Dual Tree Complex Wavelet Transform for Medical Image Fusion

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Abstract - *The fusion of images is the process of combining two or more images into a single image retaining important features from each. Fusion is an important technique within many disparate fields such as remote sensing, robotics and medical applications. Wavelet based fusion techniques have been reasonably effective in combining perceptually important image features. Shift invariance of the wavelet transform is important in ensuring robust sub band fusion. Therefore, the novel application of the shift invariant and directionally selective dual tree complex wavelet transform (dt-cwt) to image fusion is now introduced. This novel technique provides improved qualitative and quantitative results compared to previous wavelet fusion methods.*

***Key words*: Fusion, Shift invariance, DT-CWT.**

1. INTRODUCTION

In computer vision, Multisensory Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. Image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank, and Laplacian pyramid .Multi-sensor data fusion has become a discipline which demands more general formal solutions to a number of application cases. Several situations in image processing require both high spatial and high spectral information in a single image. This is important in remote sensing. However, the instruments are not capable of providing such information either by design or because of observational constraints. One possible solution for this is data fusion.

Image fusion methods can be broadly classified into two groups - spatial domain fusion and transform domain fusion. The fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS based methods fall under spatial domain approaches. Another important spatial domain fusion method is the high pass filtering based technique. Here the high frequency details are injected into up sampled version of MS images. 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. Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. Some other fusion methods are also there, such as Laplacian pyramid based, curvelet transform based etc. These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods.

2. LITERATURE SURVEY

Due to the compact and enhanced representation of information, image fusion has been employed in many medicalapplications.Forinstance,T_1 weighted(T1W) and T_2 weighted(T2W) magnetic resonance imaging (MRI) scans were fused to segment white matter lesions [6] or cerebral iron deposits [7] and to guide neurosurgical resection of epileptogenic lesions [8]. Computed tomography (CT) and MRI images were fused for neuron navigation in skull base tumor surgery [9]. Fusion of positron emission tomography (PET) and MRI images has proven useful for hepatic metastasis detection [10] and intracranial tumor diagnosis [11]. Single-photon emission computed tomography (SPECT) and MRI images were fused for abnormality localization in patients with tinnitus [12]. Multiple fetal cardiac ultrasound scans were fused to reduce imaging artifacts [13]. In addition, the advantages of image fusion over side-by-side analysis of non-fused images have been demonstrated in lesion detection and localization in patients with neuroendocrine tumors [14] and in patients with pretreated brain tumors [15]. Even if image fusion is not performed explicitly, e.g., by a CAD system, it is usually performed subconsciously by radiologists to compare images and better identify abnormalities [16].

A straight forward multimodal image fusion method is to overlay the source images by manipulating their transparency attributes [17], [18], or by assigning them to different color channels [6], [19].This overlaying scheme is a fundamental approach in color fusion, a type of image fusion that uses color to expand the amount of information conveyed in a single image [20], but it does not necessarily enhance the image contrast or make image features more distinguishable.

The pyramid transforms (PT) and the wavelet transform (WT) are the two categories of MSD schemes that are most commonly employed in image fusion. Among different PT schemes, Laplacian pyramid transform (LPT) is one of the most frequently used. A Laplacian pyramid (LP) is constructed based on its corresponding Gaussian pyramid (GP) by subtracting two adjacent levels. Thus, a DET in the LP encodes the local variations at that scale. The ratio of low-pass pyramid (RoLP) is also constructed based on GP, but by taking the ratio of two adjacent levels. The gradient pyramid (either explicitly or implicitly constructed) is another type of PT, which is built by applying gradient filters of different orientations to each level of a GP. A standard WT scheme is the discrete WT (DWT), which decomposes a signal into an MSR using scaling (low-pass filtering) and wavelet (high-pass filtering) functions. One drawback of DWT is shift-variance, which tends to cause artifacts along edges in the fused images. Hence, WT schemes that provide shift-invariance, such as dual-tree complex WT (DTCWT), were also employed in image fusion. Although theoretically the decomposition of an image can be performed iteratively until there is only one coefficient at APX, this will result in serious bias and inaccuracy in the feature selection at low-resolution levels, which impairs the fusion quality. Typically, only a few decomposition levels are therefore used in practice.

3. PROPOSED SYSTEM

3.1Wavelet transform domain

Using Fourier Transform (FT) only the global frequency content of a signal is retrieved, the time information is lost. By using wavelet analysis a multi-resolution analysis is possible. The frequency and time content of a signal is retrieved by Wavelet Transform (WT).The types of wavelet transform are i) Continuous Wavelet Transform (CoWT) ii) Discrete Wavelet Transform (DWT) iii) Complex Wavelet Transform (CWT).By using Fourier transform and Short Time Fourier Transform a multi resolution analysis is not possible so there is a restriction to use these tools in image processing systems, particularly in image de-noising applications. The multi-resolution analysis is possible by using wavelet analysis. A Continuous Wavelet Transform (CoWT) is calculated analogous to the Fourier transform (FT), by performing convolution between the signal and analysis function. The Discrete Wavelet Transform uses filter banks to perform the wavelet analysis.

