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Image Fusion Based on Transform Domain Techniques

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Abstract

Nowadays, Images have become the main source of information transfer. Every single image conveys more or less information regarding an object. Images of an object taken in various orientations convey distinct information. Here, we choose image fusion as method for conveying the exact information in a single image rather using multiple images. Image fusion is emerging as a vital technology in many applications. Image fusion is a method to use image as redundant or complementary source to extract information from them with higher accuracy or reliability. Image fusion methods can be broadly classified into two – Spatial domain fusion and Transform domain fusion. The disadvantage of spatial domain approaches is that they produce spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing, such as classification problem. This problem of spectral distortion in image fusion will be well handled by transform domain approach. Fusing the image for extracting the complete information, initially the object is sensed in different orientations and imaged. These images contain redundant or complementary information. In this paper we develop an algorithm which implements image fusion technique that provides information without redundancy. This algorithm is developed using MATLAB. We use image acquisition and image processing toolbox in MATLAB. In order to implement image fusion we make use of Wavelet Transform technique. Some of the applications of image fusion are Aerial and Satellite imaging, Medical imaging, Robot Vision, Concealed Weapon Detection, Multi Focus image fusion, Digital Camera application, Battlefield Monitoring.

Key Words: Image, Fusion, Spatial domain, Transform domain

INTRODUCTION

The full dynamic range of a real world scene is much larger than that of sensing devices that are used to capture them. When a large dynamic range must be processed using a limited-range device, one is forced to split the dynamic range into several smaller "strips", and handle each of them separately. This process produces a sequence of images of the same scene, covering different portions of the dynamic range (HDR) scene, the sequences obtained by varying the exposure settings of the sensor. When reproducing an HDR scene, the sequence is obtained by splitting the full range of the image into several sub-ranges, and displaying each separately. Indeed, in both cases we turn to a solution in the form of a variable-exposure image sequence. The major drawback of variable-exposure image sequences is their usability. This representation of image in sequences is unsuitable for many tasks, such as human interpretation or computerized analysis.

A computer could do better than a human interpretation by implementing specific techniques for handling such representations. However this can be a tedious task, since most visual applications are designed to handle single images containing all the details. It is therefore more imperative to develop techniques for merging(fusing) such image sequence into single, more informative, low dynamic range images, maintaining all the details at the expense of brightness accuracy. Image fusion provides an effective way of reducing this increasing volume of information while at the same time extracting all the useful information from the source images. Multi-sensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. It is rather impossible to obtain a single image of a 3-D scene where all parts of the scene appear well exposed. Details in under-exposed and over-exposed image areas may not be visible. Each local area in the scene may require a different shutter speed to capture the details. Image fusion combines a set of multi-exposure images of a scene obtained by a camera into a single image where all image areas appear well exposed.

Section 2 discusses about image fusion, section 3 talks about different image fusion methods, section 4 discusses about implementation of image fusion methods, section 5 projects the experimental results, and section 6 presents the conclusion.

IMAGE FUSION:

Image fusion is the process of combining information from two or more images of a scene into a single composite image that preserves relevant information and also retains the important features from each of the original images and makes it more suitable for human visual perception or computer processing.

With the recent rapid developments in the field of sensing technologies, multisensory systems have become a reality in a growing number of fields such as remote sensing, medical imaging, machine vision and the military applications for which they were first developed. As a result of these techniques there is also an increase in the amount of data available.

In order to handle these large amounts of data available, Image fusion provides an effective way of reducing this increasing volume of information while at the same time extracting all the useful information from the source images. Generally a multisensory system presents complementary information about the region surveyed. So image fusion also provides an effective method for comparison and analysis of the data. Apart from reducing the volume of information, comparison and analysis of the data, the main aim of image fusion is the creation of new images that are more suitable for human or machine perception and for further image processing tasks such as object detection, target recognition in applications like remote sensing and medical imaging. For example, visible-band and infrared images may be fused to aid pilots landing aircraft in poor visibility.

Over the past decade, research in processing and analysis of medical data has begun to flourish. Sophisticated imaging techniques such as MRI and CT scanning provide abundant information that is useful for diagnosis. These advancements have driven the need for algorithm development which in turn has provided a major impetus for new algorithms in signal and image processing.

There are two types of image fusion systems. They are:

A. Single Sensor Image Fusion System

B. Multi Sensor Image Fusion System

A. Single Sensor Image Fusion System: - In a single senor system, a sequence of images is captured by a single sensor. The sequence is then combined in one single image and is used by a human or a computer to do some task, such as object detection in a security area. This kind of system has some limitations due to the capability of the imaging sensor that is being used. The conditions under which the system can operate, the dynamic range, resolution, etc. are all limited by the capability of the sensor.

It is rather impossible to obtain a single image of a 3-D scene where all parts of the scene appear well exposed. Details in under-exposed and over-exposed image areas may not be visible. Each local area in the scene may require a different shutter speed to capture the details. Image fusion combines a set of multi-exposure images of a scene obtained by a camera into a single image where all image areas appear well exposed.

Sharp images contain more information than blurred images. Often due to great variations in a scene's depth, it is not possible to capture an image of the scene where all scene areas appear sharp. Only scene areas that are at the focus plane appear sharp and areas in front of or behind the focus plane, appear blurred.

