International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1542-1547 www.ijaem.net ISSN: 2395-5252

A Review on Image Fusion Techniques

[1]Prathima Gamini, [2]M.Phanindra Kumar, [3]M.D.R.Bhargavi, [4]G.Sai Pavan, [5]K.Rupa Sundeep
Department of Electronics and Communication Engineering
Sagi RamaKrishnam Raju Engineering College, Bhimavaram, Andhra Pradesh.

Date of Submission: 20-03-2023 Date of Acceptance: 30-03-2023

ABSTRACT:Image fusion is the process of merging pertinent data from a collection of photos into a single image, with a goal of producing fused image that is both more informative and comprehensive than any of the input images.
This article explains the PCA (Principal Component Analysis), DCTLP (Discrete Cosine Transform based Laplacian Pyramid) and DWT (Discrete Wavelet Transform) based image fusion methods' formulation, process flow diagrams and algorithms. Conventional fusion methods like PCA and DCTLP have a lot of disadvantages, however DWT based techniques are more effective since they produce better outcomes for image fusion.
This article compares and contrasts the various image fusion techniques, including PCA (Principle Component Analysis), DCTLP (Discrete Cosine Transform based Laplacian Pyramid) and DWT (Discrete Wavelet Transform).

KEYWORDS: Image fusion; principle component analysis; discrete cosine transform based laplacian pyramid; discrete wavelet transform.

I. INTRODUCTION

Fusion is a technique that may be used to enhance the quality of data from a collection of photos. The good information from each of the provided photos is combined throughout the image fusion process to create a final image whose quality is better than any of the input images. For the picture fusion process, there are crucial prerequisites.
- All relevant information from the input photos should be retained in the fused image.
-Image fusion should not introduce defects that might result in an incorrect diagnosis.

The multi-sensor data may contain many photographs of the same scene that each provide a separate piece of information in the fields of remote sensing, medical imaging and machine vision. Image fusion is necessary because optical lenses in charged coupled devices have a limited depth of focus, making it impossible to create a single picture that contains all the information about the objects in the image. Spatial domain fusion methods and Transform domain fusion methods are the two categories which comes under picture fusion techniques. Pixels from the input pictures will be immediately dealt by the spatial domain fusion method. The picture is initially translated into the frequency domain in the transform domain fusion approach. Peak Signal to Noise Ratio (PSNR), Normalised Correlation (NC) and Mean Square Error(MSE) are performance parameters that won't enhance by using the Simple Primitive Technique. Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), Morphological Processing, and Combining DWT with PCA and Morphological Techniques have recently become popular methods for fusing images.

II. IMAGE FUSION TECHNIQUES

Image fusion is a technique to create a final image with a higher quality than any of the input images.The useful information from each of the provided images is combined. Two major categories of image fusion techniques exists.
1. The spatial domain fusion approach.
2. Use the domain fusion approach.
In spatial domain approaches, work can be done directly with the picture pixels . The intended outcome is achieved by manipulating the pixel values. With approaches that use frequency domain, the picture is first converted to frequency domain. It entails computing the image's Fourier Transform first. The picture's Fourier transform is subjected to all Fusion processes and the resulting image is obtained by performing an Inverse Fourier transform. Any discipline that requires the analysis of pictures uses image fusion. For instance, computer vision, robotics, microscopic imaging,

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1542-1547 www.ijaem.net ISSN: 2395-5252

image processing from satellites, and remote sensing applications.

Spatial domain approaches include fusion techniques like averaging, the Brovey method, Principal Component Analysis(PCA) and HIS -based techniques.The high pass filtering-based methodology is a crucial spatial domain fusion tool. The spatial distortion they cause in the merged picture is a drawback of spatial domain techniques. Spectral distortion will become a negative factor,whenever further processing is required.

For the purpose of doing image fusion, many techniques have been developed. The following is a list of popular image fusion techniques:

1. Fusion based on the Intensity-Hue-Saturation (IHS) transform.
2. Fusion based on Principle Component Analysis(PCA).
3. Fusion based on multi scale transform:

a. High-pass Filtering method
b. Pyramid method
i. Gradient pyramid
ii.Gaussian pyramid
iii.Laplacian Pyramid
iv. Ratio of low pass pyramid
v.Morphological pyramid
c. Wavelet transform:
i. Stationary wavelet transform
ii. Discrete Wavelet Transform(DWT)
iii.Multi wavelet transform Stationary wavelet transform