3.2 Complex Wavelet Transform

A newly introduced technique of DWT, Orthogonal wavelet decompositions, based on separable, multi-rate filtering systems have been widely used in image and signal processing, largely for data compression. Dual-Tree complex wavelet transform [12] is introduced by Kingsbury which is a very elegant computational structure which displays near shift invariant properties.

In image processing complex wavelets have not been used due to difficulty in designing complex filters which satisfy perfect reconstruction property. To overcome this Kingsbury proposed Dual-Tree implementation of the CWT (DT CWT) [14], in which two trees of real filters are used to generate the real and imaginary parts of the a wavelet coefficients separately. The DWT suffers from following two problems 1] Lack of shift invariance these results from the down sampling operation at each level. When the input signal is shifted slightly, the amplitude of the wavelet coefficients varies so much. 2] Lack of directional selectivity - as the DWT filters are real and separable the DWT cannot distinguish between the opposing diagonal directions.

First problem of DWT can be avoided if the output of the filter from each level are not down sampled but this may increase the computational cost significantly and resulting un-decimated wavelet transform still cannot distinguish between opposing diagonals since the transform is still separable. To distinguish opposing diagonals with separable filters the filter frequency responses are required to be asymmetric for positive and negative frequencies. The way to achieve this is to use complex wavelet filters which can be made to suppress negative frequency components. Compared to separable DWT complex DWT has improved shift-invariance and directional selectivity [13]-[14].

In wavelet transform applications filter bank plays an important role. It consists of two banks namely, analysis filter bank and synthesis filter bank. The one dimensional filter bank constructed with analysis and synthesis filter bank which is shown in Fig. 1.

The analysis filter bank decomposes the input signal x (n) into two sub band signals, c (n) and d (n). The signal c (n) represents the low frequency part of x (n), while the signal d (n) represents the high frequency part of x (n). It uses filter banks to perform the wavelet analysis. The DWT decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. Using wavelet coefficient the signal can be represented in various frequency bands. Using the DWT attractive properties over linear filtering the coefficients can be processed in several ways.

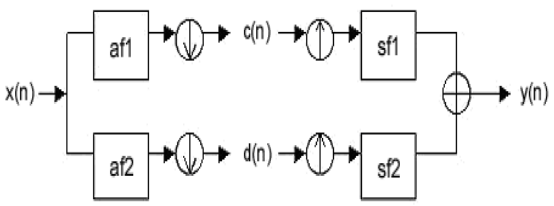

Fig -1: One dimension filter bank.

3.2 Differences between the two DWT extensions

The main differences between the dual tree Dwt and Double –Density are as follows. 1] The Dual-Tree and Double-Density DWTs are implemented with totally different filter bank structures. 2] The Dual-Tree DWT can be interpreted as a complex-valued wavelet transform which is useful for signal modeling and de-noising (the Double-Density DWT cannot be interpreted as such). 3] For the Dual-Tree DWT there are fewer degrees of freedom for design, while for the Double-Density DWT there are more degrees of freedom for design. 4] The Dual-Tree DWT can be used to implement two-dimensional transforms with directional wavelets, which is highly desirable for image processing [15].

Complex wavelet transforms (CWT) concept is introduced so that we can achieve Dual-Tree Complex DWT system. We can achieve Double-Density Dual-Tree Complex DWT system by combining the Double-Density DWT and Dual-Tree Complex DWT. Complex wavelet transforms (CWT) use complex-valued filtering (analytic filter) that decomposes the real/complex signals into real and imaginary parts in transform domain. Amplitude and phase information are calculated by using the real and imaginary coefficients.

3.3 Dual-Tree Complex WT (DTCWT)

Kingsbury's complex Dual-Tree DWT is based on (approximate) Hilbert pairs of wavelets [15]. Kingsbury found that the Dual-Tree DWT is n the second DWT [16]. Using two critically-sampled DWTs in parallel the Dual-Tree Complex DWT can be implemented as shown in early shift-invariant when the low pass filters of one DWT interpolate midway between the low pass filters of the Fig. 3.For N-point signal this transform gives 2N DWT coefficients. So this transform is known as 2-times expansive. The design of the filter is done

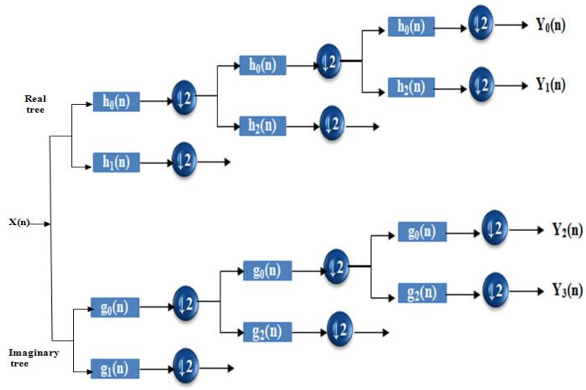

Fig -2: Design implementation of Dual-Tree Complex DWT

In such a way that the sub band signals of the upper DWT can be interpreted as the real part of a CWT and sub bands signals of the lower DWT can be interpreted as the imaginary part. For specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. In this manner, the designed DTCWT is nearly shift-invariant than the critically-sampled DWT [10]-[11]