B. Multi Sensor Image Fusion System: - In the Multi-sensor image fusion systems, the images from various sensors in the system are considered and are combined to form a composite image. As in this system the images under consideration are not from a single sensor, it overcomes the limitations of a single sensor vision system. Multiple sensors that operate under different operating conditions can be deployed to extend the effective range of operation. For example different sensors can be used for day/night operation. Joint information from sensors that differ in spatial resolution can increase the spatial coverage. The same is true for the temporal dimension. Joint information from multiple sensors can reduce the uncertainty associated with the sensing or decision process. The fusion of multiple measurements can reduce noise and therefore improve the reliability of the measured quantity. Redundancy in multiple measurements can help in systems robustness. In case one or more sensors fail or the performance of a particular sensor deteriorates, the system can depend on the other sensors. Fusion leads to compact representations. For example, in remote sensing, instead of storing imagery from several spectral bands, it is comparatively more efficient to store the fused information. In a single senor system, a sequence of images is captured by a single sensor.

IMAGE FUSION METHODS:

There are two types of image fusion methods. They are:

A. Spatial Domain Fusion

B. Transform Domain Fusion

A. Spatial Domain Fusion: - Spatial image fusion methods work by combining the pixel values of the two or more images to be fused in a linear or non-linear way. The simplest form is a weighted averaging of the registered input to give the fused image. The image fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS based methods fall under spatial domain approaches. Another important spatial domain image fusion method is the high pass filtering based technique. Here the high frequency details are inserted into up sampled version of multi sensor images. The disadvantage of spatial domain approaches is that they give us spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing.

B. Transform Domain Fusion: - The distortions produced by spatial domain fusion methods are very well handled by transform domain fusion methods. In this transform domain fusion, the individual source images are altered in to a new form by the application of a suitable transform prior to the fusion process. The new forms/transformations of source images are then fused to represent a composite image of input images. Multiscale decomposition based Transform Domain fusion methods combine the multiscale decomposition of the source images. The idea is to perform a multiscale transform (MST) on the source images, and construct a composite representation of these transformations using some sort of fusion rule, and then construct the fused image by applying the inverse multiscale transform (IMST). The basic idea of all multi resolution fusion schemes is motivated by the fact that the human visual system is primarily sensitive to local contrast changes, e.g.: edges or corners. Most commonly used multiscale decomposition fusion methods are:

(a) Pyramid Transforms

(b) Wavelet Transforms

A pyramid transform fusion consists of a number of images at different scales which together represent the original image. The different scaled images can be represented in the form of a pyramid.

An image pyramid can be described as collection of low or band pass copies of an original image in which both the band limit and sample density are reduced in regular steps. Typically, in an image pyramid every level is a factor two smaller as its predecessor, and the higher levels will concentrate on the lower spatial frequencies. An image pyramid does contain all the information needed to reconstruct the original image.

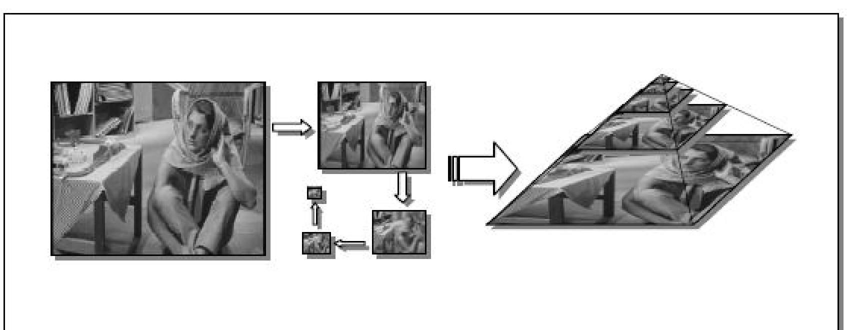


Figure 1: Block diagram of Image Pyramid

Figure 1 shows an example for image pyramid, in which different scaled images are stacked upon one another. The succeeding stacked images (next levels) are the reduced versions of the preceding images (previous levels). A multi resolution pyramid transformation decomposes an image into multiple resolutions at different scales. A pyramid is a sequence of images in which each level is a filtered and sub sampled copy of the predecessor. The lowest level of the pyramid has the same scale as the original image and contains the highest resolution information. Higher levels of the pyramid are reduced resolution and increased scale versions of the original image. Several types of pyramid decomposition or multi-scale transform are used or developed for image fusion, such as, Laplacian Pyramid, Ratio-of-low-pass Pyramid, Morphological Pyramid, and Gradient Pyramid.

