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Fusion of Medical Images using Mutli-Scale Transform and Sparse Representation

[1]**Ajay Kumar Gurrala,** [2]**D Rajitha**

[1] PG Scholar, Dept. of ECE, Chaitanya Engineering College, Vizag, AP, INDIA

[2]Associate Professor, Dept. of ECE, Chaitanya Engineering College, Vizag, AP, INDIA

Abstract

Image fusion is the technique of combining the complimentary and common elements of a series of photos to create a resulting image with greater information content from both a subjective and objective analytical standpoint. This paper presents a general image fusion framework by combining MST and SR to simultaneously overcome the inherent defects of both the MST- and SR based fusion methods. In our fusion framework, the MST is firstly performed on each of the pre-registered source images to obtain their low-pass and high-pass coefficients. Then, the low-pass bands are merged with a SR-based fusion approach while the high-pass bands are fused using the absolute values of coefficients as activity level measurement. The MST-SR is compared with the Discrete Wavelet Transform (DWT) technique. The low pass patches are Spare represented (SR) to generate the image's fused patch. To produce a single coefficients patch, the Max Absolute rule is used to the high pass patch. To generate a single fused picture, the patches from low pass and high pass fusion are joined using inverse DWT reconstruction. Various parameter settings Time elapsed, Entropy, Standard Deviation, and Mean are all calculated. Entropy is a measure of the amount of information in a system. The greater the entropy number, the more detailed the information in the image. The suggested approach has entropy of 4.22, which is much greater than the state of the art.

Keywords:

Image Fusion, DWT, Multi-Scale Transform, Spare Representation, Medical images

1. Introduction

With the advancements in the domain of information technology, there exists a deep knowledge of ocean in images from which a user intends to retrieve a relevant and specific information. By using certain number of applications, a user can extract multiple types of knowledge from images such as a creation of augmented reality-based three-dimensional simulation of skull to perform an accurate on-line surgical treatment of oral and maxillofacial infections [1]. Similarly, radiologists can use multiple imaging modalities including x-ray, positron emission tomography, computed tomography and magnetic resonance imaging for detection of acute diseases [2].

A user is required to perform a set of operations at the time of knowledge extraction which includes image segmentation and registration etc. The main goal of segmentation is to segment focused and non-focused regions in a particular image for image restoration [3]. For image processing, an input source image should be an all in focused image. Now a day, each user can capture different aspects of human life using imaging devices. The focus range of imaging devices is limited; therefore, these devices focus only on those objects which lie in its range, rest of the objects in an image tends to appear as blurry or non-focused [4]. An image is a kind of an artifact which draws a visual interpretation of a particular object in a form of two-dimensional photograph or a simple picture. Images can exist in multi-dimensions; however, the most common types of multidimensional images are two-dimensional [5] and three-dimensional images [6]. The examples of two-dimensional images are photographs, screen displays etc. Similarly, hologram or a statue is an example of three-dimensional images. The images are usually captured through photo sensing devices such as cameras, microscopes, telescopes, magnetic resonance imaging and photon emission photography etc.

An image in a real world can be defined as a function of two real time variables such as I(x; y) having a manipulation of multiple color pixels in x; y coordinate system. Advancement in the technology, have made it possible to process multidimensional images from simple digital images to advanced digital images such as electromagnetic radiations or waves to convey a particular information. Generally, an image is a combination of multiple sub-images which can be titled as regions of interest, or simply regions. In other words, we can say, an image contains a collection of objects with respect to a particular region. However, modern image processing has made it possible to select any particular region in an image to classify a particular object. The reason for this processing is two-fold; as one wants to remove the motion blur from a particular region of interest, however, other can use this to enhance a particular image in terms of its intensity.

It is a general requirement of image processing, that an image should be available in a finite size array of bits. Therefore, at the time of image processing each image is modeled over x; y coordinate system where each pixel of an image is quantized using a particular bit sequence [7]. The image processing can be further classified into two categories such as computer graphics and computer vision. In computer graphics, a user manually creates a particular image using multiple image objects such as environment, lightings etc. without capturing them from a natural environment. The most common examples of computer graphics are animated movies [8]. On the other hand computer vision is a high-level image processing, where a system intends to retrieve a signature of particular information from sequence of images such as magnetic resonance imaging etc. [9]. Now a day, image processing has become the focus of multiple scientists, because of its exponentially growing scope in scientific visualization. Currently, the scientists are solving multiple problems of science using a powerful tool of image processing.