III. PRINCIPLE COMPONENT ANALYSIS (PCA)

A useful statistical technique from linear algebra is Principal Component Analysis (PCA). Because PCA is an easy, non-parametric way of obtaining relevant information from complex data sets. It is widely used in all types of study, from neurology to computer graphics. It generates an uncorrelated feature space for images as opposed to the original multispectral feature space, which might be used for more analysis. With this method, the multispectral bands are used. The PCA converts a group of associated MS bands into a new set of uncorrelated components. For the fusion, a high-resolution PAN replaces the first component. To return the fused dataset to the original multispectral feature space, the reverse PCA transform is applied. Unlike IHS or Brovey fusions, PCA fusion does not have a band limit. Dimensionality reduction is one of the properties of the PCA. Using PCA, the features are moved from their original domain to a PCA domain where they are organized according to their variance. In order to execute image fusion, only features with a significant amount of information are kept. The PCA identifies the few components that make up the majority of the total variance in the data.

3.1. PCA Formulation:

Assume that the empirical mean of the d-dimensional random vector X is zero. In order for Y = VTX to occur, the projection matrix V would need to meet the following conditions,

The covariance of Y, or cov(Y), is a diagonal, and the inverse of V is equal to the transpose of that variable (VI = VT). Using matrix algebra

$$Cov(Y) = E\{YY^T\} \quad (1)$$

$$Cov(Y) = E\{(XV^T)(V^TX)^T\} \quad (2)$$

$$Cov(Y) = E\{(XV^T)(VX^T)\} \quad (3)$$

$$Cov(Y) = V^T Conv(X)V \quad (4)$$

Multiplying both sides of equation (4) by V gives,

$$Vcov(Y) = VV_T Conv(X) V = Conv(X) V \quad (5)$$

Equation (4) is substituted into equation (5) to get,

$$[\lambda_1 V_1, \lambda_2 V_2, \ldots\ldots, \lambda_d V_d]$$

$$= [Conv(X) V_1, Conv(X) V_2, \ ,Conv(X) V_d] \quad (6)$$

Another way to write this would be

$$\lambda i \ \ Vi = Cov(X) Vi \quad (7)$$

Where, i =1, 2, ..., d and Vi is an eigenvector of cov(X).

3.2. Process Flow Diagram:

The actual means of the input photos are removed after they are sorted in two column vectors. The final vector has n x 2 dimensions, where n is the length of each picture vector.

Get the eigen vectors corresponding to the greater eigen value after computing the eigen values for this resulting vector.

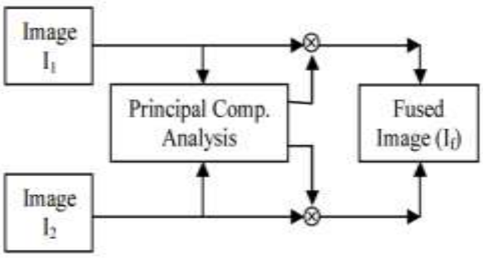

Fig.3.1 Image fusion using PCA

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1542-1547 www.ijaem.net ISSN: 2395-5252

3.3 PCA Algorithm:

Let's set up two-column vectors with the source pictures (the photos that will be combined). The following procedures were used to project this data into 2-D sub spaces:

1. Arrange the data into column vectors. The resulting matrix Z has a size of 2 x n.
2. Calculate each column's empirical mean. M_e is an empirical mean vector with a 1 x 2 dimension.
3. Take each column of the data matrix S and subtract the empirical mean vector M_e from it. The resultant matrix, called X, has a size of 2 x n.
4. To determine the covariance matrix C of X, use the formula C = X x T mean of expectation =COV(X).
5. Calculate C's eigen vectors V and eigen value D, then arrange them in decreasing order of eigen value. V and D are each of the dimensions 2 x 2.
6. To calculate PI and P2, consider the first column of V, which corresponds to a greater eigenvalue, as follows:

$P_1= V(1) / \sum V$ and $P_2= V(2) / \sum V$

IV. DISCRETE COSINE TRANSFORM BASED LAPLACIAN PYRAMID

4.1 Laplacian pyramid:

Images are down sampled at the first level of the Laplacian pyramid to obtain the lower spatial density and resolution level. Let the image's levels be L0, L1, L2, L3, and Ln. The L0 picture is down sampled to produce the L1 level, the L1 image is down sampled to obtain the L2 level, and so on. The following is how the reduction function (R) may provide this down sampling:

$$L_k= R(L_{k-1}) \quad (8)$$

Up sampling (expand) is used for picture reconstruction in order to recreate the original image. The picture reconstruction process uses the expand function (E), which reverses the reduction function (R).

