Image Enhancement using Hybrid Fusion Method

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Abstract-. As we know, the images are easily affected by the environmental conditions at a captured time. The environmental conditions like nighttime, dark background and low lighting affect the image very badly. Sometimes the image background is completely dark due to low light conditions. In this work, we use hybrid fusion to improve the quality of the image. Hybrid fusion is the combination of ICA and Exposure fusion method. Firstly we will extract the illumination and reflection image from the degraded input image. The luminance enhanced is the main feature of the fusion process. We will use the ICA fusion method to enhance the luminance quality of the degraded image. Three inputs are derived from the illuminated image — the exposure fusion feed by these three inputs which further improve the quality of luminance region by Laplacian Pyramid and Gaussian pyramid. The Laplacian pyramid is the low pass filter. Gaussian pyramid adjust the weight mapping during the fusion process. After the enhancement of luminance region, it will be added to the reflection part of the image. The image obtained from the combination of enhanced illumination image and reflection image will provide better quality. A comparatively study also provides with the help of previous work done before. The mutual information among the input image and fusion image will provide the better comparison between our work and previous work.

Keywords- *Hybrid Fusion, ICA fusion, Exposure fusion, Image enhancement.*

I. INTRODUCTION

In the present scenario, image processing is mostly used in various applications. The image processing has many fields like image enhancement, image restoration, image coding and watermarking. In the research field, image processing provides the new thoughts, emotions to the record of an event. The image processing also analyzes with computer vision, motion calculation, and video tracking field. The advantages of image processing are more in the research applications. Therefore, we use image processing in various fields. Our work is on the image Restoration field. We implement a hybrid approach to a low light image for the restoration purposes.

1.1 Modeling image degradation

The images are degraded due to the environmental condition present around the objects. Some degradation is noise, blur, distortion and color interference. This type of degradation easily identified and removed easily. But some degradation is a complex type; they are not easy to detect and resolve. The linear equation of the model

$$g = Hu^0 + v \qquad (1)$$

$H =$ point spread function, u^0 is the original image matrix, v is the additive noise in the image. various noises and blur also present in the capture image due to the physical condition of the atmosphere. Various types of issue present in the image degradation model. Some of the reason of image degradation due to (i) Blurring (ii) Noise and (iii) Contrast Interruption

(i). Blurring-The main reason behind the blurring localized averaging of pixels: the movement around the camera and image scene, lens not focused provided the condition of a blur. Blur is a type of noise present in the captured image. The motion or movement comes in the image due to blur. The blur has three categories on the basis of PSF (point spread factor). If all the pixels have the same PSF, the blur is spatially invariant.

(ii) Noise

Noise is the random fluctuation present in the image pixel intensity. The original contents of the image are disturbed, so image quality goes to the poor state. Various noise present in the image model [3].

- Gaussian Noise
- Shot Noise
- Salt and pepper Noise
- Quantization Noise

(iii) Contrast Degradation-

The contrast has the important information about the image pixels and color combination. The light reflectance and illumination obtain in the case of contrast the colors. The image contrast affected by the environmental conditions like temperature and another physical one. Contrast condition filter out the image restoration process. In image restoration process, the image fusion process involved [13]

1.2 Image Fusion

Image fusion defined as the process merging useful information of various source images which provides the more accurate image description regarding the scene then any other one source of images. The quality of the image and video reduces due to the environmental condition surrounding the object and camera. For example, low light condition in night produces low contrast image and minimize the visibility of the image [11] due to the low light and night light the image quality getting very poor. The reflection and illumination provide the suffering condition to the images and videos. Many techniques are used for the image enhancement for increasing the visibility of the images. Histogram methods were used for the better result obtaining in the image case. The Retinex theory also provided the better result for the image enhancement. It basically depends on the reflection and illumination process [6, 10, 18].Retinex theory mainly two type's single scale and multiscale retinex. The reflection is enhanced, and the illumination is estimated in retinex theory — some of the algorithm used for the tuned the variables of the retinex model [7] [18]. The Gaussian filter [19] also used for the separation of reflection and illumination. The Wiener filter provides the better performance to the resulted image in case of visibility and color change [1].The image enhancement can propose by the fusion-based method [11].

II. PROBLEM FORMULATION

Image has two main properties called illumination and reflectance. Let I be the weakly illuminated image and I_L and I_R are the extracted images from$I$.

$$I = I_L \,.\, I_R \qquad (2)$$

The images are affected by the environmental conditions like background light and nighttime. The luminance part of the image l affected generally. The pixel location in the image represent by (x, y) . Therefore $I^c(x, y)$ is actual image and$I_L^c(x, y), I_R^c(x, y)$ is the luminance and reflected images. In this c is the color channel of RGB space. To enhance the weakly illuminated image enhanced the luminance property $I_L^c(x, y)$ of the image. Here in this paper we picked the idea of luminance estimation ($I_L^c(x, y)$) from retinex method but made it less complex by proposing the simple morphological operations ($I_{L1}^c(x, y)$, $I_{L2}^c(x, y)$, $I_{L2}^c(x, y)$) for this purpose [7]. The second proposal is to fuse the single image as multi-exposure image by using hybrid fusion method. The reference paper is using fusion based on Martin paper which was published in 2007 and using pyramidal Gaussian and Laplacian model.

