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Integrated Color Image Fusion Using Joint Trilateral Filter and IBLPCA

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Abstract: **Image fusion is the method of to merge significant information from more than one image into a single image. The consequential image has enclosed all the essential information in contrast to input images. The latest image has extracts all the information from source images. Image fusion is a useful method for integration single sensor and multi-sensor images to improve the information. The key goal of vision fusion is to combining information from various images of the same view in order to deliver only the useful information. The principal component averaging (PCA) based techniques of vision fusion are more appropriate and time-saving in real-time systems utilizing PCA based standards of still images. In this paper a proficient approach for fusion of multi-focus images based on variance calculated in PCA domain is presented. This study work propose a new method which has integrate the joint trilateral filter and Principal component averaging (PCA) domain to reduce the color artifacts which will be introduced due to the transform domain technique i.e. PCA. To do the performance analysis dissimilar metrics will be considered in this paper. The performance of vision fusion is usually evaluated in terms of accuracy, PSNR i.e. Peak Signal Noise Ratio and speed etc.**

Keywords: Image fusion, Multi-focus, and PCA.

1. INTRODUCTION

Image fusion is the process of to combine relevant information from two or more images into a single image. The resulting image will contain all the important information as compare to input images. The new image will extracts all the information from source images.Image fusion is a useful technique for merging single sensor and multi-sensor images to enhance the information. The objective of image fusion is to combine information from multiple images in order to produce an image that deliver only the useful information. The discrete cosine transformation (DCT) based methods of image fusion are more suitable and time-saving in real-time systems.

Image fusion takes place at three different levels i.e. pixel, feature and decision. Pixel level is a low level of fusion which is used to analyze and combine data from different sources before original information is estimated and recognised. Feature level is a middle level of fusion which extract important features from an image like shape, length, edges, segments and direction. Decision level is a high level of fusion which points to actual target. Its methods can be broadly classified into two that is special domain fusion and transform domain fusion. Averaging, Brovery method, Principal Component Analysis (PCA), based methods are special domain methods. But special domain methods produce special distortion in the fused image .This problem can be solved by transform domain approach. The DCT based method will be more efficient for fusion.

