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Discrete wavelet transform based image fusion and de-noising in FPGA

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Abstract

Image fusion is an extensively discussed topic for improving the information content of images. The main objective of image fusion algorithm is to combine information from multiple images of a scene. The result of image fusion is a new image which is more feasible for human and machine perception for further image processing operations such as segmentation, feature extraction and object recognition. This paper explores the possibility of using the specialized wavelet approach in image fusion and de-noising. These algorithms are compared on digital microscope images. The approach uses an affine transform based image registration followed by wavelet fusion. Then the least squares support vector machine based frequency band selection for image denoising can be incorporated to reduce the artifacts. The indentations are to maximize resolution, decrease artifacts and blurring in the final super image. To accelerate the entire operations, it is proposed to offload the image processing algorithms to a hardware platform thereby the performance can be improved. FPGAs provide an excellent platform in implementing real time image processing applications, since inherent parallelism of the architecture can be exploited explicitly. Image processing tasks executed on FPGAs can be up to 2 orders of magnitude faster than the equivalent application on a general purpose computer.

Keywords: Discrete wavelet transform; Image fusion; Image registration; Image denoising; FPGA

1. Introduction

A fusion method, which is able to combine complementary directional information of a multiple image into a single super image, improves the information density. Utilizing the virtue of wavelet transforms that is multi band decomposition, best view can be selected in any given band. The fusion results show improved overall contrast. The reviewed methods do not need knowledge of the system's point spread function (PSF). The PSF independence gives the method an upper hand when used with images in environments of unknown PSF (Rubio-Guivernau et al., 2012). PSF results in the image blurring in highly optically enhanced imaging such as microscope and as such is a limiting factor of image enhancement (Swoger et al., 2007).

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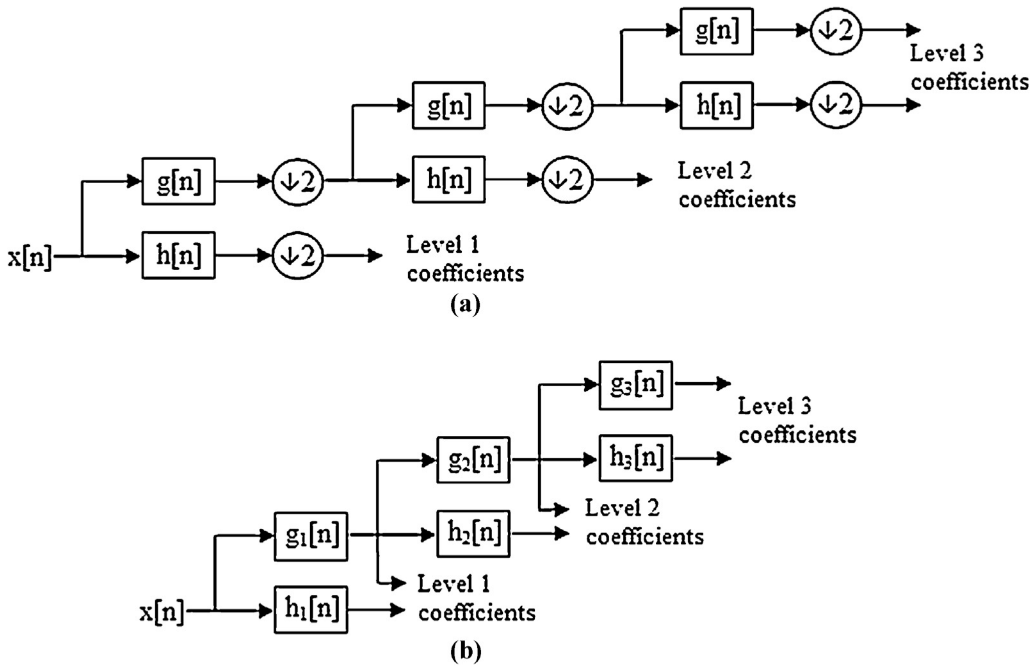

Fig. 1. Third level filter bank block diagram representation of (a) DWT and (b) UWT.

