Gaussian filter based $\grave{a}$-trous algorithm for image fusion

Susmitha Vekkot
Department of ECE
Amrita Vishwa Vidyapeetham
Bangalore -35
v_susmitha@blr.amrita.edu

Pancham Shukla
Faculty of Life Sciences and Computing
London Metropolitan University
London N7 8DB, UK.
p.shukla@londonmet.ac.uk

ABSTRACT

Image fusion integrates complementary information from various perspectives in order to provide a meaningful interpretation of useful features and textures in multisource images. Here, we present a multiresolution algorithm based on Stationary Wavelet Transform for fusion of two test images of same size. The algorithm uses a Gaussian low-pass filtering technique for the high frequency subbands of SWT decomposition. The new approach gave sharper edges and structural enhancement than region based approaches involving calculation of energy around salient features. The key feature of Gaussian filtering is the flexibility of using filters with different values for standard deviation depending on the application and the range of detail necessary for processing.

1. INTRODUCTION

Information can be obtained from variety of sources. Integration of essential information for meaningful representation of data and textures from multiple images is a hard research problem. Global and local texture representation of images can only be accomplished with both spatial and spectral information. Fusion enriches information content in images by combining registered data from multiple source images, so that the spectral quality of image is enhanced not only for the purpose of human perception but also for machine learning and computer vision based applications [3]. By Heisenbergs uncertainty, it is understood that the probability of completely representing the image in both spatial and frequency domains simultaneously is not valid [2]. Due to this constraint, multiresolution analysis gained increased momentum in signal and image processing. Wavelet transform tool is capable of capturing time and frequency data which is localised and this is done across multiple resolutions providing a directional representation which is very much needed for enhanced feature extraction [9]. Fusion can be performed on different levels be it using pixel, feature or decision constraints [7]. One of the oldest methods of image fusion is by pixel averaging. Following this, several techniques have been proposed for image fusion across multiple resolutions. Some of them like Principal Component Analysis(PCA) and Intensity Hue Saturation(IHS) have been reported in literature [1]. These techniques work well for low resolution images but have the disadvantage of colour distortion when applied to high resolution images. Multiresolution analysis proved to be a better solution as it brings together data from various perspectives, removing redundant information with reliability [15]. Modern technology has fostered the development of sophisticated algorithms for image fusion applications using the features of discrete wavelet transform (DWT) and Shift- Invariant Wavelet Transform (SIDWT) for medical, multi spectral and remote sensing test images. Formulation of a rule map for fusion of salient features in an image can be based on different assessment indices like variance [4], energy [5] or pixel fusion [11]. The shift variance of DWT can be avoided by using Stationary Wavelet Transform(SWT), also knwon as $\grave{a}$ trous algorithm [8] for fusion. SWT based decomposition gives same size subimages as no downsampling is associated with decomposition [12]. In our current work, we focus on the fusion of test images using shiftinvariant SWT algorithm involving Gaussian low-pass filtering for detail coefficients of decomposition. The succeeding section gives the background theory associated with SWT based fusion. Section 3 details the new gaussian filter based $\grave{a}$ trous algorithm proposed in this paper. In sections 4 and 5, the results obtained by applying SWT based algorithms to test images are analysed in detail. The paper is concluded in section 6.

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2. BACKGROUND THEORY

Discrete Wavelet Transformation incorporates a subband coding algorithm for computing the time frequency information. A two channel subband coding algorithm given by [10] makes use of dyadic coefficients thereby providing sufficient information for computation. The signal is decomposed into coarse approximation coefficients and finer detail coefficients. The approximation coefficients provide low frequency information which helps to identify the signal whereas detail coefficients give high frequency, low scale information. The whole process involves filtering using high pass and low pass filters and subsequent subsampling to retrieve information from all frequency bands. Dyadic wavelet representation gives no redundancy due to the decimation by 2 at each level.

