Fusion of Multifocus Gray Scale Images through Dynamic Selection of Mutual Information

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***Abstract*—**A novel image fusion algorithm based on dynamic selection of information in multifocus gray scale images is proposed in this paper. The proposed method adopts the Self Organizing Feature Map to transform the images into code books containing numerical values so that manipulation in the required form can be carried out without complications or assumptions. The proposed method is dynamic in the sense that depending on the application the fusion could be carried out. Due to the property of Self Organizing Feature Maps, there will be no loss of information during fusion and further the method is robust to remove noise in the source images during processing stage itself

***Keywords*—** Gray Scale Images, Image Fusion, Multifocus Images, Self Organizing Feature Maps.

I. Introduction

IMAGE fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. Given the same set of input images, different fused images may be created depending on the specific application and what is considered relevant information. There are several benefits in using image fusion like wider spatial and temporal coverage, decreased uncertainty, improved reliability and increased robustness of system performance. Often a single sensor cannot produce a complete representation of a scene. Successful image fusion significantly reduces the amount of data to be viewed or processed without significantly reducing the amount of relevant information.

Image fusion algorithms can be categorized into pixel, feature and symbolic levels. Pixel-level algorithms work either in the spatial domain [1, 2] or in the transform domain [3, 4 and 5]. Although pixel-level fusion is a local operation, transform domain algorithms create the fused image globally. By changing a single coefficient in the transformed fused image, all image values in the spatial domain will change. As a result, in the process of enhancing properties in some image areas, undesirable artifacts may be created in other image areas. Algorithms that work in the spatial domain have the ability to focus on desired image areas, limiting change in other areas. Multiresolution analysis is a popular method in pixel-level fusion. Burt [6] and Kolczynski [7] used filters with increasing spatial extent to generate a sequence of images from each image, separating information observed at different resolutions. Then at each position in the transform image, the value in the pyramid showing the highest saliency was taken. An inverse transform of the composite image was used to create the fused image.

In a similar manner, various wavelet transforms can be used to fuse images. The discrete wavelet transform (DWT) has been used in many applications to fuse images [4]. The dual-tree complex wavelet transforms (DT-CWT), first proposed by Kingsbury [8], was improved by Nikolov [9] and Lewis [10] to outperform most other grey-scale image fusion methods.

Feature-based algorithms typically segment the images into regions and fuse the regions using their various properties [10–12]. Feature-based algorithms are usually less sensitive to signal-level noise [13]. Toet [3] first decomposed each input image into a set of perceptually relevant patterns. The patterns were then combined to create a composite image containing all relevant patterns. A mid-level fusion algorithm was developed by Piella [12, 15] where the images are first segmented and the obtained regions are then used to guide the multiresolution analysis.

Recently methods have been proposed to fuse multi focus source images using the divided blocks or segmented regions instead of single pixels [16, 17, and 18]. All the segmented region-based methods are strongly dependent on the segmentation algorithm. Unfortunately, the segmentation algorithms, which are of vital importance to fusion quality, are complicated and time-consuming. The common transform approaches for fusion of mutifocus images include the discrete wavelet transform (DWT) [19], curvelet transform [20] and nonsubsampling contourlet transform (NSCT) [21].

Multifocus image fusion and restoration algorithm based on the sparse representation has been proposed by Yang and Li [22]. A new multifocus image fusion method based on homogeneity similarity and focused regions detection has been proposed during the year 2011 by Huafeng Li , Yi Chai , Hongpeng Yin and Guoquan Liu [23] .

Most of the traditional image fusion methods are based on the assumption that the source images are noise free, and they can produce good performance when the assumption is

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satisfied. For the traditional noisy image fusion methods, they usually denoise the source images, and then the denoised images are fused. The multifocus image fusion and restoration algorithm proposed by Yang and Li [22] performs well with both noisy and noise free images, and outperforms traditional fusion methods in terms of fusion quality and noise reduction in the fused output. However, this scheme is complicated and time-consuming especially when the source images are noise free. The image fusion algorithm based on homogeneity similarity proposed by Huafeng Li , Yi Chai , Hongpeng Yin and Guoquan Liu [23] aims at solving the fusion problem of clean and noisy multifocus images. Further in any region based fusion algorithm, the fusion results are affected by the performance of segmentation algorithm. The various segmentation algorithms are based on thresholding and clustering but the partition criteria used by these algorithms often generates undesired segmented regions.

In order to overcome the above said problems a novel method using Self-organizing Feature Maps to transform the images into code books containing numerical values which consequently helps in fusion of images dynamically to the desired degree of information retrieval depending on the application has been proposed in this paper. The proposed algorithm is compatible for any type of image either noisy or clean. The method is simple and since mapping of image is carried out by Self-organizing Feature Maps all the information in the images will be preserved.