The image stack used in the reviewed paper to demonstrate the method is digital microscopy images which employ multi-view microscopy technique. The system's point spread function (PSF) is the combination of the light source and the detection objective's PSF (Rubio-Guivernau et al., 2012; Huisken and Stainier, 2009). The image set is a multiple views of the sample, with possible multiple focal points.

1.1. Un-decimated wavelet transform

Discrete wavelet transform (DWT), which down samples the approximation coefficients and detail coefficients at each level Fig. 1(a). But the un-decimated wavelet transform (UWT) does not incorporate the down sampling operations thus the image are at same size as each level progresses, Fig. 1(b). These properties of UWT cause the difficulty of requiring memory directly proportional to the factor of original image size, which in turn makes the algorithm less feasible compared to DWT. This issue in hand is conceded a necessary evil for the fact that UWT is translation independent, which is very handy when dealing with rigid images (Wang et al., 2010; Gyaourova et al., 2002).

Apart from the translation invariance the UWT shows a better balance between smoothness and accuracy than the DWT based denoising procedures (Naga Prudhvi Raj and Venkateswarlu, 2011). Thus giving quality image fusion and denoising contributions.

1.2. Affine transform

Affine transformations include translation, scaling, shear, reflection, rotation, and their combination in any sequence. Every linear transformation is affine, but not every affine transformation is linear. The images for fusion have to be registered correctly with as much tolerance as possible. The registration error results in artifacts in the final output which will be difficult to address (Rubio-Guivernau et al., 2012). UWT offers certain immunity from these changes thus decreasing the probability of artifacts in the final volume (Gyaourova et al., 2002) (Fig. 2).

Fig. 2. Affine transform.

1.3. Least square support vector machine (LSSVM)

The support vector machine (SVM) after its introduction in 1998 has hence provided with effective classification tool based on machine learning (Li, 2009; Vapnik, 1998). SVM could be effective even with a smaller training set. Thus providing a better choice or the logical classification of noise and data in the denoising approach, the SVM solution is achieved by quadratic programming solution. This turns out to be a challenge to implement. The solution is the modified LSSVM which employ linear equations which pose lesser computational challenge. Still the network size is more than the SVM because of the selection method (Wang et al., 2010).

2. Fusion method

The overall fusion processing goes through image registration and preprocessing followed by wavelet decomposition. The decomposition coefficients are further analyzed and suitable combination is achieved. Then inverse wavelet transform is used to get the final fussed volume.

2.1. Preprocessing and registration

The image acquired from digital microscope is less susceptible to noise (Swoger et al., 2007). The more pressing concern is the blurring effects. The blurring effect causes the registration approach less effective. This problem can be overcome by introducing more views to create maximum overlapping features (Rubio-Guivernau et al., 2012). The images are passed through a cropping algorithm to reduce the size. This is to decrease size of the image volume for decreasing the implementation cost. After which an affine transform matrix manipulation to correct the rotation and translation. The value of θ is obtained from the digital microscope settings (Huisken and Stainier, 2009). This value is then fine-tuned by doing a similarity measure based registration approach. The fine tuning is required because slight variation in the angular value of digital microscope due to different reasons can cause artifacts in the final image (Swoger et al., 2007). Translation value is completely calculated from the similarity measure coefficients (Vapnik, 1998).

$$Affine\ \ transform\ \ matrix = \begin{bmatrix} \cos\theta & -\sin\theta & Tx\cos\theta - Ty\sin\theta \\ \sin\theta & \cos\theta & Tx\sin\theta + Ty\cos\theta \\ 0 & 0 & 1 \end{bmatrix}$$

Each image is then formatted to have a common size and resolution. Then mask are created with two pixel levels (low value indicating area with data and high value where data is not there) in order to discard the padded value in each image when required to avoid border artifact (Rubio-Guivernau et al., 2012).

