Applying Image Fusion Techniques for Detection of Hepatic Lesions

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Abstract: -Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. It aims at the integration of complementary data to enhance the information apparent in the images as well as to increase the reliability of the interpretation. 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. In the present work, four different image fusion techniques were implemented and applied to Computed Tomography (CT) and Magnetic Resonance imaging (MRI). These are the Laplacian Pyramid, the Wavelet Transform, the Computationally Efficient Pixel-level Image Fusion (CEMIF) method, and the Multi-focus Technique based on Spatial Frequency. Fusion results were evaluated according to three measures of performance; the entropy, the cross entropy and the spatial frequency. Image fusion techniques were applied to facilitate detection of hepatic lesions by fusing MRI and CT images at the same level. The fused images had led to higher detection accuracy than using either CT or MR images.

Key-Words: - Image fusion, Laplacian pyramid, CEMIF, spatial frequency, CT, MRI, hepatic lesions.

1 Introduction

Computed Tomography (CT) is a specialized X-ray imaging technique. It may be performed "plain" or after the injection of a "Contrast Agent". CT creates the image by using an array of individual small X-Ray sensors and a computer. By spinning the X-Ray source and the sensor/detectors around the patient, data is collected from multiple angles. A computer then processes this information to create an image on the video screen. These images are called "sections" or "cuts" because they appear to resemble cross-sections of the body. This technique eliminates the problem of conventional X-rays, where all the shadows overlap [1].

Magnetic Resonance Imaging (MRI), is a diagnostic technique that uses nuclear magnetic resonance to produce cross-sectional images of organs and other internal body structures. The patient lies inside a large, hollow cylinder containing a strong electromagnet, which causes the nuclei of certain atoms in the body (especially those of hydrogen) to align magnetically. The patient is then subjected to radio waves, which cause the aligned nuclei to flip. When the radio waves are withdrawn, the nuclei return to their original positions, emitting radio waves that are then detected by a receiver and translated into a two-dimensional picture by computer [2].

CT image is obtained without X rays. It offers high resolution in the visualization of bone structures, but its soft tissue contrast is poor. Conversely, MR imaging offers high contrast for the visualization of the soft tissue morphology, but it produces weak signal intensity in bone. Due to their complementary information, it is desired that both X-ray computed tomography (CT) and magnetic resonance imaging (MRI) are integrated [3]. To spatially relate the two datasets, image fusion techniques are employed. Fused images are valuable in clinical diagnosis, in planning surgery, and in image guided surgical interventions.

The present work aims at selecting the optimal method for fusion of MRI and CT images. This includes maximizing the entropy and the spatial frequency for the fused image.

In section 2, a brief background about four image fusion techniques will be introduced. Section 3 presents the results of applying these techniques to MRI and CT images. The conclusion is presented in section 4.

2 Image Fusion Techniques

In the present work, four different fusion approaches have been used. These are the Laplacian Pyramid, the Wavelet Transform, the Computationally Efficient Pixel-level Image Fusion (CEMIF) method and the Multi-focus Technique based on Spatial Frequency. The first two methods, were selected for being the most representative approaches. The last ones were selected to show comparisons with alternative approaches found in the literature.

2.1 Laplacian Pyramid

The Laplacian Pyramid representation was introduced by Burt and Adelson [4]. It is simple to implement and computationally efficient. The Laplacian Pyramid transform is specifically designed for capturing image details over multiple scales. Each band-pass level is sampled at precisely its Nyquist frequency making it less sensitive to noise. All these properties make the Laplacian pyramid transform a well-suited representation for the fusion task. Laplacian Pyramid 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. Given the image sequence $\{I_1, I_2, ..., I_n\}$, the entire fusion algorithm is outlined by the following steps:

1. Generate a Laplacian pyramid L_i for each of the images I_i.
2. Merge the pyramids L_i by taking the maximum at each pixel of the pyramid, obtaining the Laplacian pyramid representation L of the fusion result.
3. Reconstruct the fusion result I from its Laplacian pyramid representation.
4. Normalize the dynamic range of the result so that it resides within the range of [0,1].

2.2 Wavelet Transform

An alternative to fusion using pyramid based multi-resolution representations is fusion in the wavelet transform domain. The multiresolution wavelet representation is argued to be superior in several respects to that obtained with pyramidal methods [5]:

1. Spatial orientation is introduced in the wavelet decomposition process, unlike pyramidal representations which do not include directional information.
2. The wavelet transform can be tailored to extract highly salient textures/edges while suppressing noise through the choice of the mother wavelet and high- and low-pass filters.
3. The different scales in the wavelet decomposition have a higher degree of independence than those in the pyramidal representations, which are correlated with each other.