The outline of this paper is as follows: In. In Section II, the Self-organizing Feature Maps is briefly introduced. Section III describes the algorithm for Code Book generation using Self Organizing Feature Maps. Section IV describes the proposed method of Fusion. Section V details the Experimental Analysis and Section VI gives the conclusion of this paper.

II. SELF-ORGANIZING FEATURE MAP

Self-organizing Feature Map (SOM) is a special class of Artificial Neural Network based on competitive learning. It is an ingenious Artificial Neural Network built around a one or two-dimensional lattice of neurons for capturing the important features contained in the input. The Kohonen technique creates a network that stores information in such a way that any topological relationships within the training set are maintained. In addition to clustering the data into distinct regions, regions of similar properties are put into good use by the Kohonen maps.

Kohonen networks are grid of computing elements, which allows identifying the immediate neighbours of a unit. This is very important, since during learning, the weights of computing units and their neighbours are updated. The objective of such a learning approach is that neighbouring units learn to react to closely related signals. A Self-organizing Feature Map does not need a target output to be specified unlike many other types of network. Instead, where the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the class, the input vector is a member. From an initial distribution of random weights, and over much iteration, the Self-organizing Feature Map eventually settles into a map of stable zones. Each zone is effectively a feature classifier. The output is a type of feature map of the input space. In the trained network, the blocks of similar values represent the individual zones. Any new, previously unseen input vectors presented to the network will stimulate nodes in the zone with similar weight vectors. Training occurs in several steps and over many iterations.

Each node's weights are initialized. A vector is chosen at random from the set of training data and presented to the lattice. Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU). The radius of the neighborhood of the Best Matching Unit is now calculated. This is a value that starts large, typically set to the 'radius' of the lattice, but diminishes each time-step. Any nodes found within this radius are deemed to be inside the Best Matching Unit‘s neighborhood. Each neighboring node's weights are adjusted to make them more like the input vector. The closer a node is to the Best Matching Unit; the more its weights get altered. The procedure is repeated for all input vectors for number of iterations. Prior to training, each node's weights must be initialized. Typically these will be set to small-standardized random values. To determine the Best Matching Unit, one method is to iterate through all the nodes and calculate the Euclidean distance between each node's weight vector and the current input vector. The node with a weight vector closest to the input vector is tagged as the Best Matching Unit. After the Best Matching Unit has been determined, the next step is to calculate which of the other nodes are within the Best Matching Unit's neighborhood. All these nodes will have their weight vectors altered in the next step. A unique feature of the Kohonen learning algorithm is that the area of the neighborhood shrinks over time to the size of just one node.

After knowing the radius, iterations are carried out through all the nodes in the lattice to determine if they lay within the radius or not. If a node is found to be within the neighborhood then its weight vector is adjusted. Every node within the Best Matching Unit‘s neighborhood (including the Best Matching Unit) has its weight vector adjusted.

In Self-organizing Feature Map, the neurons are placed at the lattice nodes; the lattice may take different shapes: rectangular grid, hexagonal, even random topology. The neurons become selectivity tuned on various input patterns in the course of competitive learning process. The locations of the neurons (i.e. the winning neurons) so tuned, tend to become ordered with respect to each other in such a way that a meaningful coordinate system for different input features to be created over the lattice.

III. CODE BOOK GENERATION USING SELF-ORGANIZING FEATURE MAP

Given a two-dimensional input image pattern to be mapped onto a two dimensional spatial organization of neurons located at different positions (i, j)'s on a rectangular lattice of size nxn. Thus, for a set of nxn points on the two-dimensional plane, there would be n^2 neurons N_{ij} :$1 \le i,j \le n$, and for each neuron N_{ij} there is an associated weight vector denoted as W_{ij}. In Self-organizing Feature Map, the neuron with minimum distance between its weight vector W_{ij} and the input vector X is the winner neuron (k,l), and it is identified using the following equation.

$$\|X - W_{kl}\| = \min_{1 \le i \le n} [\min_{i \le j \le n} \| X - W_{ij} \|] \quad (1)$$

After the position of the (i,j)th winner neuron is located in the two-dimensional plane, the winner neuron and its neighbourhood neurons are adjusted using Self- organizing Feature Map learning rule as:

$$W_{ij}(t+1) = W_{ij}(t) + \alpha \| X - W_{ij}(t) \| \quad (2)$$

Where, α is the Kohonen's learning rate to control the stability and the rate of convergence. The winner weight vector reaches equilibrium when Wij (t+1)=W_{ij} (t). The neighbourhood of neuron N_{ij} is chosen arbitrary. It can be a square or a circular zone around N_{ij} of arbitrary chosen radius.