2.2. Wavelet decomposition

The fusion process begins by decomposing the image volume to frequency bands. Then these frequency bands of each image are analyzed by the set fusion rules to determine which once can be combined, which once has to be

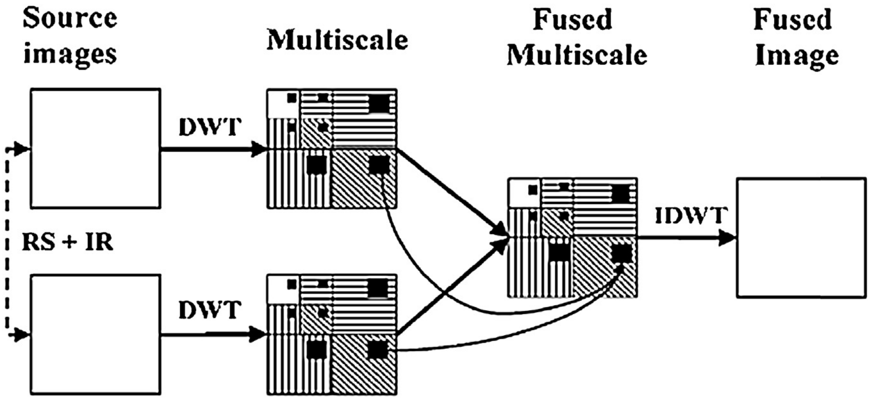

Fig. 3. Wavelet fusion process.

removed from the final volume of coefficients (Fig. 3) (Yuan and Yuan, 2012; Pajares and de la Cruz, 2004). Then inverse transform is applied to get back the image. The wavelet method used is changed as per the image set to get maximum efficiency.

As mentioned in the start the normal DWT has a greater limitation of being non-shift invariant. The result being that the images are highly susceptible to miss registration and hence forth require a very comprehensive image registration algorithm (Lewis et al., 2007). But as explained in the start the digital microscope images naturally go blurred as the depth of the imaging increases. This causes severe problems when trying to fuse images from the deeper portion of the sample.

Un-decimated wavelet transform offers shift invariance and is one of the proposed alternatives to the problem in hand. As shown in Fig. 1(b) does not down sample after each level hence as each level increases additional elements are added to decomposition (Fig. 4). The reason for the UWT to be shift invariant is the fact that the decimation actually causes non-shift invariance. Also as level increases spatial resolution becomes coarser and the size remains the same. UWT also can be called redundant as information may be retained in the adjacent levels. The levels of decomposition required are directly dependent on the resolution of the source image (Amolins et al., 2007; Pajares and de la Cruz, 2004).

UWT provide a good fusion platform and can be used in fusing the multi view images to produce a better image with higher information density. As the more views are fused in the resultant image is found to show more isotropic resolution (Swoger et al., 2007).

Another approach to interpret blurring is to consider the image as multi focused. We can use a tunable half band pair wavelet (THP) to decompose the image. THP reviewed here also does not down sample after each level. THP is a method put forth to implement a bi-orthogonal wavelet filter bank. The reason for using this wavelet method is narrow transition band between the decomposed frequency bands, resulting in better frequency selectivity (Baradarani et al., 2012).

Dual-tree complex wavelet transform (DTCWT) is also shift invariant and directionally selective. Wavelets operate better in lower dimensions preferably in 1D. Usually higher dimension are the combination of the lower dimension operation reputed as required. DTCWT unlike the other algorithm compared here performs well in higher dimensions. It can be used to fuse miss registered images, with significant edge preservation. DTCWT as it operates in the complex domain provides phase information. Other wavelet approach discussed here does not have this feature. DTCWT use real filters hence it is not purely complex wavelet (Singh and Khare, 2012).

