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Multiple Image Fusion Using Laplacian Pyramid

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Abstract: ***Image fusion is an important visualization technique of integrating coherent spatial and temporal information into a compact form. Laplacian fusion is a process that combines regions of images from different sources into a single fused image based on a salience selection rule for each region. In this paper, we proposed an algorithmic approach using a Laplacian and Gaussian pyramid to better localize the selection process. The input images are decomposed by using the Laplacian pyramid transformation. The final fused image can be obtained by using the inverse reconstruction of Laplacian pyramid transformation.***

Keywords: Image fusion, Laplacian Pyramid Decomposition, Focus Fusion, Image Enhancement, Gaussian Pyramid.

1. Introduction

The goal of image fusion is to combine relevant information from two or more source images into a single image such that the single image contains as much information from all the source images as possible [1]. Image fusion is important in many image analysis tasks in which data is acquired from multiple sources. Image fusion is also need to enhance the image quality, and the source images can be taken at different times and/or using different sensors. So some source images may contain certain occlusions and source images from different sensors with different physical features [2]. Thus, the fused image is expected to have more accurate description of the true scene and is more useful for human visual or machine perception.

At present, the existing image fusion approaches can be classified into four categories: pixel-level, feature-level, decision-level and symbol-level. From other aspect, we also can adopt the classification of image fusion. In [1], the authors advised that the fusion approaches can be classified into spatial domain and transform domain techniques. The spatial domain method uses the source image itself as image features while the transform domain method uses the transform coefficients of the source image as image features in some bases, such as the discrete wavelet transform (DWT), the discrete Fourier transform (DFT), and so on.

Most image fusion approaches in the transform domain adopt multiscale transform (MST) to all source images, and then construct a composite multiscale representation of them use different fusion rules such as choose-max and weighted-average at each scale, the fused image can then be obtained by taking the inverse multiscale transform (IMST).

In image fusion, two images are combined in best possible way to reduce the error and get maximum clarity. Also the image regions with lower clarity are analyzed and optimized with algorithm to reproduce the image with high clarity content. Features with high and low frequency intensities are summed up to get the final fused image. In my dissertation, I have implemented image fusion approach on the images with multi focus.

The main steps contain Discrete Cosine Transform (DCT), Laplacian based Fusion, Down Sampling and Up Sampling. In my dissertation, I have proposed an algorithm with decomposition level = 5 for the creation of laplacian pyramid. Level 5 ensures the high detail fusion at pixel level, thus providing seamless results with high Peak signal to noise ratio (PSNR) and lower rate of Mean square error (MSE)

2. Methodology

2.1 The Proposed Algorithm for image fusion

Step 1: Load the first image (Which has half blurred and other half visible part)

Step 2: Load the second image (Which has other half blurred and first half visible part)

Step 3: Apply set level of decomposition = 5 and initiate Laplacian based Image fusion Function.

Step 4: Multi-resolution image fusion is done using DCT as the primary phase of step 3.

Step 5: The images are up sampled (expand) to level 5.

Step 6: The two decomposed images are fused together.

Step 7: The fused image is down sampled (reduce) to original level using inverse DCT.

Step 8: Fused image is displayed and PSNR and MSE are calculated using the original image.

2.2 Discrete Cosine Transform (DCT)

It is a very important transform in image processing and it is widely accepted by researchers. Large DCT coefficients are concentrated in the low frequency region; hence, it is known to have excellent energy compactness properties and edges may contribute high frequency coefficients. The signal energy due to smooth regions is compacted mostly into DC coefficients; hence edges in the spatial domain can only contribute energy to a small number of AC coefficients. The 2D discrete cosine transform Z(u,v) of an image or 2D signal z(x,y) of size MxN is defined as [10]:

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

$$\text{Where } \alpha(u)=\begin{cases}\frac{1}{\sqrt{M}}, & u=0\\ \sqrt{\frac{2}{M}}, & 1\le u\le M-1\end{cases} \quad \text{and} \quad \alpha(v)=\begin{cases}\frac{1}{\sqrt{N}}, & v=0\\ \sqrt{\frac{2}{N}}, & 1\le v\le N-1\end{cases} \quad \text{......(1)}$$

u& v are discrete frequency variables (x,y) pixel index.
Similarly, the 2D inverse discrete cosine transform is defined as:

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

2.3 Image resizing using DCT

Image resize can be done in either spatial domain or DCT domain. Image resizing in spatial domain is computationally complex than transform domain. In DCT domain, high frequency (HF) coefficients are truncated for down sampling and assuming HF coefficients to be zero for up sampling. This approach has significant drawbacks such as blocking artifacts and ringing effects in the resized image.

