Enhanced Image Fusion Algorithm using Laplacian Pyramid and Spatial Frequency Based Wavelet Algorithm

N. Indhumadhi, G. Padmavathi

Abstract— ***The aim of image fusion is to combine relevant information from two or more source images into one single image such that the single image contains most of the information from all the source images. The successful fusion of images acquired from different modalities or instruments is of great importance in many applications, such as medical imaging, microscopic imaging, remote sensing, computer vision and robotics. The algorithm begins by applying 2D-DWT to decompose the input images. The lower approximations are subjected to pixel-based Laplacian fusion algorithm. The SF algorithm combined with wavelet fusion algorithm is used for higher approximations. The new sets of detailed and approximate coefficients from each image are then added to get the new fused coefficients. The final step then performs inverse DWT with the new coefficients to construct the fused image. Experimental results demonstrate the proposed fusion algorithm can obtain the quality output image, both in visual effect and objective evaluation criteria. Four performance metrics, namely, Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and speed of fusing images, were used during experimentation. All the experiments showed that the proposed hybrid model is an improved version to fuse images when compared with pixel-based and wavelet-based algorithms.***

Index Terms—***2D-DWT, pixel-based Laplacian fusion algorithm, SF, CWD.***

I. INTRODUCTION

With the recent rapid developments in the field of sensing technologies, single-sensor and multi-sensor systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and military applications. The result of the use of these techniques is a great increase in the amount of data, both images and videos, available. As the volume of data grows, the need to combine data gathered from different sources to extract the most useful information also increases. The technique which performs this is generally referred to as data fusion. Image fusion, an interdisciplinary of data fusion, where the data type to combine, is restricted to image format. Image fusion is a process of combining the relevant information from a set of images, into a single image, wherein the resultant fused image will be more informative and complete than any of the input images.

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It is a mechanism that uses image processing algorithms to improve the quality of information from a set of images.

In recent years, image fusion has been attracting a large amount of attention in a wide variety of applications such as Concealed Weapon Detection (CWD) [9], remote sensing [7], medical diagnosis [2], defect inspection [5] and military surveillance [1]. An image fusion algorithm considers a set of low resolution or corrupted captured images captured using imaging devices like digital camcorder. In general image fusion algorithms are desired to achieve benefits like high accuracy and reliability (by evaluation of redundant information), feature vector with higher dimensionality (by evaluation of complementary information), faster acquisition of information (simultaneous data acquisition using multiple sensors) and cost effective acquisition of information (substitution of expensive special sensors with several low-cost sensors).

Several techniques are being used for this purpose, among which Laplacian pyramid algorithms and wavelets have gained more popularity. The Laplacian image fusion algorithm integrates multisource information at the basic level and can provide more abundant, accurate and reliable detail information. Laplacian pyramid does not take into account important details like edges, boundaries and salient features larger than a single pixel. This information is normally included only in high pass subbands. Thus, applying Laplacian Pyramid algorithm to LL subband and SF-based Wavelet algorithm to higher subbands will produce quality images. Moreover, as a general tendency, most of the wavelet-based image fusion algorithms use only the high-level subbands and ignores LL subband, based on the assumption that all the values in LL subbands are approximate values and the weighted average result will be sufficient for image fusion [8]. But, ignoring LL subband loses contrast information of the original images and hence the final quality still needs to be improved. This problem can be solved by combining spatial frequency (SF) with wavelets. Thus, a combination of Laplacian pyramid algorithm and wavelets based on SF can produce high quality fusion and is proposed in this paper. The main objective of the hybrid model proposed is to develop a reliable method that represents visual information, obtained from a number of disparate images, into a single fused image without the introduction of distortion or loss of information.

The rest of the paper is organized as follows. Section 2 provides some of the previous works related to the topic. The methodology of the proposed fusion technique is presented in Section 3. Section 4 presents the results obtained during performance evaluation, while Section 5 concludes the work with future research directions.

II. REVIEW OF LITERATURE

The concept of data fusion goes back to the 1950's and 1960's, with the search for practical methods of merging images from various sensors to provide a composite image which could be used to better identify natural and manmade objects. terms such as merging, combination, synergy, integration, and several others that express more or less the same concept have since appeared in the literature. The idea of combining multiple image modalities to provide a single, enhanced picture offering added value to the observer or processor is well established, but the technology to realize it is somewhat less mature.