2.3. Fusion rules

The fusion rules are the algorithmic protocols used to decide whether derived coefficients should be fused with the coefficients of another image. The rules generally define the combination of higher order bands as the high frequency components represent the features in the image. Hence they are used to get the fusion parameters. The low frequency regions represent smooth regions of the image hence are usually not used (Nason, 1995; Lewis et al., 2007). The image

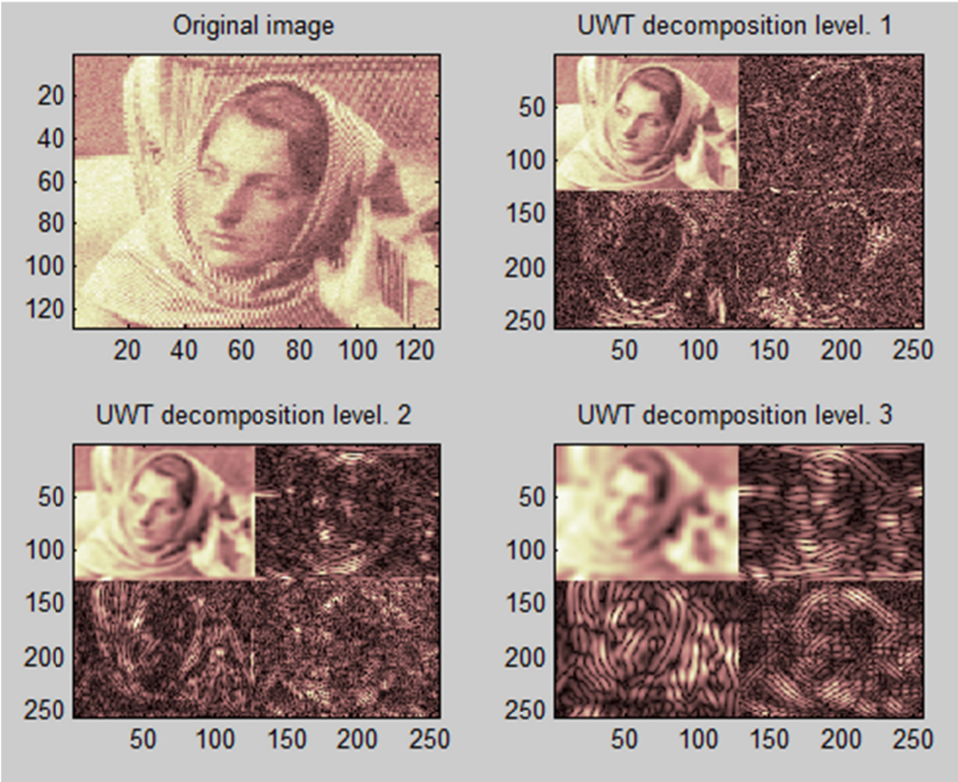

Fig. 4. Level 3 UWT decomposition.

denoising approaches are also used in deciding whether a given coefficient should be used in the final coefficient pool. If noise image bands are used then the final image will turn out to be noise (Wang et al., 2010; Motwani et al., 2004). The appropriate matching is down using the similarity measure of coefficients. Usually the edges and other significant features are matched. The region based matching is found to be more fruitful than the pixel level based approach (Lewis et al., 2007).

2.4. Inverse transform

Once the fusion volume coefficients are finalized then the image is put through the inverse transform of the transform used to create the coefficients. The inverse transform will get back the image into spatial domain (Fig. 5).

3. Denoising method

The image noise can be removed using any spatial or transform domain filter. But wavelet filters provide better multi resolution approach which is very important for the image set of digital microscope (Motwani et al., 2004). Besides for image fusion we already have converted the image into frequency domain.

Once coefficients are passed through the selection mentioned in the fusion rules and confirmed, then a denoising technique is adopted to refine the image of noise. A LSSVM based algorithm is used to achieve this. The machine learning approach can give the denoising more versatility, giving system the ability to adapt according to the image noise challenges without actually having to change the denoising algorithm (Li, 2009).