The definition of a mathematically expanded function is

$$L'_k= E(L'_{k-1}) \quad (9)$$

The pyramid pictures are used to produce image recontraction by

$$L_{k+1}=R(L_k) \quad (10)$$

$$l_k=L_k -E(L_{k+1}) \quad (11)$$

4.2 Discrete Cosine Transform:

The discrete cosine transform is a very practical transformation with many uses in research and engineering for the compression of pictures. Decorrelation, energy compaction and separability are the characteristics of DCT.The picture is changed from the spatial domain to the frequency domain.

$$F(u,v)=\left(\frac{2}{N}\right)^{\frac{1}{2}}\left(\frac{2}{M}\right)^{\frac{1}{2}}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\Lambda(i)\Lambda(j).$$
$$\cos\left[\frac{\pi.u}{2.N}(2i+1)\right]\cos\left[\frac{\pi.u}{2.M}(2j+1)\right].f(i,j)$$
(12)

Where

$$\Lambda(\xi)=\begin{cases}\frac{1}{\sqrt{2}} & \text{for } \xi=0\\ 1 & \text{otherwise}\end{cases}$$

4.3 Functionality:

The list of features that the programme or application offers is shown below. The user interface will provide the user with access to all functionalities.

1. Explore the two photos that has to be combined.
2. Transform the pictures into TIF format.
3. Create a grayscale version of the pictures.
4. The photos should be resized to 512*512.
5. Convolute the picture using the mask to apply Pyramid to the resized image.
6. The convolved picture should be given a median filter.
7. Display the image.

The picture data is decorrelated using the DCT transform. An picture is commonly divided into 8x8 blocks in DCT. Each of these blocks is converted into 64 DCT coefficients. DCT coefficients come in two varieties: AC and DC. The average value of the sampled data is given by the DC coefficient. The remaining coefficients are referred to as AC coefficients.

The following is the equations of the 2D discrete cosine transform Z(u,v) of a 2D picture or signal z(x,y) of size MxN;

$$Z(u,v)=\alpha(u)\alpha(v)\sum_{x=0}^{M-1N-1}\sum_{y=0}^{M(x,y)} z\cos\left(\frac{\pi(2x+1)u}{2M}\right)$$
$$\cos\left(\frac{\pi(2y+1)v}{2N}\right), \begin{matrix}0\le u\le M-1\\0\le v\le N-1\end{matrix} \quad (13)$$

Where

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1542-1547 www.ijaem.net ISSN: 2395-5252

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{M}}, u = 0 \\ \sqrt{\frac{2}{M}}, 1 \leq u \leq M-1 \end{cases}$$

$$\alpha(v) = \begin{cases} \frac{1}{\sqrt{N}}, v = 0 \\ \sqrt{\frac{2}{N}}, 1 \leq v \leq N-1 \end{cases}$$

U & V are discrete frequency variables
(x, y) pixel index.

Similarly, the 2D inverse discrete cosine transform is defined as:

$$z(x,y) = \alpha(u)\alpha(v)\sum_{u=1}^{M-1,j-1}\sum_{i=0}^{M}\alpha(u)\alpha(v)Z(u,v)\cos\left(\frac{\pi(2x+1)u}{2M}\right)\cos\left(\frac{\pi(2y+1)v}{2N}\right), \begin{matrix} 0 \leq x \leq M-1 \\ 0 \leq y \leq N-1 \end{matrix} \quad (14)$$

The two techniques of constructing and reconstructing the Laplacian pyramid approach are shown below in Fig.4.1 and Fig.4.2. There are two more phases known as reduction and expansion in each of the two processes, construction and reconstruction.