In the past few years computing power has advanced sufficiently to finally enable affordable, real-time image fusion systems to become a reality and the field has started to move out of the research laboratories and into real products. Although algorithmic techniques for fusing images are now well known and understood, challenges remain with regard to exploiting different sensor modalities, robustness to environmental and operational conditions and proving performance benefit, to name but a few. This chapter provides a broad review of the field of image fusion, from initial research published to the latest technology being developed and systems being deployed.

III. PROPOSED METHOD

The literature study emphasize the fact that even though several algorithms have been proposed for combining various features of images, the image fusion field, still has not reached its maturity. In particular, the current market demand needs to investigate the design of a general framework for combination of different fusion approaches and develop new approaches that combine aspects of pixel/feature/decision level image fusion. This work focuses on both these requirements and proposes a method that integrates the Laplacian pyramid algorithm, wavelets and spatial frequency. Although the fusion can be performed with more than two input images, this study considers only two input images. The algorithm is shown in Figure 1.

The algorithm decomposes the input image using 2D-DWT. The lower approximations are subjected to Laplacian pyramid algorithm. The SF algorithm combined with wavelet fusion algorithm is used for higher approximations. The new sets of detailed and approximate coefficients from each image are then added to get the new fused coefficients. The final step performs Inverse DWT with the new coefficients to construct the fused image. The two main components of the proposed algorithm are the Laplacian Pyramid algorithm and the wavelet algorithm and are explained in the following sub-sections.

i. Laplacian Pyramid

The Laplacian Pyramid [6] implements a "pattern selective" approach to image fusion, so that the composite image is constructed not a pixel at a time, but a feature at a time. The basic idea is to perform a pyramid decomposition on each source image, then integrate all these decompositions to form a composite representation, and finally reconstruct the fused image by performing an inverse pyramid transform. The general algorithm is shown in Figure 2. The first step is to construct a pyramid for each source image. The fusion is then implemented for each level of the pyramid using a feature selection decision mechanism. The feature selection method selects the most salient pattern from the source and copies it to the composite pyramid, while discarding the least significant salient pattern. In this way, all the locations where the source images are distinctly are selected. The salient component is selected using Equation (1).

$$F_i(x,y) = \begin{cases} A_i(x,y) & \text{if } |A_i(x,y)| > |B_i(x,y)| \\ B_i(x,y) & \text{Otherwise} \end{cases} \quad (1)$$

where A and B are the input images and F is the fused image and $0 \le i \le N-1$.

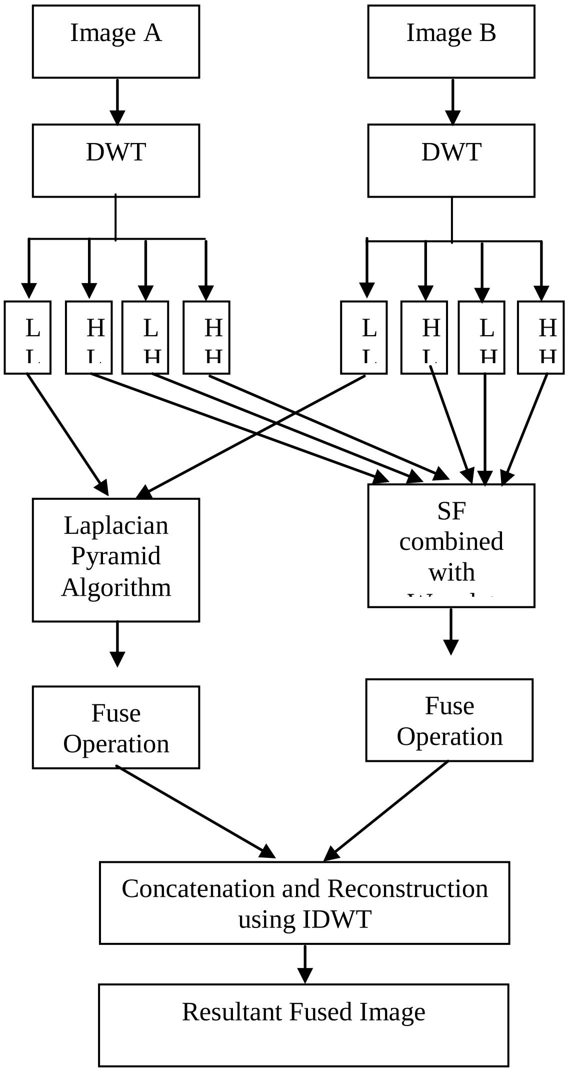

Figure 1: Proposed Hybrid Model

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In order to eliminate isolated points after fusion, a consistency filter is applied (Equation 2).

