Multi-focus Gray Scale Image Fusion: A Comparative Analysis

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Abstract—The main objective of image fusion is to combine information from more than one image of the same scene. The resulting image is more suitable for human as well as machine perception or further image-processing tasks as image segmentation, object recognition and feature extraction. In this paper, principal component analysis based and average pixel level base approach is proposed for pixel level image-fusion. The fused image can effectively improve the image contrast and clarity, and produce effective vision quality. The fusion image can be compared with the results obtained by PCA and average pixel level, and a robust analysis was done through the experimental analysis. Finally, the experimental results indicate that the PCA based proposed novel algorithm ensure the integrity, continuity and accurate information.

Keywords: Image fusion, Acquisition model, PCA, average pixel level, MRI.

I. INTRODUCTION

Image fusion is capable of integrating information from different images to produce more useful information. The fusion process integrates the redundant as well as complementary information present in input signals in such a way that the fused signal describes the true source better than other individual signals. The exploitation of the redundant information improves the accuracy as well as reliability where as the integration of complementary information improves the interpretability of the signal. In the fusion process, both the input images should have registered to each other with high precision value and then apply various types of fusion methods like PCA, average or wavelet etc and finally both the images are fused to generate final image which is more clear, informative as compared to both of the input images.

The PCA or hotelling transformation is a statistical approach based on eigen vectors and eigen values which is basically used for data dimension reduction. PCA is also use as an intermediate stage in the other type of processing such as reduction, classification, change detection and image fusion [a1]. These approaches mainly focus on grayscale images so in this paper work we present algorithms which fuse the gray scale images. This fusion process is based on PCA, wavelet, average spatial method at pixel level [1, 2, 3].

Based on the features of the observed images in fusion process, these are categorized in three classes [1, 2]:

- Common feature: Features which is present in all the observed images.
- Complementary Feature: The features which is present in one of the observed image and is absent in other image, is known as complementary feature.
- Noise: Feature which is random in nature and do not contain any relevant information, can be considered as noise.

The goal of fusion algorithms presented in this paper is to select the feature type automatically and fuse the information appropriately. In case of similar features, the algorithms should perform an averaging operation and in case of complementary feature, the fusion algorithm should select the feature which contains more relevant information.

II. IMAGE ACQUISITION MODEL

Let $I_0(x, y)$ is the true image which is inspected by n different sensors and $I_1(x, y), I_2(x, y), ..., I_n(x, y)$ are the corresponding n measurements. The local affine transform relates the input pixels and the corresponding pixels in the measured image. It is defined as [1]:
\[ I_i(x, y) = \beta_i(x, y) * I(x, y) + \eta_i(x, y), \]
where \( 1 \leq i \leq n \) ................. (1)

In the above equation,
\[ \beta_i(x, y) : \text{Gain noise of } i^{th} \text{ sensor at location } (x, y); \]
\[ \eta_i(x, y) : \text{Sensor noise of } i^{th} \text{ sensor at location } (x, y); \]

The main goal of image fusion is to estimate \( I(x, y) \) from \( I_i(x, y), 1 \leq i \leq n. \)

In the extreme case, let two sensors \( I \) and \( j \) (\( i \neq j; 1 \leq i, j \leq n \)) have complementary information at position \( (x, y) \). If \( \beta_i(x, y) \neq \beta_j(x, y) \) and
\[ \beta_i(x, y), \beta_j(x, y) \in \{0,1\}. \]

In other case if two sensors \( I \) and \( j \) have redundant information if \( \beta_i(x, y) = \beta_j(x, y) \).

Here, the local affine transform relates the local information content in a mathematically convenient manner. This is the main advantage of local affine transform model [1, 2, 3]. This model can be used in many applications such as radar, satellite, GIS, visual and IR imaging, color doppler, ultrasound and MRI imaging etc to produce the complementary as well as redundant information available at local level in measured image. The image acquisition model used in this paper work is very helpful in the above mentioned areas of image processing and also contributes in the field of computer vision.

III. IMAGE FUSION

In general, the image fusion tries to integrate the information from multiple images taken from same scene in order to achieve a new and better fused image. This fused image consist best information coming from the original images.

Let \( I_0(x, y) \) be the true image and in order to estimate \( I_0(x, y) \) from equation (1), we consider that
\[ I_0(x, y), I_i(x, y) \geq 0, (1 \leq i \leq n) \]

