Mean Approximation Image Fusion Algorithm using Wavelet Transforms

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Abstract: **This paper speaks about image fusion algorithm using Wavelet Transforms. Image Fusion is a methodology to combine two or more images to obtain more detailed image. Here the fusion of magnetic resonance (MR) and computed tomography (CT) images is being done. The main objective behind fusing these images of the same organ is to come up with a single image having more precise information about that organ for better diagnosis. There already had some attempts proposed for fusion of these CT and MRI images using Wavelets. But medical images contain several shapes and objects, for such an image to be more dominantly under-standable, image fusion using wavelet transform has been developed with the latest software LabVIEW. The fusion process has been applied in three different ways for the transformed coefficients of images. Final results have proven that fusion of images using Bi-Orthogonal4 transform in LabVIEW gave better results compared to other transforms. Hence the above said algorithm has been implemented on MyRio device.**

Keywords — Image fusion, MRI and CT images, myRIO, Spearman-Correlation Coefficient(SCC), PSNR, Wavelet transform.

I. INTRODUCTION

Image Fusion is a type of Information Fusion. It is the process of merging two images of same scene to form a single image with as much information as possible. Fusion of images is very important in different image processing fields such as remote sensing, satellite imaging and medical imaging. This concept goes back to 1950's and 1960's to provide fused image which could be useful for better identification of natural and manmade objects. A single fused image contains more information compared to the individual source images.

Some concepts such as intensity-hue-saturation (HIS) [1], Brovey transform(BT) [2], Principal Component Analysis (PCA) [2] provide superior visual high-resolution multispectral images but they ignore the requirement of high-quality synthesis of spectral information. Again these fusion algorithms can be based on spatial and transform domain. These spatial domain fusion algorithms include average method, max-abs method, min-abs method[3], and weighted average method which mainly try to remove unwanted sharpen edge information. On the other hand, the transform domain algorithms focus on characterizing the features of an image.

Our proposed concept is very simple. The main objective of medical imaging is to obtain a high resolution image which will have better details possible for the sake of diagnosis[4]. In this paper, three different wavelet coefficients namely Haar, Biorthogonal-2 and Biorthogonal-4 have been obtained and then fused those coefficients using different fusion methods. As already have seen from the background works image fusion can be carried out at three different levels: pixel level, feature level and decision level[5].

The structure of the paper is as follows. The immediate section describes the principles of wavelet transforms-DWT .Followed by a section which discusses about the simple averaging and PCA techniques. The next section discusses the image quality measurement parameters. Section IV shows the mathematical analysis and the Spearman Correlation Coefficient (SCC). Next, the experimental results are analyzed. Finally, this proposed method is compared with already developed image fusion methods .

II. TRANSFORM TECHNIQUES

WAVELET TRANSFORMS:

It is basically the common form of fusion algorithm because of its simplicity and its ability to preserve the time and frequency details of the images that are to be fused [4]. Discrete Wavelet theory is an extension of Fourier theory in many aspects. In this the signal is projected on a set of wavelet functions. It provides good resolution in both time and frequency domains. Its main idea is to multi differentiate by decomposing image of different spatial domain and independent frequency.

A. HAAR TRANSFORM:

The Haar transform has evolved as a tool for sequence of rescaled "square-shaped" functions which together form a family of wavelets[7]. The Haar wavelet function $\psi(t)$

$$\psi(t)=\begin{cases}1 & 0\le t<1/2\\ -1 & 1/2\le t<1\\ 0 & otherwise\end{cases} \quad \ldots\ldots\ldots \quad (1)$$

Its scaling function $\varphi(t)$ can be described as

$$\phi(t)=\begin{cases}1 & 0\le t<1\\ 0 & otherwise\end{cases} \quad \ldots\ldots\ldots\ldots..(2)$$