2.4 Down Sampling (Reduce Function)

To down sample the image by a factor of two, the following procedure is carried out as shown in Fig below. The image is divided by non-overlap blocks of size 8x8. Each block is then transformed into DCT domain. The 4x4 low frequency (LF) coefficients out of each 8x8 DCT block $\{I_i(m,n), 0\le m,n\le 3, i=1,2,...,4\}$ shown in Fig below. A 4x4 IDCT is applied on the LF coefficients to get down sampling. In this way, four consecutive 8x8 blocks become four consecutive 4x4 blocks in spatial domain. This image in spatial domain can be down sampled by repeating the same procedure. This procedure is called reduction function.

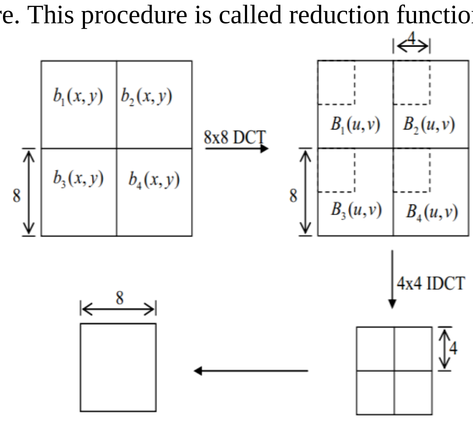

Fig.1 Down sampling process

2.5 Up Sampling (Expand Function)

Up sampling the image by a factor of two can be done by reversing the above procedure described in section 3.2.1. The image to be up sampling a factor of two is divided into 4x4 blocks. Four consecutive 4x4 blocks are transformed into DCT domain as shown in Fig. below. These are treated as Low Frequency (LF) coefficients and used as the LF components in the 8x8 blocks and the reaming High Frequency (HF) coefficients are assumed to be zero. Then consecutive 8x8 blocks in DCT domain are converted into spatial domain (up sampling) by applying 8x8 IDCT. This procedure is called expand function.

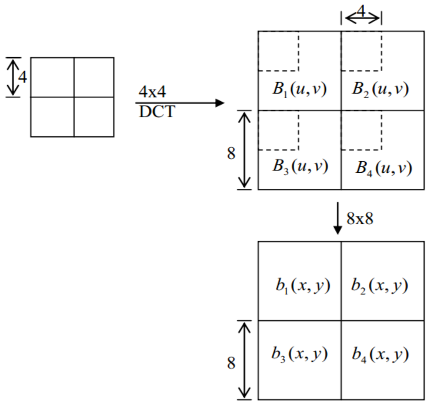

Fig.2 Up sampling process

2.6 Laplacian Pyramid

The procedure for Laplacian pyramid construction and reconstruction is illustrated in Fig. below. The image at the 0^{th} level Z_0 of size MxN is reduced (down sampling) to obtain next level Z_1 of size 0.5Mx0.5N where both spatial density and resolution are reduced. Similarly, Z_2 is the reduced version of Z_1 and so on. The level to level image reduction is performed using the function reduce R.

Reduction Function R: $Z_k = R(Zk-1)$ ……(3)

The reverse of function reduce is expand function E(Up sampling). Its effect is to expand the image of size MxN to image of size 2Mx2N.

Expand Function E :

$$\hat{Z}_k = E(\hat{Z}_{k+1}) \text{ ……(4)}$$

Construction of pyramid is done using

$Z_{k+1}=R(Z_k)$ ……(5), $l_k=Z_k - E(Z_{k+1})$ ……(6)

where l_0 , l_1, …… l_{k-1} are Laplacian image pyramids that contain band pass filtering images and keeping these records to utilize on reconstruction process and $z_k$is the coarser level image. The
k levels of image pyramid are represented as P_k -> $\{z_k, l_0, l_1, \dots, l_{k-1}\}$.

At coarser level $\hat{Z}_k = Z_k$ ……(7)

Since there is no more decomposition beyond this level,

$$\hat{Z}_{k-1} = l_{k-1} + E(\hat{Z}_k) \text{……(8)}$$

2.7 Fusion

Let, there are two images (I1 and I2) to be fused. Pyramid construction is done for each image and keeping the error records. Denote the constructed k levels of Laplacian image pyramid for 1st image is

$${}^1P_k \to \{{}^1Z_k, {}^1l_0, {}^1l_1, \dots, {}^1l_{k-1}\} \quad \text{……(9)}$$

And similarly for 2nd image

$${}^2P_k \to \{{}^2Z_k, {}^2l_0, {}^2l_1, \dots, {}^2l_{k-1}\} \text{……(10)}$$

Then the image fusion rule is as follows:

At k^{th} level, ${}^fZ_k = ({}^1\hat{Z}_k + {}^2\hat{Z}_k)/2$ ……(11)

For k-1 to 0 levels

$${}^fZ_{k-1} = {}^fl_{k-1} + E({}^fZ_k) \quad \text{……(12)}$$

Where

$$ {}^{f}l_{k-1} = \begin{cases} {}^{1}l_{k-1} & \left|{}^{1}l_{k-1}\right| \ge \left|{}^{2}l_{k-1}\right| \\ {}^{2}l_{k-1} & \left|{}^{1}l_{k-1}\right| < \left|{}^{2}l_{k-1}\right| \end{cases} \qquad \ldots\ldots(13) $$

and the magnitude comparison is done on corresponding pixels.

