Dual Tree Complex Wavelet Transform and Robust Organizing Feature Map in Medical Image Fusion Technique

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Abstract— Magnetic Resonance Imaging (MRI) and Computer Tomography (CT) techniques in medical image has revolutionized for medical diagnosis. From CT coordinate system, Intensity based image registration is used in MRI image. Image fusion is an advanced tool in medical imaging. To make a medical diagnosis easier and accurate, image fusion combines MRI and CT images into a single image, which contains the relevant information from the original source images. Image fusion technique is based on Dual Tree Complex Wavelet Transform (DT-CWT) and Robust Self Organizing Feature Mapping (Robust SOFM) neural network. DT_CWT decomposes the images in a multi-scale and multi-direction to extract important features. The Robust SOFM neural network is utilized to recognize the complementary features. These features are integrated using a criteria based on activity level. Fused of both MR, CT images are made from a fused feature set. Finally the fused image is attained by executing Inverse Dual Tree Complex Wavelet Transform (IDTCWT). The experimental results show that the proposed algorithm can significantly outperform image fusion technique and has a better Peak Signal to Noise Ratio (PSNR) value as compared with other transforms, DWT, FDCT, NSCT, and DTCWT.

Keywords: Intensity based Image Registration, Dual Tree Complex Wavelet Transform, Robust Self Organizing Feature Mapping.

1. Introduction

Medical imaging is the technique of making visual representations of the inner part of a body of clinical and medical analysis. Medical imaging tries to reveal inner structures covered up by the skin and bones, and in addition to diagnose and treat disease. Additionally, medical imaging secures a database of typical anatomy and physiology to make it conceivable to recognize abnormalities. Multimodality medical images are required to support more accurate clinical data for doctors to manage with medical diagnosis, such as X-ray, CT, MRI, and magnetic resonance angiography (MRA) images [1]. These medical images generally provide correlative and occasionally conflicting data. The CT images can yield information about bones, implants with less distortion, however it cannot identify physiological changes. The MR images can yield information about typical and neurotic soft tissue data; however, it cannot help the bones information. In this situation, fusion of the multimodal medical images only sufficient to provide accurate clinical necessities to the doctors. Thus, the fusion of the medical images is essential and very challenging in research areas [2]. Image registration process performs to transform different coordinate systems into one coordinate system. Intensity based image registration is used for medical images, because it registers entire images or sub-images and correspond feature points in images [3].

Image fusion is defined as the methodology of combing multiple input images or their features into a single image without loss of information [4–5]. Thus, the fused image contains a more accurate and more suitable for human visual [6]. The fusion of medical images not only lead to additional clinical information compare with the individual images, but also reduce the storage cost of storing single fused image rather than multi source images. Generally, the image fusion methods can be grouped into three levels, such as pixel, feature, and decision levels.

Image fusion based on Discrete Wavelet Transform (DWT) developed faster. It has good time-frequency characteristics. The drawback of DWT is that problem of filling missing data occur. Fast Discrete Curvelet Transforms (FDCT) [7] is simpler, faster, and less redundant than DWT. Non-Subsampled Contoulet Transform (NSCT) can be partitioned into two stages incorporates Non-Subsampled Pyramid (NSP) and Non-Subsampled Directional filter bank (NSDFB). The main disadvantage of curvelet method is that it has the disadvantage of poor directional specificity. The DTCWT is an enhancement to the discrete wavelet transform (DWT), with main properties: It is close to shift invariant and directionally selective in two or higher dimensions. It achieves with a redundancy factor of two dimensional signals, which is substantially lower than DWT. The multi-dimensional DT-CWT is non-separable and it is based on a computationally efficient and separable filter bank (FB). In a neural network, Kohonen proposed SOFM network in 1981. SOFM is based on Artificial Neural Network (ANN), the nodes of which become particularly tuned to different input signal patterns through an unverified learning process.
Any dimension of the SOFM input signals can be transformed into a one-dimensional or a two-dimensional discrete grid. And it depends upon the human cerebral cortex function imitation. SOFM has the characteristics of automatic identification and classification. The SOFM neural network [8] algorithm is an unsupervised learning, can automatically classify the samples and achieve better classification results in less number of trained samples. Most importantly, as compare with SOFM, Robust SOFM networks can parallel processing to improve the speed of the operation twice.