Following these points, we suggest our objectives as:

- To enhance the low light image using luminance estimation and fusion algorithm
- To combine the ICA image fusion with Gaussian and laplacian pyramidal fusion algorithm to enhance the image.
- To compare the results on the criteria of SSIM (structural similarity index), VHS (human visual system) etc.

III. PROPOSED WORK

The images which are captured by the optical imaging device usually degraded due to the presence of weakly illuminated environments around them. The weakly illuminated environment conditions are backlighting, nighttime and non-uniform illumination. In this work, we use an efficient hybrid fusion based method for enhancing the weakly illuminated image.We use this method for the single image enhancement process. Our main focus on image enhancement in very weakly illumination conditions — a brief description of the algorithm given below.

1. A weakly illuminated image considers as the input image which is represented by I. The image affected by the environment conditions like nighttime, lightning, and background etc. at the capture time are weakly illuminated.
2. Extract the illumination and reflectance image from the input image which is represented by the L and R.
3. The illumination image obtained with the help of gradient sparsity function.
4. After obtaining the illumination,an image derived three inputs form them. The illuminated image is $I(L)$ and the three inputs are $I_1(L), I_2(L)$ and $I_3(L)$.
5. Apply Hybrid fusion process on the three derived inputs. It is the combination of ICA based fusion and Exposure-based fusion.
6. The ICA based fusion applied to the derived inputs and the output of the ICA fusion provides to the exposure fusion. The Laplacian and Gaussian pyramid are the basic features of the hybrid fusion.
7. The illuminated enhance image which is obtained from the hybrid fusion combine with the reflectance image.
8. After the combination, we obtained an enhanced image from the weakly illuminated image.

A weakly illuminated image is taken as the input. By using the gradient sparsity extract the luminance and reflected the image from the input image.

3.1 Image segment into Luminance and Reflectance

Let I is the input image and L_1, L_2 are the combined layers of the observed image

$$I(i, j) = L_1 + L_2 \qquad (3)$$

We use the gradient sparsity to provide the importance on the two layers gradients. The layer L_2 is smoother than the layer L_1 which means large gradients related to the L_1. The two layers probabilities defined as the

$$P_1(x) = \frac{1}{z} max \left\{ e^{-\frac{x^2}{\sigma_1^2}}, \in \right\} \qquad (4)$$

$$P_2(x) = \frac{1}{2\pi\sigma_2^2} e^{-\frac{x^2}{\sigma_2^2}} \qquad (5)$$

x is the gradient value and $\sigma_1 and \sigma_2$ are the small values of two narrow gaussian, z is the normalization factor. We developed a model by using the equation 4 and 5 for separation of layers from the input image. The maximizing probability is $P(L_1.L_2)$, this condition is achieved by taking the negative log of equation 4 and 5.

$$-logP_1(x) = min\left\{\frac{x^2}{\sigma_1^2(-log\epsilon)}, 1\right\} + C_1 \qquad (6)$$

$$-logP_2(x) = \frac{x^2}{\sigma_2^2} + C_2 \qquad (7)$$

In equation 6 and 7 the C_1 and C_2 are the constants and $-logP_2(x)$ is in L_2 form and $-logP_1(x)$ is in altered L_2 form. Above equations 6 and 7 further modified as

$$\rho(x) = \min(\frac{x^2}{k}, 1) \qquad (8)$$

Here k is the small constant number and ρ is similar to the sparse penalty. The two layers are independent so $P(L_1, L_2) = P(L_1).P(L_2)$and derivative filter output are also independent, therefore the minimizing probability becomes

$$-log\ P(L_1, L_2) = \min_{L_1L_2} \sum_{i,j}\left(\rho(L_1 * f_j)_i + \lambda(L_2 * f_j)_i^2\right) \qquad (9)$$

Here i is the pixel index and f_j represents different derivative filter.λ is control the smoothness of the outputL_2. The final equation for the image separation layer is

$$\min_{L_1} \sum_i\left(\sum_{j=1,2}\rho(f_i^j L_1) + \lambda(f_i^3 L_1 - f_i^3 I)^2\right) \qquad (10)$$

$$s.t\ lb_i \leq (L_1)_i \leq ub_i$$

The equation 10 represents the non-convex form due to present of $\rho(x)$ component. So, we applied half quadratic separation scheme to solve the problem of non-convex. In this method an external variable g_i^j is added at each pixel which allow to move $f_i^j L_1$ term outside the $\rho(.)$ function. The new cost function is now [24]

$$\min_{L_i g_j} \sum_i\left(\sum_{j=1,2}(\beta\ (f_i^j L_1 - g_i^j\ )^2 + \rho(g_i^j\ )) + \lambda(f_i^3 L_1 - f_i^3 I(i,j))^2\right) \qquad (11)$$

The auxiliary variable g_i^j is update keeping L_1 fixed.

$$g_i^j = \begin{cases} f_i^j L_1, & (f_i^j L_1)^2 > \frac{1}{\beta} \\ 0, & otherwise \end{cases} \qquad (11)$$

Compute L_1 with a fixed value of auxiliary variable g^j from the equation 10.