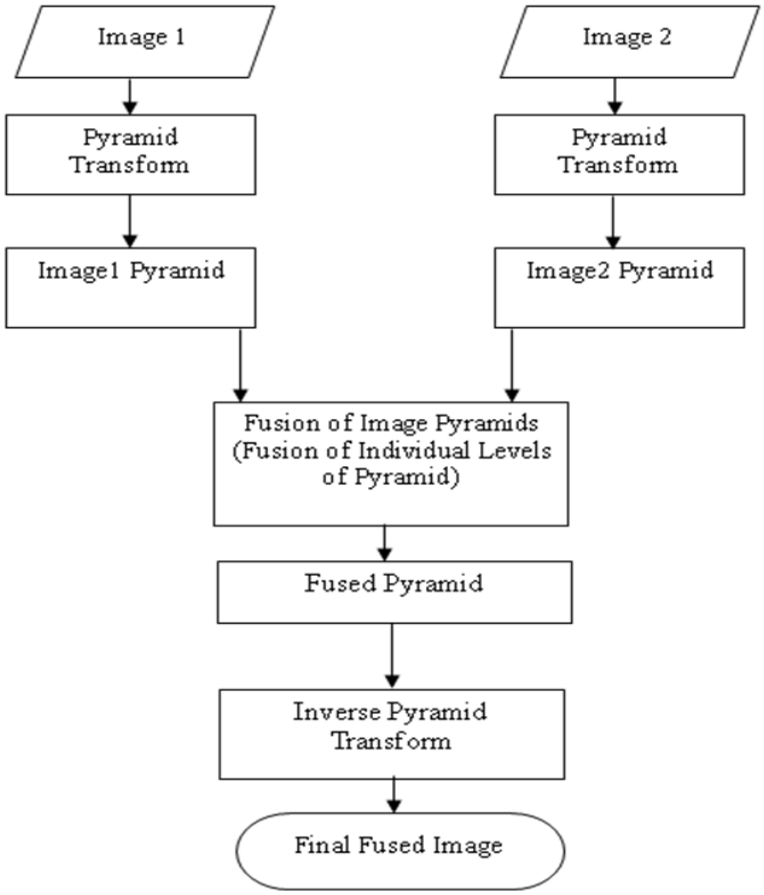


Figure 2: Block diagram of Image Fusion using Pyramid Transform

The steps involved in this method are:

1) Here in the first step we read two input images of same size.

2) Image pyramids are constructed for individual images by applying the pyramid transform to individual input images.

3) Now the two image pyramids are fused together forming a single image pyramid i.e., fused pyramid. This can be done by averaging or by taking the maximum coefficient values of the levels of the pyramid.

4) By fusing pyramids we get fused pyramid. Then with the application of the inverse pyramid transform to this fused pyramid we get the final fused image for the given input images.

Here are some major advantages of pyramid transform, it can provide information on the sharp contrast changes, and human visual system is especially sensitive to these sharp contrast changes. It can provide both spatial and frequency domain localization.

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. Wavelets are a type of multi-resolution function approximation that allow for the hierarchical decomposition of a signal or an image. The Wavelet transform is a useful method to fuse images. Here the source images are first decomposed in to wavelets using wavelet transform. These wavelet decompositions are then fused to form fused wavelets by selecting the appropriate wavelets. The inverse transform is applied to the fused wavelets for getting the fused image. The wavelet transform has several advantages over other pyramid-based transforms: It provides a more compact presentation, separates spatial orientation in different bands, and decorrelates interesting attributes in the original image. Wavelet methods are also a way to decompose image into localized scale specific signals. Wavelet transforms are linear and square integrable transforms whose basis functions are called wavelets. In the traditional wavelet based fusion once the imagery is decomposed via wavelet transform a composite multi-scale representation is built by a selection of the salient wavelet coefficients. The selection can be based on choosing the maximum of the absolute values or an area based maximum energy. The final stage is an inverse discrete wavelet transform on the composite wavelet representation.

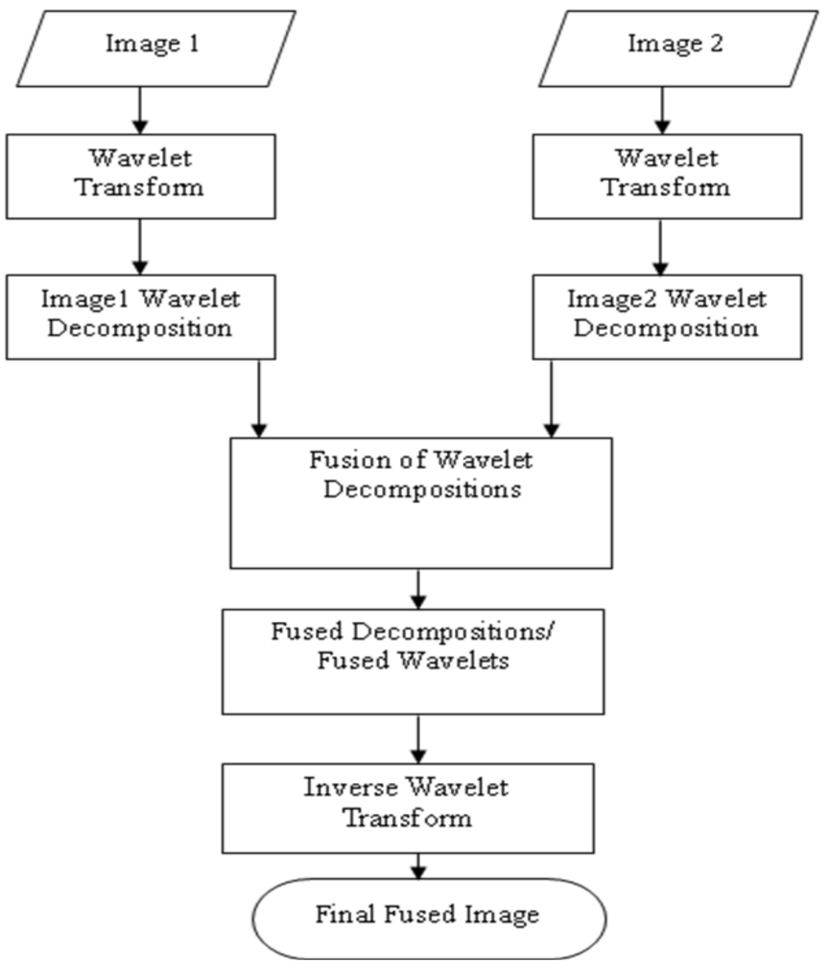


Figure 3: Block diagram of Image Fusion using Wavelet Transform

Figure 2.3 shows the block diagram for image fusion using wavelet transform method.
The steps involved in this method are
1) The first step is same as that of pyramid transform i.e., reading two input images of same size.
2) Second step is the application of wavelet transform to individual input images.
3) As a result of the second step we get the separate wavelet decompositions for input images.
4) These decompositions are now fused together to form fused decompositions/ fused wavelets.
5) Next step is the application of inverse wavelet transform. By applying the inverse wavelet transform we get the final fused image for the given input images.

