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Review on Image Fusion Techniques

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ABSTRACT

Information from multiple images which must be for same sense but with different sensors or focused on different objects is known as Image Fusion. The result of Image fusion is again an image of same sense but having better quality & more informative. The most important features from images are first identified & they are transfer into a new image without loss. This information can be used for different purpose like classification, interpretation, segmentation & compression. The basic requirement of Image fusion is to identify. This paper reviews different levels through which image fusion can be done. Then it introduce performance measures, & review of different Fusion algorithms.

Keywords: — Image fusion, spatial domain, transform domain, statistical domain

I. INTRODUCTION

One of the major research field of image processing is Image Fusion. It is also called as “Pansharpenig “, a process of fusing image details from two or more images into single one where fused image is more informative & of better quality. It will be more suited for human vision. Image fusions have different application areas like remote sensing, medical imaging, computer vision, microscopy imaging, surveillance system etc. Actually it is the mechanism to improve the quality of images for specific purpose.

Image fusion can occur at signal, pixel, and feature & decision level [1]. In Signal level fusion several signals are combined to provide a signal that has same general format as the source signal. In pixel level fusion or image level fusion images are combined by assuming individual pixel values. In feature level fusion, fusion process is based on features on set of regions in input image like shape, contrast & texture. At last decision level or symbol level fusion comprises of sensor information fusion, after processing image by each sensor& some preliminary determination has been made like entity’s location, attribute, identity etc. & after understanding of image merge the interpretation of different images. Any Fusion Algorithm should satisfy some generic requirements to enhance interpretation for human observer[2]: i) Preserve all relevant information in the fused image.

ii) Minimize any artifacts or inconsistency which can mislead the human observer or any subsequent image processing steps

iii) Irrelevant features & noise should be suppressed.

Preprocessing steps for Image Fusion:

Image Input
↓
Image Registration
↓
Image Resampling
↓
Image Fusion
↓
Fused Image

II. PERFORMANCE MEASURES

Few quantitative comparison between different fusion algorithms are provided by Performance parameters, focusing at estimating the definition of an image [3].

A. Peak Signal to Noise Ratio (PSNR)

SNR is the ratio between maximum possible value of signal & power of distortion noise which affects the quality of its representation. Largest PSNR value better the result PSNR is given by:

$$PSNR = 10\log 10\left(\frac{MAX^2 I}{MSE}\right)$$

B. Entropy(EN)

It is measure of information quantity contained in an image. Higher the entropy, more the information image having. Entropy is given by:

$$E = -\sum_{i=0}^{L-1} p_i \log_2 p_i$$

C. Mean Square Error (MSE):

The Mean Square Error (MSE) is a well-known parameter to evaluate the quality of the fused image which is given by:

$$MSE = \frac{1}{mn}\sum_{j=0}^{n-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]$$

D. Maximum Difference (MD):

Maximum difference is defined as a difference between two pixels.

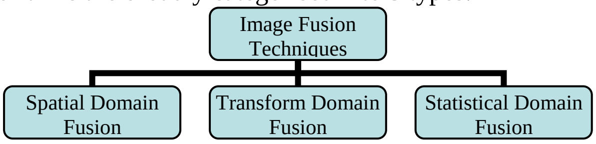
$$MD = Max|A_{ij} - B_{ij}|\ i = 1, 2, \ldots m;\ j = 1, 2, \ldots n$$

E. Overall Cross Entropy(OEC):

It reflect the difference between two source images & the fused image. Smaller the OCE better the fusion results *obtained.*

III. IMAGE FUSION TECHNIQUES

Image fusion is the branch of data fusion where dtisata found in the form of array of numbers representing colour, temperature, distance, brightness &other properties. This data can be 2-D, 3-D, or even higher dimensions. Image fusion algorithms are broadly categorised into 3 types:



A) Spatial Domain Fusion

This technique uses local spatial features like gradients, spatial frequency and local standard deviation. It directly relates with image pixels. Pixel values are changed to get desired result. The main drawback of this fusion technique includes spectral degradation [4]. Some of the Spatial Domain Techniques are:

i. Averaging

Focused regions of the image have higher pixel level intensity as compared to other part of image. This is the method which obtain output image where all regions are in focus. Here weighted average of input image is calculated & reflect the result on fused image. The main advantage fast speed & disadvantage is clear objects are not seen. Mathematical expression for this is:

$$I_f=(C_0*I_1+C_1*I_2)/(C_0+C_1)$$

ii. Select maximum/minimum

It is non-linear operation. In select maximum method pixel having maximum intensity is selected from every corresponding pixel of input image & used as resulting pixel. Similarly in select minimum method pixel having minimum intensity is selected from every corresponding pixel of input image & used as resulting pixel.

