ORIGINAL ARTICLE

Performance Comparison of Different Wavelet Families Based on Bone Vessel Fusion

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Abstract

Aim: Image fusion has been a widely used application in the field of medical diagnosis. Hence, a very little amount of literature has been found out on Bone and vascular image fusion. Wavelet has been a revolutionary tool for the better representation and reconstruction of images. This article aims at testing the performance of the various wavelet families on the fusion of bone vessel fusion. **Materials and Methods:** A mask image displaying the osseous information and a digital subtraction angiography (DSA) image containing the vascular details are chosen to test the performance of various wavelet families on their fusion. **Results and Discussions:** The Daubechies Wavelet works best among all the families, but wavelets, in general, are not able to perform well on image fusion as a low amount of $Q^{AB/F}$ has been achieved. **Conclusion:** Although the wavelets have been used widely in the context of image fusion they are not working well with DSA and mask image fusion. We have portrayed the limitation of wavelet on bone vascular image fusion.

Key words: Biorthogonal, Coiflet, Daubechies, Discrete Meyer, Haar, reverse biorthogonal, symlet

INTRODUCTION

Image fusion produces a single fused image from a set of input images. Image fusion gives an effective method to homogenize the visual 2-D data from different sets of images. The fused image comprises of far more degree of information than a singular image which aids for precise human or computer perception and computer vision tasks such as feature extraction, medical diagnosis, and segmentation. The objective of information fusion is to improve the accuracy of image interpretation[1-6] and analysis by making use of complementary information. Image fusion has been widely exploited at three levels pixel level fusion, decision level fusion and feature level fusion. Source images could possess a variety of nature such as multimodal, multisensory, and multifocal.[7,8] Image fusion is an important field of application in military surveillance, remote sensing, satellite communication biometrics, and medical image diagnosis or radiology. A plethora of image fusion[9,10] experiments are being conducted on computed tomography (CT) to diagnose a tumor in legs, positron emission tomography and single photon emission computed tomography to monitor blood clotting in different parts of the body. One of the very important contains the osseous information, and digital subtraction angiography (DSA) which is obtained by subtracting the pre-contrast image from the contrast-induced image contains the vascular information. These images are fused to obtain an enhanced image[11-18] with the much higher amount of information travel that can abridge the time between disease diagnosis and patient care by helping medical practitioners to have a precise and an accurate diagnosis.

With the arrival of the wavelet theory, the attribute of the multiscale decomposition of wavelet is used in image fusion. The wavelet transform has been a revolutionary milestone in the field of 2-D signal analysis. It overcame the limitation of Fourier transform in terms of harmonic analysis by adding the element of scale. One of the major properties of wavelets is that they are localized in time which have them very useful for the processing of nonstationary signals. The main difference between wavelet and Fourier Transform is that wavelet transform has time domain representation along with

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frequency domain analysis. Hence, small temporal changes in the input signal can alter almost all the coefficients of the Fourier transform. A basic wavelet has two components mother wavelet that decomposes the function and the number of decomposition levels.[19-21]

In this article, the work is centered on the application of various mother wavelet families on osseous and vascular image fusion. The performance of all the mother wavelets is assessed on bone and vascular image fusion. A concrete theoretical background along with implementation and testing has been done. The rest of the articles is organized as follows: Section 2 develops the theoretical background for wavelet and its families. Section 3 presents the objective evaluation metrics. Section 4 consists of the proposed methodology. Section 5 presents the results and discussions. Section 6 gives the conclusion and future scope.

WAVELET AND ITS FAMILIES

In this section, we will briefly describe the various wavelet families which include the working principle, typical advantages, and disadvantages. Wavelets[22-24] are the mathematical tools that convert the data into various coefficients and then analyze each coefficient at a resolution matched to its scale. The wavelets have a cutting edge over the Fourier transform by registering the discontinuities and sharp spikes contained in the signal. The main and most important property of the wavelet is to provide the ability to view the image at different scales or resolutions. It can be metamorphically understood as looking through large or small windows to notice gross and small features, respectively. The wavelet algorithm works with the adoption of the wavelet prototype function and is popularly called mother wavelet.