Wavelet transform fusion schemes offer several advantages over similar pyramid based fusion schemes when it comes to image fusion

(a) The wavelet transform provides directional information while the pyramid representation doesn't introduce any spatial orientation in the decomposition process.

(b) In pyramid based image fusion. The fused images often contain blocking effects in the regions where the input images are significantly different. No such artifacts are observed in similar wavelet based fusion results.

(c) Images generated by wavelet image fusion have better signal-to- noise ratios (PSNR) than images generated by pyramid image fusion when the same fusion rules are used. When subject to human analysis wavelet fusion results are also better perceived.

IMPLEMENTATION OF IMAGE FUSION:

We have implemented the Laplacian method as an example of pyramid transform image fusion. This method also serves as a reference for evaluating the performance of wavelet transform image fusion. The algorithmic explanation and flowchart for the method implemented are as follows.

Algorithm 1:

Step 1: Reading two input images to be fused. The images should be of same size.

Step 2: Construction of Gaussian pyramid for each input image.

Step 3: Construction of Laplacian pyramid for each input from the Gaussian pyramid.

Step 4: Fusion of individual levels of the pyramid. As a result of this we get a fused pyramid.

Step 5: Reconstruction of the fused image from the fused pyramid.

These are the algorithmic steps for Laplacian pyramid image fusion.

Flowchart 1:

Figure 4: Flowchart for Laplacian Pyramid Transform Image Fusion

The flowchart for the method of fusion is shown in the figure 4. The flowchart consist of five blocks A, B, C, D, E.

Block A: This block reads two images and compares the size of the images. If size is same for both images, the process flows to block B otherwise an error message is given and terminates the process.

Block B: This block constructs the pyramids. First the Gaussian pyramid is constructed by obtaining each level of the pyramid as a reduced version of the previous level. In the second step of this block, it constructs the Laplacian pyramid by taking the difference between the levels of the Gaussian pyramid. Finally Laplacian pyramid levels for both the images are created in this block. The process proceeds to block C.

Block C: This is the fusion block. It performs the fusion of individual levels of the Laplacian pyramids of both the given images by choosing the maximum coefficients between the corresponding levels of the pyramids and process flows to next block. If it is the last level of pyramid, then average of the coefficients is considered for fusion and the process goes to the block E.

Block D: As this flowchart is recursive with number of levels of the pyramid as a count value. This block decreases the count value in each iteration and checks for the last level of the pyramid. If it encounters the last level, then process flows to block C where averaging of the images is done. Else it flows to block E for further processing.

Block A is the comparison block. Block B is the pyramid block. Block C is the fusion block. Block D is the last level detection block. As a result of these blocks we get the fused pyramid.

Now comes the reconstruction block for reconstruction of the fused image from the fused pyramid i.e., block E.

Block E: This block is a reconstruction block. This performs the reconstruction in the reverse order i.e., from last level to first level. In the last level of the pyramid fusion is done by averaging the reduced images producing fused last level. This fused last level is expanded and added to the previous level image of the Lapalcian pyramid. This process is continued till the first level is reached. Finally as a result of this block we get a fused image for the given input images.

This is another transform domain method for image fusion. We have implemented this method by making use of some built in functions from the matlab and some user defined functions are also created. The algorithm and flowchart are as follows:

Algorithm 2:

Step 1: Reading the two images of same size as input.

Step 2: Wavelet decompositions of the input images by wavelet transformation.

Step 3: Fusion of wavelet decompositions of two images to form a single set of wavelet decompositions.

Step 4: Inverse wavelet transform on the fused decompositions gives the fused image.

These are the algorithmic steps for achieving image fusion using wavelet transforms.

Flowchart 2:

The flowchart for wavelet transform image fusion is given by figure 5. It consist of four blocks namely A, B, C, D.

Block A: This block reads two images and compares the size of the images. If size is same for both images, the process flows to block B otherwise an error message is given and terminates the process.

Block B: This block performs the wavelet transform on the images and generating the wavelet decompositions. This can be considered as forward transform block. Wavelets are formed in this block.

Block C: This block is the fusion block. Fusion is done by choosing the maximum coefficients from the wavelets of the two images. As a result of this block we get fused decompositions.

These blocks generate the decompositions for individual images and create a fused decomposition set.

