respectively, and the output brightness range is $[q_0, qk]$, the desired output histogram can be approximated with (16) by its corresponding continuous probability density as follows:

$$q_0\ q_k - q_0 \quad p0 \quad h_0(s)ds \quad (17)$$
$$MN \text{-------------} ds$$

Z. Xu et al.: Colour Image Enhancement by Virtual Histogram

$q = T(p) = q_k \quad q_0 \quad ^p \quad (s)ds + q_0$

Approach

The discrete approximation of the continuous pixel brightness transformation from Equation (18) is, therefore, given by

$$q = T(p) \quad !>h_0(i) \quad q_0 \quad (19)$$
$$MN \quad i=p_0$$

Thus, the quantisation step-size is obtained as follows

$$qk \sim q0) \quad qk \sim q0$$
$$MN \quad MN \quad (20)\ )$$
$$+ vh_{Yv}(p_i))$$

On the right-hand side of Equation (20), the second term is used to enhance contrast for a specified range *[Pk10, Pk1*]; $wh_{Yw}(i) = 0$, if p_i is not in the range of *[Pk10, Pk1*]; the third term, basically as the first term (input histogram of the

p_0

image), is dependent on the image structure, though the parameter *v* can be adjusted. In most cases, *v* is fixed as 1, since the enhanced result is not very sensitive to the change of the *v* (see Fig.1). Fig1.c and Fig1.d show the results of the tested image enhanced by the proposed method with different values of *v*. Through (20), it can be clearly seen how the output interval value between adjacent two brightness values is produced one by one and how the parameters make contribution to every output brightness level for contrast enhancement since human vision is very sensitive to the interval value $\boldsymbol{A}q$ [12, 20]. The default values of these parameters are: $Pk10 = 0$, $P_{k1} = 30$ and $w = 2$. The parameters can be adjusted by an image interpreter to meet his or her specific requirements. For many cases, the proposed approach with the default values of the parameters works well without user intervention, as changes of the parameters do not affect the enhanced result very much (see Fig.1). Fig1.b Fig1.c and Fig1.d show the results of the tested image enhanced by the proposed method with different values of its parameters.

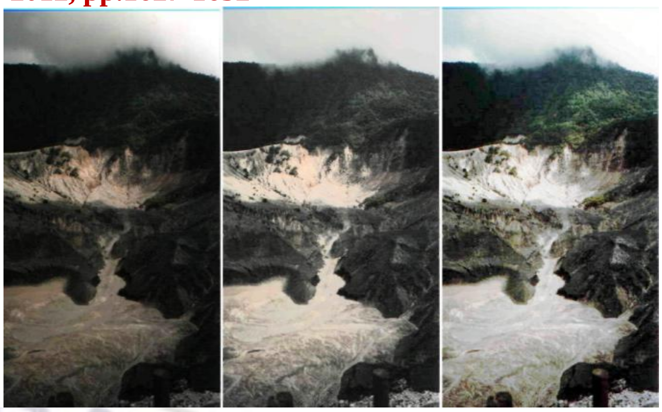
It is noted that the number of reconstruction levels of the enhanced image must be less than or equal to the number of levels of original image to provide proper intensity scale redistribution if all pixels in each quantization level are to be treated similarly [12].

When the contrast of a dark area of an image whose histogram spans a broad range of the display scale is enhanced, the bright areas of the image may be out of the display range as a result of the above rescaling as defined by (19). When the contrast of a bright area of an image whose histogram spans a broad range of the display scale is enhanced, the dark areas of the image may also be out of the display range as a result of the above rescaling as defined by (19). Therefore, a hard-limit is needed to map the output image pixel values back into the display range [9]. However, the simple hard-limiting method is only suitable for an output image with only a few pixels whose brightness values are outside $[q_0, qk]$.

In order to avoid or to greatly reduce the brightness range of the output image, a rescaling constraint is employed using parameter t, which is introduced in the proposed method limit the maxima of $\boldsymbol{A}q$ within t, and to smooth the enhancement contrast over the full brightness scale. Consider a patch of light of intensity $I + AI$ surrounded by a background of intensity I and $\boldsymbol{AI}$ is actually similar to t for human vision. Over a wide range of intensities, it is found that the ratio the AI/I, called the Weber fraction, is nearly constant at a value of about 0.02[2], so the default value of t is set to 3. The rescaling process also relieves further the undesired property of the traditional histogram equalization technique, which tends to reduce contrast near histogram minima.