The first step in the denoising is creating the feature vector and training objective with wavelets in the high frequency sub band. Then binary map and support value corresponding to the coefficients are formed. The feature vector is selected using the support value and the training object as the preliminary binary map. LSSVM training is the second step in the process. Once the LSSVM training is completed then the model is used in classifying the high frequency sub bands

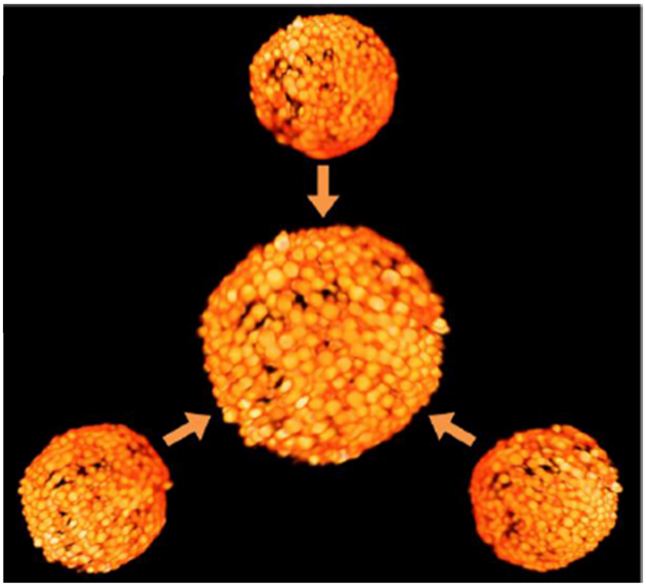

Fig. 5. Fusion of the three different views of a sea urchin embryo (Rubio-Guivernau et al., 2012).

into noisy and noise free. Then all the noisy high frequency coefficients are put through thresholding to remove noise (Wang et al., 2010). The thresholding are done using two methods: soft and hard thresholding. The soft thresholding is preferred over hard thresholding because of fewer artifacts after the process (Fig. 6) (Grace Chang et al., 2000).

4. Comparative study

Comparative study focuses on comparing UWT and DTCWT based on three parameters namely edge strength, fusion factor and fusion symmetry Table 1. The UWT and DTCWT share the fact that they can be effectively used for fusing multi view images. THP on the other hand is better suited for multi focus images.

Edge strength is a sobel edge operator based normalized weighted performance of a fused image 'F' with respect to input image A and B. Sobel edge is it calculate by finding the derivative along x axis G_x and y axis G_y direction for an image, then obtaining $G = \sqrt{G_x^2 + G_y^2}$. Higher value of Edge strength is desired for better edge information.

Fusion factor is the ratio of mutual information between source images and fused image. That is the fused image 'F' is compared with first image 'A' this value is added with the value obtained by doing the same process with the fused image 'F' and image 'B' $FF = I_{FA} + I_{FB}$. Higher value represents better data density.

Fusion symmetry is symmetrical relationship of the images and the fused image $FS = |I_{FA}/(I_{FA} + I_{FB}) - 0.5|$ [7]. Lower the value of the fusion symmetry the better the result. In total the Edge strength describe the survival for sharp features after fusion.

Table 1
Comparison of UWT and DTCWT methods (Singh and Khare, 2012).

Image set	Method	Edge strength	Fusion factor	Fusion symmetry
Set 1	UWT	**0.6805**	**1.7031**	**0.3680**
	DT CWT	0.6278	1.0324	0.3784
Set 2	UWT	**0.6534**	**4.9597**	0.1968
	DT CWT	0.6091	4.3229	**0.1659**
Set 3	UWT	0.5094	**3.5746**	0.0447
	DT CWT	**0.5228**	3.0621	**0.0029**