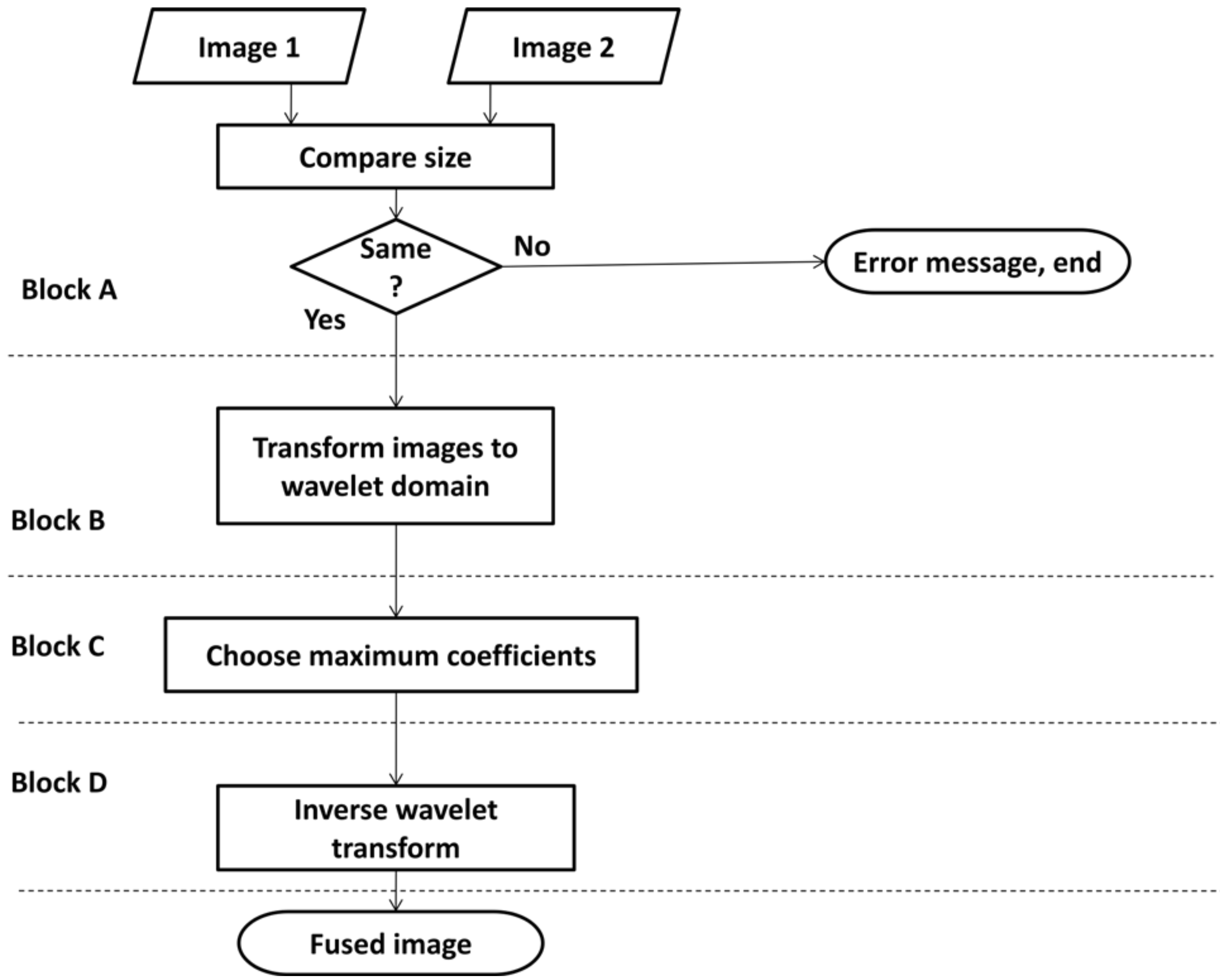


Figure 5: Flowchart for Wavelet Transform Image Fusion

Block D: This block performs inverse operation to that of block B. Inverse wavelet transform is applied to fused set of decompositions producing a final fused image. This can be treated as inverse block.

From the block D we get the output of fusion i.e. fused image.

EXPERIMENTAL RESULTS:

Any image fusion algorithm can be assessed using two categories of performance measurement parameters which are subjective and objective. Subjective indices rely on the ability of people's comprehension and are hard to come into application. While objective indices can overcome the influence of human vision, mentality and knowledge, and make machines automatically select a superior algorithm to accomplish the mission of image fusion. We use the objective indices Mean Square Error and Peak Signal to Noise Ratio for evaluating the performance of image fusion techniques

The MSE compares the two input images and finds the error at each pixel by subtraction and finds the mean square of the resultant error. In this paper we have two given images and one final fused output image, so first we find separate MSEs comparing the fused image with two given images. Hence we get two MSEs, now these are averaged for getting the overall MSE. So the MSE is the error between the output fused image and input images. As a first step in the calculation the difference at each pixel is calculated and the result of this difference is the error between the two images. To better represent the error we square the error and find its mean. This is the resultant MSE. This is given by following equation.

Mean Square Error (MSE) = $(1/m*n)*[\sum_{i=1 \text{ to } m}\sum_{j=1 \text{ to } n} (X_1(i, j)-X_2(i, j))^2]$

Where X_1 and X_2 are two input images.

Peak Signal to Noise Ratio (PSNR) is a better metric for evaluating the performance of image fusion technique since it takes the signal strength into consideration along with the noise.

Peak Signal to Noise Ratio (PSNR) = $10*\log_{10}(MAX^2/MSE)$

Where MAX is the maximum signal power in the fused image and MSE is the overall mean square error.

We have implemented the image fusion techniques of Laplacian pyramid transform method and wavelet transform method. The inputs and outputs for these implementations are the images. This chapter shows the inputs used for our implementation and their corresponding output images by using the methods, Laplacian pyramid transform and wavelet transform. Also the metrics MSE and PSNR are calculated with these inputs and outputs for both methods. This chapter also evaluates the performance of both the methods.