If an image with its histogram basically concentrated in a very bright region, the image can be first inversed. Then, the proposed method is applied and the resultant image is inversed back, to ensure above constraints being met and to work more effectively.

4. Expected outcome of the proposed work



(a) (b) (c)

(d) (e) (f)

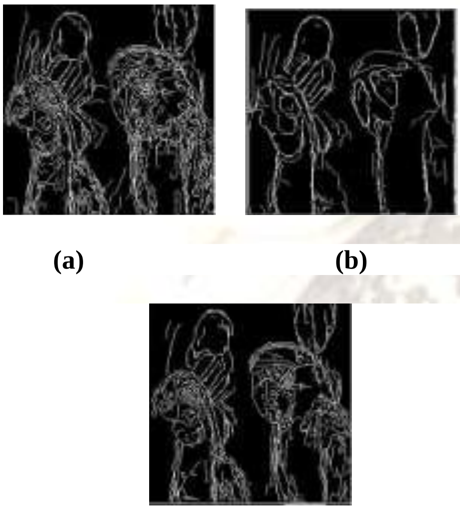
Fig. 1. The enhancement results for test image *Mountain*, a) original image, b) output of the proposed approach-1, c) output of proposed approach-2, d) output of proposed approach-3, e) output of modified linear stretching, f) output of histogram equalization.

(a) (b)

(c) (d)

(e) (f)

Figure 2. a) original image, b) impulse noise image corrupted by noise density 0.4, c) median filter, d) VMF, e) SMF f) Fused image.



(a) (b)

(c)

Figure 3. Edge detection using canny filter
a) Original noise free image
b) Noise image
c) Resultant image by our method

5. CONCLUSION

In this paper, a new hybrid approach based on a virtual histogram modification for color image enhancement and Image fusion technique for removing impulse noise in digital images is proposed. The image captured by the sensor undergoes filtering by different smoothing filters and the resultant images are fused to attain high quality image. The novelty of the proposed method is that color image enhancement is based on modification of a virtual histogram distribution, which is a new way to integrate color and brightness information extracted from salient local features, for global contrast enhancement. The special contributions of the proposed method are the output value scaling bounds control and output range boundary control for the enhancement mechanism to ensure the better maintenance of colour for the enhanced images. The proposed approach introduces the parameters to increase the visibility of specified features, portion or aspects of the image. If the parameters are set up to default values, the proposed method will work as an automatic process. The proposed approach has a potential for various applications to enhance specific categories of images, such as surveillance videos/images, biomedical images and satellite images.

REFERENCES

[1] R. H. Laskar, B. Bhowmick, R. Biswas and S. Kar," Removal of impulse noise from color image" , 2009 IEEE.

[2] James C. Church, Yixin Chen, and Stephen V. Rice , "A Spatial Median Filter for Noise Removal in Digital Images", 2008 IEEE.

[3] Cristian Munteanu and Agostinho Rosa, "Gray-Scale Image Enhancement as an Automatic Process. Driven by Evolution," *IEEE Transactions on Systems , Man, and Cybernetics—part b: Cybernetics,* vol. 34, no. 2, April 2004.

[4] William K. Pratt, *Digital Image Processing*, John Wiley & Sons, 2008.

[5] G. Ramponi, N. Strobel, S. K. Mitra, and T.-H. Yu, "Nonlinear Un-Sharp Masking Methods for Image Contrast Enhancement," *J.Electron. Imaging*, vol. 5, no. 3, pp. 353–366, 1996.

[6] R. C. Gonzalez and P. Wintz. *Digital Image Processing*, 2nd Ed., Prentice Hall, 2002.

[7] J. B. Zimmerman, S. M. Pizer, E. V. Staab, J. R. Pery, W. McCartney, and B. Brenton, "An evaluation of the effectiveness of adaptivehistogram equalization for contrast enhancement," *IEEE Trans. Med. Imag.*, vol. 7, pp. 304–312, Dec. 1988.

[8] Ehsan Nadernejad, "Edge Detection Techniques:Evaluations and Comparisions" Applied Mathematical Science Vol. 2, 2008, no. 31, 1507 – 1520.

[9] S.Indu , Chaveli Ramesh, " A noise fading technique for images highly corrupted with impulse noise", Proceedings of the ICCTA07 , IEEE.