2. LITERATURE SURVEY

Image Fusion is used extensively in image processing systems. Various Image Fusion methods have been proposed in the literature to reduce blurring effects. Many of these methods are based on the post-processing idea. In other words, Image fusion enhances the quality of image by removing the noise and the blurriness of the image. R. Vijayarajan et al. (2014) [1] has discussed that image fusion is a technique of integrating all applicable and balancing information from images of similar source or various sources into a single merged image without any degradation. A novel pixel level fusion called Iterative block level principal component averaging fusion is planned by separating source images into smaller blocks, thus principal components are calculated for applicable block of source images has been explored. Qingping Li et al. (2013) [2] has discussed that in image fusion area, basic pixel-based image fusion methods are responsive to imperfections of source images, and it therefore has much power on the feature of the fusion results. Focusing on this trouble, a region-based multi-focus image fusion method is planned based on the local spatial frequency (LSF). compute LSF for each pixel of source images, and a s fragmentation of the average image is introduced to fragment the source images has been explored. Huaxun Zhang et al. (2013) [3] has discussed that a method of medical image fusion based on wavelet theory is introduced. Medical image fusion have three steps, they are image processing, image list and image fusion. Image processing get across multi resolution features of wavelet to denoise, image list pass the wavelet analysis to achieve biggish transform point and obtain image edge to attain immediate, image fusion use dis-assumble image to various frequency sub-band to save all information to have a ideal fusion has been explored. Rishu Garg et al. (2014) [4] has discussed that image fusion is a method of combining source images i.e. multi-modal, multi-focus etc. to achieve a novel more useful image. Multi-focus image fusion algorithm combines various images having various blocks in focus. Functions of image fusion contains secluded sensing, digital camera etc. Different multi-focus image fusion algorithms which use various focus determine such as spatial frequency, energy of image laplacian, morphological opening and closing etc. has been explored. Wang Yang et al. (2013) [5] has discussed that medical image fusion is a type of latest equipment including medical image treatment and diagnosis. It can be practical to a wide mixture of medical fields such as clinic diagnosis and treatment, computer as istant diagnosis, long-distance medical treatment, radiation treatment and surgery arrangement plan, etc. Digital image fusion is a inclusive information of the multiple source images in order to achieve more exact, more inclusive and more consistent explanation for a exact region or objective, so that it can help the subsequent testing and accepting of the image. The purpose, substance, methods and arrangement of medical image fusion has been explored. Mohammed Hossny et al. (2013) [6] has been discussed that image fusion procedure merges two images into a single more useful image. Objective image fusion presents metrics rely primarily on measuring the quantity of information transferred from every source image into the fused image. Objective image fusion metrics have evolved from image dealing distinction metrics. Additionally, researchers have developed many additions to image distinction metrics in order to improved value the local fusion worthy characteristics in source images. The development of objective image fusion presentation metrics and their individual and objective confirmation has been explored. Mingjing Li et al. (2013) [7] has been discussed that image fusion can be performed at various levels: pixel, feature and decision-making levels. Pixel level image fusion refers to the dealing and synergistic mixture of information gathered by different imaging sources to offer a improved kind of a views. The pixel level image fusion is the direct fusion in the unique information layer, so the quantity of information reserved most. Almost all image fusion algorithms developed to date fall into pixel level. An overview of the most commonly used pixel-level image fusion algorithms and various explanation about their comparative powers and weaknesses has been explored. Rong Fan et al. (2014) [8] has been discussed that in the method of image fusion, the spectral resolution of the antenna makes the information of image fusion be simple to misplace and so affects the feature of the image. Usual image fusion algorithm has great quantity of estimate and reduced real-time performance and does not carefully think the manipulation of fusion policies of low frequency component and the neighborhood features of high-frequency factor on the fusion at the similar time, so it cannot get the perfect fusion result. In order to explain this trouble the non-linear weighted multiband fusion algorithm which introduced the non-linear weighted value has been explored. P. Devaki et al. (2014) [9] has been discussed that in the current past the images of different fields are being measured for processing for different purposes. An algorithm for protecting the secret image whose confidentiality requirements to be maintained, and also to validate the distributor who distributes that secret image to various users has been explored. Om Prakash et al. (2013) [10] has been discussed that the purpose of image fusion is to merge applicable information from two or more images of the similar views into a particular merged image which is more informative and is more suitable for person and machine perception. In current past, various methods of image fusion have been planned in literature both in spatial domain and wavelet domain. Spatial domain based methods generate spatial distortions in the fused image. Spatial domain distortion can be well handled by the use of wavelet transform based image fusion methods. A pixel-level image fusion scheme using multi-resolution Biorthogonal wavelet transform (BWT) has been explored. Lixin Liu et al. (2013) [11] has been discussed that usual techniques of multi-focus image fusion have high calculation and cause blocking outcome or artificial outcome easily. An efficient multi-focus image fusion technique based on the lifting method of wavelets has been explored. K Sharmila et al. (2013) [12] has been discussed that medical image fusion is the techniques of deriving essential information from multi-modality medical images. This derived information can be used for different purposes like diagnosing diseases, detecting the tumor, surgery treatment. This kind of information cannot be obtained using particular modality image. Therefore, the drawbacks of particular modality medical image has smooth the technique for the process of combining various modality images such as computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT) into a particular image. Hence, the above described method of combining multimodality images in to a particular fused image can be done using image fusion methods. A new image fusion method Discrete Wavelet Transform-Averaging-Entropy-Principle Compon-ent Analysis method [DWT-A-EN-PCA] and the results of planned system are compared with other existing fusion methods using quantitative metrics such as, Entropy (EN), Signal to Noise Ratio (SNR) and Fusion Symmetric (FS) for performance evaluation has been explored. Gazal Malhotra et al. (2014) [13] has been discussed that image fusion extracts the information from different images of a particular view to achieve a final image which has more information for human optical perception and is more helpful in additional vision processing. The multi-focus image fusion has become one of the popular procedures in vision processing. Different digital image fusion algorithms have been developed in a number of functions. The AC-DCT based better fusion using edge preserving smoothing and DRSHE has been explored. Ashwini Galande et al. (2013) [14] has been discussed that medical image fusion is the scheme to get better the image content by fusing images taken from various imaging equipment like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and single photon emission computed tomography (SPECT). The purpose of image fusion is to merge more useful information and eliminate redundant information from supply registered images. Image fusion methods are generally classified into two categories i.e Pixel level image fusion and transform based image fusion has been explored. Radhika.V et al. (2014) [15] has been discussed that image fusion is the method of combining helpful information gathered from various optical sensors to present sub-stantial image information. The fused image contains improved information than any particular source image. The statistical methods are used as feature measure to identify the significance of the image or sub image. Commonly most of the images are affected by Gaussian sound. Statistical measures like uniformity and softness recognize irregularity in the images in turn recognize the sub images having less noise. Hence, uniformity and softness in spatial domain for image fusion has been explored. Vivek Kumar Gupta et al. (2013) [16] has been discussed that in remote sensing functions, the growing accessibility of space borne sensors gives a motivation for various image fusion algorithms. secluded sensing image fusion plans at integrating the information suggested by information obtained which cover various segments of the electromagnetic spectrum at various spatial, sequential and spectral resolutions so that get multi-temporal, multi-resolution and multi-frequency image information for functions of characteristic removal, modelling and categorization. The merged or fused image is more helpful for human perception as well as for automatic computer testing task such as characteristic removal, segmentation and object detection. Indian Space Research Organization has recently launched RISAT-1 having microwave imaging antenna and microwave SAR information for image fusion technique analysis has been explored. Xiangda Sun et al. (2013) [17] has been discussed that the source image was decayed into the low pass and directional band-pass coefficients by non-sub-sampled contourlet transform (NSCT) for multi-sensor image fusion of the similar view. The low-pass component uses the fusion technique of better the energy contrast, it fully obtain into account the energy contrast of coefficient as well as the adjacent coefficient features.