The wavelet transform of any function y(t) at a point of time and scale is a way of convolving of wavelet obtained by translation and dilation of the mother wavelet with the given signal.

$$W_X(T,a) = \int_{-\infty}^{\infty} y(t) \, {}^{1}\!/\!_{\sqrt{a}} \, \psi^{*}\left(\frac{t-T}{a}\right) dt$$

where T is any point in time, and a represents the scale, $\psi^{*}_{(a,T)}$ (t) is the wavelet function, and y(t) is the given input signal. Wavelet does the mapping of the observations of the signal to a linear expansion of coefficients which can convey the behavior of the function at some time around a specific point in time. Wavelet has a number of families namely Biorthogonal, Coifflet, Daubechies, Discrete Meyer, Haar wavelet, reverse biorthogonal wavelet and Symlet.[22-24] These type of mother wavelets vary in terms of length of the support of mother wavelet, the speed of the decaying of the coefficients, symmetry and orthogonality and biorthogonality of the resulting functions. There are several kinds of design properties which are required to be fulfilled by a transform to be efficient wavelet system-orthogonality, compact support defined by the length of the filters, rational coefficients, symmetry, smoothness, and interpolation.

Biorthogonal wavelet and reverse biorthogonal wavelet

Biorthogonal wavelet[22-24] exhibits the properties of linearity which is advantageous for image and signal reconstruction. Biorthogonal systems provide an additional degree of freedom than the orthogonal wavelets. These wavelets are a compactly supported wavelet which provides symmetrical and exact reconstructions with finite impulse response filters. Reverse biorthogonal wavelet is obtained by biorthogonal wavelet pairs.

Daubechies wavelet

It is an orthogonal wavelet family named after a Belgian physicist Ingrid Daubechies.[22-24] The key characteristic of Daubechies wavelet is the availability of maximum number of vanishing moments for some predefined support length. The types of Daubechies mostly used in practical applications are db2/db20, which represent the number of decaying moments. The number of these moments is equal to half the length of the support in case of Daubechies. The name of the Daubechies is represented as dbN where N gives the order of the Daubechies wavelet. N usually varies from 1 to 8.

Haar wavelet

Haar wavelet[22-24] was the first mother wavelet proposed by Alfred Haar and is known for having shortest length of support among all orthogonal wavelets. It has got only one vanishing moment which makes it unsuitable for reconstruction of the smooth functions. However Haar wavelet is conceptually simple and fast, easily detects the information which is time localized and is memory efficient. Haar wavelet is discontinuous and resembles a step function. It represents the Daubechies 1 wavelet function. Haar decomposes the signal into two sub-signals of half the length.

Symlets

Symlets[22-24] are Daubechies least symmetric wavelets and are very compactly supported. The construction of symlets is very similar to that of Daubechies but their symmetry is stronger than that of Daubechies.

Coifflets

Coifflet[22-24] were designed by Ingrid Daubechies and Ronald Coiffman and is more symmetrical than the Daubechies mother wavelet and has a support size of 3q-1 instead of 2q-1 which is the case in Daubechies.

Discrete Meyer wavelet

Meyer wavelets[22-24] are orthogonal and have symmetric scaling wavelet function. It is band limited and has infinite number of supports but has faster decaying than sync wavelet and is infinitely times differentiable.

OBJECTIVE EVALUATION METRIC

A quantitative evaluation metric known as $Q^{MN/F}$ factor[25] is used to evaluate the image fusion quality. It does not require any reference image to calculate the fusion quality.

