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An Efficient Multi-Focus Image Fusion Scheme Based On PCNN

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Abstract- **Optics of lenses with a high degree of magnification suffers from the problem of a limited depth of field. As the focal length and magnification of the lens increase, the depth of field decreases. As a result, it is often not possible to get an image that contains all relevant objects in focus. To overcome the problem of finite depth of field, image fusion technique is designed which combines the information from multiple images, with the same scene, into one image. For the fusion problem of the multi-focus image of the same scene, an efficient image fusion scheme is proposed based on Pulse Coupled Neural Network (PCNN) model. PCNN is a feedback network and each PCNN neuron consists of three parts: the receptive field, modulation field and pulse generator. It has some characteristics, such as: pulse coupling, variable thresh-old, generating synchronous pulse and multiplication modulation, etc.In order to avoid the influence of noise and select the coefficients of the fused image properly, different sub band coefficients employ different selection principles. The fused image with more information about the edge, texture and better contrast as well as more similar with original image can be obtained.**

Keywords— Multi-Focus, Image Fusion, Pulse Coupled Neural Networks

I. INTRODUCTION

In applications of digital cameras, when a lens focuses on a subject at a certain distance, all subjects at that distance are sharply focused. The objects which are not at the same distance are out of focus and theoretically are not sharp. This is because of a finite depth of field. To obtain an image with every object in focus, an image fusion technique is required to fuse the images. The purpose of image fusion is to combine information from multiple images into a single image that ideally contains all the important features from each of the original images. During the fusion process, all the important visual information found in the input images must be transferred into the fused image without introduction of artifacts.

The Image Fusion Technique is required for images captured with different camera settings in order to obtain single fused image which consists of the information combined from multiple images. The optical lenses in cameras are having limited depth of focus so it is not possible to obtain an image having all objects in focus. The purpose of image fusion is to combine information from multiple images into a single image that ideally contains all the important features from each of the original images. During the last decade, a number of techniques for multi-focus image fusion have been proposed. Pulse coupled neural network (PCNN) is a novel artificial neural network model [1]. It has been efficiently applied to image processing in applications such as image segmentation, image fusion, and image recognition. It is characterized by the global coupling and pulse synchronization of neurons. These characteristics benefit image fusion which makes use of local image information. The value of single pixel in spatial or MSD domain [8] is used to motivate one neuron. In addition, because each neuron has one input, usually multiple PCNN models are needed when applied to image fusion. The motivation is to obtain improved performance parameters with efficient image fusion output, which will help to achieve the efficiency of the proposed system.

II. LITERATURE REVIEW

In this section we present some earlier work related to various image fusion techniques such as multiscale decomposition method, discrete wavelet transform, Lifting Stationary Wavelet Transform, Non Subsampled Contourlet Transform, Principal Component Analysis, Pulse Coupled Neural Networks. In order to effectively retain details and suppress noise, a multi-focus image fusion method based on Surfacelet transform and compound PCNN can be used. Surfacelet transform is used to decompose the original image into a number of different frequency band sub-images. Compound PCNN model is a combined model of PCNN and dual-channel PCNN which is to select the fusion coefficients from the decomposed coefficients. The fusion coefficients are decided by compound PCNN[1]. Based on the PCNN model and contrast modulation method, a new multi-focus image fusion method is given. The characteristic of image region clustering enhances the veracity of contrast. Then using the normalization contrast modulation gets two fusion images. Finally, use local variance to get the new fusion image.The experiment indicates that the fusion image contains more information about the edge, texture and detail, and it has a better contrast. Compared with the common methods, the innovative method embodies better fusion performance in information, standard and average grads[2]. Medical image fusion plays an important role in clinical applications such as image-guided surgery, image-guided radiotherapy, noninvasive diagnosis, and treatment planning. In order to retain useful information and get more reliable results, a novel medical image fusion algorithm based on pulse coupled neural networks (PCNN) and multi-feature fuzzy clustering is proposed. It makes use of the multi-feature of image and combines the advantages of the local entropy and variance of local entropy based PCNN[6]. This image fusion method can better preserve the image de- tails and robustness and significantly improve the image visual effect than the other fusion methods with less information distortion. In order to evaluate the information of the input images with better quality of image, a new criterion is proposed to give better quality of image using PCA, by denoising and bilateral gradient based sharpness criterion that is evaluated using the gradient information of the images. Then the proposed method is further exploited to perform weighted aggregation of multi focus images. The experimental results show that the proposed method is better than the other method in terms of quality matrices like Mutual information, spatial frequency and Average difference[9].