3. Gaps In Literature Survey

By conducting the review it has been found that the most of the existing literature has neglected at least one of the following.

As most of the existing methods are based upon transform domain therefore it may results in some color artifacts which may reduce the performance of the transform based vision fusion methods.

It is also found that the problem of the uneven illuminate has also been neglected in the most of existing work on fusion.

Most of the existing work has focused on gray scale images not much work is done for color images.

4. Proposed Algorithm

4.1 Steps of proposed approach:

The detailed algorithm for the proposed approach is given below:

4.1.1 Principal component analysis fusion

PCA is an effective de-correlation and dimensionality reduction method which has found wide applications in pattern recognition, compression, fusion and noise reduction. PCA evaluates eigen-vectors and eigen values globally and concentrates energy of pixels on a small subset of PCA dataset. Let x_i and x_j are the two images to be fused and expressed as column vectors as given by

$$I_{x_i}=\begin{bmatrix} I_{x_1} \\ I_{x_2} \\ \vdots \\ I_{x_I} \end{bmatrix} \quad \text{and} \quad I_{x_j}=\begin{bmatrix} I_{x_1} \\ I_{x_2} \\ \vdots \\ I_{x_I} \end{bmatrix}; \qquad (1)$$

I is number of pixels

The covariance matrix of between two source images is given by

$$cov\left(I_{x_i}, I_{x_j}\right) = E\left[\left(I_{x_i} - \mu_i\right) - \left(I_{x_j} - \mu_j\right)\right] \qquad (2)$$

Mean of all pixels is

$$\mu_i = \left(\frac{1}{I}\right)\sum I_{x_i} \text{ and } \mu_j = \left(\frac{1}{I}\right)\sum I_{x_{ij}} \qquad (3)$$

Diagonal matrix D_m of eigen values and full matrix M whose columns are the corresponding eigen vectors are computed. Eigen values and eigen vectors are arranged in descending order and first 2 × 2 values from M and D_m matrices are taken for fusion. The normalized components n_1 and n_2 are computed from M based on following conditions and should be less than one If $D_m(1,1)$> $D_m(2,2)$

$$n_1 = \frac{M(1,1)}{M(1,1)+M(2,1)}; \quad n_2 = \frac{M(2,1)}{M(1,1)+M(2,1)}; \qquad (4)$$

else

$$n_1 = \frac{M(1,1)}{M(1,1)+M(2,1)}; \quad n_2 = \frac{M^P(2,1)}{M(1,1)+M(2,1)}; \qquad (5)$$

n_1 and n_2 are the weights of input images in the fusion rule and the rule for PCA fusion is given by

$$z = n_1 \times I_{x_i} + n_2 \times I_{x_j} \qquad (6)$$

Weights for fusion rule, n_1 and n_2, decide the amount of information fused from each source image.