B. BI-ORTHOGONAL:

This transform decomposes the available images into different spatial frequency bands like high-high, low-high, high-low at different scales and low-low band at the thickest scale. We already have this minimum knowledge that L-L band contains average image information and the other bands contain the directional information. These higher values point to edges or lines since they correspond to sharper brightness change. Now this information at each layer of decomposition is perfectly unique[6]. These scale functions $\phi(t)$ and $\hat{\phi}(t)$, wavelet function $\psi(t)$and $\hat{\psi}(t)$ satisfies:

$$\sum_{n\in Z} a_n \tilde{a}_{n+2m} = 2.\delta_{m,0} \quad \ldots\ldots (3)$$

Then the wavelet sequences can be determined as

$$b_n = (-1)^n \tilde{a}_{M-1-n} \quad (n=0,\ldots\ldots,\ N-1) \ldots\ldots(4)$$

$$\tilde{b}_n = (-1)^n a_{M-1-n} \quad (n=0,\ldots\ldots,N-1) \ldots\ldots(5)$$

III. FUSION METHODS

The limited focus depth of the optical lens made it not possible to get an image that contains all relevant objects in focus. Inorder to get an image with every entity in focus we can go for a multi-focus image fusion process that gives the images with better view for human or machine perception. Here Pixel-based, region-based and wavelet based fusion algorithms were implemented.

i. SIMPLE AVERAGE

It is a fact that sections of images that are in focus be likely to to be of higher pixel intensity. Now the value of the pixel P (i, j) of each image is taken and then added. This sum is then divided by two to get the average. This average value is given to the corresponding pixel of the output image which is given in equation (1). And this process is repeated for all pixel values of an image.

$$k(i.j)=\{X(i,j)+Y(i,j)\}/2 \quad \ldots\ldots..(6)$$

Where X (i , j) and Y (i, j) are two input images.

ii. MAXIMUM APPROXIMATION

The greater the pixel values the more is the image focused. Accordingly, this algorithm chooses the in-focus regions from every input image by choosing the greatest value for each pixel, resulting in highly focused output. The value of the pixels of each image is taken and compared to each other. The greatest pixel value is assigned to the corresponding pixel.

iii. MEAN APPROXIMATION:

Here the resultant fused image is obtained by considering the average intensity of corresponding pixels from both of the input images.

$$F(i,j)=(A(i,j)+B(i,j))/2 \quad \ldots\ldots..(7)$$

Where

A(i, j) and B(i, j) are the input images and F(i, j) is the fused image.

Weighted averages can also be considered for further analysis.

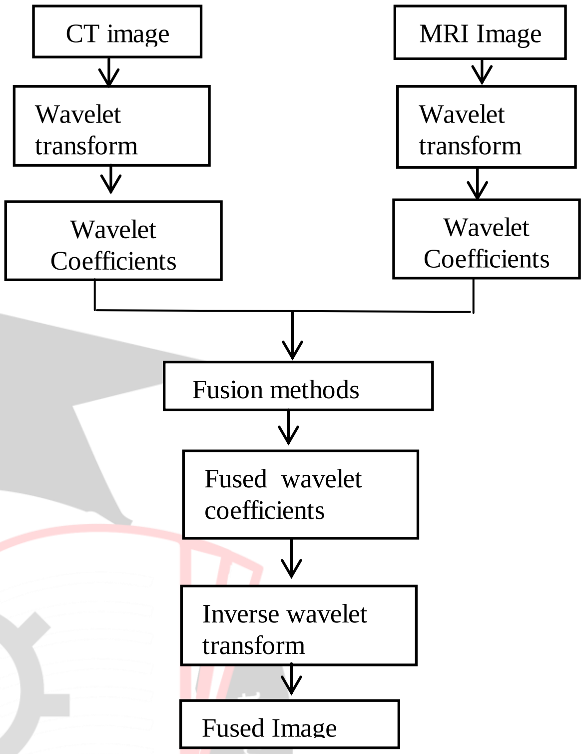

FIG 1: FLOW GRAPH OF DWT BASED IMAGE FUSION

IV. IMAGE QUALITY ASSESSMENT PARAMETERS:

1.MEAN-SQUARED ERROR(MSE):

It is widely used to measure the degree of image distortion because they can represent the overall gray-value error contained in the entire image[7].

It is defined as

$$MSE=\frac{1}{M*N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[X(i,j)-Y(i,j)]^2 \ ..(8)$$

Where X (i, j) refers to fused image

Y(i, j) refers to reference image

M, N refers to number of pixels in image.

2.PEAK SIGNAL TO NOISE RATIO(PSNR):

It is defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the dependability of its representation[8]. Commonly many signals have a wide dynamic range and that is why PSNR is usually expressed in logarithmic decibel scale.

For peak signal to noise ratio (PSNR) assume an input image X (i, j) which contains MxN pixels and the processed image Y (i, j).