The wavelet transform decomposes the image into low-high, high-low, and high-high spatial frequency bands at different scales and the low-low band at the coarsest scale. The L-L 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. 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 [6], [7]. In the present work, the 'biorthogonal' wavelet was selected as a basis function.

2.3 CEMIF

This fusion system is based on an adaptive, multi-resolution approach with a reduced number of levels. The goal of this technique is to reduce the computational complexity of multi-resolution systems, such as the Laplacian pyramid and Wavelet transform, while preserving the robustness and high image quality of multi-resolution fusion. The spectral decomposition employed in this system represents a simplified version of the conventional Gaussian-Laplacian pyramid approach [8].

Multi-scale structure is simplified into two levels of scale only, the background and the foreground levels. The former contains the DC component and the surrounding base-band and represents large scale features. The latter contains the high frequency information, which means small scale features. Signal fusion is performed at both levels independently. Background signals, obtained as the direct product of the average filtering, are combined using an arithmetic fusion approach. Foreground signals produced as the difference between the original and background signals are fused using a simple pixel-level feature selection technique. Finally, the resulting, fused, foreground and background signals are summed to produce the fused image.

2.4 Spatial Frequency

It is simply a pixel level image fusion algorithm based on the spatial frequency. Spatial frequency measures the overall activity level in an image. It was demonstrated that it could be used to reflect the clarity of an image [9]. To calculate spatial frequency, consider an image of size $M \times N$, where M equals to the number of rows and N the number of columns. The row and column frequencies of the image are given respectively by:

$$RF = \sqrt{\frac{1}{MN} \sum_{m=0,n=1}^{M-1,N-1} \left[F(m,n) - F(m,n-1)\right]^2} \tag{1}$$

and

$$CF = \sqrt{\frac{1}{MN} \sum_{n=0,m=1}^{N-1,M-1} \left[F(m,n) - F(m-1,n)\right]^2} \tag{2}$$

Where *F(m,n)* represents the intensity of the pixel at row *m* and column *n*. The total spatial frequency of the image blocks is given as:

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

A methodology of five steps whereby multiple small images can be quickly processed to provide a clearer and larger one with more information is described in [10]. These steps include noise removal, histogram equalization, registration of the two images, fusion with spatial frequency, and finally increasing the resolution.

3 Results

The test set of 15 image pairs collected in the period 1999-2002 as a part of the University of Manchester image fusion research program is used in the present work [11]. The four fusion algorithms were then applied to each image pair. Fig.1 shows the results of applying fusion techniques to a pair of images.

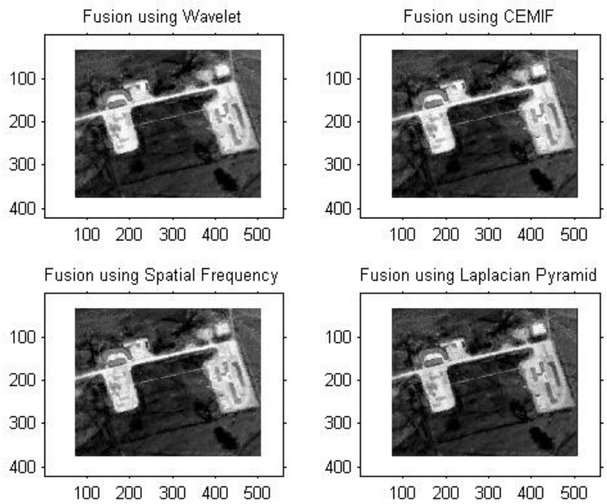

Fig.1 Fusion results

In the literature, almost all image fusion evaluations are done qualitatively because of the user perception factor [12, 13]. However, there are some quantitative criteria that can be used. Some of them need an ideal composite image (RMSE, mutual information, differential entropy), while some others do not (standard deviation, entropy, cross entropy, spatial frequency). In the present work, the second group of measures were applied.

The standard deviation is defined as the square root of the variance. It reflects the spread in the data. Therefore, a high contrast image will have a high variance, and a low contrast image will have a low variance. Due to the dependence of this measure on illumination, it was excluded as a performance criterion for our application.

The entropy measures the information content in an image. The cross-entropy measures the similarity in information content between the source and the fused images. Spatial frequency measures the overall activity level in an image [9]. These three criteria were used to evaluate the four fusion techniques. Table 1 summarizes the image fusion performance assessment for each technique. The average values for input entropy and input spatial frequency were 5.2614 and 23.6 respectively.