Similarly, the reflection portion extract from the input image I.

$$\min_{R} \sum_i\left(\sum_{j=1,2}\rho(f_i^j R) + \lambda(f_i^3 R - f_i^3 I(i,j))^2\right) \qquad (12)$$

$$s.t\ I_i \leq R_i \leq 0$$

The smoothness weight λ is near to zero. The luminance and reflection features of the image extracted from the input image I [24].

3.2 Input Derive

Three inputs are $I_1(i,j), I_2(i,j)\ and\ I_3(i,j)$ derived from the actual image $I(i,j)$ .First input is I_1 which is the actual extracted luminance$I$. This input contains the real information about the image and avoid distortion. The second input is I_2 designed to address the global luminance which clarifies the dark regions of the image. The gamma correction and sigmoid function are used improved global luminance. We obtained a second input I_2 suing the arc tangent transformation of the input image.

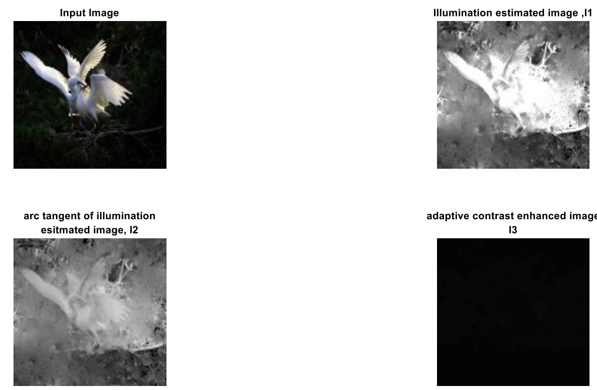


Figure 1 Derived inputs

$$I_2(i,j) = \frac{2}{\pi}\arctan(\lambda I(i,j)) \qquad (13)$$

As studied earlier λ is the parameter which control the degree of luminance,

$$\lambda = 10 + \frac{1 - I_{mean}}{I_{mean}} \qquad (14)$$

I_{mean} is the mean estimated illumination I. Its value decides the luminance darker or not. The smaller value of mean estimation indicates the darker luminance and higher value indicates the luminance perfect.

The third inputI_3 designed to improve the local contrast using the CLAHE scheme. It applied directly on the estimated illumination$I$.

3.3 Hybrid Fusion

Hybrid fusion is the combination of ICA based fusion and Exposure fusion. Firstly, the ICA based fusion method applied to the illumination image. In exposure fusion method the colors, contrast a pixel of the image filter by Laplacian pyramid. The Gaussian pyramid adjusted the weight of the luminance image.

ICA based Fusion- The luminance fusion process performs by the independent component analysis (ICA) method. The ICA is the transform based fusion method. The process of the transform is understood as information of the image and result obtained by the statistical signal processing technique called the ICA. The algorithm which used for the training process extracts a random quantity of these patches and selected for the similar content as the images [21]. Then lexicographic ordering provides the transformed to the vectors image pitch

$x_w(t)$ and mean value of each vector subtract from the transformed vector.

$x_w(t) = Bu(t)$ (15)

$u(t) = B^{-1}x_w(t) = Ax_w(t)$ (16)

Here B is the matrix which provides the set of the projection bases and $u(t)$ is the sparse formation of input image. The PCA (principle component analysis) method applied on the selected patches normally $K < N^2$ used for the important bases. In case of multiple images take as input than the ICA train the bases of the image.

The transform estimation of ICA performed then image fusion process by ICA performed. Each patch of $N \times N$ size isolates from each image $x(i,j)$ and reshape the component to obtain$x(t)$. The vector normalizes for the zero mean which was estimated previously $x(t)$ and then subtracted local mean MN (t). This information of transform vector and mean local vector save for the reconstruction process. The input vector of the image $x(t)$transformed in to the ICA domain vector which is represented by $u(t)$ as in the equation 4.15. In ICA technique the optimal de -noising also available by using the sparse code shrinkage coefficient