Now peak signal to noise ratio (PSNR) in dB,

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$$PSNR = 10 * \log_{10} \frac{(L-1)^2}{MSE} \quad \text{.......... (9)}$$

L represents number of gray levels.

3.ENTROPY

It is a measure about much information is encoded in a message. The more the entropy, higher is the information content. It is also a measure of uncertainty in a message. Information and uncertainty are equivalent notions. Common units of entropy are bits per symbol.
Image entropy is calculated with the formula

$$Entropy = \sum_i p_i \log_2 p_i \quad \text{............(10)}$$

Where P_i is the probability that the difference between 2 adjacent pixels is equal to i, and Log_2 is the base 2 logarithm.

IV. STANDARD DEVIATION

It is a measure that is used to compute the amount of variation or dispersion of a set of data values. The standard deviation of a random variable is the square root of its variance. The equation of the standard deviation is

$$s = \sqrt{\frac{\sum_{i=1}^{N} |A_i - \mu|^2}{N-1}} \quad \text{..............(11)}$$

V. SPEARMAN-CORRELATION COEFFICIENT(SCC)

It is a non-parametric measure of rank correlation between two images or variables. It describes how well the relation between two images can be maintained using a monotonic function[9].
For some cases Spearman correlation between two variables is equal to Pearson correlation.
Spearman correlation lies between the ranges -1 to +1.

$$rs = 1 - \frac{6 * \sum d^2}{n(n^2-1)} \quad \text{...............(12)}$$

Where d is commonly the difference between the to ranks of each observation.

n is the number of such observations.

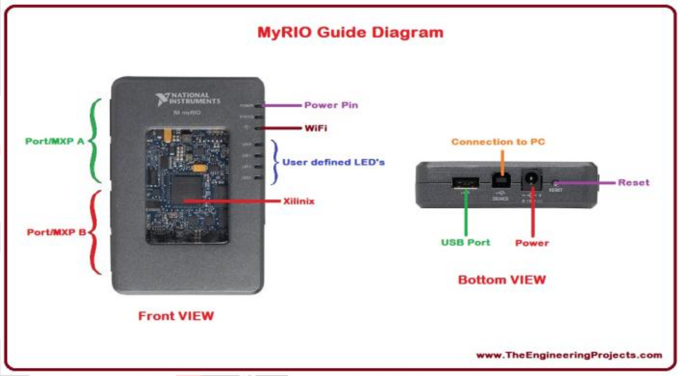
HARDWARE:

Here we have implemented this entire process using LabVIEW software and the hardware component used is the myRIO.

LabVIEW:

LabVIEW is a graphical programming environment that students can use to quickly develop applications that scale across multiple platforms and Operating System. Simply, LabVIEW VIs are graphical, driven by dataflow and event-based programming.

LabVIEW programs are called virtual instruments, or VIs, because their appearance and operation often imitate physical instruments, such as oscilloscopes and multimeters. LabVIEW contains a comprehensive set of tools for acquiring, analyzing, displaying, and storing data, as well as tools to help you troubleshoot the code you write.

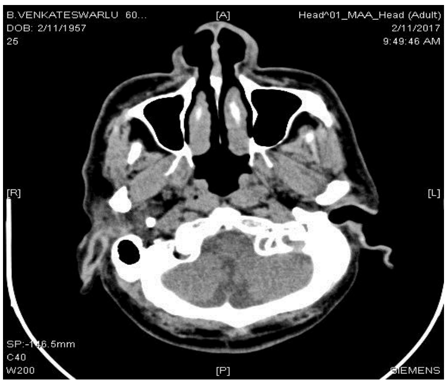


myRIO:
RIO – Reconfigurable I/O device.
The NI

myRIO embedded device is created to "do real-time applications".NI myRIO is a reconfigurable and reusable teaching tool that helps to learn a wide variety of engineering concepts as well as complete design projects.