4.1.2 Block processing for the proposed algorithm

Dividing image into small blocks is subjective based on gray level profile of images to be fused. In this work, size of the blocks is not generalized for all images and suitable value for size of the block is experimented to get maximum AMI.

$$\text{Size of blocks} = \frac{S}{2^i} \times \frac{S}{2^i}; \qquad (7)$$

Where S= is number of rows and columns in source images

$$\text{Number of blocks} = P = 2^i \times 2^i = 2^{2i}; \qquad (8)$$

Where $i = 1,2,3 \ldots ....$

4.1.3 Iterative block level principal component averaging fusion

Source images are split into P number of blocks. PCA is implemented for the relevant blocks of source images. Principal components are evaluated for the all the blocks as specified. Principal components for all P number of blocks are given as n_1^p and n_2^p. Average of all the principal components are given by

$$n_{1(av)} = \frac{1}{2^{2i}}\sum_{p=1}^{2^{2i}} n_1^p; \quad n_{2(av)} = \frac{1}{2^{2i}}\sum_{p=1}^{2^{2i}} n_2^p; \qquad (9)$$

$i = 1,2,3,4$

i is subjective for different fusion input images. $n_{1(av)}$ and $n_{2(av)}$ constitute weights for fusion rule and the fused image is given by

$$z_{(IBLPCA)} = n_{1(av)} \times I_{x_i} + n_{2(av)} \times I_{x_j} \qquad (10)$$

Algorithm

(1) Divide the input images into p blocks, where P is given by $P = 2^{2i}$; For $i = 1; P = 4$;
(2) Evaluate principal components for P blocks and given by n_1^p and n_2^p
(3) Find out $n_{1(av)}$ and $n_{2(av)}$ as given in Eq. (9)
(4) Fused image is obtained as given in Eq. (10)
(5) Evaluate AMI between fused image and the source images

(6) Repeat steps (1)–(4) for $i = 2,3,4$;

For particular value of i, maximum AMI is obtained which gives better fusion result and apply JTF as follow:

Joint trilateral filter (JTF)

Joint trilateral filter (JTF) is to overcome the gradient reversal artifacts occuring. The filtering process of JTF is firstly done under the guidance of the image J which can be another reference image or the input image T itself. Let T_r and J_r be the intensity value at pixel r of the minimum channel image and guided input image, v_i be the kernel window centered at pixel i, to be consistent with bilateral filter. JTF is then formulated by

$$JTF(T)_r = \frac{1}{\sum_{s\in v_i} V_{JTF_{rs}}(J)} \sum_{s\in v_i} V_{JTF_{rs}}(J) T_s$$

where the kernel weights function $V_{JJTF_{pq}}\ (J)$can be written by

$$V_{JTF_{rs}}(J) = \frac{1}{|V|^2} \sum_{i:(r,s)\in V_i} \left(1 + \frac{(J_r-\mu_i)(J_s-\mu_i)}{\sigma_i^2 + \in}\right)$$

Where μ_i and σ_i^2 are the mean and variance of guided image J in local window V_i, |V | is the number of pixels in this window. When both J_r and J_s are concurrently on the same side of an edge, the weight assigned to pixel s is large. When J_r and J_s are on different sides, a small weight will be assigned to pixel s.

4.2 Performance Metrics

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert. The human visual system (HVS) is so complicated that it is not yet modelled properly. Therefore, in addition to objective evaluation, the image must be observed by a human expert to judge its quality. There are various metrics used for objective evaluation of an image. Some of them are Peak Signal To Noise Ratio (PSNR), Mean Square Error (MSE), Root Mean Square Error (RMSE), Average Error, Normalized Cross-Correlation (NCC).

Peak Signal to Noise Ratio (PSNR):

The PSNR block computes the peak signal-to-noise ratio, between two images. The ratio is often used as a quality measurement between the original and a fused image. The higher the PSNR better the quality of the fused or reconstructed image. PSNR value is computed by following equation:

$$\text{PSNR}=10log_{10}\left(\frac{R^2}{MSE}\right)$$

Mean Square Error (MSE):

Mean square error is a measure of image quality index. The large value of mean square means that image is a poor quality. Mean square error between the reference image and the fused image. MSE value is computed by following equation:

$$\text{MSE}=\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij} - B_{ij}\right)^2$$

Where A_{ij} and B_{ij} are the image pixel value of reference image.