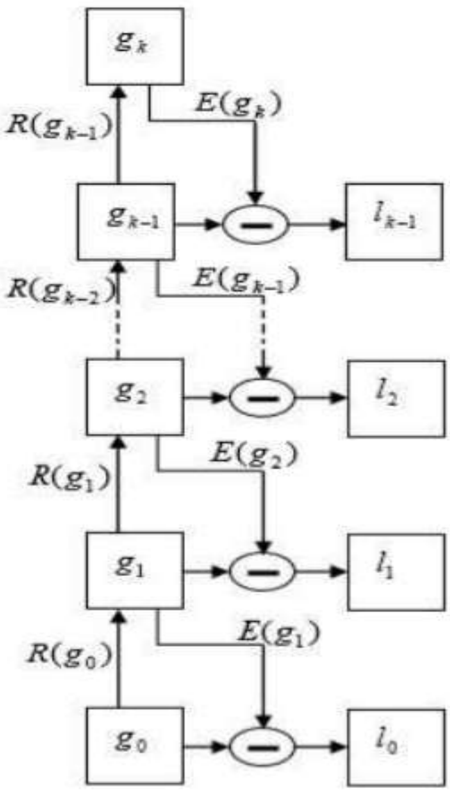

Fig.4.1 Construction flow diagram of pyramid

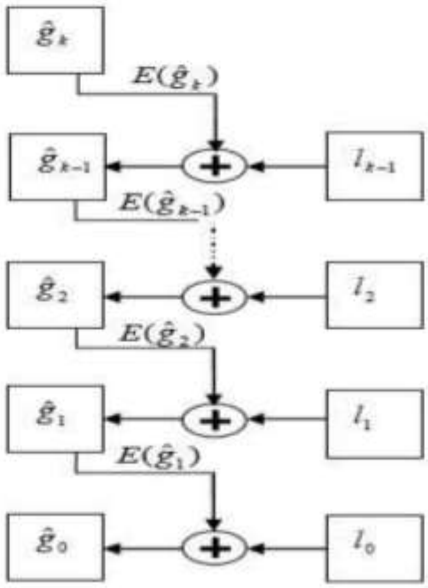

Fig.4.2 Reconstruction flow diagram of pyramid

In the reduction function, the picture at level g0 (the top level), which has a mxn matrix in size, is reduced to a (m/2)x(n/2) matrix to produce level g1, where both the spatial density and spectral resolution have been decreased from the g0 image level. To obtain the next lower level, g2, and so on, the same stages of reduction are performed by using the Discrete Cosine Transform (DCT) . The inverse of the Discrete Cosine Transform is used to reduce the picture. The following is the reduction function's calculation formula:

Reduction Function R:

$$g_k = R(g_{k-1}) \quad (15)$$

The expansion function, which expands the picture with size mxn to produce the image with size 2mx2n at the following level, is the reverse of the reduction function. Applying m number of 0's and n number of 0's in the horizontal and vertical directions, respectively to the inverse discrete cosine transform, allows for this operation to be accomplished.

Expand Function E:

$$\hat{g}_k = E(\hat{g}_{k+1}) \quad (16)$$

Construction of pyramid is done using Fig.4.1

$$g_{k+1} = R(g_k)$$
$$l_k = g_k - E(g_{k-1}) \quad (17)$$

Where l_0, l_1, $l_2, \cdots l_{k-1}$ are Laplacian image pyramids, which maintain band pass filtered pictures for use in reconstruction processes and are the coarser level images.

The K-levels of the Image Pyramid are shown as

$$p_k \rightarrow \{g_{k,0,}l_1,......l_{k-1}\}$$

At coaser level

$$\hat{g}_k = g_k$$

Given that beyond this point, there is no more decomposition.

Reconstruction of pyramid is done using Fig.4.2

$$\hat{g}_{k-1} = l_{k-1} + E(\hat{g}) \qquad (18)$$

V. DISCRETE WAVELET TRANSFORM(DWT)

The Discrete Wavelet Transform technique is one of the methods used to combine pictures, in which the source images are first converted using DWT to the wavelet coefficients for each scale level. Next, using a specific fusion rule, the fusion of source pictures is performed that correspond to the wavelet coefficient of the source images. Simple addition or averaging can be used in this rule. By using the inverse of DWT to calculate the wavelet coefficients for each level of the fused picture, a single output image is ultimately constructed. The theory of the wavelet transform is based on the compression of the picture.

The Multi-Resolution Analysis(MRA) may be used to include wavelet theory into the picture fusion process. An intermediary representation between the Fourier and spatial representations is offered by the multi-resolution wavelet transform. High visual quality is provided in the spatial and Fourier domains using it. The picture is transformed from the spatial transform domain to the frequency transform domain using the 2-D Discrete Wavelet Transformation (DWT). For fusing the picture, DWT employs a two channel filter bank. To create a 2-D decomposition of the image, a 1-D discrete wavelet transformation (DWT) can also be applied along the rows and columns of the images.

The pictures are divided into mean-mean, mean-max, mean-min, max-mean, max-max, max-min, min-mean, min-max, min-min frequency components using the wavelet transform (DWT).In DWT image fusion, the DWT technique may be applied to input pictures to get wavelet coefficients and create the necessary image. The next step is to use the inverse of DWT to recreate the final fused picture. In DWT, relatively simple operations like pixel selection, addition, subtraction, or averaging are carried out using image fusion algorithms. The fundamental processes used to separate the input pictures into a collection of functions further referred to as wavelets. In DWT, an image's wavelet transform is calculated, adjustments are performed in the last phase, and then the inverse of the wavelet is used to produce a high-quality picture as a result.