Mathematical expression for this is:

$$I_f(x,y)= \max(I_1(x,y),I_2(x,y))$$

OR $$I_f(x,y)= \min(I_1(x,y),I_2(x,y))$$

iii. Brovey Transform

It is also known as 'color normalized fusion' as it involves RGB color transform method. It fuses images from different sensors. The resultant image can be used for visual interpretation. The spectral feature of pixels are not changed. Rather it transforms luminance information to panchromatic images. It uses addition, multiplication, division for fusion of three multispectral bands. It was developed to visualize increase contrast in low & high ends of image histogram.(i.e. to provide contrast in water, shadow & high reflectance area like urban features)[6]. Mathematical expression for this is:

$$Fi = \frac{Mi}{\sum_{i=1}^{N} Mj+P}$$

iv. Intensity Hue Saturation (HIS)

This technique is a colour fusion technique, which effectively separates spatial (intensity) and spectral (hue and saturation) information from an image [7]. Here RGB image is first converted into intensity (I) hue (H) and saturation (S) components. In the next step, the intensity is substituted with the high spatial resolution panchromatic image. The last step performs the bands. In this method three multispectral bands R, G and B of low resolution. Finally, an inverse transformation from IHS space back to the original RGB space yields the fused RGB image, with spatial details of the high resolution image incorporated into it. The intensity I define the total colour brightness & exhibits as the dominant component. After resolution using the high resolution data, the merge result is converted back into the RGB after applying IHS [8].This method is one of the most frequently used methods for sharpening.

v. High Pass Filter (HPF)

High Pass Filter is a statistical/numerical method. The HPF method submits the high spatial resolution imagery to a small convolution mask (3 x 3) which acts upon the high-frequency spatial information (Pohl, 1998), effectively reducing the lower frequency spectral information of the high spatial resolution image. The filtered result is then added to the Multispectral data and the result divided by two to offset the increase in brightness values:

$$HPF_{i,j,k}=(MS_{i,j,k}+FP_{i,j})/2$$

Where HPF is the output image and i and j are pixels of band k. FP is the filtered result of High-Pass Filter, This technique preserves the multispectral data while incorporating the spatial resolution of the PN data [9].

vi. Principal Component Analysis(PCA)

This method is extensively used in image compression & classification. PCA is a vector space transform which transforms a number of correlated variables into uncorrelated variables. The uncorrelated variables are called Principal Components [10].

PCA method [9] enables us to compress the data without information loss. Method of PCA is as follows:-

Get the data. (pixel information)
Subtract mean value.
Calculate the covariance matrix.
Calculate Eigen vectors and Eigen values of covariance matrix.
Choosing components from the Eigen vectors and producing a feature vector.
Feature Vector = (eig1 eig2 eig3 … eign)

Deriving the new dataset.

New Dataset = Feature Vector * Data Adjust

New Dataset of all the input images are formulated and the sum of the pixel values forms the fused image matrix. In PCA method, the resultant fused image will be of high spatial quality.

B) Transform Domain Fusion

Here image is first transformed into transform domain. On that image all fusion transform operations are performed & at the end inverse of Fourier Transform is performed to get the desired image.

i. Discrete Wavelet Transform(DWT)

It is based on wavelet idea where transformation is baed on set of wavelet functions. It provides good resolution in time & frequency domain. It uses low pass filter & high pass filters. Wavelets use scaling & translation operations. Here input images are decomposed into two sub-bands (low & high) using wavelet transform & then they are fused using fusion methods available. At last inverse I applied on fused coefficients to form result. This technique needs number of convolution calculations requires more memory resources & takes much time which hinder its applications for resource constrained battery powered visual sensor nodes[11].

ii. Discrete Cosine Transform(DCT)

DCT based fusion methods need less energy as compare to the DWT techniques thus it is appropriate to use DCT fusion methods for resource constrained devices. As computational energy required is less than the transmission energy, data is compressed and fused before transmission in automated battle fields where the robots collect image data from sensor network. In this technique input images and fused images both are coded in JPEG (Joint Photographic Experts Group) format. Contrast sensitivity method is used to form the fused image. The contrasts of the consequent AC (Alternating current) coefficients of different blurred images are compared and the AC coefficient having the largest value is particularly chosen as the AC coefficient for the image formed after fusion. DCT representation of the fused image is found by calculating the average of all the DCT representations of all the input images but it has unwanted blurring effects which decreases the quality of the fused image.

iii. Stationary Wavelet Transform(SWT)