ALGORITHM

a. The image A (i,j) of size 2^N x 2^N is divided into blocks, each of them of size2^n x 2^n pixels, n < N.

b. A Self-organizing Feature Map Network is created with a codebook consisting of M neurons (mi: i=1, 2,.....M).

c. The total M neurons are arranged in a hexagonal lattice, and for each neuron. There is an associated weight vector Wi = [wi_1 wi_2.....$wi_2^{2n]}$.

d. The weights vectors are initiated for all the neurons in the lattice with small random values.

e. The learning input patterns (image blocks) are applied to the network. The Kohonen's competitive learning process identifies the winning neurons that best match the input blocks. The best matching criterion is the minimum Euclidean distance between the vectors. Hence, the mapping process Q that identifies the neuron that best matches the input block X is determined by applying the following condition.

$$Q(X) = \arg_i \min \| X - W_i \| \quad i = 1,2,\ldots\ldots M \quad (3)$$

f. At equilibrium, there are m winner neurons per block or m code words per block. Hence, the whole image is represented using m number of code words.

g. The indices of the obtained code words are stored. The set of indices of all winner neurons along with the codebook are stored.

h. The reconstructed image blocks of same size as the original ones, will be restored from the indices of the code words.

IV. PROPOSED METHOD OF FUSION

For discussion purpose let us consider two multifocus grayscale 8 bit images of the same scene or object. The first image say image 'A' is decomposed into sub-images and given as input to the Self-organizing Feature Map Neural Network. In order to preserve all the gray values of the image, the codebook size an 8 bit image is chosen to be the maximum possible number of gray levels, say 256. Since the weight values after training has to represent the input level gray levels, random values ranging from 0 to 255 are assigned as initial weights.

When sub-images of size say 4 x 4 is considered as the input vector, then there will be 16 nodes in the input layer and the Kohonen layer consists of 256 nodes arranged in a 16 x 16 array. The input layer takes as input the gray-level values from all the 16 pixels of the gray-level block. The weights assigned between node j of the Kohonen layer and the input layer represents the weight matrix. For all the 256 nodes we have W_{ji} for j = 0,1,…,255 and i = 0,1…15. Once the weights are initialized randomly network is ready for training.

The image block vectors are mapped with the weight vectors. The neighborhood is initially chosen; say 5 x 5and then reduced gradually to find the best matching node. The Self-organizing Feature Map generates the codebook according to the weight updation. The set of indices of all the winner neurons for the blocks along with the code book are stored for retrieval.

The image 'A' can be retrieved by generating the weight vectors of each neuron from the index values, which gives the pixel value of the image. For each index value the connected neuron is found. The weight vector of that neuron to the input layer neuron is generated. The values of the neuron weights are the gray level for the block. The gray level value thus obtained is displayed as pixels. Thus we can get the image 'A 'back in its original form.

Adopting the same procedure the second image say 'B' is processed and a code book will be generated for this image. Since the features in the second image are the same, when this image is given as input to the trained Network the code book for the Image 'B' will be generated in minimum simulation time without loss in information. Also since the images are registered the index values which represent the position of pixels will be the same in both the images

Now we have the two images in code book form in terms of numerical values such that any form of manipulation could be done in no time. In this manner we could generate the code book for any number of multifocus images to fuse them to get the optimized fused image. Also the required information could be retrieved from any image from the corresponding code book and fused to get the desired image depending on the application.

In our method of fusion of the two images, for the same index value the value of the neuron weights of the two images are compared and the optimal value is selected. The procedure is repeated for all the indices until a weight vector of optimal strength is generated. The image retrieved from this optimal weight vector is the fused image which will represent all the gray values in its optimal values. The procedure can be repeated in various combinations with multiple images until the desired result is achieved.

V. EXPERIMENTAL ANALYSIS AND RESULTS

In order to evaluate the Fusion performance of the proposed method we have fused two images by selecting the high frequency gray levels of the two images. The high frequency levels generally correspond to pixels with sharper brightness in the image, and thus to the salient features such as edges, line, regions boundaries, and so on. For experimental purpose images of standard images with various levels of deviation have been fused and the results compared with the standard image in terms of RMSE, PSNR and Correlation Coefficient (CC) The smaller the RMSE value, the better the fused image. The Correlation Coefficient is a measure of relativity between the source image and the corresponding fused image. The CC measure should be as close to 1 as possible.

The experimental results obtained for fusion of two standard images adopting the proposed method are shown in Tables I and II.