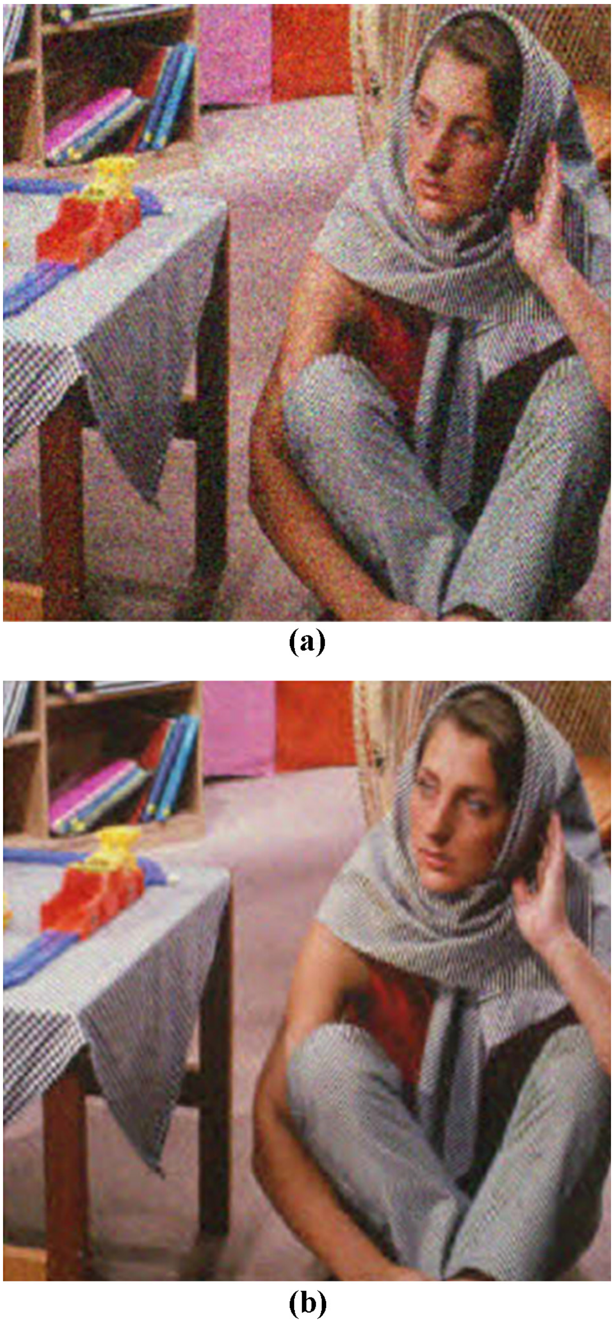

Fig. 6. Noise image (a) and de-noised image (b) (Wang et al., 2010).

Fusion factor says the amount of information translated in to the fused image. Fusion symmetry tells us whether the fused image shares symmetric property with the parent images. If the symmetric property is high then the image is more close to one of the image and not an ideal combination of the parent images. The Table 1 describes the results obtained for three set of medical images after this fusion process. For the set 1 image the UWT was most fruitful with better edges, information and less symmetry. Set 2 UWT achieve good edge strength and information but comparatively has higher symmetry. Set 3 is inconclusive, but proves how the DTCWT is close to achieving good result when compared to DTCWT.