III. SYSTEM MODEL DESCRIPTION

In this section, we introduce the implementations details. The below fig 1 shows the block diagram of implementation system for multi-focus image fusion.

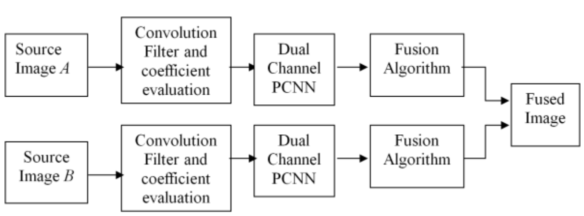

Fig 1: Block Diagram of Implementation System for Multi-Focus Image Fusion

It gives the basic idea about the complete process of image fusion for multi-focus images based on convolution filtering and Dual Channel PCNN. The first step includes accessing images having different focuses, which are to be fused further. The key challenge of multi-focus image fusion is how to evaluate the blurriness of each image and then select information from the most informative (sharp) image. The preprocessing steps include Convolution Filters to modify the spatial frequency characteristics of image. So convolution filter is applied on the input images. This helps to remove noise from the image to get better quality output of fused image. The features such as gradient strength and phase coherence are extracted. These features are used further along with the Pulse Coupled Neural Networks output to fuse the images. The frequency coefficients of source images are used to train the Dual channel PCNN. The output of PCNN and the features including Gradient Strength and Phase Coherence of the input images taken are used to fuse images together. The steps followed are explained as follows.

1] Input the source Images: Two multi-focus images are taken as an input to the image fusion system. Here, in one image, focus is on one object and in another image, focus is on another image. These images are converted to double precision before undergoing the further process of filtering.

2] Convolution Filtering: The next step involves convolution filtering. Convolution is a general purpose filter effect for images. It works by determining the value of a central pixel by adding the weighted values of all its neighbors together. The matrix of weights is called the *convolution kernel*, also known as the *filter*. The output is a new modified filtered image. The purpose of convolution filtering of images is to smooth, sharpen, intensify and enhance the images. After convolution filtering, certain features such as gradient strength and phase coherence are extracted.

3] Dual Channel Pulse Coupled Neural Networks: The third step of the multi-focus image fusion is Dual Channel PCNN. A PCNN neuron contains two main compartments: the Feeding and Linking compartments, F_{ij} and L_{ij}, respectively. Each of these communicates with neighboring neurons through the synaptic weights M and W respectively. Each retains its previous state but with a decay factor. S_{ij} is the input stimulus such as the normalized gray level of image pixels in (i, j) position. The input stimulus i.e. the pixel intensity is received by the feeding element and the internal activation element combines the feeding element with the linking element. This element value is compared with a dynamic threshold value. The internal activation element accumulates the signals and then fires the output element. The output of the neuron is then iteratively fed back to the

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element with a delay of one iteration. The features extracted images after applying convolution filter are used to train the dual channel PCNN. The neuron generates a pulse, called a firing. In fact, after n iterations, the number of firings of the neuron is used to represent the information of the image at the corresponding point. Firing map is constructed by the number of firings and is regarded as output of PCNN. After processing the images using dual channel PCNN, the final output image is obtained by using features extracted in 2nd step and output of PCNN, which is the fused image. The figure below shows the Dual Channel PCNN Model.