Root Mean Square Error (RMSE): RMSE is a frequently used measure of the differences between values predicted by a model or an estimator and the values. RSME value is computed by following equation:

$$\operatorname{RMSD}(\hat{\theta}) = \sqrt{\operatorname{MSE}(\hat{\theta})} = \sqrt{\operatorname{E}((\hat{\theta} - \theta)^2)}.$$

Average Error: Average error is used to find the average of errors between source and fused image. Average error is calculated by using the given equation:

$$\left(l(m,n) - p(m,n)\right)$$

where $l(m,n)$ is the referenced image and $p(m,n)$ is the fused image

Normalized Cross-Correlation (NCC):

Normalized cross correlation is used to find out similarities between fused image and registered image is given by the following equation:

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij} * B_{ij}\right)$$

As shown in the below given figures, we are comparing the results of various images. As results show that our proposed approach results are much better than exiting approaches. The developed approach is compared against some well-known methods available in literature. After the results, we are comparing the proposed approach against the existing methods.

5. Experimental Set-Up

In order to implement the proposed algorithm, design and implementation has been done in

Table 5.1 Images taken for experimental analysis

Image name	Format	Size in K.Bs (Partially blurred 1)	Size in K.Bs (Partially blurred 2)
Image01	.jpg	21.6	21.2
Image02	.jpg	25.7	25.7
Image03	.jpg	24.4	23.9
Image04	.jpg	26.0	24.8
Image05	.jpg	22.7	23.5
Image06	.jpg	28.1	28.6
Image07	.jpg	29.6	29.5
Image08	.jpg	25.0	25.2
Image09	.jpg	19.7	23.4
Image10	.jpg	13.2	13.2

MATLAB using image processing toolbox. The developed approach is compared against some well-known image fusion techniques available in literature. After these comparisons, we are comparing proposed approach against existing approach using some performance metrics. Result shows that our proposed approach gives better results than the existing techniques. Table 5.1 is showing the various images which are used in this research work. Images are given along with their formats. All the images are of same kind and passed to proposed algorithm.

5.2 Experimental results

Figure 5.1 has shown the input images for experimental analysis. Fig.5.1 (a) is showing the left image and fig.5.1 (b) is showing the right image. The overall objective is to combine relevant information from multiple images into a single image that is more informative and suitable for both visual perception and further computer processing.

Fig 5.1 Input Image

Fig 5.1(a): Left blurred Image

Fig 5.1(b): Right blurred Image

Fig 5.2 Final Filtered Image

Fig 5.3 Trilateral Final Fused Image

Figure 5.2 has shown the final filtered image. The output image has contained low brightness and low contrast as compare to original blurred images to be fused which have degraded the quality of the image.

Figure 5.3 has shown the output image taken by the integrating IBLPCA and JTF based image fusion with nonlinear enhancement. The image has contained the balanced color and brightness as the original images to be fused. The quality of output image is quite good with our proposed method with respect to all the techniques discussed.

6. Performance Analysis

This section contains the cross validation between existing and proposed techniques. Some well-known image performance parameters for digital images have been selected to prove that the performance of the proposed algorithm is quite better than the existing methods.

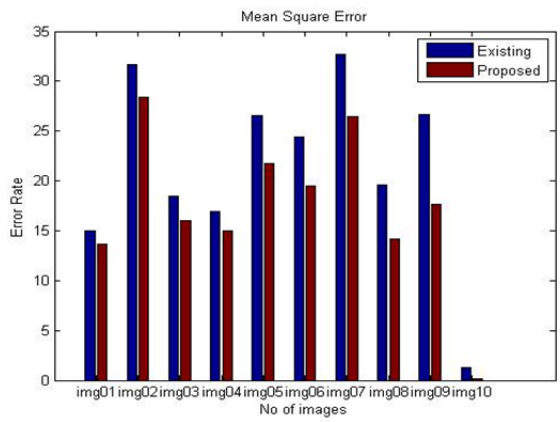
6.1 Mean Square Error Evaluation

Table 6.1 is showing the quantized analysis of the mean square error.