Stationary wavelet transform is developed to overcome the translation invariance. DSWT removes the down-samplers and up-samplers in DWT and up-sample particular filtration by simply inserting zeroes in between to separate out coefficients. In this algorithm, filters are primary placed on the particular rows then on the columns to create transform coefficients. Four images produced are of same size as of original image but resolution is half as compare to the original image. These transformed coefficients are fused and inverse discrete stationary wavelet transform is applied to form fused image.

iv. Pyramid Based Method

The basic principle here is to decompose the original image into pieces of sub-images with different spatial resolutions through some mathematical operations. A pyramid structure is an efficient organization methodology for implementing multiscale representation and computation. A pyramid structure can be described as a collection of images at different scales which together represent the original image. A pyramid image consists of a set of low pass filters through which the image pass through. An image at a particular level will be half the size of the same image in the latter level. Pyramid transforms of the input images are formed, they are combined and taken the inverse pyramid which forms the fused image.

A pyramid transform [3]is accomplished by the following three steps :

• Decomposition
• Formation of the initial image for re-composition
• Re-composition

Decomposition is the process by which a pyramid is generated at each level of the fusion process. The following steps are performed m number of times, if m is the predefined depth of fusion.

• Low pas s filtering: The input images are filtered by using the predefined filters according to the pyramidal method.

• Pyramid is formed from the filtered input Images using Burt's method or Lis Method.

• The input images are decimated to half their s ize , which would act as the input image matrices for the next level of decomposition.

Input images are merged after decomposition which is the input to re-composition. The re-composition is the process by which the final image is created from the pyramids formed as a result of decomposition. It is done by performing the following steps m number of times.

- The input image is un-decimated to the level of re-composition.
- The un-decimated matrix is filtered with transpose of the filter vector used in decomposition process.
- After this filtered matrix is merged with the pyramid formed at the respective level of decomposition.
- The newly formed image matrix would act as the input to the next level of re-composition.
- At the final level of re-composition process, fused image is the resultant image.

Different pyramidal methods differ in the filters they use for low pas s filtering, these are:

a) Filter Subtract Decimate (FSD) Pyramid

Decomposition phase filters the input image by the low pass filter, W= [1/16, 4/16, 6/16, 4/16, 1/16].

The low pass filtered input images are subtracted in order to form the pyramid. Now the pyramid is decimated by halving the number of rows and columns. Re-composition phase un-decimates the pyramid by duplicating the number of rows and columns. Again the pyramid is fed into a low pass filter 2*W. Matrix addition of the pyramid at the corresponding levels form the final pyramid.

b) Laplacian Pyramid

Laplacian pyramid is similar to FSD except that the low pass filtering is done by 2*W.

c) Ratio Pyramid

It is similar to FSD, but rather than subtraction in the decomposition phase, pixel wise ratio is calculated.

d) Gradient Pyramid

The difference between FSD and this method is that a low pas s filter, V = [1/ 2, 1/4, 2/4] is used along with the low pas s filter W. In addition to this four directional filters are used.

Horizontal Filter:

$$\begin{pmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

Vertical Filter:

$$\begin{pmatrix} 0 & 1 & 0 \\ 0 & -2 & 0 \\ 0 & 1 & 1 \end{pmatrix}$$

Diagonal Filter:

$$\begin{pmatrix} 0 & 0 & 0.5 \\ 0 & -1 & 0 \\ 0.5 & 0 & 0 \end{pmatrix} \quad \begin{pmatrix} 0.5 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0.5 \end{pmatrix}$$

e) Morphological Pyramid

In order to avoid the effect of noise, two stages of image filtering are done – image opening and image closing. Image opening is performed by combining image erosion after image dilation. Image closing is performed by combining image dilation after erosion.

C) Statistical Domain Fusion

It is used to solve the two main problems that are caused in image fusion namely color distortion and operator or dataset dependency. It uses statistical variables such as least squares, average of the local correlation or the variance with the average of the local correlation techniques to find the best result [5].

a) Local Mean Matching (LMM)

The general Local Mean Matching (LMM) and Local Mean Variance Matching (LMVM) algorithms to integrate two images, PAN into MS resampled to the same size as P, are given by [12,13] as follow:

$$F_{k(i,j)} = P_{(i,j)} \times \frac{\bar{M}_{k(i,j)(w,h)}}{\bar{P}_{(i,j)(w,h)}}$$

Where $F_{k(i,j)}$is the fused image $P_{(i,j)}$ and $M_{(i,j)}$ are respectively the high and low spatial resolution images at pixel coordinates (i,j); $M_{k(i,j)(w,h)}$ and $P_{(i,j)(w,h)}$ are the local means calculated inside the window of size (w,h), which used in this study a 11*11 pixel window.

