Improved performance of Image Fusion by MSVD

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Abstract :- **Image Fusion is a method, in which two relevant Image get combine and generate a new Image. The generated image has excellent clarity as compared to the previous input image. Image Fusion Technique is improving the performance of the images and increase the application of Image Fusion. In the Base paper, they present Wavelet Transform for Fusion the Two-Dimensional Multiresolution 2-D image. The applications of the Image fusion is using various fields like multi - Focus Images, CT, Multi-Sensor Satellite image and MR of the Human Brain. In this Paper , we proposed the MSVD (Multi-resolution Singular Value Decomposition) methodology for improve the performance of the image fusion . For show the improvement of the image fusion , we show the results in the form of PSNR(Peak Signal to Noise Ratio) , MSE(Mean Square Error) , CR(Cross Correlation) . For improve the performance of image fusion , PSNR and CR will be increase and MSE will decrease .**

Keyword :- *Image Fusion, Wavelet Transform, Fused Images, Wavelet based Fusion, Multi-Resolution, Multi-sensor image fusion, multi-resolution SVD, Image Fusion Performance Evaluation Metrics.*

I. INTRODUCTION

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects (like multi-sensor, multi-focus and multimodal images). For example, in multi-focus imaging one or more objects may be in-focus in a particular image, while other objects in the scene may be in focus in other images. For remotely sensed images, some have good spectral information whereas others have high geometric resolution. In the arena of biomedical imaging, two widely used modalities, namely the magnetic resonance imaging (MRI) and the computed tomography (CT) scan do not reveal identically every detail of brain structure. While CT scan is especially suitable for imaging bone structure and hard tissues, the MR images are much superior in depicting the soft tissues in the brain that play very important roles in detecting diseases affecting the skull base.

These images are thus complementary in many ways and no single image is totally sufficient in terms of their respective information content. The advantages these images may be fully exploited by integrating the complementary features seen in different images through the process of image fusion that generates an image composed of features that are best detected or represented in the individual images. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics. The first step toward fusion, which may be interpreted as a preprocessing step is the registration which brings down the constituting images to a common coordinate system as fusion of images is meaningful only when common objects in images have identical geometric configuration with respect to size, location and orientation in all the images. In the next step, the images are combined to form a single fused image through a judicious selection of proportions of different features from different images.

Fusion techniques include the simplest method of pixel averaging to more complicated methods such as principal component analysis and wavelet transform fusion. Several approaches to image fusion can be distinguished, depending on whether the images are fused in the spatial domain or they are transformed into another domain, and their transforms fused.

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image [1]. The resulting image will be more informative than any of the input images [2].

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. Image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank, and Laplacian pyramid.

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A. Levels Of Image Fusion

- Pixel Level :- This is most his simple technique in image fusion done at lowest level. In this combine the values and intensities of two input images based on its average, gives the single resultant image.

- Feature Level :- It justifies with the features of image like if one image has its distorted eye other have distorted any feature like head, nose. In this level of technique easily extract the features of both similar images individually, then fusion algorithm gives the enhanced image after feature extraction.

- Block or Region Based :- In region based fusion occurs according to the pixel blocks of the image. Blocks level technique is highest level technique. It is multistage representation and measurements are calculated according to the regions.

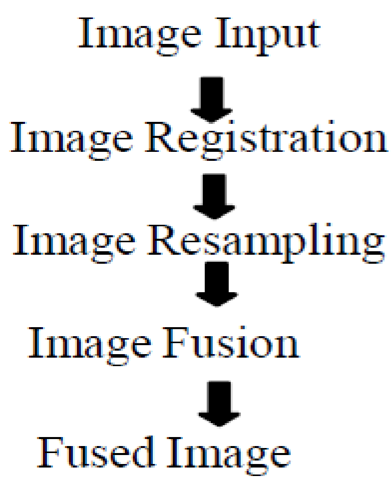


Fig.1:- Preprocessing steps for image fusion

II. WAVELET TRANSFORM AND WAVELET BASED FUSION

Wavelet transform is a powerful mathematical tool used in the fields of signal processing. It is used to divide the given function or signal into different scale components such that each scale component can be studied with a resolution that it matches. Wavelets to be the foundation of new powerful approach to signal processing and analysis called the Multi-resolution Theory. The same approach has been extended to multi-dimensional signal decomposition. In a multi-focus and multi-sensor image acquisition system, the size, orientation and location of an object relative to its „own‟ background may not be identical in all the images of different modalities. Integration or fusion of multi-focus or multi-sensor information is possible only if the images are registered or positioned with respect to a common coordinate system. Image registration (in case of fusing two images) is the process of determining correspondence between all points in two images of the same scene or object.