Image name	Existing Value	Proposed Value
Image01	14.994176	13.623008
Image02	31.630432	28.443376
Image03	18.469616	16.051920
Image04	16.960592	14.983408
Image05	26.512752	21.732496
Image06	24.404240	19.471696
Image07	32.720336	26.504736
Image08	19.610240	14.21374
Image09	26.701104	17.695696
image10	1.236480	0.199296

Table 6.1 Mean Square Error

As mean square error need to be reduced therefore the proposed algorithm is showing the better results than the available methods as mean square error is less in every case.



Graph 6.1 MSE of Existing and Proposed Approach for different images

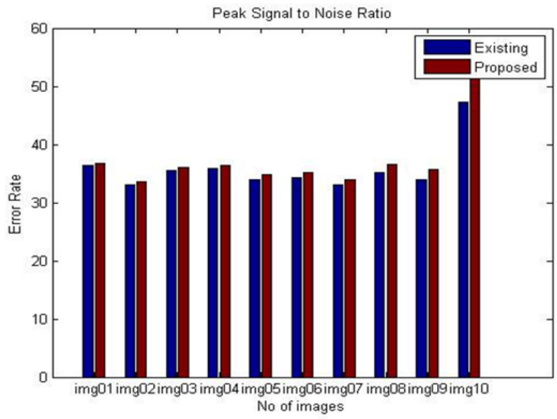
Graph 6.1 has shown the quantized analysis of the mean square error of different images using fusion by existing approach (Blue Color) and Proposed Approach (Red Color). It is very clear from the plot that there is decrease in MSE value of images with the use of proposed method over existing methods. This decrease represents improvement in the objective quality of the image.

6.2 Peak Signal to Noise Ratio Evaluation

Table 6.2 is showing the comparative analysis of the Peak Signal to Noise Ratio (PSNR). As PSNR need to be maximized; so the main goal is to increase the PSNR as much as possible. Table 6.2 has clearly shown that the PSNR is maximum in the case of the proposed algorithm therefore proposed algorithm is providing better results than the available methods.

Image name	Existing Value	Proposed Value
Image01	36.3716	36.7881
Image02	33.1298	33.5910
Image03	35.4662	36.0755
Image04	35.8364	36.3747
Image05	33.8963	34.7597
Image06	34.2562	35.2368
Image07	32.9826	33.8976
Image08	35.2060	36.6037
Image09	33.8655	35.6521
image10	47.2089	55.1358

Table 6.2 Peak Signal to Noise Ratio



Graph 6.2 PSNR of Existing and Proposed Approach for different images

Graph 6.2 has shown the quantized analysis of the peak signal to noise ratio of different images using fusion by existing approach (Blue Color) and Proposed Approach (Red Color). It is very clear from the plot that there is increase in PSNR value of images with the use of proposed method over existing methods. This increase represents improvement in the objective quality of the image.

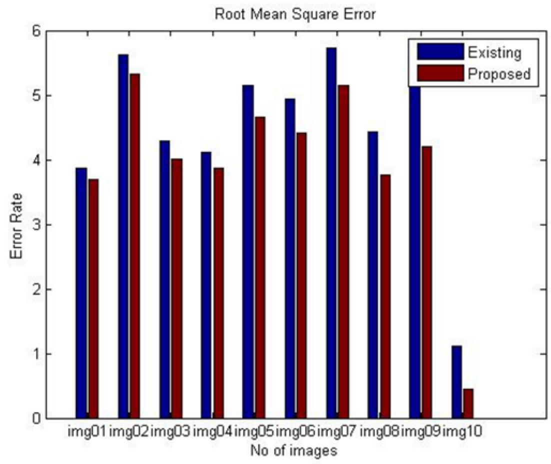
6.3 Root Mean Square Error Evaluation

Table 6.3 is showing the comparative analysis of the Root Mean Square Error (RSME). As RSME need to be minimized; so the main goal is to decrease the RSME as much as possible. Difference needs to be minimized; so the main objective is to reduce the RSME as much as possible.