It can be shown from the results that all fusion algorithms have led to an improvement in both the entropy and the spatial frequency. Although it seems that the Laplacian pyramid method has the highest performance measures, a statistical test of hypothesis (t-test) at 0.05 level of significance between each pair of fusion methods has shown that there is no significant difference between the four fusion techniques.

Algorithm	**Entropy**	**C.E.**	**S.F.**
Laplacian	5.435	1.044e-4	28.3
Wavelet	5.411	8.98e-4	26.27
CEMIF	5.37	7.14e-5	27.688
S.F.	5.38	7.38e-4	26.19

Table 1 Image fusion performance assessment

C.E.: Cross entropy

S.F. : Spatial Frequency

3.1 Detection of Hepatic Lesions

Patients with known or suspected hepatic lesions who were eligible for surgery underwent dual-phase helical CT and phased array MRI. MRI imaging found additional lesions not detected on CT in some patients while CT detected additional lesions not seen on MRI imaging [14]. Fusing MRI and CT images made complete detection for these lesions. The four fusion techniques were applied to six cases. Results were compared both qualitatively and quantitatively.

Fig.2 shows the input CT and MR images. Fig.3 shows the results of fusing the two images to detect hepatic lesions. Table 2 presents the quantitative measures of performance for each algorithm. The average values for input entropy and input spatial frequency were 5.5026 and 18.7 respectively.

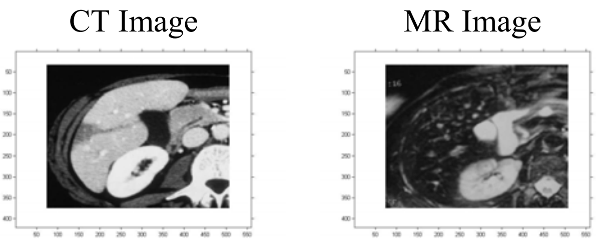

Fig.2 CT and MR input images

For all cases, it is noted that all fusion techniques have led to a fused image that is qualitatively better than the original ones. Using quantitative measures, Wavelet fusion has given the highest entropy while the CEMIF technique has the least value for entropy.

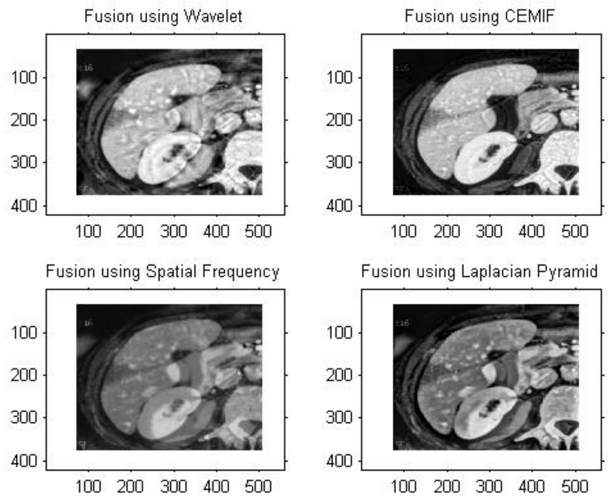

Fig. 3 Fusion Results

Algorithm	**Entropy**	**C.E.**	**S.F.**
Laplacian	5.8544	-8.362e-5	19.80
Wavelet	5.8919	-6.886e-5	18.7603
CEMIF	5.8350	-7.482e-5	20.2404
S.F.	5.6510	1.0108e-5	17.9497

Table 2 Measures of Performance

4 Conclusion

Four image fusion algorithms have been applied to multimodality medical images. They are based on the Laplacian pyramid, the CEMIF, the Wavelet transform, and the Spatial frequency. Three meaningful performance evaluation metric based on entropy, cross entropy, and spatial frequency were used to assess the effectiveness of different image fusion algorithms. Results on a test set of fifteen images have proved that there is no significant difference between the performance of the four fusion algorithms. It is also noted that the best performance criterion should be linked with the specific application. Image fusion techniques were utilized to facilitate detection of hepatic lesions by fusing MRI and CT images at the same level. Results have shown that Wavelet method is more suitable than other techniques for fusing medical images. In addition, the fused CT-MRI image contains more information than the source images. As a conclusion, fusion of CT and MR images leads to higher diagnosis accuracy. Thus, image fusion can be considered as an assistant diagnostic tool especially when CT and MR scans give different results.

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