2.1 Stationary Wavelet Transform

Though the decimated non-redundant DWT is a widely used and robust tool for multiresolution analysis, it has the disadvantage of shift sensitivity caused by aliasing arising due to subsampling at every level of decomposition. Stationary Wavelet Transform(SWT), otherwise known as $\grave{a}$-trous algorithm is a redundant representation which is not shift sensitive. A detailed description of SWT can be obtained from [12], [6]. The shift-sensitivity of DWT can be avoided by using undecimated wavelet transforms without subsampling. Thus, aliasing is avoided and each subband will be

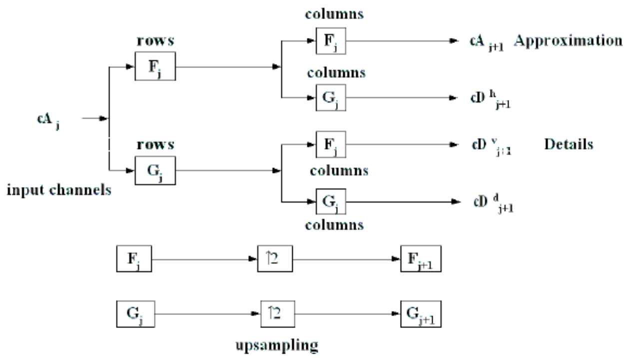

Figure 1: Steps involved in SWT decomposition:The row and column entries are filtered using low pass filter F and high pass filter G to yield approximations cA_{j+1} and horizontal, vertical and diagonal details cDh_{j+1}; cDv_{j+1}; cDd_{j+1}. The subsampling stage is avoided and filters are subjected to upsampling by padding with zeros. Here the decomposition coefficients at each level are of the same size as the input signal

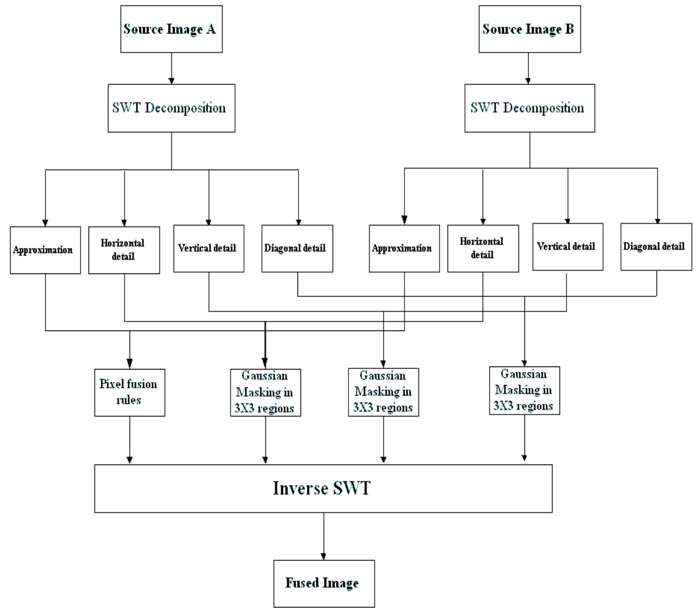

Figure 2: SWT fusion algorithm based on Gaussian filtering:The source images A and B are decomposed using SWT to yield approximation and detail coefficients of the same size as the original images. The low frequency approximations are fused using pixel selection techniques while horizontal, vertical and diagonal details are subjected to 3X3 Gaussian filtering to yield new set of details which are inverse transformed to get the final fused image.

identically sized with the original signal. In most applications, non-redundant form of DWT called standard DWT is used for signal analysis and synthesis. But in applications where redundancy of wavelet coefficients is required, Stationary Wavelet Transform (SWT) is used. SWT is very much similar to DWT except that in SWT, instead of subsampling, the filter computation is performed by padding with zeros after the filtering operation. Thus the approximation and detail subbands have identical size as the source image. Fig.1 gives the basic steps involved. Image fusion using SWT algorithms are very much similar to DWT, difference being the high amount of redundancy due to absence of subsampling.