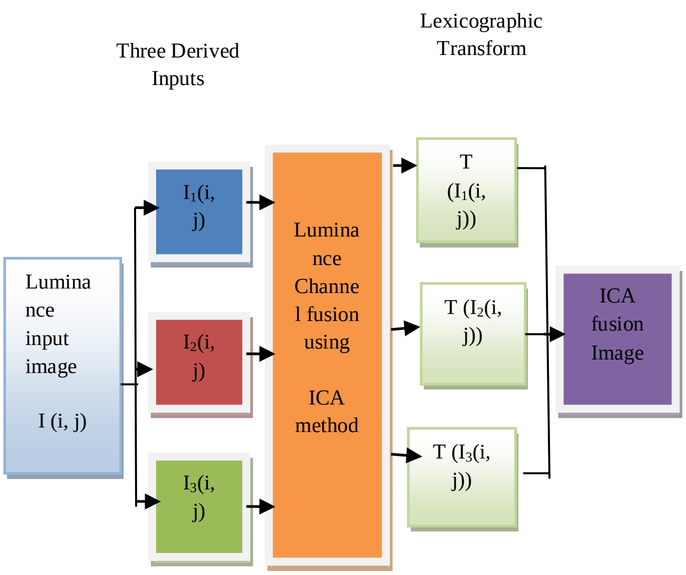


Figure 2 Image Fusion using the ICA method

The image $f(i,j)$synthesiszed by the spatially average image patches $u_f(t)$ as consider in the analysis steps. Some rules are also used in the ICA fusion technique. Absolute Maximum rule- this rule is used to obtain the maximum absolute coefficient of the images which fused by the ICA process. Some information is clearly passed to the output, and some are distorted like intensity information. Averaging rule- it provides the Mean value or average values of the coefficient. A low pass filter is used for that rule. It gives correct color contrast information to the images. Weight Combination pixel-based rule ($w(t)$-this rule is formed for the combine the weight of the multi input in the ICA representation. The weight combination rule used for the best result obtained to the fusion technique.

Exposure fusion

The color channel fusion explains with the help of quality measures of the image. In this case the best quality of the image obtained by using some features of color channels. Firstly, the set of quality measure obtained then the weight map process applied. The output image formulates combining by the stack using the weighted blending. The quality measures explain below:

Quality Measures- The multi images are used for the fusion process. The weight of the images may be different; color can be bright or dull for some images, and some images detail not fulfill the requirement. So, these errors can be removed by analyzing some parameters of the image.

Contrast- in this portion the Laplacian filter applied to the grey scale version of each image and obtained the absolute value through the filter response. A simple detector used for the contrast is C. The main purpose provides the weight to the edges and texture detail which are the main component of images [21, 22].

Saturation- When the long exposure is taken by the cameraman the desaturated colors are obtained. The saturation color provides vivid quality to the images. So the saturation measure S provides to the image exposure which calculated the standard deviation with the R, G and B channels at each pixel [21, 23].

Well, exposedness- The exposedness of pixels depends on the raw intensities of the channels. The weight on the intensity based on the Gauss curve where the value of intensity near 0.5 to the curve. $\exp(-\frac{(i-0.5)^2}{2\sigma^2})$ where the value of σ is 0.2 in implementation case. The Gauss curve is multiplied by the measure E.

The complete weight of the pixels measured by these features extracted from the images. The equation of combination of different weights at the pixel is

$$(W_{ij}) = (C_{ij})^{WC} \times (S_{ij})^{WS} \times (E_{ij})^{WE} \quad (17)$$

Here the parameters are the features which used for the fusion process $C = contrast$, $S = saturation$ and $E =$ well exposedness and weight provided across them areWC, WS and WE. (ij) here ij is, the pixels of the image. The final combine weight (W_{ij}) obtained and it is used for the guidance of fusion process.

If the weights increase quickly than there will be the appearance of disturbing seams. The reason is while combining images they have different absolute intensities due to their different exposure time. This problem can be avoided by the use of Gaussian filter which provides smoothing to the weight maps. But this filter has some drawbacks like halos around the edges of the image and loss some information related to them. Multi-resolution blend technique is used for

Figure 3 Weight mapping

seamlessly blend the two images using the alpha mask and works at multiple resolutions using a pyramidal image decomposition. As shown in figure 4 the input image decomposed into the Laplacian pyramid, which contains the bandpass filter at different scales level mapping process. The pyramid $L\{R\}^l$ is collapsed to compute R . The multi resolution techniques only blend the image features. There is variation in the weight map can affect variation appear in the actual images like edges. The flat portion of the images has negligible coefficient magnitude so they not, affected by the variation of weight maps. For implementation on to the color images the blending of each color channel separately will provide the better results.