This assumption is valid for many devices such as IR cameras, digital cameras etc. Let the sensor noise \( \eta_1(x, y), \eta_2(x, y), \ldots, \eta_n(x, y) \) are zero mean random variables which are independent of each other. The standard deviation of \( \eta_i(x, y) \) is represented as \( \sigma_i \), which is known a priori and independent of spatial location \( (x, y) \) [1, 2, 4]. Now consider the equation (1), we get
\[
\begin{bmatrix}
I_1 \\
I_2 \\
\vdots \\
I_n \\
\end{bmatrix} = 
\begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_n \\
\end{bmatrix}
\begin{bmatrix}
I_0 \\
\eta_1 \\
\eta_2 \\
\vdots \\
\eta_n \\
\end{bmatrix}
\]

\[ \begin{bmatrix}
11 \\
12 \\
\vdots \\
In \\
\end{bmatrix} = 
\begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_n \\
\end{bmatrix}
\begin{bmatrix}
I_0 \\
\eta_1 \\
\eta_2 \\
\vdots \\
\eta_n \\
\end{bmatrix} \]

\[ \begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_n \\
\end{bmatrix} \begin{bmatrix}
I_0 \\
\eta_1 \\
\eta_2 \\
\vdots \\
\eta_n \\
\end{bmatrix} \]

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I_1 \\
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\beta_1 \\
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\end{bmatrix} \begin{bmatrix}
I_0 \\
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I_0 \\
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\eta_n \\
\end{bmatrix} \]

\[ \begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_n \\
\end{bmatrix} \begin{bmatrix}
I_0 \\
\eta_1 \\
\eta_2 \\
\vdots \\
\eta_n \\
\end{bmatrix} \]
We can represent this equation in other form:

\[ I = \beta I_o + \eta \]  \hspace{1cm} (3)

Where

\[ I = [I_1, I_2, ..., I_n]^T, \quad \beta = [\beta_1, \beta_2, ..., \beta_n]^T, \]

\[ \eta = [\eta_1, \eta_2, ..., \eta_n]^T \]

For notational simplicity, we dropped the reference to pixel location \((x, y)\) from equation (3).

Now we get a re-arranged equation as:

\[ \beta^N I = I_0 + \beta^N \eta \]  \hspace{1cm} (4)

Where \(\beta^N = (\beta^T \beta)^{-1} \beta^T\)

The main goal of image fusion process is to estimate \(I_o\) \(\forall (x, y)\) from equation (4). In equation (4) \(\beta^N\) is unknown and must be estimated from image \(I_i(x, y)\). If \(\beta^N\) is known, a common approach to estimate \(I_o\) from measurement \(I\) minimize the cost of function \(\| \beta^N I - I_o \|\). This can be solved by using least square estimate i.e. \(I_o = \beta^N I\).

In general \(\beta\) is known, therefore, to estimate \(\beta_i\) \((1 \leq i \leq n)\), first consider the gain of sensor varies mildly from one spatial location to another. We consider \(\beta_i\) as a constant over a small region of sensor image. Thus, splitting the input images into small region of size \(p \times q\) and compute the sensor gain for each region. We assume here, \(\beta_i \in [0, 1]\ \forall (1 \leq i \leq n)\).

From equation (3), in absence of noise the variance of the observed images \(I_1, I_2, ..., I_n\) are related to each other through sensor gains \(\beta_1, \beta_2, ..., \beta_n\). Therefore, variance to estimate \(\beta\) for observed images \([1, 2, 5]\).

Let \(\rho\) and \(\mu = (\mu_1, \mu_2, ..., \mu_n)^T\) are principle eigen value and principle eigen vector of correlation matrix \(\sum_v\), where

\[ \sum_v = \frac{1}{(p \times q)} - 1 \sum_{k=1}^{p \times q} a_k \alpha_k^T \]  \hspace{1cm} (5)

Where \(a_k = [I_1^k, I_2^k, ..., I_n^k]\)

Let us consider the rank of matrix \(\sum_v = 1\)

Therefore, \(\rho\) and \(\mu\) can be related to the sensor gain, which is defined as

\[ \rho = c(\beta_1^2 + \beta_2^2 + ... + \beta_n^2) \]  \hspace{1cm} (6)

\[ \mu = (\mu_1, \mu_2, ..., \mu_n)^T \alpha [\beta_1, \beta_2, ..., \beta_n]^T \]  \hspace{1cm} (7)
Where \( C = \sum_{k=1}^{pxq} Io / ((pxq - 1)) \)

Now, we propose the following rules to estimate the \( \beta \) for region \( R \). These rules are given as:

1. Compute \( \sum_v \) for a block and estimate \( \mu \), where \( \mu^T \mu = 1 \).

2. Use \( \beta_1 = \beta_2 = \ldots = \beta_n = 1 \) \( \mu_1 = \mu_2 = \ldots = \mu_n \)

3. Otherwise Consider \( \beta = \mu \) and repeat this process for each region.

Now sensor gain vector \( \beta \) is independent of \( Io \) and its derivatives. Now for pixel-wise image fusion process, we can consider an approach proposed by Rudin et al in [1, 3], who presented an iterative solution:

\[
I_{o}^{k+1} = I_{o}^{k} - \tau \left( \nabla \cdot \left( \nabla f_{o}^{k} \right) + \lambda \left( I_{o}^{k} - \beta^* I \right) \right)
\]

Where \( K, \tau_k \), and \( \cdot \) represents iteration number, step time, dot product respectively and \( \lambda_k \) is defined as:

\[
\lambda_k = -\frac{1}{\int \sigma^2 dx dy} \int \left( I_{o}^{k} - \beta^* I \right) \nabla \cdot \left( \nabla I_{o}^{k} \right) dx dy
\]

General Image Fusion Algorithm:

Input: n co-registered input images.
Output: Fused image.
Step-1: Sensor gain estimation
(i) Split each input image into L blocks each having size pxq.
(ii) For each block (i=1,2,..,L)
Evaluate the sensor gain by solving equation (5), (6) and rule (1), (2).
Step-2: Fusion process
For pixel-wise image fusion using equation (8) and by solving it iteratively, we get the fused image.