3. GAUSSIAN FILTER BASED À-TROUS ALGORITHM

This paper proposes a structure enhancing fusion method which combines pixel averaging and region based gaussian filtering. Pixel averaging operate by taking the mean of individual pixels in the image, but omits important details like salient features over a region. Energy based fusion assumes that energy is highest around salient features but at times fail to remove disturbing artifacts and noise embedded in images. These practical insufficiencies of conventional fusion rules prompted the development of a structure enhancing à- trous algorithm as an extension of the hybrid architecture proposed in [14]. Fig.2 gives the steps involved in the fusion of two registered test images using the Gaussian low-pass filtering of the detail coefficients. The steps involved in the Gaussian filter based algorithm are given below.

- Read the two MXN source images A and B which are to be fused.
- Perform decomposition of the two source images using Stationary Wavelet Transform to give approximations (LL) and horizontal, vertical and diagonal detail (LH,HL,HH) subbands at decomposition level L. Each subband is of the same size as the original source image.
- The approximation subbands are fused using pixel selection algorithms based on averaging the decomposition coefficients.

A fusion decision rule is formulated which is given by (1):

$$LL_f(i,j) = [A(i,j) + B(i,j)]/2 \quad (1)$$

where $LL_f(i,j)$ are the set of fused approximation values, i and j are the pixel positions.

- The LH, HL and HH subbands from source images A and B are subjected to a 3X3 Gaussian low-pass filter with standard deviation 0.5. The gaussian filtering and subsequent addition operations can be denoted as :

$$LH_f = G(LH_A) + G(LH_B) \quad (2)$$

$$HL_f = G(HL_A) + G(HL_B) \quad (3)$$

$$HH_f = G(HH_A) + G(HH_B) \quad (4)$$

- The fused approximations and details are subjected to inverse SWT to get the fused image.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments were conducted on source images which were subjected to gaussian blur and moderate noise. The algorithm is tested on a wide variety of images under different constriants like varying foci, dust or speckles on one side or partial blur. The results obtained through these experiments are given by Figs. 3, 4, 5, 6 and 7 .

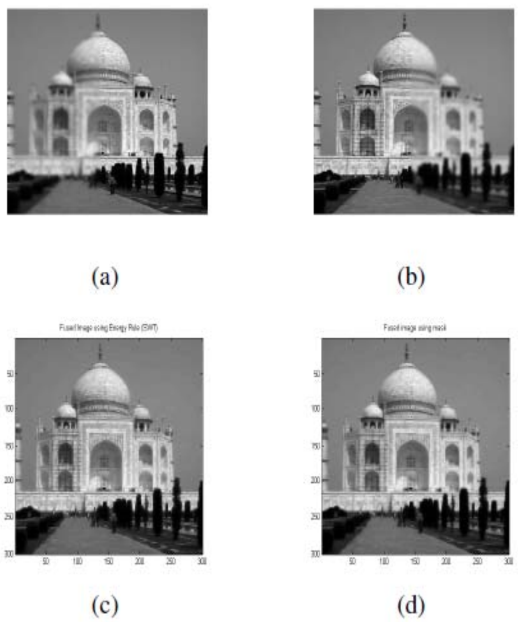

Figure 3: (a)Taj image with left blur(300X300, TIFF format)(b)Taj image with right blur(300X300, TIFF format).(c) gives fused image using energy rule while (d) gives the fused image using gaussian filtering.

Figure 4: (a)Lenna image with left blur(512X512, JPEG format)(b)Lenna image with right blur(512X512, JPEG format).(c) gives fused image using energy rule while (d) gives the fused image using gaussian filtering.