As shown in the above figure 4 the l-th level of Laplacian pyramid of decomposition of image A is $L\{A\}^l$ and for the image B is $L\{B\}^l$ similarly for the Gaussian pyramid $G\{A\}^l$ and $G\{B\}^l$. Then combined fused images after both the filters.

$$L\{R\}_{ij}^l = \sum G\{W^\wedge\}_{ij}^l L\{I\}_{ij}^l \quad (18)$$

The equation 18 is considered as the $L\{R\}_{ij}^l = I(L)$, which is the luminance enhanced image.The output of the Laplacian pyramid is weight the average of the actual Laplacian decomposition for the level l. It is provided to the gaussian pyramid for the weight

Combine the reflectance and illumination

Now we have the two terms one is called luminance and other is called reflectance. The luminance fused image is obtained by the equation 18 and reflectance image is $I(R)$. So, the final fusion process obtained by combined both of the cases.

$$I_{Hybrid\ Fusion}(i,j) = L\{R\}_{ij}^l . I(R) = I(L).I(R) \quad (19)$$

Here $I(L)$ is the enhanced luminance image and $I(R)$ is the reflection image which extract from the original image in initial stage of the work. The multi resolution technique is used for the luminance enhancement.

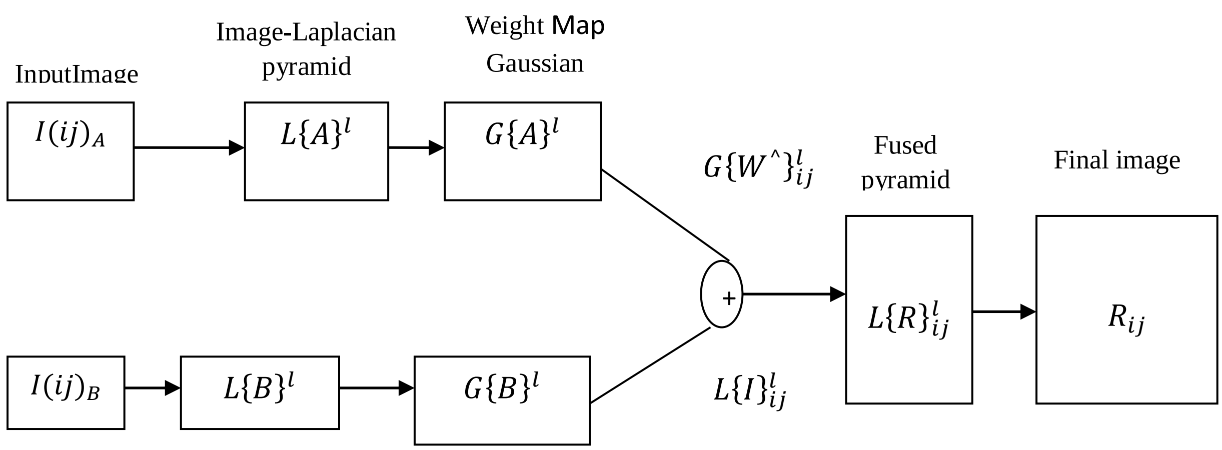
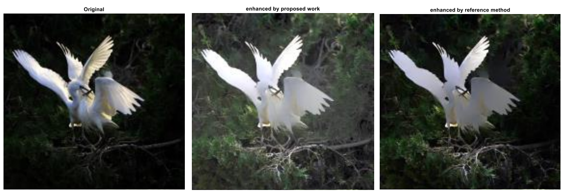


Figure 4 color fusion enhancement using the Laplacian pyramid and Gaussian pyramid [22

VI. RESULTS AND DISCUSSION

4.1 Qualitative assessments

There are three images are shown in figure 5. Image 5 (a) shows the actual input image which is a weak illuminated image. figure 5 (b) shows the image after the hybrid fusion implementation on the input image. the color and contrast of the image are bright and higher. Luminance and reflection properly enhanced in this case. figure 5 (c) shows the resulting image of the reference method. The quality of this image is not better than the proposed work image. The reference algorithm (Xu et.al) cannot handle the dark regions properly due to they enhance the contrast while improving the luminance. Proposed method output image brighter than the reference method output image.



(a)original (b) our method (c) reference

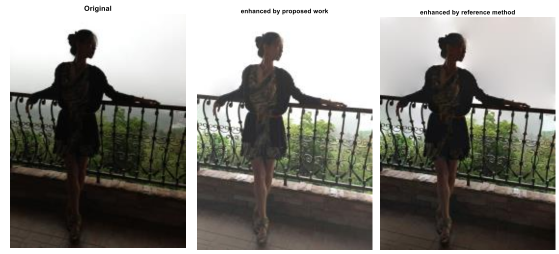
(d)original (e) our method (f) reference

Figure 5 Comparison of images (a), (d)Original (b), (e) our work (c), (f) reference work

The experimental results of the proposed algorithm compared with the reference algorithm. our method provides better result for the image fusion process. The degraded image is enhanced by the hybrid fusion method more accurately. The enhancement process is basically depending on the image quality measure.