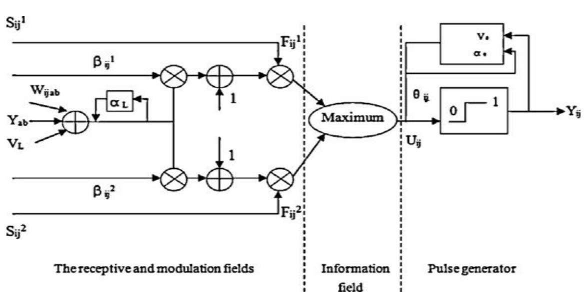

Fig 2: Dual Channel PCNN Model

In Dual Channel PCNN model, the receptive field consists of two external output $F_{ij}[n]^1$ and $F_{ij}[n]^2$ which are defined as,

$$F_{ij}[n]^1 = S_{ij}[n]^1 \quad \text{and} \quad F_{ij}[n]^2 = S_{ij}[n]^2$$

In modulation field, firing mapping image is defined as,

$$U_{ij}[n] = \max(F_{ij}[n]^1(1+\beta_{ij}^1 L_{ij}[n]),F_{ij}[n]^2(1+\beta_{ij}^2 L_{ij}[n])$$

where,

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1]$$

The pulse generating domain pulse output of neuron is defined as,

$$\mathrm{Yij}[n] = \begin{cases} 1, & \mathrm{Uij}[n] > Tij[n] \\ 0, & Otherwise \end{cases}$$

And Dynamic threshold is defined as,

$$T_{ij}[n] = e^{-\alpha_T} T_{ij}[n-1] + V_T Y_{ij}[n]$$

Where,

$S_{ij}[n]^1$ & $S_{ij}[n]^2$ – Input Stimulus represent pixel value of image

$L_{ij}[n]$ – Linking Input

$U_{ij}[n]$ – Firing Mapping image i.e. Internal activity of neuron

W_{ijkl} – Synaptic Connections

β – Linking weight

V_L & V_T - Normalization Constants

$Y_{ij}[n]$ – Pulse Output of Neuron

Image Fusion Algorithm: Image Fusion algorithm specifies the step by step implementation of the proposed Multi-focus Image fusion system based on convolution filtering and dual channel pulse coupled neural networks. After applying this algorithm on input images, performance parameters can be evaluated depending upon the output fused image obtained.

Suppose N is the time of iterations. The steps of proposed Image Fusion Algorithm are as follows:

1. Read the two gray-scale images with different focuses.
2. Remove the noise from input images, in order to avoid errors.
3. Set parameters p_w, p_α and p_β to adjust the contribution of the criterions used in algorithm. For different images p_w, p_α and p_β can be adjusted accordingly.
4. Calculate gradient strength and phase coherence of the input images.
5. Every image gets a series of high and low frequency sub-bands after decomposing image A and B in spatial domain.
6. The normalization of high and low frequency sub-bands with weighted average coefficients of source images.
7. Fire times of coefficients of wavelet decomposition are evaluated after normalization using dual channel PCNN.
   i. Initialization: $L_{ij}[0]=0$, $U_{ij}[0]=0$, $Y_{ij}[0]=0$, $T_{ij}[0]=0$.
   ii. According to mathematical expressions defined for Dual channel PCNN, calculate the values of $L_{ij}[n]$, $U_{ij}[n]$, $Y_{ij}[n]$ and $T_{ij}[n]$.
   iii. If n=N is satisfied, the iteration finishes.
8. Using the gradient strength and phase coherence obtained in step 4 and the PCNN output in step 7 fused the images processed through convolution and dual channel PCNN.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In order to evaluate the fusion performance, certain parameters are defined. These parameters evaluate the fusion quality information, spatial frequency, correlation and SNR between source images and fused image.