There are many transform methods, discrete wavelet-transform (DWT) [1], DCHWT [2], Laplacian Transform (LP) [4], Fast discrete curve let transform (FDCT) and Dual tree complex wavelet Transform (DTCWT). In transform method, the rules of fusion are either applied for high pass band or low pass band which will have significant results of the combined image. In transform-based approach, the low and high frequency components are differentiated. The high frequency components contain information about structure of an image. Sparse Representation (SR) method highlights essential features that can hold only less information in the sparse matrix. So, this is used for low frequency components. There are three different steps in transform domain approach. The coefficients of the image are obtained by decomposition of the image. Then, the image is combined by using the rule of image fusion. To obtain the fused image, inverse transformation is applied.

2. Proposed Methodology

In this work, the sparse coding technique is employed for the fusion of MST low-pass bands. One possible way to get the training patches is sampling from the corresponding MST low-pass bands which are obtained from some training images under the same decomposition condition. However, in this case, the dictionary learning process should be repeated once either the selected transform domain or even one specific parameter (such as the decomposition level or selected image filter) is changed. Obviously, this will decrease the flexibility and practicality of the fusion method to a large extent. In this paper, we aim to learn a universal dictionary which can be used in any specific transform domain and parameter settings. As is well known, the MST low-pass band obtained by image filtering can be viewed as a smooth version of the original image. Since the numerous ‘‘flat’’ patches contained in a natural image can be well sparsely represented by a dictionary learned from natural image patches, it is theoretically feasible to use the same dictionary to represent the patches in the low-pass bands so long as the mean value of each sampled patch is subtracted to zero before training. In this situation, the mean value of each atom

in the obtained dictionary is also zero, so the atoms only contain structural information. For an input patch to be represented, its mean value should also be subtracted to zero before sparse coding. Thus, we can directly use natural image patches to learn a universal dictionary. The schematic diagram of the proposed fusion framework is shown in Fig.1.