Wavelets are given by DTCWT in six distinct directions. There are two wavelets in each direction. In each direction, one of the two wavelets can be interpreted as the real part and the other wavelet can be interpreted as the imaginary part of a complex-valued two dimensional (2D) wavelet. The DTCWT is implemented as four critically sampled separable 2D DWTs operating in parallel. Different filter sets are used along the rows and columns [10] [11].Fig4 shows the flowchart of Dual-Tree Complex DWT. This gives the steps of implementation of DTCWT.

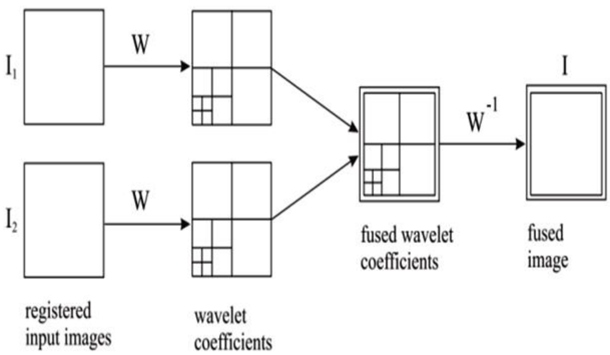

Fig -3: Fusion of the wavelet transforms of two images.

4. EXPERIMENTAL RESULTS

The following results depict the medical (MRI) images that are used for image fusion.

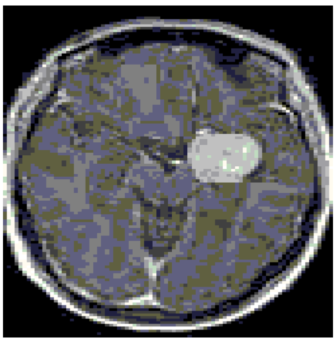

Fig -4: Input image 1

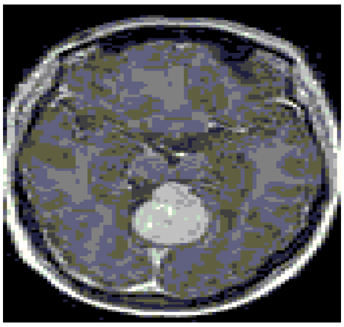

Fig -5: Input image 2

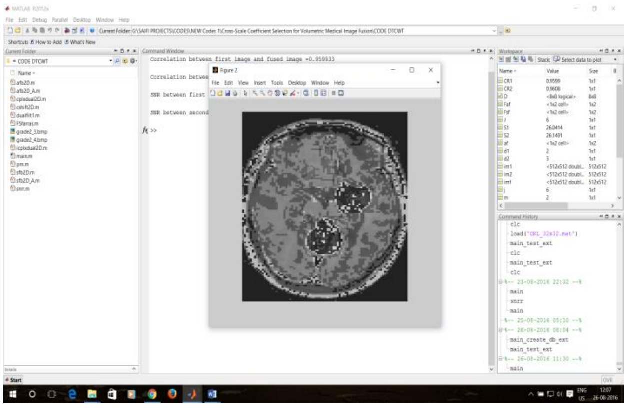

Fig -6: Fused Output image

The correlation and SNR values are as follows:

- Correlation between first image and fused image =0.959933
- Correlation between second image and fused image =0.960828
- SNR between first image and fused image =26.04 db
- SNR between second image and fused image =26.15 db

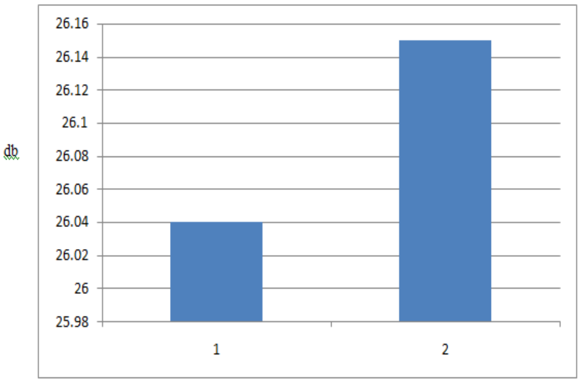

Fig -7: Bar graph showing SNR values

5. CONCLUSION

In this paper, we proposed a DT-CWT based fusion rule, which selects an optimal set of coefficients for each decomposition level and guarantees intra scale and inter scale consistencies. Experiments on volumetric medical image fusion demonstrated the effectiveness and versatility of our fusion rule, which produced fused images with higher quality than existing rules.

7. REFERENCES

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