- **Mutual Information**

Mutual information expresses how much information of source image is fused into the result image. The larger the mutual information is, the better the fusion effect. Suppose that A and B are source images and F is the fused image, then the calculation of mutual information between A and F, B and F are respectively shown as formulas:

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$$I_{AF} = \sum_{a,f} p_{AF}(a,f) \log \; p_{AF}(a,f) / p_A(f)\, p_F(f)$$

$$I_{BF} = \sum_{b,f} p_{BF}(b,f) \log \; p_{BF}(b,f) / p_B(f)\, p_F(f)$$

Where,

p_{AF} & p_{BF} - Joint Histogram of the source images.

F, p_A, p_B, p_F - Histograms of A, B, F

a, b, f - pixel values of respective image.

The calculation of mutual information is given by formula:

$$MI = I_{AF} + I_{BF}$$

- **Spatial Frequency**

Spatial frequency is defined as:

$$SF = \sqrt{RF^2 + CF^2}$$

where RF and CF are the row frequency

$$RF = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [f(x,y) - f(x,y-1)}$$

and Column Frequency

$$CF = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [f(x,y) - f(x-1,y)}$$

respectively and f(x,y) is the fused image.

- **Correlation between Input Images and Fused Image**

The correlation between two images is given as,

$$Corr[A,B] = \frac{\text{cov}\,[A,B]}{\sqrt{\text{var}\,[A]\text{var}\,[B]}}$$

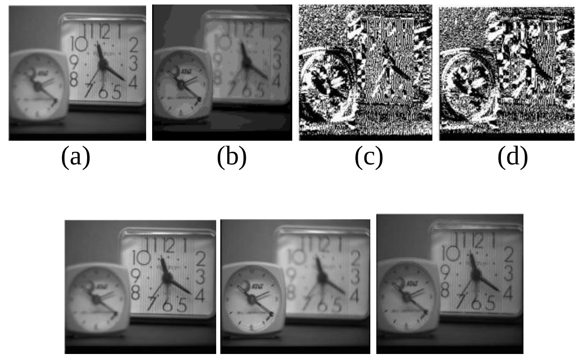
- **Signal to Noise Ratio (SNR)**

The signal-to-noise ratio is used in imaging as a physical measure of the sensitivity of a imaging system. SNR is defined as a ratio of signal and RMS noise and is given by,

$$SNR = \frac{\text{Signal}}{\text{RMS Noise}}$$

Experiments were performed on different types of images to evaluate the performance of PCNN based image fusion technique.

The two multi-focus 'Clock' images are input to the system. Then these images undergo the process of convolution filtering and then passed through the Dual Channel PCNN to produce the output fused image. The implementation results for these images are shown below. Fig. 3 shows the input 'Clock' images; the output images of convolution filter; the output images of the dual channel PCNN; the final output fused image.

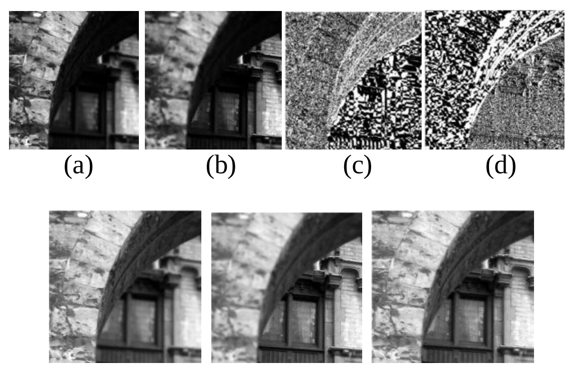


(a) (b) (c) (d)

(e) (f) (g)

Fig 3: Results for 'Clock' images (a)Focus on right; (b)Focus on left; (c)&(d)Convolution filter output; (e)&(f)PCNN output images; (g)Final output Image

The two multi-focus 'Arch' images are input to the system. Then these images undergo the process of convolution filtering and then passed through the Dual Channel PCNN to produce the output fused image. The implementation results for these images are shown below. Fig. 4 shows the input 'Arch' images; the output images of convolution filter; the output images of the dual channel PCNN; the final output fused image.