- It is a multifunctional portable and compatible device

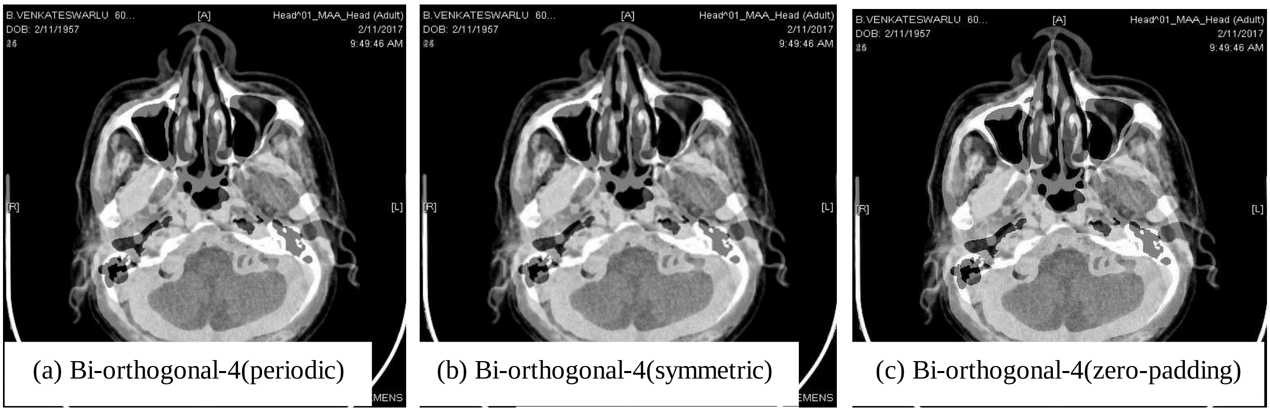
VI. SIMULATION RESULT:



CT Image

MRI image

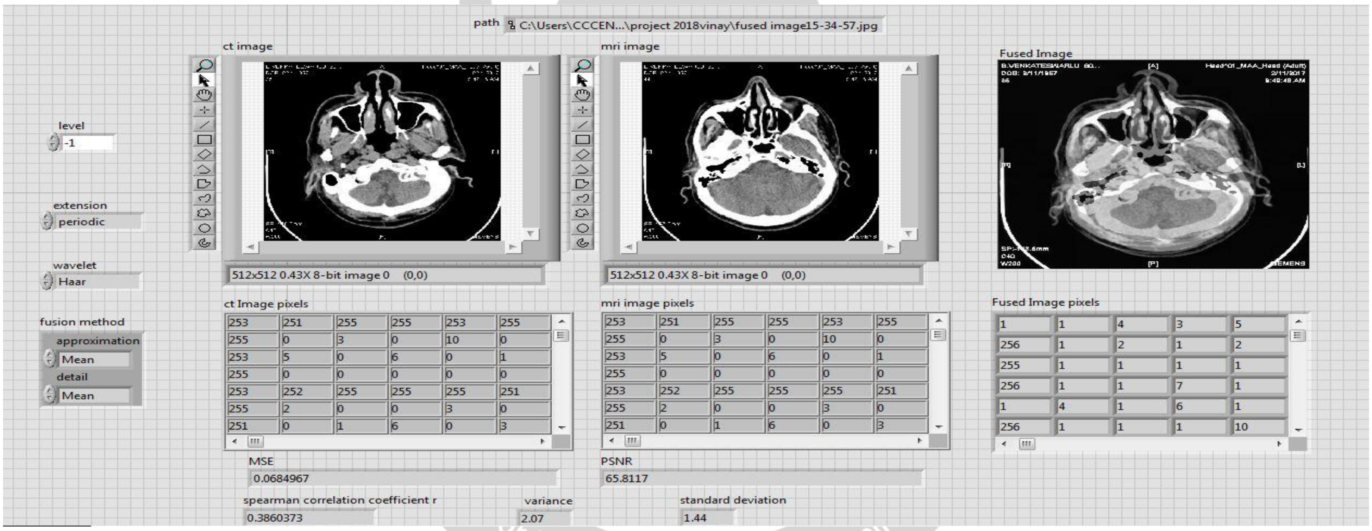
FIG 3. INPUT IMAGES



(a) Bi-orthogonal-4(periodic) (b) Bi-orthogonal-4(symmetric) (c) Bi-orthogonal-4(zero-padding)

FIG 4. FUSED IMAGES

The fig 3 and fig 4 shows the input images and corresponding fused images with different extension windows for Bi-orthogonal 4 transform technique.