The image which is brighter gets the higher image fusion quality. Above figure 6 provides the comparison among the various images which enhanced by the Hybrid fusion method (proposed method) and Xu et.al method (reference method). Figure 6 (a), (b) and (c) shows the fusion process of the street image. The original image represents in figure 6 (a) which affect by weakly illuminated environmental conditions, the bright background and dark foreground present in the same capture scene. Figure 6 (b) and (c) shows the image enhanced by the proposed method (Hybrid fusion) and reference method (Xu et.al method The Xu et.al algorithm only deals with dark regions of the image by improving luminance. The unnatural appearance also occurs in the sky region of the street image in figure 6 (c) due to the over enhancement. This problem is removed by Hybrid fusion which is represented in figure 6 (b). The Woman image shown in figure 6 (d) the clothes and face of the image is dark. The background of the image is bright, and foreground of the image is dark.

(a)original (b) our method (c) reference



(d)original (e) our method (f) reference

(g)original (h) our method (i) reference

(j)original (k) our method (l) reference

(m)original (n) our method (o) reference

Figure 6 different image comparison among the propose Method and X.fu et.al method, (a) (d)(g) (j) (m) are the original images, (b) (e) (h). (k) (n) are the proposed method (Hybrid fusion) enhanced images, and (c) (f) (i) (l) (o) are the reference method enhanced images

The image is shown in figure 6 (f) obtained by Xu et.al fusion method. The white brightness present in the image due to over compresses the luminance. The Hybrid fused image is shown in figure 6 (e) it enhances the dark foreground while maintaining the bright background without introducing contaminants.

Figure 6 (g) and (j) represent the original captured image, which is highly affected by the low light conditions. The image of nighttime and snacks suffers from low light conditions. The contrast of the image is very low — the image enhanced by the Xu et.al method shown in figure 6 (i) and (l). The images of nighttime and snacks are darker when fused by the reference method. This issue is removed by using the Hybrid fusion for the enhancement of the image. The result of hybrid fusion enhanced image shown in figure 6 (h) and (k).

Figure 6 (m) shows the image of a girl. In this image the bright and dark areas present in the same region as shown on the girl clothing. The image shown in figure 6 (o) create over stretched contrast, and some area is over enhanced which loses some details. These all drawbacks will improve by hybrid fusion method.

Quantitative Analysis

The comparison of two fusion methods depends on the quality of the fused image. The image quality gets better when the edges information is proper on to the fusion image edges. Table 1 represents the obtained matrices parameters for hybrid fusion method and Xu et.al method.

Table 1 Comparison of resulting parameters of different images

Image	Proposed Method					Xueyangfu et.al method (reference)				
	MF (Mutual Information)	MSSIM (MEAN of structural similarity)	QG (Gradient-based fusion performance)	Jpeg Quality score	Res (perceptual quality metrice)	MF (Mutual Information)	MSSIM	QG (Gradient-based fusion performance)	Jpeg Quality score	Res (perceptual quality metrice)
Street	258.89	0.99	0.16	27.05	0.50	248.22	1	0.0064	56.67	0.48
Woman	86.48	0.99	0.17	26.15	0.57	27.44	1	0.0056	53.32	0.37
Night time	705.09	0.99	0.16	23.73	0.55	566.90	1	0.0059	53..07	0.49
Snacks	105.50	0.99	0.16	20.40	0.60	86.95	1	0.0068	49.82	0.61
Girl	76.92	0.99	0.18	26.39	0.65	29.60	1	0.0063	53.71	0.61
Parking Buses	95.56	0.99	0.18	24.49	0.58	38.21	1	0.0059	50.53	0.58
Bird	207.71	0.99	0.16	27.92	0.73	100.77	1	0.0064	53.29	0.74
Average	296.59	0.99	0.16	25.16	0.59	156.87	1	0.0061	51.83	0.55

The overall comparison shown in the table1 and mutual information is better for the hybrid fusion method. The mutual information of the input images to the output images based on the various other parameters as shown in table.