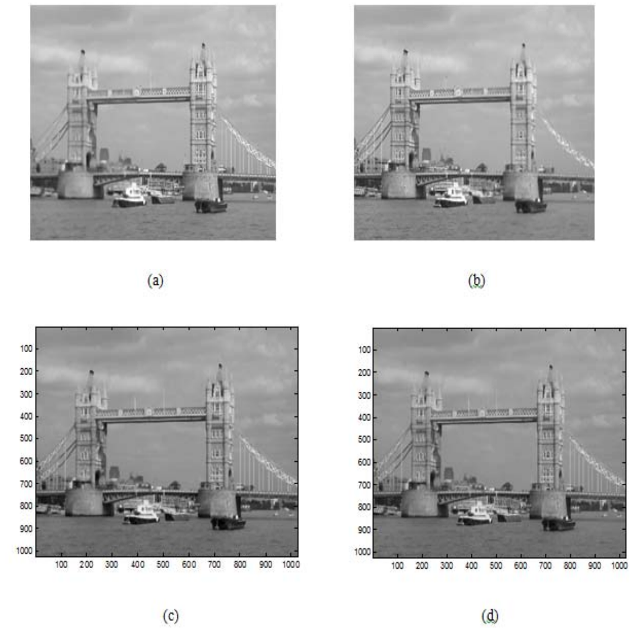

Figure 5: (a)Towerbridge image with dust/speckles in left(1024X1024, JPEG)(b)Towerbridge image with dust/speckles in right (1024X1024, JPEG).(c) gives fused image using energy rule while (d) gives the fused image using gaussian filtering.

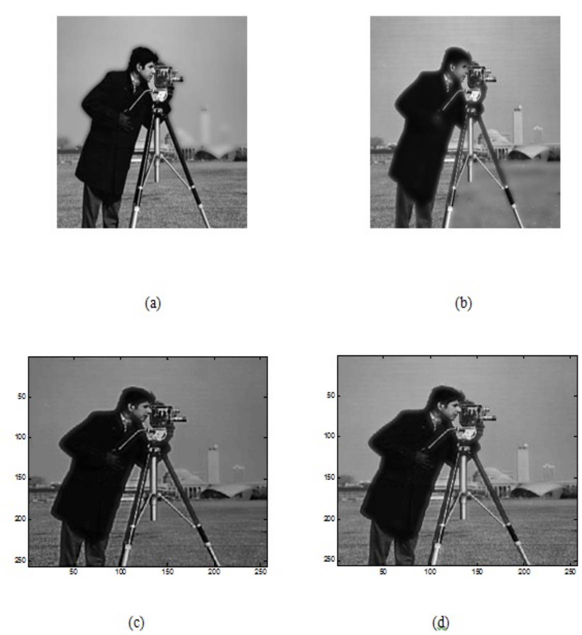

Figure 6: (a)Cameraman image with background blur(128X128, TIFF format)(b)Cameraman image with foreground blur(128X128, TIFF format).(c) gives fused image using energy rule while (d) gives the fused image using gaussian filtering.

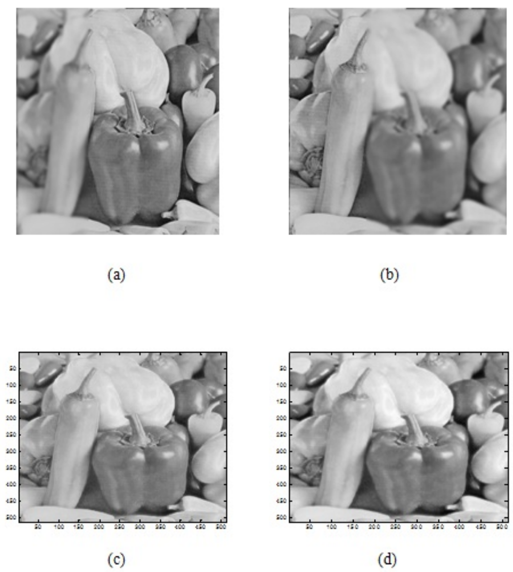

Figure 7: (a)Peppers image with left blur(512X512, PNG format)(b)Peppers image with right blur(512X512, PNG format).(c) gives fused image using energy rule while (d) gives the fused image using gaussian filtering.