(a) (b) (c) (d)

(e) (f) (g)

Fig 4: Results for 'Arch' images (a) Focus on left; (b) Focus on right; (c)&(d) Convolution filter output images; (e)&(f) PCNN output images; (g) Final output Fused Image

Table 1 shows the different performance parameter values for different images taken under consideration. When compared these values, it is observed that the proposed system gives better quality fused image for the 'Arch' image than other images of 'Book' and 'Pepsi'.

Performance Parameters	Clock Image	Pepsi Image	Arch Image
Mutual Information	8.54	8.26	8.64
Spatial Frequency	14.35	14.82	19.88
Correlation between (a)&(g)	0.98	0.99	0.99
Correlation between (b)&(g)	0.97	0.97	0.98
SNR between (a)&(g)	30.37 db	31.95 db	27.10 db
SNR between (b)&(g)	28.63 db	27.43 db	25.71 db

Table 1: Performance parameter values for different Multi-focus image

The performance parameters for different images can be represented in the form of graphs as shown in figure below:

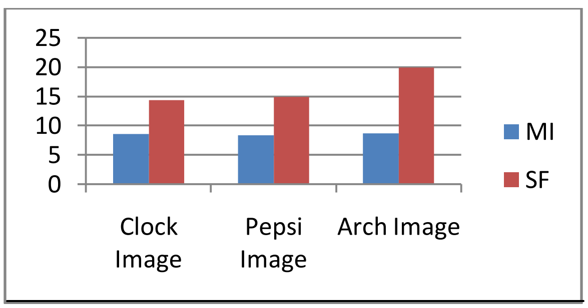


Fig 5: Performance parameters for different multi-focus images

Table 2 shows the comparison of amount of mutual information and spatial frequency among various papers and proposed scheme.

	Mutual Information	Spatial Frequency
Bilateral	6.02	13.71
Gradient Pyramid	3.97	13.78
NSCT	6.74	14.56
Surfacelet + PCNN	7.45	14.02
Convolution + PCNN	8.54	16.35

Table 2: Performance parameter values for various image fusion techniques

The performance parameters for various image fusion techniques can be represented in the form of graphs as shown in figure below. It gives comparison of performance parameters between different image fusion techniques. It is observed that the performance of the proposed method (i.e. Convolution + PCNN) is better than other previous methods used for image fusion.

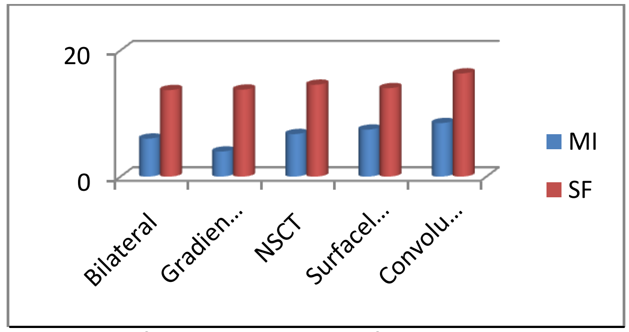


Fig. 6: Performance parameters for various image fusion techniques

V. CONCLUSION

In this work under consideration, an efficient Multi-focus image fusion technique has been developed using Convolution Filtering and Dual channel pulse coupled neural network. The performance parameters are evaluated and compared for different multi-focus images. The experimental results show that the proposed method outperforms the other methods by mutual information. Furthermore, compared with other existing image fusion techniques, the proposed scheme provides efficiency in terms of the performance parameters such as Mutual Information, spatial frequency as given in the graphical representation of these performance parameters. In many fields like Medical, Satellites, remote sensing, etc., the important information about the objects to be detected from the images is essential. Based on this viewpoint, the proposed algorithm can be extended to fuse other multi-sensor images, such as medical images, remote sensing images, and so on.

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