We used two set of images for our paper. The images used as the inputs are shown in the figure 5.1 and figure 5.2. For the purpose of evaluating the methods used for fusion we used the same set of images in figure 5.1and figure 5.2 to both the techniques as inputs.

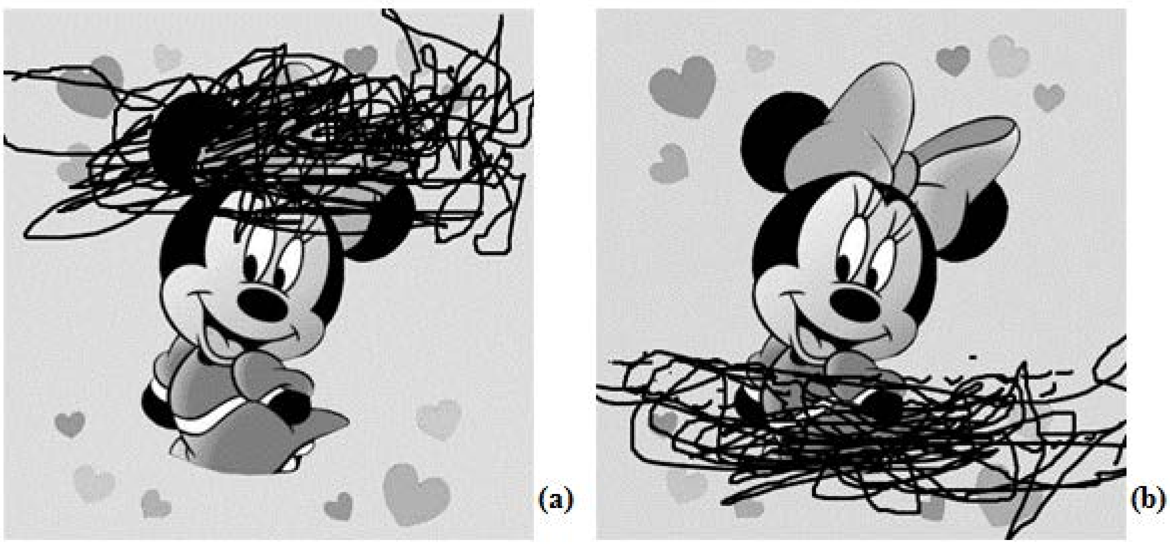


Figure 6: Set I (a) Image 1 (b) Image 2

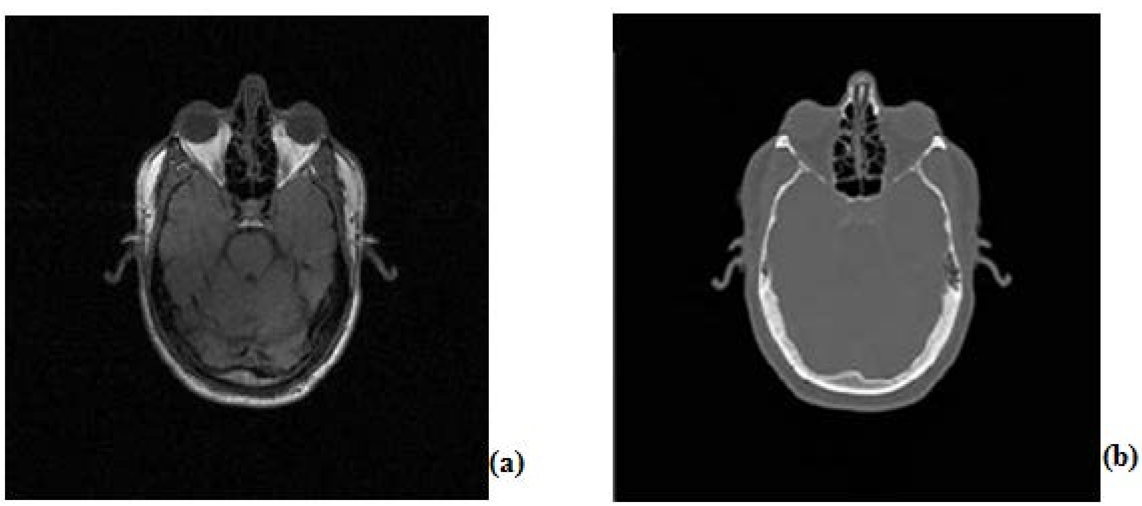


Figure 7: Set II (a) Image 1(MR) (b) Image 2(CT)

These set of images are taken as the bit map image (BMP format). The first set consists of two cartoon pictures and the second set consists of CT image and MR image, these are the medical images. Fusion of these images is called medical image fusion, which is very much useful for medical analysis.

The two sets of images shown in the figures 6 and 7 are used as input to the function implementing Laplacian method. The code is implemented repeatedly for different number of levels i.e., considering various pyramid levels.

First consider the set I images and next set II images as inputs. The outputs generated by this fusion method using set I as input for different number of pyramid layers are shown in the figure 8.