Image name	Existing Value	Proposed Value
Image01	3.8722	3.6909
Image02	5.6241	5.3332
Image03	4.2976	4.0065
Image04	4.1183	3.8708
Image05	5.1491	4.6618
Image06	4.9401	4.4127
Image07	5.7202	5.1483
Image08	4.4283	3.7701
Image09	5.1673	4.2066
image10	1.1120	0.4464

Table 6.3 Root Mean Square error

Table 6.3 has clearly shown that RSME Difference is less in our case therefore the proposed algorithm has shown significant results over the existing algorithm. Table 6.3 Root Mean Square Error plot that there is decrease in RSME value of images with the use of proposed approach. This decrease represents improvement in the objective quality of the image.



Graph 6.3 RSME of Existing and Proposed Approach for different images

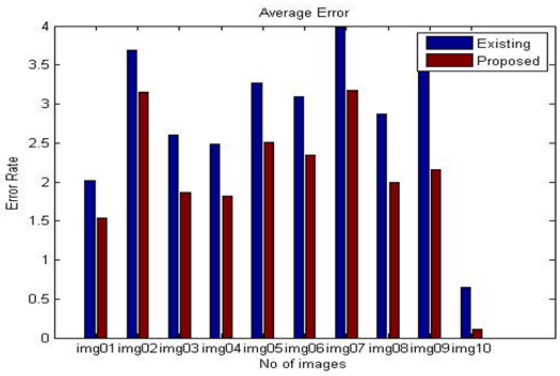
Graph 6.3 has shown the quantized analysis of the Detailed Variance of different images using fusion by existing approach (Blue Color) by Proposed Approach (Red Color). It is very clear from the plot that there is decrease in RSME value of images with the use of proposed approach. This decrease represents improvement in the objective quality of the image.

6.4 Average Error Evaluation

Table 6.4 is showing the comparative analysis of the Average Error. As Average Error needs to be minimized; so the main goal is to decrease the Average Error as much as possible. Difference needs to be minimized; so the main objective is to reduce the Average Error as much as possible. Table 6.4 has clearly shown that Average Error Difference is less in our case therefore the proposed algorithm has shown significant results over the existing algorithm.

Image name	Existing Value	Proposed Value
Image01	2.0199	1.5366
Image02	3.6844	3.1485
Image03	2.5967	1.8645
Image04	2.4878	1.8196
Image05	3.2693	2.5105
Image06	3.0984	2.3433
Image07	3.9814	3.1759
Image08	2.8765	1.9982
Image09	3.4477	2.1555
image10	0.6449	0.1097

Table 6.4 Average Error



Graph 6.4 Average Error of Existing and Proposed Approach for different images

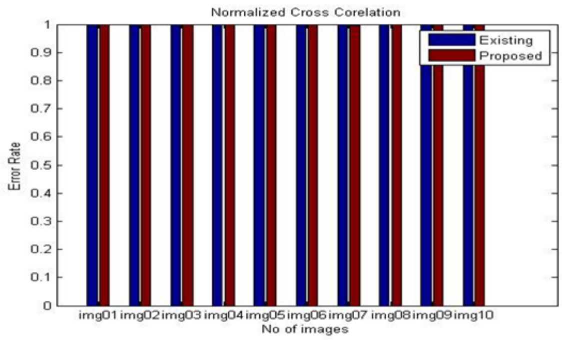
Graph 6.4 has shown the quantized analysis of the Average Error of different images using fusion by existing approach (Blue Color) and Proposed Approach (Red Color). It is very clear from the plot that there is decrease in Average Error value of images with the use of proposed method over existing methods. This decrease represents improvement in the objective quality of the image.

6.5 Normalized Cross-Correlation Evaluation

Table 6.5 is showing the comparative analysis of the Normalized Cross-Correlation (NCC). As NCC needs to be close to 1, therefore proposed algorithm is showing better results than the available methods as NCC is close to 1 in every case.

Image name	Existing Value	Proposed Value
Image01	0.9996	0.9987
Image02	0.9996	0.9981
Image03	0.9996	0.9984
Image04	0.9990	0.9979
Image05	0.9995	0.9988
Image06	0.9989	0.9972
Image07	0.9982	0.9951
Image08	0.9995	0.9987
Image09	0.9987	0.9972
image10	0.9997	1.0000

Table 6.4 Normalized Cross Correlation



Graph 6.5 NCC of Existing and Proposed Approach for different images

Graph 6.5 has shown the quantized analysis of the Normalized Cross-Correlation of different images using fusion by existing approach (Blue Color) by Proposed Approach (Red Color).). It is very clear from the plot that there is value of NCC is close to1in every case with the use of proposed method over other methods. This represents improvement in the objective quality of the image.