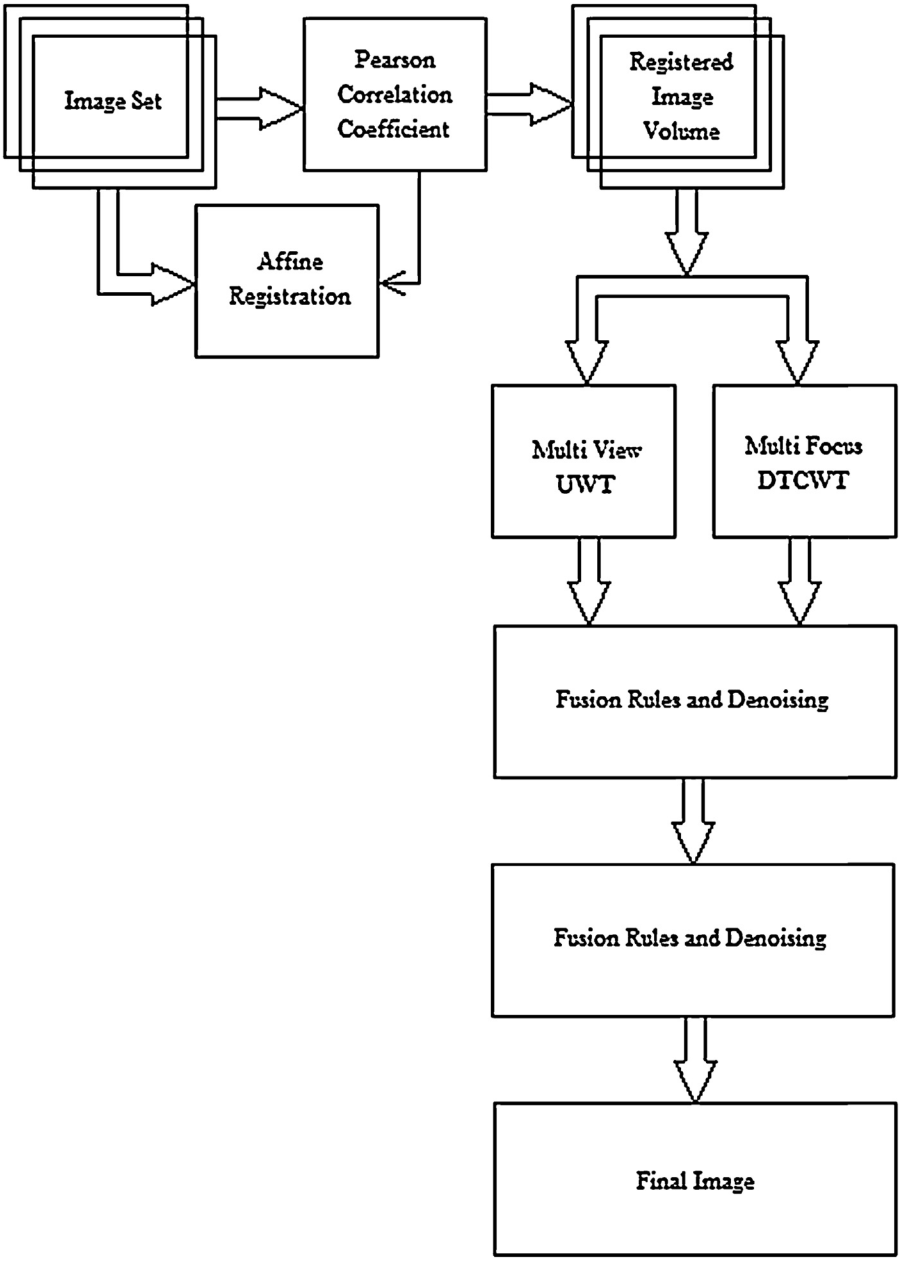

Fig. 7. Block diagram representation of the proposed model.

5. Proposed model

We are proposing a UWT based image fusion and denoising approach on an image set resisted by affine transform and Pearson correlation coefficient as shown in Fig. 7. The UWT was chosen as per the comparative study down illustrated in Table 1. The image set we are using is assumed to be rigid images hence rotation and translation are the only affine transform correction needed. Pearson correlation coefficient is calculated in all cases to determine the correct registration of the image.