IV. APPLIED FUSION METHODS

A. Principle Component Analysis

The PCA is statistical approach based on eigen values and eigen vectors. In this paper, a PCA-based algorithm is proposed to extract the pixels from stacked input images [5, 6]. The aim of PCA at reducing a large set of variables to a small set, which contains the relevant and useful information that was available in large data set. PCA technique enables us to create and use reduced set of variables, known as principle factor. PCA use reduced set which is easier to analyze and interpret. PCA can be carried out in two ways: First, a standard method, in this method all available bands participate in the fusion process. Second, Optional PCA method, in this method a group of bands are combined due to correlation matrix [1, 7, 8].
The PCA based image fusion algorithm is developed in MATLAB and this algorithm is defined as:

1) Algorithm
   a. Load input images Img1, Img2 and pass in the given method as a parameter.
   b. Define imageFusionPCA(Img1, Img2) method in steps given below:
   c. Check size of input images as \([m, n] = \text{size}(Img1)\);
   d. \([p, q] = \text{size}(Img2)\);
   e. If\((m=p) \text{ or } (n=q)\)
      Error('Input Images used here are not having same size');
   f. Compute and select the eigen values of image Img1, Img2.
      \([V, D] = \text{eig}([\text{Img1(:)}, \text{Img2(:)}]);\)
   g. Now, compute normalized eigen values, ( here nev is a variable which represent normalized
      eigen value)
      If\((D(1,1) > D(2,2))\)
      \(nev = V(:, 1)./ \text{sum}(V(:,1));\)
      else
      \(nev = V(:, 2)./ \text{sum}(V(:,2));\)
   
g. Now compute the fused image
      \(\text{fusedImage} = \text{nev}(1) \times \text{I1} + \text{nev}(2) \times \text{I2};\)

B. Spatial Average Method
   This is simple and basic method for image fusion, this method takes the average of the source image pixel by pixel basis. If the image have 3 bands R, G, B. Then, this method takes the average of corresponding two bands of \(\text{CX}\) and \(\text{CY}\) generates one band of \(\text{CF}\).
   \[
   \text{CF}(m,n,i) = \frac{\text{CX}(m,n,i) + \text{CY}(m,n,i)}{2}
   \]
   Where \(i=R, G, B\) and \((m, n)\) are the pixel location in spatial domain in the image.

Along with the simplicity this method has reduced contrast and also has some other undesired side effect.

2) Algorithm
   a. Load input images Img1, Img2 and pass in the given method as a parameter.
   b. Define imageFusionAverage(Img1, Img2, t) method in steps given below:
   c. switch(t)
      case 1:
      fuseImage = Img1;
      case 2:
      fuseImage = Img2;
      case 3:
      fuseImage = (Img1+Img2)/2;
      Otherwise:
      Error('You have given unknown option');
   
d. End

V. EXPERIMENTAL RESULTS

In the experimental result, the fusion algorithms used in this paper is to select the feature type automatically and fuse the information appropriately. In this work, In case of similar features, the algorithms should perform an averaging operation and in case of complementary feature where the fusion algorithm should select the feature which contains more relevant information. The PCA method produces much better result in which the edges are more pinpointed and continuous and resulting image is more informative.
In the above experimental results as shown in figure-1 and figure-2, in which first row represents input image and second row represent the fused image by average and PCA methods respectively. Fused image given by PCA method produce better results than other evaluation criteria.

1) Performance Analysis
The table given below represents the performance summary of the given image fusion algorithms. As the SNR is reduced the performance of the pca based algorithms approaches better than average [9, 10]. For the low SNR, the algorithm tends to over smooth the edges of the fused images.

<table>
<thead>
<tr>
<th>Image</th>
<th>SNR</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRI Image</td>
<td>1.83</td>
<td>1.75</td>
</tr>
<tr>
<td>Watch Image</td>
<td>2.45</td>
<td>3.05</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

This paper first overview the two fusion methods, and then compare the performance of both methods. These methods first fused the images and then compare evaluate the activity level of each pixel to get a decision map. In this process, we consider the high frequency components as compare to low frequency component. Finally we did the comparative analysis of both the methods and the performance is analyzed with the help of SNR, PSNR, Maxerror. In the further studying, we consider the full use of these coefficients and use other fusion algorithms and indexes might produce better results.

REFERENCES

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