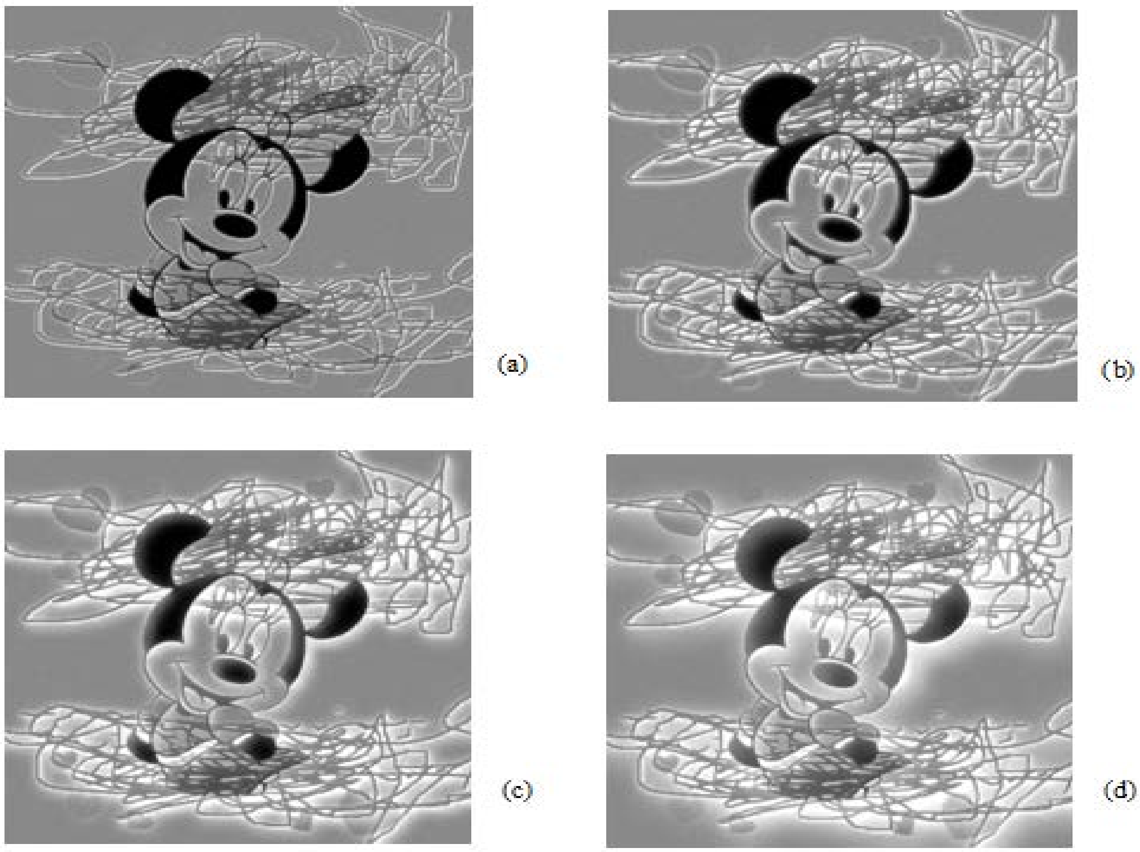


Figure 8: Laplacian Transform Fusion technique outputs with set I inputs for n number of pyramid levels (a) n = 1, (b) n = 2, (c) n = 3, (d) n = 4

The performance of Laplacian Fusion technique is found by calculating mean square values and peak signal to noise ratio as shown in the table 1

.

Table 1: MSE and PSNR values calculated for set I inputs using Laplacian technique

Number of pyramid levels (n)	Overall Mean square error (MSE)	Peak signal to noise ratio (PSNR)
n= 1	181.0515	58.8375
n = 2	163.3877	59.8640
n =3	147.2855	60.9015
n =4	132.9890	61.9226

From the table 1 it can be seen that, as the number of levels of the pyramid increases, the mean square error goes on decreasing and the peak signal to noise ratio is increasing. Hence the error is reduced and signal to ratio

is increased, which means the performance is better for n=2 than for n=1; for n=3 than for n=2; for n=4 than for n=3. Still higher value for n is not possible for this set of images.
Now considering the set II inputs, the corresponding outputs are