7. CONCLUSION

The main focus of vision fusion is to integration information from numerous images of the identical view in order to bring only the useful information. The principal component averaging (PCA) based techniques of vision fusion are proper and time-saving in real-time systems using PCA based standards of still images. In this paper a well-organized approach for fusion of multi-focus images on the basis of discrepancy calculated in PCA province is presented. In this paper, we propose a new method which has combine the joint trilateral filter and iterative block level principal component averaging (IBLPCA) province to decrease the color artifacts which has been introduced suitable to the transform domain technique i.e. PCA. To do the result evaluation different metrics has been considered. The result evaluation of vision fusion is usually evaluated in terms of accuracy, PSNR and speed.

REFERENCES

[1] R.Vijayarajan, Iterative block level principal component averaging medical image, *fusion Optik 125 (2014) 4751–4757.*

[2] Qingping Li, Region-based Multi-focus Image Fusion Using the Local Spatial Frequency, *IEEE 25th Chinese Control and Decision Conference (CCDC), 3792-3796, 2013.*

[3] Huaxun Zhang, A Way of Image Fusion Based on Wavelet Transform, *IEEE 9th International Conference on Mobile Ad-hoc and Sensor Networks, 498-501, 2013.*

[4] Rishu Garg, Survey on Multi-Focus Image Fusion Algorithms, *RAECS UIET Panjab University Chandigarh, 06 – 08 March, 2014.*

[5] Wang Yang, Research and development of medical image fusion, *IEEE North Eastern University, Shenyang, 307-309, 2013.*

[6] Mohammed Hossny, Image Fusion Metrics: Evolution in a Nutshell, *UK Sim 15th International Conference on Computer Modelling and Simulation, 443-450, 2013.*

[7] Mingjing Li, Review on Technology of Pixel-level Image Fusion, *2nd International Conference on Measurement, Information and Control, 341-344, 2013.*

[8] Rong Fan, Non-linear Weighted Multiband Fusion Image Algorithm, *IEEE Workshop on Electronics, Computer and Applications, 449-452, 2014.*

[9] P. Devaki, A Novel Algorithm to Protect the Secret Image fusion and verifying the Dealer and Secret Image, *IEEE Fifth International Conference on Signal and Image Processing, 77-80, 2014.*

[10] Om Prakash, Biorthogonal Wavelet Transform Based Image Fusion Using Absolute Maximum Fusion Rule, *IEEE Conference on Information and Communication Technologies (ICT),577-582,2013.*

[11] Lixin Liu, An Effective Wavelet-Based Scheme for Multi-focus Image Fusion, *IEEE International conference on Mechatronics and Automation August 4-7, Takamatsu, Japan, 1720-1725, 2013.*

[12] K Sharmila, Hybrid Method for Multimodality Medical image fusion using Discrete Wavelet Transform and Entropy concepts with Quantitative Analysis, *IEEE International conference on Communication and Signal Processing, April 3-5, India, 489-493, 2013.*

[13] Gazal Malhotra, Improved Multi-focus image fusion using AC-DCT, edge Preserving Smoothing and Drshe, *International Conference on Computer Science, Cloud Computing and Applications July 24-25,India, 124-130, 2014.*

[14] Ashwini Galande, The Art of Medical Image Fusion: A Suervey, *IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI), 400-405, 2013.*

[15] Radhika.V, Performance Evaluation of Statistical Measures for Image Fusion in Spatial Domain, *IEEE International Conference on Networks & Soft Computing, 348-354, 2014.*

[16] Vivek Kumar Gupta, Analysis of Image Fusion techniques over Multispectral and Microwave SAR images, *International conference on Communication and Signal Processing, April 3-5, India, 1037-1042, 2013.*

[17] Xiangda Sun, Improved Energy Contrast Image Fusion based on Non-subsampled Contourlet Transform, *IEEE 8th Conference on Industrial Electronics and Applications (ICIEA), 1610-1613, 2013.*