LABVIEW FRONT PANEL:

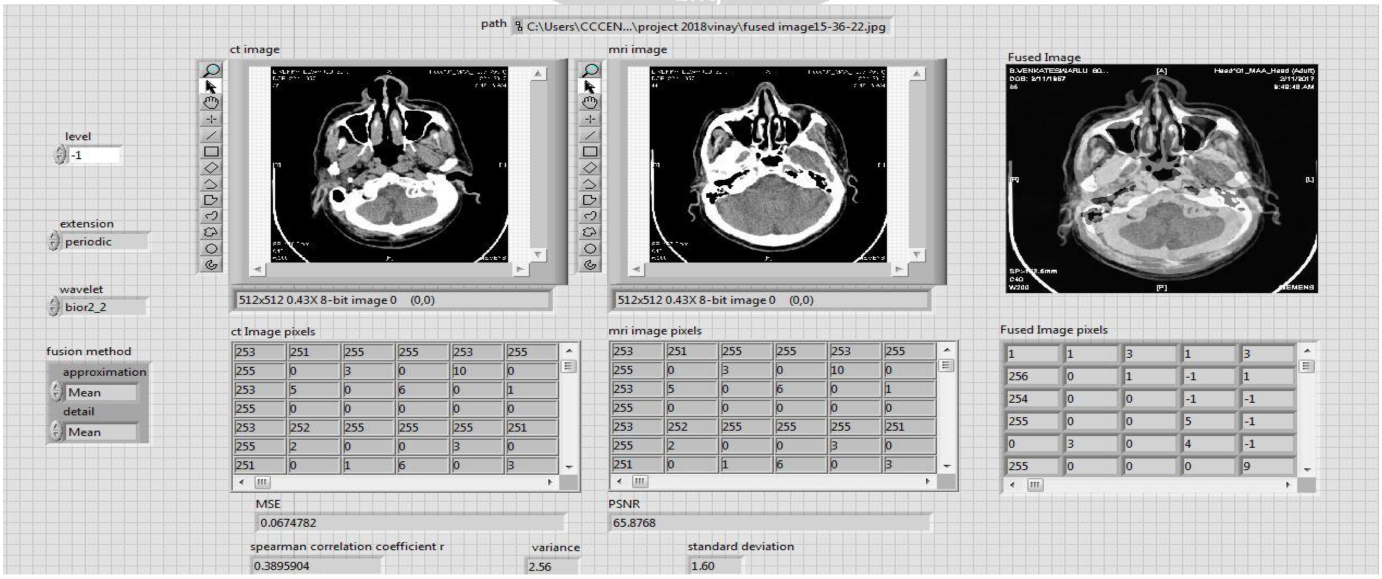


FIG 6: BI-ORTHOGONAL 2 WITH PERIODIC EXTENSION

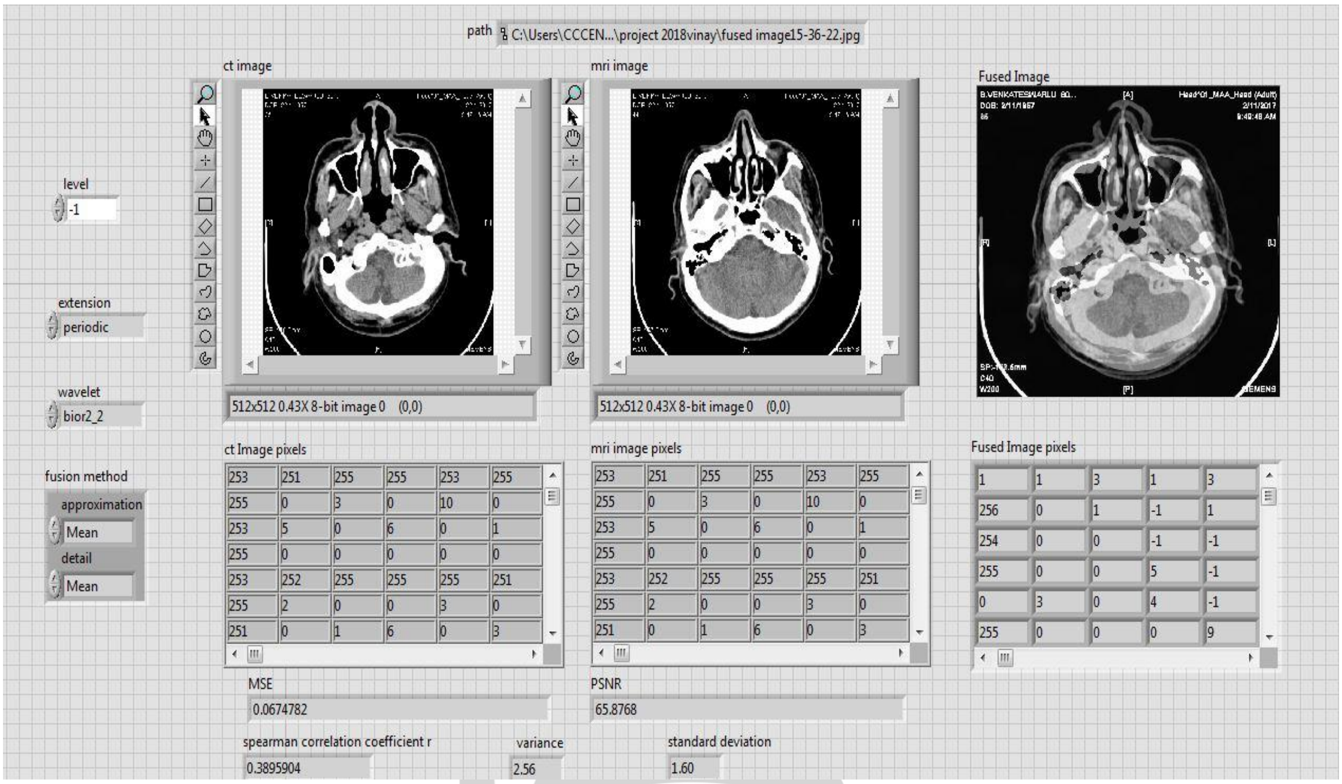


Table-1: Periodic Extension

	MSE	PSNR	Standard deviation	Variance	Spearman correlation coefficient
Haar	0.0705566	65.683	1.44	2.07	0.3860373
Bi-orthogonal-2	0.0674782	65.8768	1.60	2.56	0.3895904
Bi-orthogonal-4	0.0684967	65. 8117	2.01	4.04	0.4742625

Table-2: Symmetric Extension:

	MSE	PSNR	Standard deviation	Variance	Spearman correlation coefficient
Haar	0.0684967	65. 683	1.44	2.07	0.3860373
Bi-orthogonal-2	0.0705566	65. 8117	1.58	2.49	0.3108882
Bi-orthogonal-4	0.0674782	65. 8768	2.71	7.36	0.5073762

Table-3: Zero Padding Extension

	MSE	PSNR	Standard deviation	Variance	Spearman correlation coefficient
Haar	0.0705566	65.8117	1.44	2.07	0.3860373
Bi-orthogonal-2	0.0664073	65. 683	1.45	2.09	0.4242379
Bi-orthogonal-4	0.0684967	65. 9423	3.59	12.87	0.4752962

VIII. RESULTS AND DISCUSSION

In this paper Mean approximation image fusion algorithm has been applied on CT and MRI images. The input images are decomposed using discrete wavelet transform with three different extensions namely zero padding, symmetric and periodic. Input images have been decomposed using different wavelet transforms like Haar, Bi-orthogonal2 (Bior2) and Bi-orthogonal4 (Bior4). The quality assessment parameters like MSE, Standard Deviation, Variance, PSNR and Spearman correlation coefficient were measured for all the output images and are shown in the tables. Table.1 represents the parameters for Mean approximation fusion with Haar, Bior_2 and Bior_4 transforms with periodic extension window. Table.2 represents the parameters for Mean approximation fusion with Haar, Bior_2 and Bior_4 transforms with symmetric extension window.Table.3 represents the parameters for Mean approximation fusion with Haar, Bior_2 and Bior_4 transforms with zero padding extension window. From the above results, it is observed that the Bi-orthogonal 4 yields better results in all aspects. Hence, an executable (.exe) file has been generated for Bi-orthogonal4 transform and the same has been implemented on NI MyRio. The corresponding images are given in fig.4.

IX. FUTURE SCOPE

In this paper, an image fusion algorithm Mean approximation has been implemented with three different wavelet transform techniques Haar, Bi-orthogonal2 and Bi-orthogonal4 in bothe software (LabView) and hardware (NI MyRio). The quality assessment parameters for the above said algorithm are compared. As the Bi-orthogonal4 transform yields better results, an executable (.exe) file has been generated and dumped in to NI MyRio device. The quality assessment parameters for the output image obtained from MyRio also to be determined including time and power consumptions. So that these algorithms can be applied for real time applications in medical diagnosis.

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