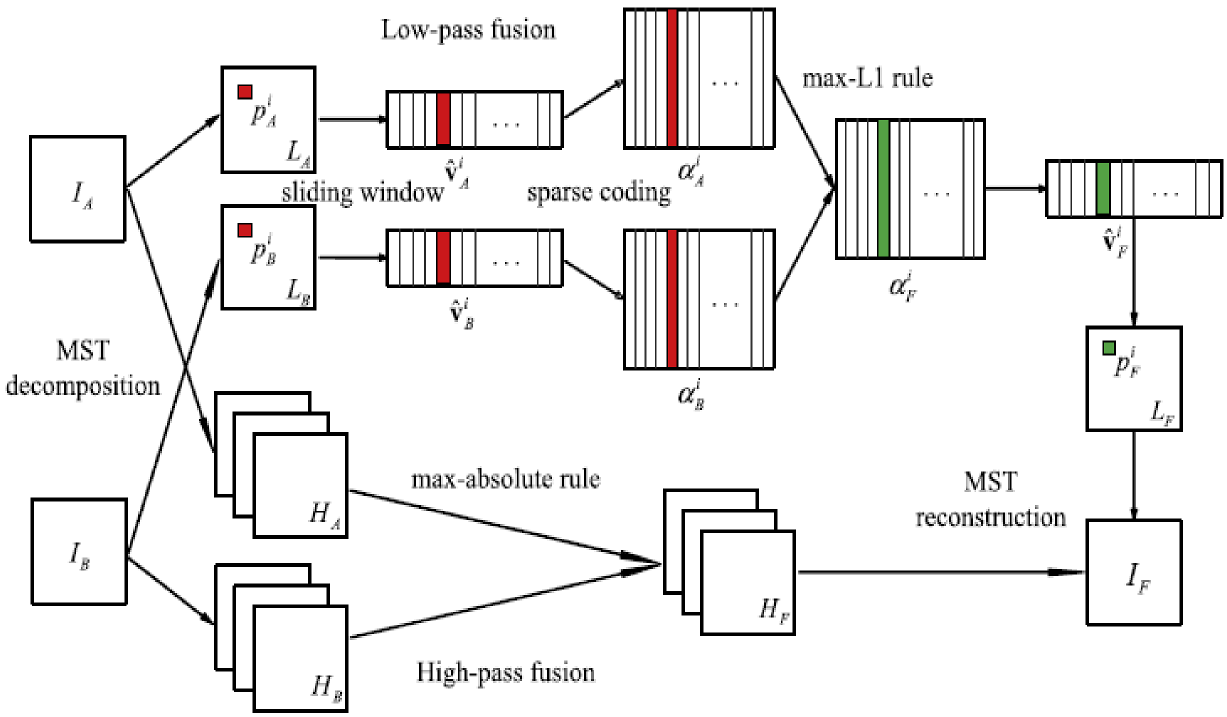


Fig1. The schematic diagram of the proposed fusion framework

For simplicity, only the fusion of two source images is considered while the proposed framework can be straightforwardly extended to fuse more than two images. The notations used in the fig1 are, $I_A, I_B - Source\ Images,\ L_A, L_B - Source\ low\ pass\ bands,$

$H_A, H_B - Source\ high\ pass\ bands,\ I_F - Fused\ Images$

$L_F - Fused\ low\ pass\ band\ ,\ H_F - Fused\ high\ pass\ band$

$p_A^i, p_B^i - sources\ images\ patches,\ \ \alpha_A^i, \alpha_B^i - sources\ images\ patches$

$\hat{V}_A^i, \hat{V}_B^i - Source\ image\ vectors\ ,\ p_F^i - Fused\ image\ patch$

$\hat{V}_F^i - Fused\ image\ vector\ ,\ \alpha_F^i - Fused\ sparse\ vector$

A. Create dataset of the image

To create a file which has different gray scale and other images? These pictures might be from Google or websites or manually taken.

B. Pre-Processing

In this process, the rule of Gamma correction is applied to the input image from the dataset to change the color contrast of the selected image. Further, masking is incorporated to smoothen the noise of the chosen image from the set. An important factor to consider is to select the images such that they are similar in size for fusion.

C. Discrete Wavelet Transform (DWT) and Multi Scale Transform (MST)

DWT

The information in the Image will differ from pixel to pixel on the image. Some part of the image will have more information. Therefore, a good resolution is needed. Whereas in some parts of the images, prickly resolution is sufficient. A multi resolution image will give all the data on the extent of the information that is available in various parts of the image.

MST

Step1. MST decomposition- perform a specific MST on the two source image $\{I_A, I_B\}$ to obtain their low pass bands $\{L_A, L_B\}$ and high pass bands which are uniformly denoted as $\{H_A, H_B\}$.

Step2. Low pass image fusion

i. apply sliding window technique to divide L_A and L_B into image patches of size $\sqrt{n} \times \sqrt{n}$ from upper left to lower right with a step length of s pixels.

ii. For each position i rearrange $\{p_A^i, p_B^i\}$ into two column vectors $\{v_A^i, v_B^i\}$ and then normalize each vectors mean value to zero.

iii. Calculate the sparse coefficient vectors

iv. Merge α_A^i and α_B^i with the ''max-L1'' rule to obtain the fused sparse vector.

v. Iterate the above process for all the source image patches to obtain all the fused vectors.

Step3. Step 3: High-pass fusion.

Merge H_A and H_B to obtain $H_F$with the popular ''max-absolute'' rule using the absolute value of each coefficient as the activity level measurement. Then, apply the consistency verification scheme (see in [5]) to ensure that a fused coefficient does not originate from a different source image from most of its neighbors. This can be implemented via a small majority filter.

Step 4: MST reconstruction.

Perform the corresponding inverse MST over LF and HF to reconstruct the final fused image I_F.

D. Sparse Representation (SR)

The SR based methodology gives the coefficients of sparse matrix with the help of the complete functions that is available in MATLAB. And later these coefficients are merged by using chosen max absolute methodology. In the end, the merged image undergoes reconstruction from the merged coefficients of the SR representation by utilizing the functions