The most common form of transform image fusion is wavelet transform fusion. In common with all transform domain fusion techniques the transformed images are combined in the transform domain using a defined fusion rule then transformed back to the spatial domain to give the resulting fused image. Wavelet transform fusion is more formally defined by considering the wavelet transforms „w‟ of the „n‟ registered input images Ij(x,y), j=1,2…n together with the fusion rule „f‟. Then, the inverse wavelet transform w-1 is computed, and the fused resulting image I(x,y) is reconstructed as depicted in 2.

A scheme for fusion of „n‟ registered set of images of same scene obtained through different modalities. The basic idea is to decompose each registered image into sub-images using forward wavelet transform which have same resolution at same level and different resolution at different levels. Information fusion is performed based on the high frequency (detailed coefficients) sub-images and resulting image is obtained using inverse wavelet transform. The proposed scheme uses two criterions namely the „gradient‟ and „smoothness‟ measure which we discuss first.

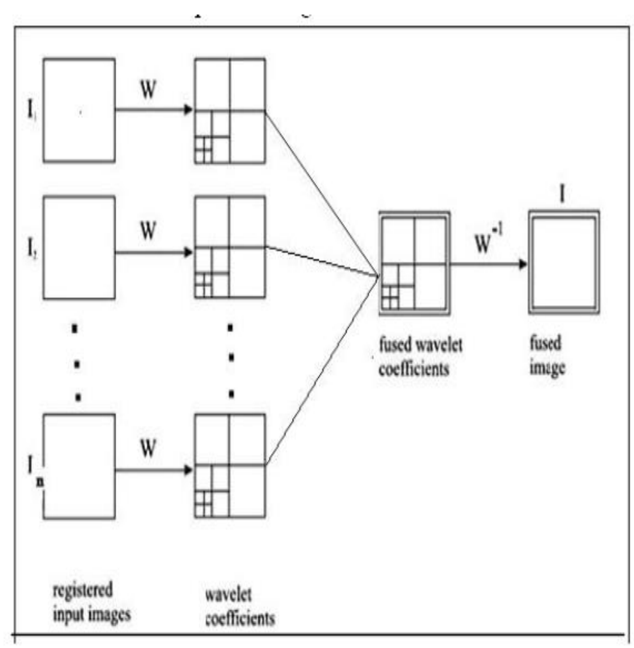


Fig 2: Fusion of wavelet transforms of Images

A. The Correlation Measure

The fusing ability of the algorithm is measured quantitatively by means of, say, pixel-gray-level correlation between two images. The correlation between two images f(x, y) and g(x,y) is defined as

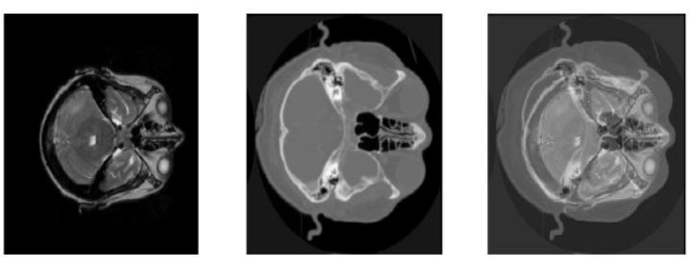
$$CR(f,g) = \frac{\sum_{x,y}(f(x,y) - \overline{f})\ (g(x,y) - \overline{g})}{\sqrt{\sum_{x,y}(f(x,y) - \overline{f}\,)^2}\ \sqrt{\sum_{x,y}(g(x,y) - \overline{g})^{\,2}}} \quad (1)$$

And N is the total number of pixels in either of the images. The HAAR Wavelet was used as the mother wave and the resolution parameter *'j'* was taken up to 6. The use of HAAR wavelet was for the ease of implementation. Our aim was to go for a multi-resolution description of the image prior to fusion for which we need a filter, without loss of generality we chose HAAR Wavelet. The fused image enjoys relatively high correlation with either of the images. This implies features of both the images are transported to the fused image. We did not restrict our algorithm to work on any specific type/class of images .Equal contribution of each low frequency sub image was considered in the experiments.