Let M and N be two source images to be fused together. $Q^{MN/F}$ gives the measure of the edge information infused in the fused image which has traveled from the source image. It is measured between 0 and 1 where the closer value to 1 gives better fusion results. The mathematical formula for the performance metric of a given process that fuses M and N is given by:

$$Q_{X=1}^{X} = \frac{\sum_{x=1}^{X}\sum_{y=1}^{Y} Q^{MF}(x,y)\, w_x(x,y) + Q^{NF}(x,y) w_y(x,y)}{\sum_{x=1}^{X}\sum_{y=1}^{Y} W_m(x,y) + W_n(x,y)}$$

Q^{MF} and Q^{NF} are edge preservation values which are weighted by $W_m(x,y)$ and $W_n(x,y)$ where x and y denotes the number of pixels. The loss of information in a particular fusion algorithm can be calculated by subtracting the value of $Q^{MN/F}$ factor from one as the values are complimentary to each other.

Averaging fusion rule

When an image is acquired the pixels in focus get higher pixel intensity values and hence are more striking visible. However, taking an averaging of the pixel intensity values is a way of obtaining all regions in focus. Our main objective is to form conglomerated or integrated the view of the bone and vessel imagery so that vascular information is as much in view as the osseous information. In case of min-max rule, the intensities of pixels in a single image are carried in the fused image while the intensity values of other pixels in the source image are left behind. Hence to equally represent the osseous and vascular information averaging fusion rule is used instead of min-max rule.

PROPOSED METHODOLOGY

The main objective of the present study is to present an overview of the implementation of various wavelet families over a fusion of bone and vessel information. The study aims at a selection of the most suitable wavelet function for this type of fusion. The proposed methodology can be illustrated in Figure 1.

The detailed steps can be given as follows:

- The raw data are the osseous image (mask image) and DSA image (vascular information).
- The mask and DSA images are reconstructed using biorthogonal at order 2.2 and at level 2, Coifflet at order 2 and at level 2, Daubechies at order 8 and level 2, Discrete Meyer at order 2 and level 2, Haar at order 2 and level 2 Reverse biorthogonal at order 2.2 and level 2 and symlet at level 2 and order 2.
- The transformed wavelet coefficients are fused together by averaging fusion method.
- The inverse transform is applied on the fused coefficients to obtain reconstructed fused image.

RESULTS AND DISCUSSIONS

The raw data are shown in Figure 2 which is mask image which contains the bone information, and the DSA image contains the vascular information. Both the source images are transformed using different wavelet families, namely, Biorthogonal, Coifflet, Daubechies, Discrete Meyer, Haar wavelet, reverse biorthogonal wavelet and Symlet at level 2. The image coefficients are represented as a linear expansion of thresholds. The images are reconstructed using these transforms to obtain a better fusion quality. The linear expansion of coefficients is fused together by averaging fusion rule and then inverse wavelet transform is applied to obtain the reconstructed fused image. Each inverse transform is characteristic of its mother wavelet family. The fused

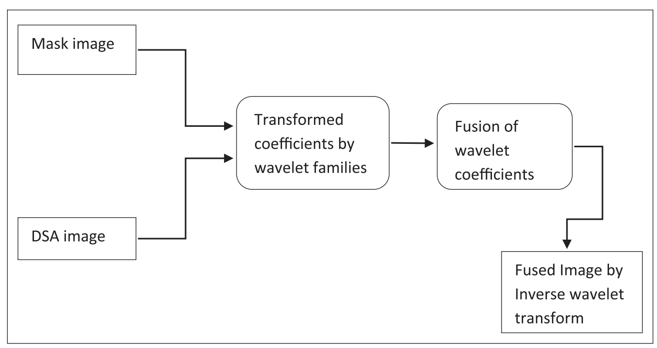

Figure 1: Proposed methodology

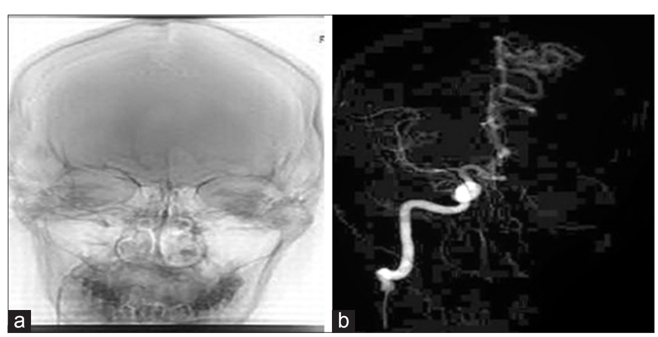

Figure 2: (a) Mask image, (b) digital subtraction angiography image (source images)