$$F_N(x,y) = \frac{A_N(x,y) + B_N(x,y)}{2} \quad (2)$$

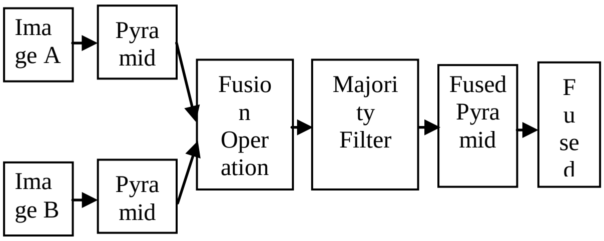


Figure 2: Laplacian Pyramid Fusion Algorithm

ii. SF-based Wavelet Algorithm

An alternative to fusion using pyramid based multiresolution representations is fusion in the wavelet transform domain. The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale. The LL band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines. Li *et al*. [3] proposed a selection based rule to perform image fusion in the wavelet transform domain. Since larger absolute transform coefficients correspond to sharper brightness changes, a good integration rule is to select, at every point in the transform domain, the coefficients whose absolute values are higher.

The algorithm uses wavelet transform to decompose images into a multiresolution scheme and then uses decision rules or weighting, to combine the input images into a single fused one. A pixel level image fusion algorithm based on the spatial frequency ([3], [4]) is presented in this section. This method has the advantage of being computationally simple and can be used in real-time applications. Spatial frequency measures the overall activity level in an image. For an M x N image F, with the gray value at pixel position (m, n) denoted by F(m,n), its spatial frequency is defined using Equation (3).

$$SF = \sqrt{RF^2 + CF^2} \quad (3)$$

where RF and CF are the row frequency and column frequency (Equations 4 and 5) respectively.

$$RF = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}(F(m,n) - F(m,n-1))^2} \quad (4)$$

$$CF = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}(F(m,n) - F(m-1,n))^2} \quad (5)$$

The SF can be used to reflect the clarity of an image. Without regard to noise, the large value of SF demonstrates that the image is sharp. The main steps of the Fusion Algorithm based on SF and Wavelet is given below and is schematically shown in Figure 3. The algorithm initially decomposes the input images into a series of subbands using DWT.

1) To image A, calculate SF value for three high pass subbands and sum them up for every corresponding points, and the same to B.
2) In order to diminish disturbance of noise, the standard Gauss function is used.
3) Compare the SF value correspondingly and construct resultant image.

$$F(x,y) = \begin{cases} I_A(x,y) & SF_A(x,y) > SF_B(x,y) \\ I_B(x,y) & SF_A(x,y) < SF_B(x,y) \\ (I_A + I_B)/2 & \text{Otherwise} \end{cases} \quad (6)$$

4) Verify and correct the fusion result in step 3 with saliency checking as in previous methods. In this case the aim of this process is to avoid isolated blocks instead of isolated points.

IV. EXPERIMENTAL RESULTS

Techniques for performing image fusion vary widely depending on the specific application, imaging modality, and other factors. Each imaging modality has its own idiosyncrasies with which to contend. There is currently no single fusion method that yields acceptable results for all types of applications. The present research work proposes an algorithm that is more general and can be applied to a variety of image data. The performance of the proposed research work was analyzed using various experiments and the results obtained were compared with its existing base counterparts, Laplacian Pyramid and SF combined with Wavelet based fusion algorithms. This section presents the experimental results obtained during performance analysis.