5. PERFORMANCE EVALUATION

Quantitative evaluation is conducted using performance strategies Root Mean Square Error(RMSE) and Peak Signal to- Noise Ratio (PSNR)[14]. A graphical comparison can be obtained from Fig. 8.

Table 1: EXPERIMENTAL RESULTS USING ENERGY BASED AND GAUSSIAN FILTERING BASED ALGORITHMS FOR SWT BASED IMAGE FUSION

Source Images	Fusion Rule	RMSE	PSNR in dB
Tower bridge	Energy	9.42	28.65
Tower bridge	Gaussian filtering	7.16	31.03
Cameraman	Energy	8.78	29.25
Cameraman	Gaussian filtering	6.75	31.54
Peppers	Energy	7.82	30.30
Peppers	Gaussian filtering	5.82	32.90
Lenna	Energy	6.18	32.30
Lenna	Gaussian filtering	4.87	34.40
Taj Mahal	Energy	10.81	27.45
Taj Mahal	Gaussian filtering	8.23	29.80

From Fig. 8 and Table 1 it can be seen that Gaussian low-pass filtering helps in structural and salient feature enhancement in images and gives a higher value for Signal-to-Noise Ratio and least RMSE in all test cases. The db2 wavelet in daubechies wavelet family is used for decomposition. A comparison is made with fusion based on retaining the salient features with maximum energy. The Gaussian filter based algorithm gives enhanced structures and clearer boundaries with good subjective as well as objective performance. The better performance in terms of lower MSE and higher PSNR indicates the potential for development of sophisticated algorithms on the principle of mask based fusion detailed in this paper.

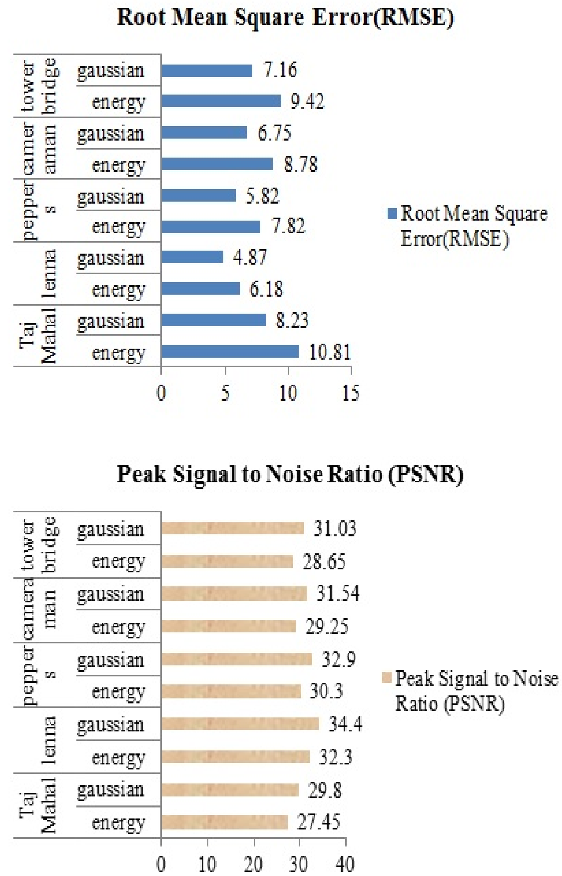

Figure 8: Performance Evaluation of Energy based and Gaussian filter based fusion using objective measures:(a)Fusion rule versus Mean Square Error (b)Fusion rule versus PSNR

6. CONCLUSION

This paper is in sequel to [13] which introduces the concept of filter masking in wavelet based image fusion. Here SWT based algorithm is used for fusion which involves filtering of detail coefficients of decomposition using a randomly generated Gaussian low-pass filter. The results obtained by both subjective and objective evaluations are promising and can be further extended to various medical, remote sensing and multi sensory test images to obtain images with better structure and edge enhancement capabilities.

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