b) Local Mean & Variant Matching (LMVM)

The LMVM algorithm is given by:

$$F_{k(i,j)} = \frac{(P_{(i,j)} - \bar{P}_{(i,j)})\sigma_{M_{k(i,j)(w,h)}}}{\sigma_{P_{(i,j)(w,h)}}} + \bar{M}_{k(i,j)}$$

Where σ is the local standard deviation. The amount of spectral information preserved in the fused product can be controlled by adjusting the filtering window size [12]. Small window sizes produce the least distortion. Larger filtering windows incorporate more structural information from the high resolution image, but with more distortion of the spectral values [14].

c) Regression Variable Substitution(RVS)

This technique is based on inter-band relations. Due to the multiple regressions derives a variable, as a linear function of multi-variable data that will have maximum correlation with unvaried data. In image fusion, the regression procedure is used to determine a linear combination (replacement vector) of an image channel that can be replaced by another image channel [21]. This method is called regression variable substitution (RVS) [3,11] called it a statistics based fusion, which currently implemented in the PCI& Geomatica software as special module, PANSHARP – shows significant promise as an automated technique. The fusion can be expressed by the simple regression shown in the following eq.

$$F_k = a_k + b_k * p$$

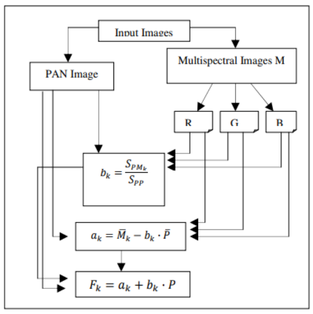


Fig: Schematic of Regression Variable Substitution

The bias parameter a_k and the scaling parameter b_k can be calculated by a least squares approach between the resampled band MS and PAN images. The bias parameter a_k and the scaling parameter b_k can be calculated by using eq. (4 & 5) between the resample bands multispectral M_k and PAN band P.

$$b_k = \frac{s_{PM_k}}{s_{PP}} \quad \text{----(4)} \qquad a_k = \bar{M}_k - b_k \cdot \bar{P} \quad \text{-----(5)}$$

d) ***Local Correlation Modelling (LCM)***

The basic assumption is a local correlation, once identified between original (M^{low}), band and down sample the PAN (P^{low}) should also apply to the higher resolution level. Consequently, the calculated local regression coefficients and residuals can be applied to the corresponding area of the PAN bad. The required steps to implement this technique, as given by [22 are:

1. The geometrically co-registered PAN band is blurred to match the equivalent resolution of the multispectral image.
2. The regression analysis within a small moving window is applied to determine the optimal local modeling coefficient and the residual errors for the pixel neighborhood using a single M_k^{low} and the degraded panchromatic band P^{low} in this study is a 11*11 pixel window.

$$M_k^{low} = a_k \times P^{low} + b_k + e_k$$

$$e_k = M_k^{low} - (b_k + a_k \times P^{low})$$

Where a_k and b_k are the coefficients which can be calculated by using equations (4 & 5), e_k the residuals derived from the local regression analysis of band k.

3. The actual resolution enhancement is then computed by using the modelling coefficients with the original PAN band , where these are applied for a pixel neighbourhood the dimension through the resolution difference between both images thus [22]:

$$F_k = a_k + b_k * p + e_k$$

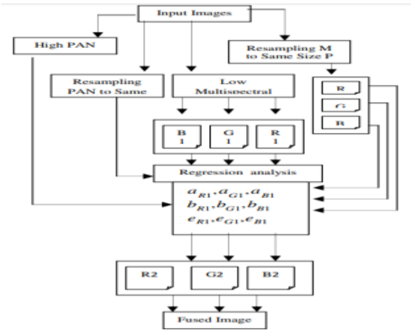


Fig. Flowchart of Local Correlation Modelling

IV. CONCLUSIONS

This paper performs survey on different image fusion techniques & describes different image fusion algorithms. Depending on type of application & requirements of user different fusion algorithms can be chosen. The review gives different spatial domain techniques, providing spatial resolutions but having image blurring problems. Different wavelet transforms techniques providing high quality spectral content but give translation invariance. To overcome this Stationary wavelet Domain is used. While Statistical Domain Fusion will resolve main two problems i.e. color distortion & operator dependency. BY this review it is found that most of the present methods are focused on particular things like majority rely on transformation but color artifacts may occur which reduce performance while in some cases uneven illuminate has not been considered. Maximum focus is on Gray scale images in most of the cases. Thus in future work should be on removing these gaps by combining different techniques to approach better results.

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