A. Test Dataset

The proposed algorithm was tested with seven pairs of images (Figure 3). Each image is used as a representation of different applications. The first and second set of images, Figure 4a and 4b, called Clock and Pepsi represent the situation where, due to the limited depth-of-focus of optical lenses in cameras, it is not possible to get an image which is in focus everywhere. The third set of images, Figure 4c, corresponds to concealed weapon detection example. In this case, a millimeter wave sensor is used in combination with a visual image. An example of fusion applied to medicine is represented in the forth set of images, Figure 4d. Image 1 of this example was captured using a nuclear magnetic resonance (MR) and Image 2 was captured using a computed tomography (CT). Remote sensing is another typical application for image fusion. Image 4e illustrates the captures of two bands of a multispectral scanner. And finally, Figure 4f and 4g, are composed by a visible camera image and an infrared camera image, taken for navigation and surveillance applications respectively.

Four performance metrics were used during experimentation to evaluate the efficiency of the proposed algorithm. They are Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR)
and Speed of Fusion.

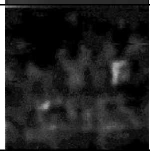
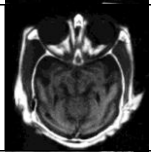
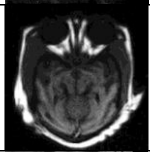
	Name	Image A	Image B
(a)	Clock		
(b)	Pepsi		
(c)	Weapon		
(d)	Medical		
(e)	Satellite		
(f)	Navigation		
(g)	Surveillance		

Figure 3: Test Images

B. RMSE

Table I shows the results obtained while testing the algorithms with respect to Root Mean Square Error (RMSE).

From the results projected, it is clear that the proposed method shows significant improvement in terms of Root Mean Square Error (RMSE) when compared with its traditional Laplacian pyramid and SF combined with wavelet models. It could further noticed, that the algorithm produce best result for satellite image, indicating that the algorithm is best suited for remote sensor image fusion applications. Following this, the clock and pepsi images showed better RMSE values, showing that it is well-suited for depth-focus camera images also. The performance of the algorithm slightly degrades for weapon detection application. While considering RMSE, the proposed algorithm showed 36.01% and 24.08% efficiency gain over Laplacian pyramid and SF+wavelet fusion algorithm.

Table I: RMSE

Image	Laplacian Pyramid	SF + Wavelet	Proposed
Clock	7.774	6.303	**4.920**
Pepsi	7.178	6.032	**4.768**
Weapon	7.975	6.887	**5.017**
Medical	7.792	6.642	**5.008**
Satellite	7.124	6.028	**4.581**
Navigation	7.779	6.520	**4.978**
Surveillance	7.911	6.710	**4.983**

C. Peak Signal to Noise Ratio (PSNR)

PSNR is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction images. The PSNR value obtained for the selected seven test images for the three algorithms is shown in Table II.

Table II: PSNR

Image	Laplacian Pyramid	SF + Wavelet	Proposed
Clock	37.08	38.87	**41.25**
Pepsi	37.91	39.12	**41.89**
Weapon	34.97	36.97	**39.13**
Medical	36.14	37.94	**40.56**
Satellite	38.36	39.52	**42.24**
Navigation	36.55	38.24	**40.80**
Surveillance	35.59	37.43	**40.26**

From the table, it is clear that again the proposed algorithm produce quality fusion image than the existing algorithms. This is evident from the high PSNR values obtained. While analyzing the PSNR values to ascertain the application for the algorithms, the same trend as with RMSE is reproduced. According to the results, the proposed algorithm is best suited for satellite images, followed by camera images, navigation, medical, surveillance and lastly the weapon detection algorithm. Even though weapon detection appears last; it still produces a high PSNR of 39.13dB which indicates that the proposed method can be used for concealed object detection also. The proposed algorithm showed an average PSNR efficiency gain of 10.32% when compared with Laplacian pyramid algorithm and 6.31% when compared with SF + Wavelet based fusion algorithm. This indicates that the proposed algorithm is best suited for all types of image fusion applications.

D. Fusion Speed

Table III shows the time taken by the algorithm to perform the fusion operation when presented with two input images of the same size. The algorithm was tested on a Pentium IV machine with 4GB RAM and the application was developed in MATLAB 2009a. From the obtained values, it could be seen that the application has very little impact on the fusion speed. The speed difference is less 0.03 seconds for Laplacian pyramid and SF-wavelet based algorithms, while it is even lesser with proposed hybrid algorithm (0.02 seconds).