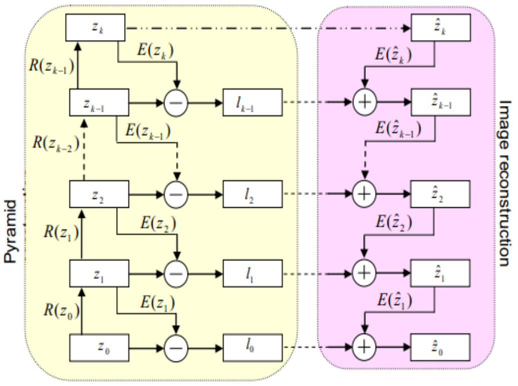

Fig. 3 Laplacian Pyramic Construction

The pyramid $I_f = {}^{f}z_0$ is the fused image.

3. Results

3.1 Fusion Quality Evaluation Metrics

Fusion quality can be evaluated visually. Human judgment decides fusion quality. Human object evaluators give grade to corresponding image (fused) and average the grade. This type of evaluation has some drawbacks such as the grade is not accurate and it depends on the human observer's ability.

To avoid these drawbacks, quantitative measures are used for accurate and meaningful assessment of fused images.

3.2 Peak Signal to Noise Ratio (PSNR)

PSNR will be high when the fused and reference images are alike. Higher value means better fusion. It is computed as:

$$ PSNR = 10\log_{10}\left(\frac{L^2}{RMSE}\right) \qquad \ldots\ldots(14) $$

Where L is the number of gray levels in the image.

3.3 Standard Deviation (SD)

Important index to weight the information of image, it reflects the deviation degree of values relative to mean of image. The greater the SD, more dispersive the gray grade distribution is. Standard deviation would be more efficient in the absence of noise [30]. An image with high contrast would have a high standard deviation. It is calculated using the formula

$$ SD = \sqrt{\frac{1}{MN}\sum_{i,j=1}^{M,N}\left(I_f(i,j)-\mu\right)^2} \qquad \ldots\ldots(15) $$

3.4 Spatial Frequency (SF)

SF indicates the overall activity level in the fused image. The spatial frequency for the fused image I_f of dimension MxN is defined as follows:

Row frequency:

$$ RF = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=1}^{N-1}\left[I_f(i,j)-I_f(i,j-1)\right]^2} \qquad \ldots\ldots(16) $$

Column Frequency:

$$ CF = \sqrt{\frac{1}{MN}\sum_{j=0}^{N-1}\sum_{i=1}^{M-1}\left[I_f(i,j)-I_f(i-1,j)\right]^2} \qquad \ldots\ldots(17) $$

Spatial Frequency:

$$ SF = \sqrt{RF^2 + CF^2} \qquad \ldots\ldots(18) $$

3.5 Percentage Fit Error (PFE)

$$ PFE = \frac{norm(I_r - I_f)}{norm(I_r)} * 100 \qquad \ldots\ldots(19) $$

where norm is the operator to compute the largest singular value.It is computed as the norm of the difference between the corresponding pixels of reference and fused images to the norm of the reference image. This will be zero when both reference and fused images are exactly alike and it will be increased when the fused image is deviated from the reference image.

3.6 Result Table

Image Name	PSNR	PFE	SD	SF
Aero.jpg	42.82	01.46	48.54	16.12
Bee.jpg	37.70	07.83	45.92	17.92

Table No.1 Results Table

Fig. 4 First half image during result

Fig. 5 Second half image during result

Fig.6 Output image after fusion

4. Conclusion

The multiple image fusion algorithm have proved to be a successful approach. It has provided with good image quality parameters like Peak signal to Noise Ratio (PSNR), Spatial Frequency (SF), Standard Deviation (SD) and Percentage fit Error (PFE). The proposed algorithm fuses the images as required with the minimum artifacts. The seams formed at level 5 of the decomposition are negligible at the level 0. Less amount of noise has proved to be the high efficiency factor of the image fusion technique. Also the difference is calculated between the original image and the image formed by the fusion using the proposed algorithm.

The algorithm easily selects the high clarity image parts from the two available half images and provides the result. Thus we conclude that the, use of Laplacian based technique at level 5 has proved to be more effective than the algorithms proposing level 4 down-sampling.

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