In case of a multi focus issue in the image set the wavelet approach is changed from UWT to DTCWT to get the maximum capability. The sobel edge operator is used to determine the blurring of the images to effectively make this

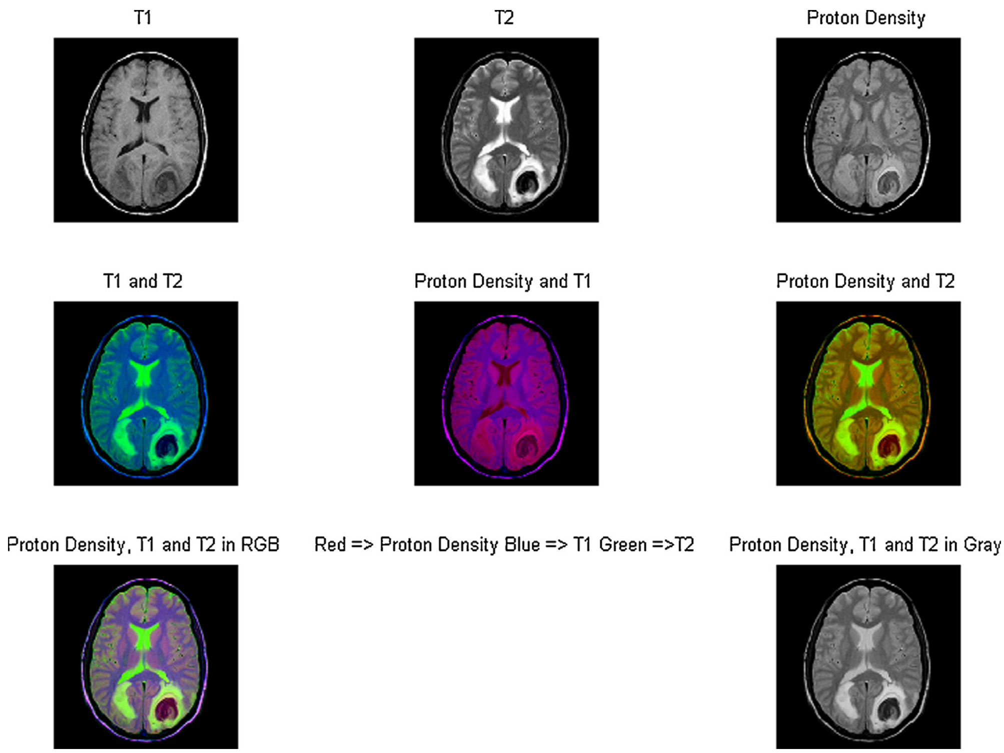

Fig. 8. Fused Image using Daubechies mother wavelet using Undecimated wavelet transform.

switch. The fusion rules designed based on the analysis of the directional information of the wavelet confidents. Finally the inverse wavelet is used to retrieve the fused image from the coefficient.

Once the model is demonstrated effectively in the MATLAB simulation the algorithm will be implemented on a reconfigurable architecture. The implementation will focus on achieving real time processing expiring the inherent parallel programming.

6. Results and discussion

We currently have reached at the point of effectively fusing the images using the Daubechies mother wavelet using Undecimated wavelet transform on a T1, T2, proton density MRI image of a patient suffering from sarcoma (Fig. 8). The tool used for fusing the images is MATLAB. The next step is to implement this algorithm in FPGA and scale up to perform real time operations.

7. Conclusion

The review of different techniques for image registration and image fusion based on wavelet transform was done. The conclusions are that the UWT is good for fusion when a multi view image fusion needed to be done. The THP is good when multi focus images are processed. The DTCWT can be used in either case with a higher computational expense. Coming to image denoising, LSSVM was found to be better over the SVM in denoising as per the papers reviewed. We have effectively fused the T1, T2, proton density MRI image of a patient suffering from sarcoma using Daubechies mother wavelet using Undecimated wavelet transform using MATLAB. But the vital part of analysis rests on the hardware synthesis of image fusion algorithm. The phenomenal part of the research area is focused on the FPGA implementation of the algorithm and the scaling up of the algorithm to perform real time operations. Though the principle behind our research work has begun to come alive, the structural edifice is still an ongoing process awaiting may be many surprises and challenges.

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