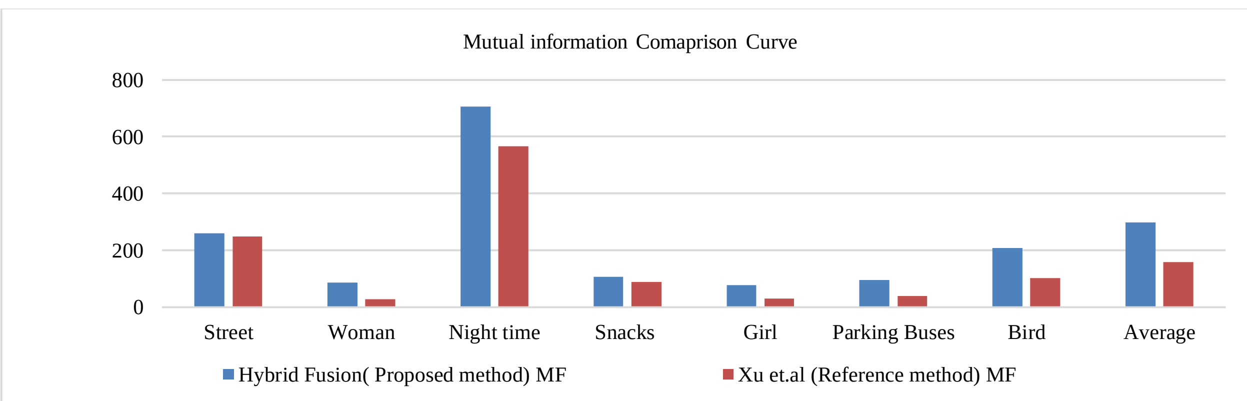


Figure 7 Mutual Information Comparison curve

The quantitative measure of the mutual dependence of two variables called Mutual information. We can define the mutual information with the help of two variables through mathematical formulation. The two discrete random variables are U and V[25]

$$MF(U;V) = \sum_{v\in V}\sum_{u\in U}\rho(u,\ v)log_2\frac{\rho(u,\ v)}{\rho(u),\rho(v)} \quad (20)$$

$\rho(u,\ v)$ is the joint probability distribution function of U and V. $\rho(u)$ and $\rho(v)$ are the marginal probability distribution functions of U and V. Let the input image is

$A(i,j)$ and the fused image is $F(i,j)$The mutual information of a single input image is M_F^A. It can be measure as [25]

$$M_F^A = Mf(A,F)$$

$$M_F^A = \sum_{i,j}\left(h_{AF}(i,j)log_2\frac{h_{AF}(i,j)}{h_A(i)h_f(i)}\right) \quad (21)$$

$h_{AF}(i,j)$ Indicates the normalized joint grey level histogram of images $A(i,j)$ and fused image$F(i,j)$.

Figure 7 shows the comparison curve for the tested image on the basis of mutual information transfer from the input image to the source image. The Hybrid fusion method provides a better result than the Xu et.al method. The quality of the image and pixel information basically depends on the mutual information of the fused image.

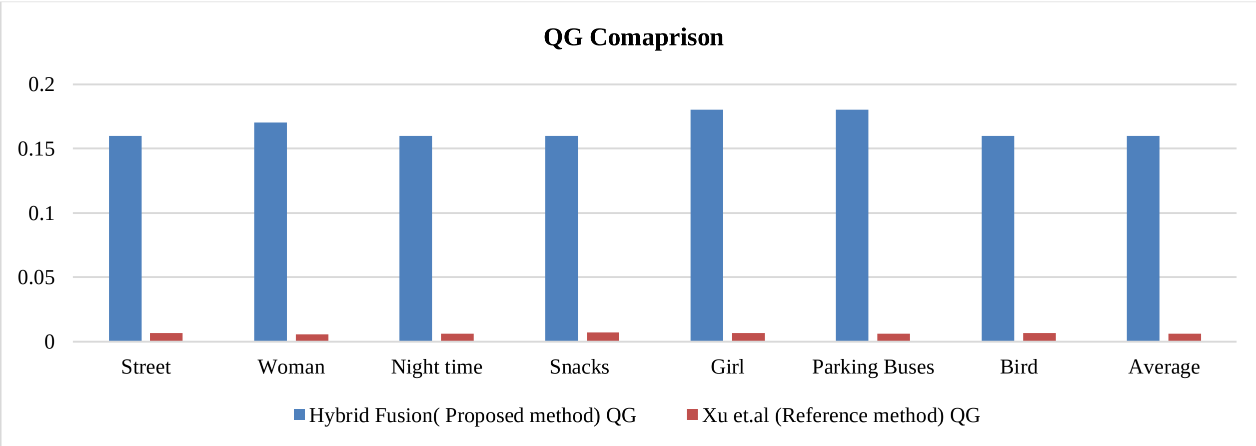


Figure 8 Gradient-based Fusion Performance Comparison Curve

The transformation of features from the input image to the output image is proposed by the gradient-based fusion matrices. It evaluates the amount of edge information which is transferred from the input image to the fused image. A Sobel edge operator is applied obtained the edge strength of input image $A(i,j)$, $g_A(i,j)$and the orientation is $\alpha_A(i,j)$ [24]

$$g_A(i,j) = \sqrt{S_A^x(i,j)^2 + S_A^y(i,j)^2} \quad (22)$$

$$\alpha_A(i,j) = tan^{-1}\left(\frac{S_A^x(i,j)}{S_B^y(i,j)}\right) \quad (23)$$

Here $S_A^x(i,j)$ and $S_B^y(i,j)$ are the convolved results with the horizontal and vertical Sobel. The relative strength and the orientation values between the input image A and the fused image F are

$$\text{Relative strength } (G^{AF}(i,j)) = \begin{cases} \frac{g_F(i,j)}{g_A(i,j)}, & g_A(i,j) > g_F(i,j) \\ \frac{g_A(i,j)}{g_f(i,j)}, & otherwise \end{cases} \quad (24)$$

$$\text{Orientation value}(\Delta^{AF}(i,j)) = 1 - \frac{|\alpha_A(i,j) - \alpha_F(i,j)|}{\pi/2} \quad (25)$$