Table III: Fusion Speed (Seconds)

Image	Laplacian pyramid	SF + Wavelet	Proposed
Clock	3.21	2.97	**2.46**
Pepsi	3.20	2.99	**2.45**
Weapon	3.20	2.97	**2.45**
Medical	3.22	2.98	**2.44**
Satellite	3.22	2.96	**2.44**
Navigation	3.19	2.98	**2.44**
Surveillance	3.19	2.97	**2.44**

The results that consider time for speed performance estimation, shows that the proposed hybrid model that combines Laplacian pyramid and SF+Wavelet algorithms is the fastest among all the three. The proposed model showed an average speed gain of 23.67% and 17.71% when compared with Laplacian pyramid and SF + Wavelet based fusion algorithms.

E. .Visual Result

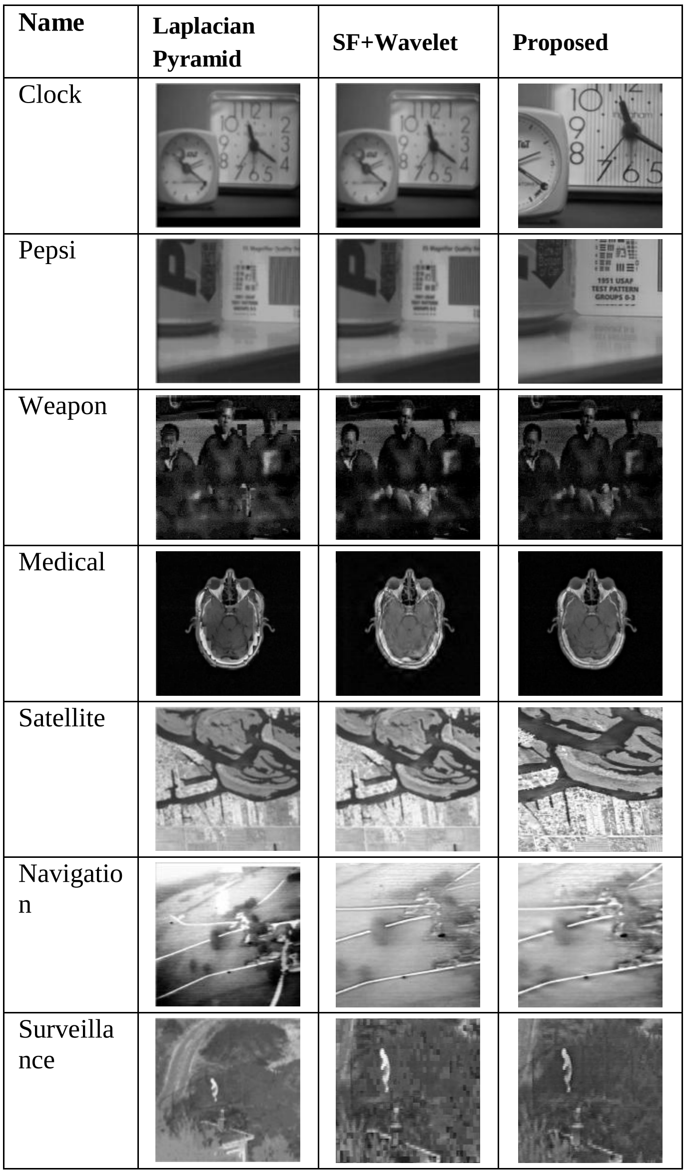


Figure 4: Fusion Results

The fusion results of the three algorithms are shown in Figure 4. Comparing the visual results, it is evident that the proposed hybrid model that combines Laplacian pyramid fusion algorithm with Spatial Frequency based Wavelets produce quality images with good visual clarity.

V. CONCLUSION

The present work considers the amalgamation of two frequently used techniques, namely, Laplacian Pyramid fusion algorithm and wavelet-based fusion algorithm combined with spatial frequency for combining two images. The main aim is to perform image fusion to enhance the resultant image. The results from the various experiments show that the proposed hybrid model is an improved version and is on par with the performance of the existing algorithms for image fusion. In future, the work is planned to be extended to use classifiers for more accurate results..

VI. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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