In the first experiment a pair of multi-focus image was taken. In figure 3(a) the clock in front is in focus while in figure 3(b) the clock at the back is focused. Figure 3(c) shows the image obtained after fusion. CT-MR image pair was taken up for second experiment. Figure 4(a) is the CT image of the human brain showing bones and hard tissue. Figure 4(b) is the MR image show in soft t issues. The fused CT-MR image is shown in figure 4(c).

(a) (b) (c)

Fig 3 :- (a) First Image ,(b) Second Image , (c) Fusion Image



(a) (b) (c)

Fig 4 :- (a) First Image ,(b) Second Image , (c) Fusion Image

III. PROBLEM STATEMENT

The fusion of images is the process of combining two or more images into a single image retaining important features from each of the images. A scheme for fusion of multi-resolution 2D gray level images based on wavelet transform is presented in the base paper . If the images are not already registered, a point-based registration, using affine transformation is performed prior to fusion. The images to be fused are first decomposed into sub images with different frequency and then information fusion is performed using these images under the proposed gradient and relative smoothness criterion. Finally these sub images are reconstructed into the result image with plentiful information. A quantitative measure of the degree of fusion is estimated by cross-correlation coefficient and comparison with some of the existing wavelet transform based image fusion techniques is carried out. It should be noted that the proposed algorithm is domain independent.

That means it uses knowledge of neither the imaging device nor the objects being imaged. Therefore, it can be applied to fusion of different kinds of multi-modal images. Second, as the actual fusion is done during the construction of modified coefficients, the scheme has been extended to fusion of „n" images as already proposed in the algorithm. In the base paper , by use Wavelet transform they are giving the results of CR(Image Correlation) parameters . We can further improve the performance of the CR by use proposed methodology . The value of PSNR and CR can increase while the value of MSE can be decrease .

IV. PROPOSED METHODOLOGY

Multi-resolution singular value decomposition is very similar to wavelets transform, where signal is filtered separately by low pass and high pass finite impulse response (FIR) filters and the output of each filter is decimated by a factor of two to achieve first level of decomposition. The decimated low pass filtered output is filtered separately by low pass and high pass filter followed by decimation by a factor of two provides second level of decomposition.

$$X_1 = \begin{bmatrix} x(1) & x(3) & \cdot & \cdot & x(N-1) \\ x(2) & x(4) & \cdot & \cdot & x(N) \end{bmatrix} \qquad \ldots (2)$$

Multi-resolution Singular value decomposition (MSVD) is one of the possible factorization of a rectangular matrix that has been largely used in information retrieval for reducing the dimension of the document vector space. The decomposition can be defined as follows. Given a generic rectangular n × m matrix A, its singular value decomposition is:

$$A = U \sum V^T \qquad \ldots\ldots\ (3)$$

where U is a matrix n × r, V^T is a r × m and Σ is a diagonal matrix r × r. The two matrices U and V are unitary, i.e., $U^TU = I$ and $V^TV = I$. The diagonal elements of the Σ are the singular values such as $\delta_1 > \delta_2 > \delta_r > 0$ where r is the rank of the matrix A. For the decomposition, SVD exploits the linear combination of rows and columns of A.

A first trivial way of using MSVD as unsupervised feature reduction is the following. Given E as set of training examples represented in a feature space of n features, we can observe it as a matrix, i.e. a sequence of examples $E = (e_1....e_m)$. With MSVD, the n × m matrix E can be factorized as $E = U \Sigma V^T$. This factorization implies we can focus the learning problem on a new space using the transformation provided by the matrix U. This new space is represented by the matrix:

$$E' = U^T E = \Sigma V^T \qquad ..... (4)$$

where each example is represented with r new features. Each new feature is obtained as a linear combination of the original features, i.e. each feature vector e_l can be seen as a new feature vector $e_l' = U^T e_l$. When the target feature space is big whereas the cardinality of the training set is small, i.e., n >> m, the application of MSVD results in a reduction of the original feature space as the rank r of the matrix E is r < min(n,m).

A more interesting way of using SVD as unsupervised feature selection model is to exploit its approximated computations, i.e. :

$$A \approx A_k = U_{m*k} \Sigma_{k*k} V^T_{k*n} \qquad ....(5)$$

where k is smaller than the rank r.

An important step towards de noising is to get multi resolution SVD (MSVD). To obtain MSVD of an image A, of size [M x N], A is reshaped to get A1 matrix of size [4 x MN/4]. The SVD of A1 obtained as

$$[U \;\; S] = SVD(A1) \qquad .....(6)$$

and T matrix is

$$T = U^T A1 \qquad ....(7)$$

The T matrix is of size [4 x MN/4]. The first, second, third and fourth row of T matrix are reshaped to get [M/2 x M/2] size matrices called as Y.LL, Y.LH, Y.HL and Y.HH. The Y.LL band contains the low frequency details.