The edge strength and orientation preservation value defined in equation 26 and 27

$$Q_g^{AF}(i,j) = \frac{\Gamma_g}{1+e^{kg(G^{AF}(i,j)-\sigma_g)}} \quad (26)$$

$$Q_\alpha^{AF}(i,j) = \frac{\Gamma_\alpha}{1+e^{k\alpha(\Delta^{AF}(i,j)-\sigma\alpha)}} \quad (27)$$

Therefore, the overall edge information value is

$$Q^{AF}(i,j) = Q_g^{AF}(i,j)Q_\alpha^{AF}(i,j) \quad (28)$$

The feature-based information metrics is very important for the comparison point of view. The quality of the metrics depends on the feature's transformation metrics of the image [25].

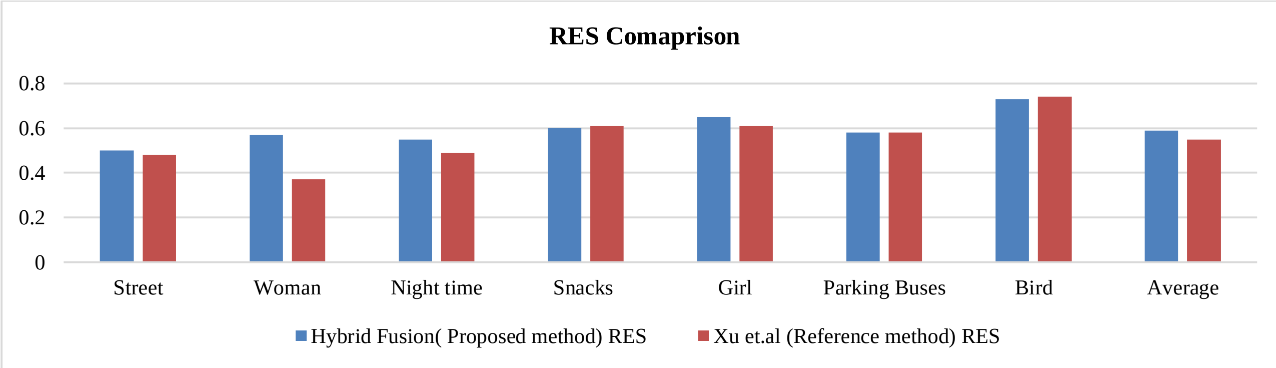


Figure 9 Perceptual Quality Comparison curve

Figure 10 shows the comparison curve for the pixel level performance measurement of the image. The proposed method performance measure is better for the different algorithm.

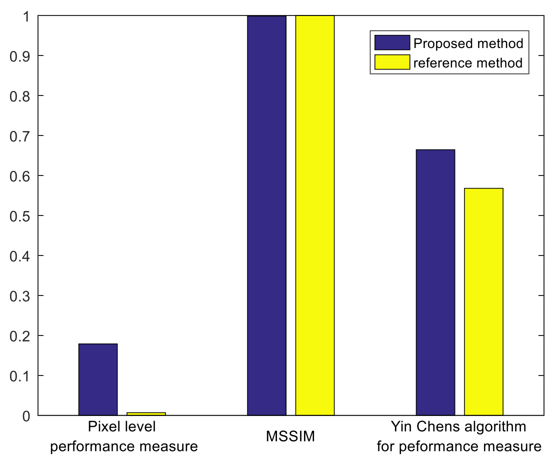


Figure 10 pixel level comparison curve

In the MSSIM and Yin chance algorithm our method provides higher performance. The yellow bar represents the reference method, and the blue bar represents the proposed method of image fusion. The pixel level performance is better for the Hybrid fusion method. The ICA and Exposure fusion provide the proper enhancement to the image pixel. Hybrid fusion provided better results than the MSSIM and Y.C algorithm.

V. CONCLUSION

The images captured during the weakly illuminated conditions called the degraded image. In this work, we enhanced the weakly illuminated image with the help hybrid fusion method. The hybrid fusion method is the combination of Independent Component Analysis method and Exposure fusion method. The ICA fusion method used for enhanced the luminance property of the image. The three inputs of luminance image are derived by the ICA fusion method. The output of the ICA fusion method provides to the exposure fusion method. In the exposure fusion method, the Laplacian pyramid and Gaussian pyramid provided a better weight adjustment luminance image. The quality of measure technique applied in the exposure fusion method for the enhancement quality of the image. The luminance enhanced image added to the reflectance image which provided the fused image with high-quality information. The image fused by the hybrid fusion method provides the better result than the reference method.

VI. REFERENCES

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