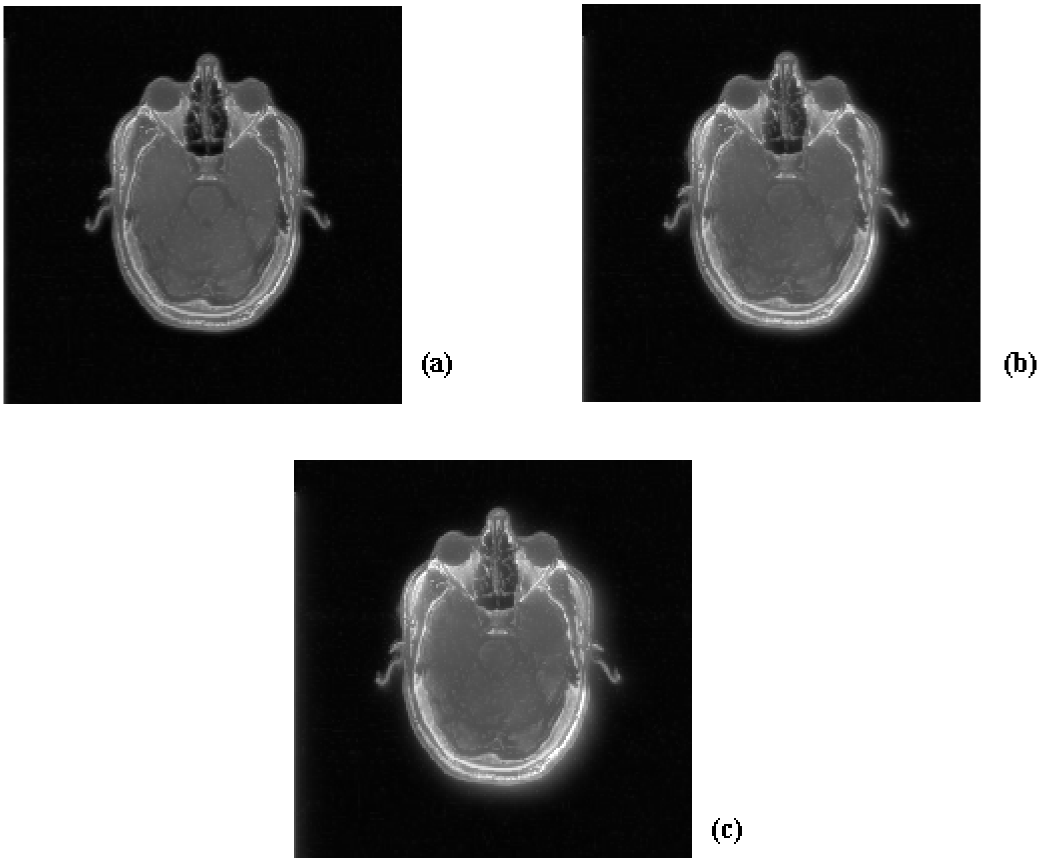


Figure 9: Laplacian Transform Fusion technique outputs with set II inputs for n number of pyramid levels

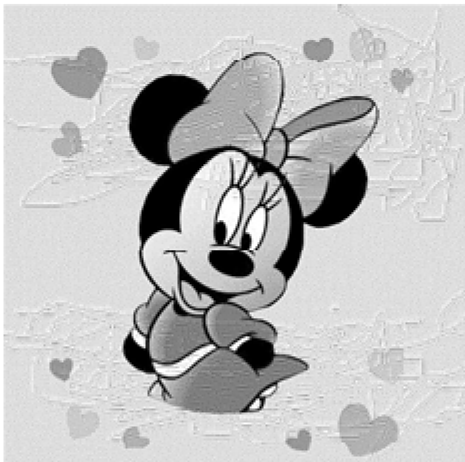
(a) n = 1, (b) n = 2, (c) n = 3

The MSE and PSNR values are calculated and tabulated in the table 2. As the number of pyramid levels increases the PSNR value also increases and average of PSNR value is approximately 84. This produces the output fused image which is suitable for medical analysis of the images.

Table 2: MSE and PSNR values calculated for set II inputs using Laplacian technique.

Number of pyramid levels (n)	Overall Mean square error (MSE)	Peak signal to noise ratio (PSNR)
n= 1	21.1026	78.9515
n = 2	14.4655	84.1076
n =3	8.6828	89.2118

We have implemented wavelet fusion using fusmx function which selects the maximum values of the wavelets for fusion of images. Here the outputs are obtained for n=1 and n=2.


(a)

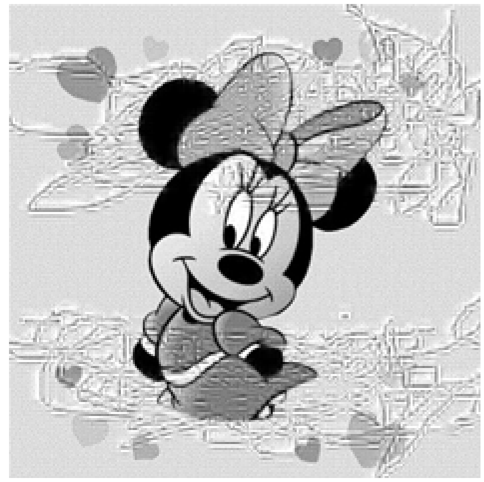

(b)

Figure 10: wavelet transform fusion technique outputs with set I inputs for n number of decomposition levels

(a) n = 1, (b) n = 2

The table 3 gives the values of MSE and PSNR obtained for the images shown in figure 10. From the table we can infer that this method produces better results for fusion of images compared to Laplacian method of fusion.

Table 3: MSE and PSNR values calculated for set I inputs using Wavelet Transform Fusion technique

Number of Decomposition levels (n)	Overall Mean square error (MSE)	Peak signal to noise ratio (PSNR)
n= 1	39.1383	82.3457
n = 2	49.6746	83.3528

By considering the second set of images the output is given in figure 11 and its performance values are shown in the table 4.


(a)

Figure 11: wavelet transform fusion technique outputs with set II inputs for n number of decomposition levels (a) n = 1

This table shows that fusion using this method produces a better result than the former method with a PSNR value of 95.0033.

Table 4: MSE and PSNR values calculated for set II inputs using Wavelet Transform Fusion technique.

Number of Decomposition levels (n)	Overall Mean square error (MSE)	Peak signal to noise ratio (PSNR)
n= 1	5.9531	95.0033

CONCLUSION:

This paper performs the fusion of images using transform domain techniques of Laplacian pyramid transform and Wavelet transform. The results obtained for corresponding methods using three sets of input images were shown in the chapter 5 which includes one input set as a real world images and corresponding outputs. For performance evaluation we made use of two metrics mean square error (MSE) and peak signal to noise ratio (PSNR). For all the outputs we have calculated these values and are tabulated. From these MSE and PSNR values, we are able to conclude that Wavelet Transform image fusion method produces the better fused image compared to Laplacian method of fusion. From the view of subjective evaluation it may be difficult to judge which method is the best method for image fusion, but from the view of objective evaluation it is clear from the results shown above, that Wavelet Transform fusion method is more reliable.

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