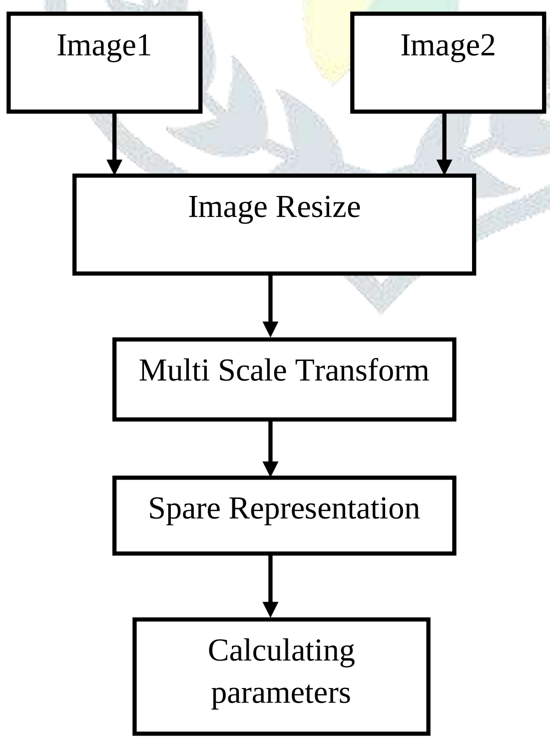


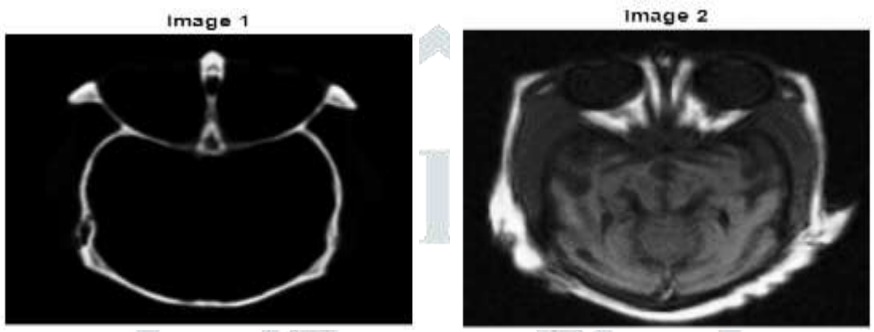
Fig2. Flowchart of proposed method

3. Results and Discussion

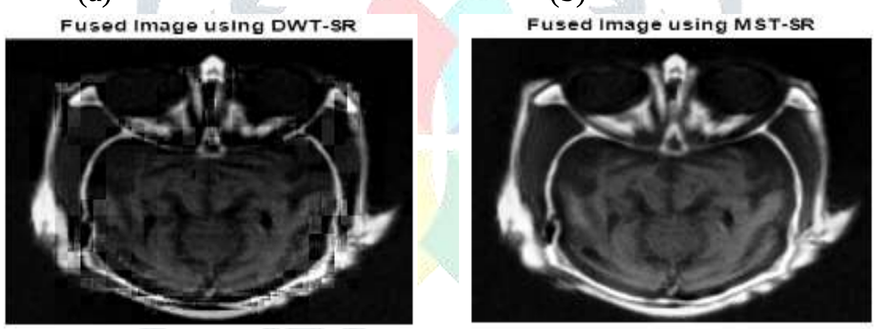
By using MST and Sparse representation different medical images such as MRI, CT and PET are used to evaluate the parameters Elapsed Time, Entropy, Standard Deviation and Mean. Fig3 shows the two source images from the data base and the fused image implemented by proposed approach. It is not an easy task to quantitatively evaluate the quality of a fused image since the reference image (ground truth) does not exist in practice. In recent years, many fusion metrics have been proposed, but none of them is universally believed to be always more reasonable than others for various fusion scenarios. Thus, it is usually necessary to apply several metrics to make a comprehensive evaluation.

Case1.

In this MRI and PET images are considered and fused together. The results obtained using DWT-SR and MST-SR is shown below.