TABLE I. LENA

Deviation σ	0.5	0.10	0.15
RMSE	7.9323	8.9124	9.1421
PSNR	39.136	38.630	38.520
cc	0.9235	0.9123	0.9754

TABLE II. BARBARA

Deviation σ	0.5	0.10	0.15
RMSE	6.4356	8.9124	10.2412
PSNR	48.144	48.130	48.108
cc	0.9523	0.9548	0.9965

From the results it is observed irrespective of the deviation the quality of the fused images does not change appreciably which depicts the robustness of the proposed method.

Fig.1. (a)

Fig.1. (b)

Fig.1. (c)

Fig.2. (a)

Fig.2. (b)

Fig.2. (c)

Figures 1. (a) , 1.(b) 2. (a) and 2. (b) are the multi focused images. Images1. (c) and 2.(c) are the fused images

To make better comparison the difference images between the source image and the fused image obtained are shown in the figures below.

Fig. 3(a) shows the difference image between the source image 1. (a) and the fused image 1.(c) of Lena and Fig.3(b) shows the difference image between the source image 1.(b) and the fused image 1.(c) of Lena.

Fig. 4(a) shows the difference image between the source images 2.(a) and the fused image 2.(c) of Barbara and Fig.4(b) shows the difference image between the source image 2.(b) and the fused image 2.(c) of Barbara.

The difference between the source image and the fused image should be zero. So the lower residue features in the difference image means the better performance of the fusion method in transferring features of source images to fused image.

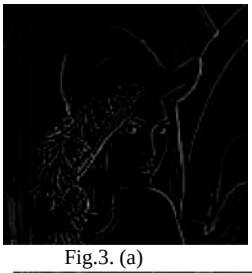

Fig.3. (a)

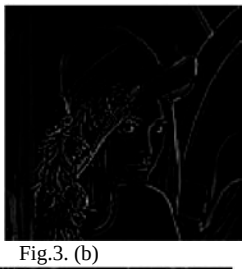

Fig.3. (b)

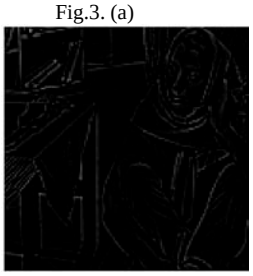

Fig.4. (a)

Fig.4. (b)

The robustness of the proposed algorithm that is to obtain consistent good quality fused image with different categories of images like standard images, medical images, satellite images has also been evaluated. The fused images obtained are shown below.

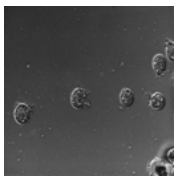
Fig.5.a

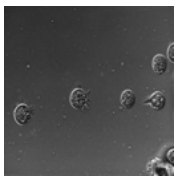
Fig.5.b

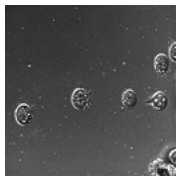
Fig.5.c

Figures 5.(a) and 5.(b) are the multi focused images. Of bacteria image. Fig.5(c) is the fused image.

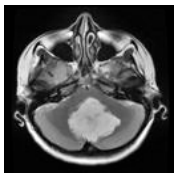
Fig.6.a

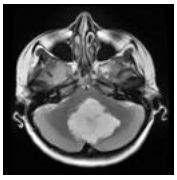
Fig.6.b

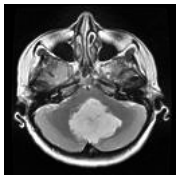
Fig.6.c

Figures 6.(a) and 6.(b) are the multi focused images. Of medical image (MRI of Head). Fig.6(c) is the fused image.


Fig.7.a


Fig.7.b


Fig.7.c

Figures 7.(a) and 7.(b) are the multi focused images. Of satellite image. Fig.7(c) is the fused image

The quality of the fused images obtained for various types of images are shown in Tables III and IV.

TABLE III

Images	RMSE		
	Image A	Image B	Fused Image
Bacteria	6.8548	6.7421	6.227
Satellite map	4.0043	5.325	3.8171
MRI -Head	4.3765	4.9824	1.5163

TABLE IV

Images	PSNR		
	Image A	Image B	Fused Image
Bacteria	28.194	27.989	32.5841
Satellite map	32.077	31.582	33.2772
MRI -Head	30.787	33.901	45.3924

VI. Conclusion

In this paper, a new multifocus image fusion method is proposed. The advantage of Self organizing Feature Map is that after training, the weight vectors not only represents the image block cluster centroids but also preserves two main features. Topologically neighbour blocks in the input vectors are mapped to that of topologically neighboring neurons in the code book. Also the distribution of weight vectors of the neurons reflects the distribution of the weight vectors in the input space. Hence their will not be any loss of information in the process. The method is simple requiring less simulation time than the traditional methods and also dynamic which also could be used to retrieve only the information that is required and fuse them to save time in transmission. The experimental results have justified the robustness of this simple method.

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