A. MSVD Algorithm

Step 1:- Input Image A
Step 2:- A is (256,256)
Step 3:- Reshape A toA1
Step 4:- A1 is (4,16384)
Step 5:- [U S]=svd(A1)
Step 6:- U is (4,4) and S is (4,16384)
Step 7:- T=UT A1
Step 8:- T is (4,16384)
Step 9 :- Output Y.LL=Reshape(T(1,:),128,128)
Step 10:- Y.LH=Reshape(T(2,:),128,128)
Step 11:- Y.HL=Reshape(T(3,:),128,128)
Step 12:- Y.HH =Reshape(T(4,:),128,128)
Step 13:- Y.LL,Y.LH,Y.HL,Y.HH are each(128,128)

B. IMSVD Algorithm

Step 1:- Input Y.LL,Y.LH,Y.Hl,Y.HH and U
Step 2:- T1(1, :)=Reshape((Y.LL),1,16384)
Step 3:- T1(2, :)=Reshape ((Y.LH),1,16384)
Step 4:- T1(3, :)=Reshape((Y.HL),1,16384)
Step 5:- T1(4, :)=Reshape ((Y.HH),1,16384)
Step 6:- A2=UT1
Step 7:- A2 is (4,16384)
Step8:- Reshape A2 to get back A
Step 9:- A is (256,256)

To get the inverse multi resolution transform (IMSVD), Y.LL, Y.LH, Y.HL and Y.HH are reshaped to get T1 matrix of [4 x M N/4] size. Next A2 matrix is calculated as

$$A2 = U\, T1 \qquad .....(8\,)$$

where U is the matrix obtained from (2). A2 matrix is now reshaped to get back the A matrix of size [M x N].

V. RESULTS

Figure 5 is showing the first image of the image fusion . As we can see in the image 5 the first Aircraft image is Blur and second aircraft image is clear .

Fig 5:- Input image 1

Figure 6 is showing the second image of the image fusion. In this first image is clear and second image is Blur . For image fusion combined the both images and find the completely clear image .

Figure 7 :- Input image 2 for image fusion

Figure 8 is showing the output image for the wavelet Based image fusion. As we can see from the figure 8 , both the aircraft images are clear .

Figure 8 :- Output Image of Wavelet transform

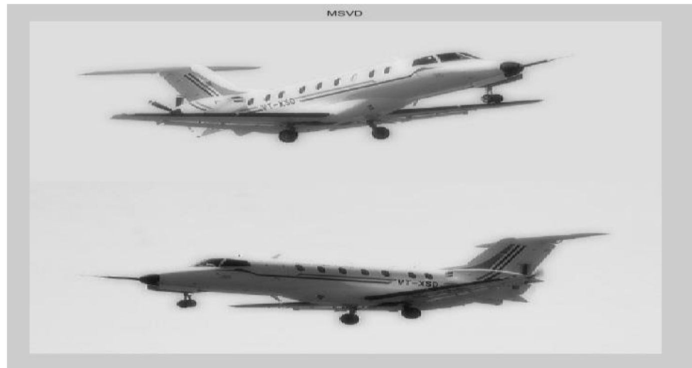


Figure 9 :- Output Image of MSVD

Figure 9 is showing the waveform for the MSVD . As we can see from the figure 9 the both the aircraft images are clear . But the performance of the image fusion is good for the MSVD technique.

	PSNR	MSE	CR
MSVD	26.89	0.13	0.98
Wavelet Transform	26.64	0.14	0.97

Table I :- Comparison Table for image fusion MSVD and Wavelet transform

Table I is showing the comparison in between MSVD and Wavelet transform . As we can see , from the Table I PSNR and CR is high for the MSVD and MSE is low for the MSVD . It is showing that the image fusion performance is good for the MSVD.

VI. CONCLUSION & FUTURE SCOPE

In this Paper , A novel image fusion technique based on multi-resolution singular value decomposition (MSVD) has been presented and evaluated. The performance of this algorithm is compared with image fusion technique by wavelets. It is concluded that image fusion by MSVD perform better as compare to wavelet transform in terms of PSNR , MSE , CR. In the future ,we can further improve the performance of the PSNR and MSE by improve MSVD algorithm . In the future , we can also increase some parameters also for show the results comparison .

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