5.1 DWT Flow diagram:

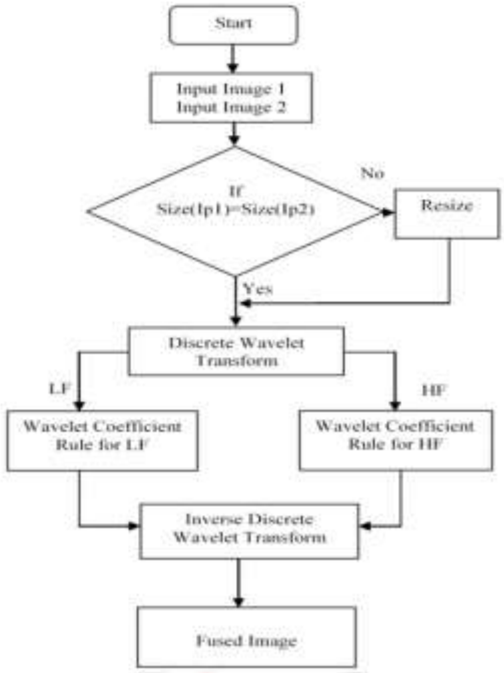

Fig.5.1: Flow diagram for DWT

5.2 DWT Algorithm:

1. Read two source photos and resize them to the same size.
2. Decompose source photos into low pass and high pass sub images using the Mallet method.
3. Four sub images for each level can be received.
4. Three high pass sub pictures and one low pass sub image (Horizontal, Vertical, Diagonal).
5. To find fused coefficients, apply the maximum wavelet coefficients rule.
6. Construct using the Mallet reconstruction technique using the combined coefficients of the low pass and high pass. The combined picture is acquired.
7. Determine the Entropy, the Correlation Coefficient, the Mean Values, and the Root Mean Square (RMS).
8. Compared to other wavelets that are already in existence.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 1542-1547 www.ijaem.net ISSN: 2395-5252

VI. CONCLUSION

The three techniques for image fusion are discussed in this paper. Principal Component Analysis, Discrete Wavelet Transform, and Discrete Wavelet Transform are its foundations.

It can be concluded that PCA and DCT based image fusion techniques can be employed for applications that don't need greater accuracy and quality. In contrast, DWT based fusion algorithms provides better-quality fused pictures than that of PCA and DCT based methods.

REFERENCES

[1]. V.P.S. Naidu and J.R. Raol, "Pixel-level Image Fusion using wavelets and Principal Component Analysis ," Defence Science Journal, VoI. 58, No. 3, May 2008, pp. 338-352 02008,DESIDOC.

[2]. Nirosha Joshitha J, R. Medona Selin,"Image Fusion using PCA in Multifeature Based Palm print Recognition,"International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-2, Issue-2, May 20 I 2.

[3]. VPS Naidu,"Discrete Cosine Transform based Image Fusion techniques," Journal of Communication, Navigation and Signal Processing (January 2012) VoI. I, No. I, pp. 35-45.

[4]. Rupinder Kaur, Er.Harjit Singh, "Review on image fusion and its techniques".Published by IRACST- International Journal of Computer Networks and Wireless Communications (IJCNWC), ISSN: 2250-3501 Vol.5, No.2, April 2015.

[5]. Sweta K. Shah, Prof. D.U. Shah, "Comparative Study of Image Fusion Techniques based on Spatial and Transform Domain".Published by International Journal of Innovative Research in Science, Engineering and Technology Vol. 3, Issue 3, March 2014.

[6]. Nisha Gawari, Dr. Lalitha.Y.S," Comparative Analysis of PCA, DCT & DWT based Image Fusion Techniques" Published by International Journal of Emerging Research in Management &Technology ISSN: 2278-9359 (Volume 3, Issue-5).May 2014.

[7]. A. Toet, L.J. Van Ruyven and J.M. Valeton, "Merging thermal and visual images by a contrast pyramid", Opt. Eng. 28(7), pp.789-792, 1989.

[8]. Pajares.G and Cruz.J (March 2004), 'A wavelet based image fusion tutorial' ,Pattern recog, Vol .37,No.9,pp no 1855-1872.

[9]. N.Ahmed, T. Natarajan and K.R.Rao, "Discrete Cosine Transform", IEEE Trans. On Computers, Vol.32, pp.90-93, 1974.

[10]. Sweta K. Shah, Prof. D.U. Shah "Comparative Study of Image Fusion Techniques based on Spatial and Transform Domain," in International Journal of Innovative Research in Science, Engineering and Technology , Vol. 3, Issue 3, March 2014.