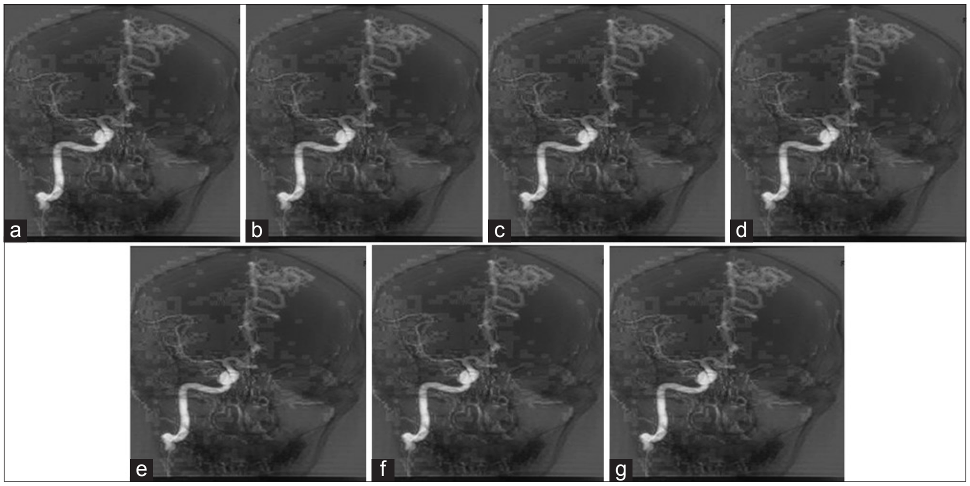

Figure 3: Fused results, (a) Biorthogonal wavelet, (b) Coifflet, (c) Daubechies, (d) Discrete Meyer, (e) Haar, (f) Reverse biothogonal, (g) symlet

Table 1: Objective evaluation

Wavelet variants	$Q^{AB/F}$	$L^{AB/F}$
Bior (2.2)	0.5450	0.455
Coiflet (2)	0.5329	0.467
Daubechies (8)	0.5528	0.447
Discrete Meyer (2)	0.5498	0.450
Haar (2)	0.5452	0.455
Reverse biorthogonal (2.2)	0.5455	0.454
Symlet (2)	0.5320	0.468

images obtained by fusing DSA and mask images using variants of wavelet transform are shown in Figure 3. The objective evaluation is shown in Table 1 which shows the total amount of information travel and the edge information transfer from source images to the fused image.

The images reconstructed with Daubechies 8 wavelet transform has the highest value of $Q^{AB/F}$ of 0.5528, and Symlet shows the least amount of $Q^{AB/F}$ of 0.5320. This can be attributed to the fact that Daubechies wavelet has the maximum number of vanishing moments whereas Symlets have a lack of symmetry. This shows that Daubechies give the highest amount of edge information transfer among the mother wavelets. However, the maximum amount of $Q^{AB/F}$ among all the wavelets is 0.5530 averaged which is not a suitable value for edge information transfer. Hence, it can be said that wavelets are not suitable for image fusion as the highest amount of $Q^{AB/F}$ factor is very low as compared to what is recorded in literature. It can be attributed to the fact that wavelets are not able to register the discontinuities along directions other than vertical and horizontal one.

CONCLUSION

We have conducted a series of an experiment on bone and vascular image fusion by using various families of the wavelet transform. Although Daubechies can perform well among all the wavelet, the overall performance of the wavelet is not up to the mark.

Attributing to fact that wavelet transform are not directionally sensitive. Hence, it is proven that Wavelet transform along with its families is not suitable for bone vessel fusion. However, one can try various other transform techniques and could combine wavelet transform with other image processing tools as wavelet alone is not able to represent image information efficiently.

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