(a) (b)

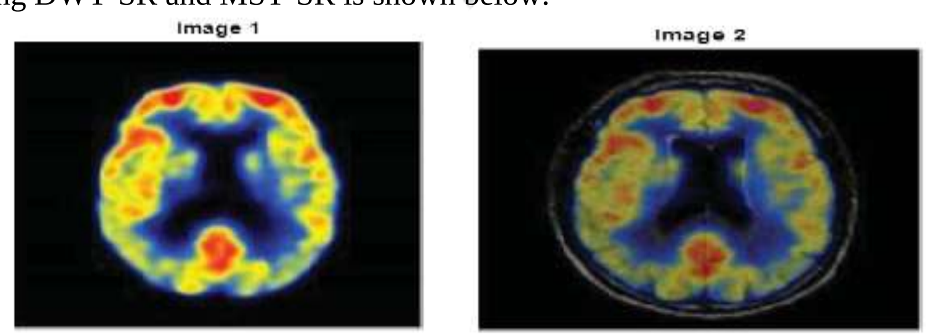


(c) (d)

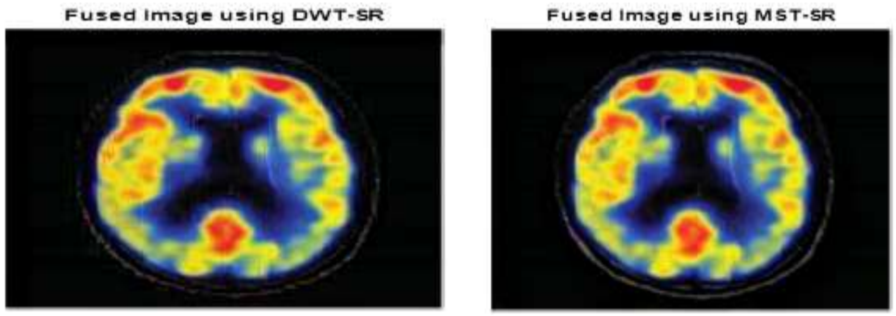
Fig 3. (a) MRI image (b) PET image (c) DWT-SR fused image (d) MST-SR fused image

Case2.

In this CT and PET images are considered and fused together. In this case, colour images are considered. The results obtained using DWT-SR and MST-SR is shown below.



(a) (b)



(c) (d)

Fig 4. (a) CT image (b) PET image (c) DWT-SR fused image (d) MST-SR fused image

Parametric Evaluation

Entropy (E)

It determines the amount of information in a picture. It is the average number of bits required to quantize the image's intensity. Entropy would be high in a picture with a high information content. E is defined as follows:

$$E = -\sum_{g=0}^{L-1} p(g) log_2 p(g)$$

Standard deviation (STD)

It is a contrast measure in the merged pictures. Indeed, a greater SD indicates that more contrast is presented.

$$STD = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-\mu)^2}{MN}}$$

Mean (M)

Mean value is the sum of pixel values divided by the total number of pixel values. ... Means are often used in geometry and analysis; a wide range of means have been developed for these purposes. In contest of image processing filtering using mean is classified as spatial filtering and used for noise reduction.

$$M(\bar{X}) = \frac{\sum X}{n}$$

The parameters evaluated using different techniques are compared and shown in table 1 and table 2 for different cases.

Table1. Comparison of results for case 1

Parameter/ Technique	DWT-SR	**Proposed MST-SR**
Entropy	3.43	**3.90**
STD	61.29	**53.87**
Mean	70.33	**88.54**
Process Time	1.04 sec	**0.14 sec**

Table2. Comparison of results for case 2

Parameter/ Technique	DWT-SR	**Proposed MST-SR**
Entropy	3.89	**4.33**
STD	74.26	**73.71**
Mean	83.13	**84.39**
Process Time	1.87 sec	**0.16 sec**

4. Conclusion

The main disadvantages of implementing the DWT, MST and SR individually are improper decomposition of the multimodal images with Computational complexity and increase in execution time. In this project, we present a general image fusion framework with multi-scale transform (MST) and sparse representation (SR). In the framework, the low-pass MST bands are merged with the SR-based scheme while the high-pass bands are fused using the conventional ‘‘max-absolute’’ rule. The advantages of the proposed fusion framework over conventional MST- and SR-based methods are first analyzed theoretically, and then experimentally verified. An algorithm was implemented for fusing the images by combining MST and sparse representation (SR) for multimodal images of MRI/CT/PET which helps in Diagnosis of ailments and treatment can be done at early stages. Various parameters like Elapsed time, Entropy, Standard Deviation and mean are evaluated for this technique. The entropy shows a better result when compared to previous work. Higher the entropy value provides higher intensity value. This work can be extended to evaluate for various multimodal images and improve the elapsed time and Entropy by implementing using spatial domain techniques. The same way evolutionary algorithms like genetic algorithm, firefly algorithm can be used for fusion of medical images.

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