This paper is classified as follows. Section II starts with a brief review of DT-CWT. Section III presents Robust SOFM neural network algorithm. Section IV describes the proposed algorithm. Experimental results of the proposed technique presented in Section V. And finally Section IV concludes this paper.

2. Dual Tree Complex Wavelet Transform

The DWT is predominantly acquired by a perfect reconstruction (PR) filter bank (FB) on its lowpass output, and decomposes a discrete-time signal according to octave-band frequency decomposition. Though, the DWT is not only far away from shift invariant, but also not generate a geometrically oriented decomposition in multiple dimensions. Additionally the wavelet FB used by the DWT, the DT-CWT [9-11] uses a second wavelet FB. Particularly, the second wavelet FB is decomposed so that its impulse responses are almost same to the discrete Hilbert transforms (DHT) of the first wavelet FB. At that point, the first FB as the real part and the second FB as the imaginary part of a complex transform. The frequency response of each one channel is important for the DT-CWT to possess its desirable properties.

As compared with real valued DWT, DT-CWT has two advantages. 1. It has better edge representation. 2. Approximate shift-invariant property. The DT-CWT utilizes two genuine DWTs; 1. The real part of the DWT transforms 2. The imaginary part of the DWT transforms. The analysis and synthesis FBs utilized to implement the DT-CWT are represented in Fig. 1 and Fig. 2. The two real DWTs utilize two separate sets of filters, with each one fulfilling the PR conditions. These sets of filters are designed together; hence the overall transform is almost analytic. The DT-CWT consists of two DWTs operating in parallel on an input signal as outlined in Fig. 1. Let $h_o(n)$ and $h_i(n)$ denote that the low-pass and high-pass filter pair for the upper FB respectively, and let $h'_o(n)$ and $h'_i(n)$ denote that the low-pass and high-pass filter pair for the lower FB respectively.

Therefore the first and second wavelet FBs are associated as $\psi(t)$ and $\psi'(t)$ respectively. The wavelet $\psi(t)$ is characterized by

$$\psi(t) = \sqrt{2} \sum_n h_i(n) \phi(2t - n),$$

(1)

Where

$$\phi(t) = \sqrt{2} \sum_n h_o(n) \phi(2t - n).$$
The second wavelet $\psi'(t)$ is characterized in terms of $[h_0(n), h_1(n)]$.

In addition to fulfilling the conditions of PR, the filters are designed so that the complex wavelet $\psi(t) = \psi(t) + j\psi'(t)$ is almost analytic. Identically, it is designed that $\psi'(t)$ is similar to the Hilbert transform of $\psi(t)$ denoted as $\psi'(t) = \mathcal{H}(\psi(t))$.

The inverse DT-CWT transform is as simple as the forward DT-CWT transform. To inverse the transform, each of the real and the imaginary parts are inverted. To obtain the final output, the inverse of each of the two real DWTs is averaged. Note that the novel signal $x(n)$ can be recovered from either the real or imaginary part. If the real of two DWTs are signified by the square matrices $F_h$ and $F'_h$, then the DT-CWT can be represented by the rectangular matrix

$$F = \begin{bmatrix} F_h & 0 \\ 0 & F'_h \end{bmatrix}.$$  

If the vector $x$ signifies a real signal, then $w_h = F_h x$ and $w'_h = F'_h x$ signifies the real and imaginary parts of the DT-CWT respectively. Then complex coefficients can be characterized by $w_h + jw'_h$.

An inverse of $F$ can be defined as

$$F^{-1} = \frac{1}{2} \begin{bmatrix} F_h^{-1} & F_h^{-1} \\ F_h^{-1} & F_h^{-1} \end{bmatrix},$$

And verified as

$$F \cdot F^{-1} = \begin{bmatrix} F_h & 0 \\ 0 & F'_h \end{bmatrix} \cdot \frac{1}{2} \begin{bmatrix} F_h^{-1} & F_h^{-1} \\ F_h^{-1} & F_h^{-1} \end{bmatrix} = \frac{1}{2} |I + I| = I.$$

The main factor of one half between the forward and inverse transforms, to attain

$$F: = \frac{1}{\sqrt{2}} \begin{bmatrix} F_h & 0 \\ 0 & F'_h \end{bmatrix}, F^{-1} = \frac{1}{\sqrt{2}} \begin{bmatrix} F_h^{-1} & F_h^{-1} \\ F_h^{-1} & F_h^{-1} \end{bmatrix}$$ (2)

Fig. 2. Synthesis FB for the DT-CWT

If the transpose of $F_h$ is its inverse $F_h^T \cdot F_h = F_h^T \cdot F_h = I$, Then, two real DWTs are orthonormal transforms. Here, the transpose of the rectangular matrix $F$ is also an inverse $F^T \cdot F = I$. Eq. (2) can be described that the IDT-CWT can be performed utilizing the transpose of the forward transform of the DT-CWT. From eq. (2), the dual-tree wavelet transform maintains the real parts and imaginary parts of the complex wavelet transform coefficients individually. However, the complex coefficients can be calculated by utilizing the following form:

$$F_{c} = \begin{bmatrix} I & jI \\ jI & -I \end{bmatrix} \cdot \begin{bmatrix} F_h \end{bmatrix},$$ \hspace{1cm} (3)

$$F_{c}^{-1} = \begin{bmatrix} F_h^{-1} & F_h^{-1} \end{bmatrix} \cdot \begin{bmatrix} I & jI \\ jI & -I \end{bmatrix},$$ \hspace{1cm} (4)

In eq. (3), the complex sum/difference matrix is unitary.
Hence, if two real DWTs are orthonormal transforms, then DT-CWT satisfies \( F_c \cdot F_c^* = I \), where * denotes conjugate transpose. For a real N-point signal, eq. (3) yields 2N complex coefficients, although N of these coefficients is the complex conjugates to other N coefficients. Eq. (3) classified that for a general complex N-point signal, it yields 2N complex coefficients. Hence, for both real and complex input signals, the CWT is twice expansive. When the real parts of two DWTs are orthonormal and the \( \frac{1}{\sqrt{2}} \) factor is included in eq. (2), the DT-CWT increases a Parseval’s energy theorem, i.e., the input energy signal is equivalent to the energy in the wavelet domain

\[
\sum_{j,n} (|d_j(n)|^2 + |d_j^*(n)|^2) = \sum_n |x(n)|^2.
\]

The DT-CWT is easy to implement. Because no data flow between the two real DWTs, it can be implemented in both software and hardware.

3. Robust Self-Organizing Feature Map (Robust SOFM)

The SOFM neural network structure is demonstrated in Fig. 3. SOFM network consists of two layers: 1. Lower layer for input, 2. Upper for the output layer.

![The SOFM structure](image)

SOFM network is connected fully, each one of input neuron nodes is connected to all output neuron nodes. Whenever the Euclidean Distance (ED) is the minimum, input neurons, input vectors and the weights of output neurons are activated. At this point the connection weights are modified by the network at termination condition. The output neuron is called as the competitive winning neuron. Although in a few regions SOFM algorithm gets problematic. The SOFM network convergence speed is slow.

In SOFM, few neurons in the output layer weights regularly win probability and adjust, but few neurons weights infrequently adjust effeitely. And the network’s learning process and results are unfair at different initial conditions and input samples. The main advantage is that the following features are dealing with the unidentified image. Robust SOFM is used to enhance the convergence speed of the SOFM neural network and by utilizing of limited samples train neural network and also enhance the classification accuracy of neural network. Hence, Robust SOFM successfully reduces the calculation time of SOFM. This Robust SOFM algorithm enhances the compression ratio as well as reducing the search range and computation time.
4. Proposed Method

In the proposed method is demonstrated in Fig. 4. The following steps describe the proposed algorithm.
1. Select Medical images; MRI and CT. And obtained images are progressively decomposed by DT-CWT. Select Medical images; MRI and CT. The intensity based image registration done in MRI to position same coordination. And obtained images are progressively decomposed by DT-CWT.
2. DT-CWT generates sets of coefficients (Approximation and Details) at each level of decomposition. The coefficients at each level represent sets of the image feature vector. Features can be the pixel intensities.

\[ \psi(t) = \sqrt{2} \sum_{n} h_1(n) \varnothing(2t - n) \]

Where

\[ \varnothing(t) = \sqrt{2} \sum_{n} h_0(n) \varnothing(2t - n). \]

Fig. 4. Proposed Architecture for image fusion
To fulfill the PR conditions, the filters are designed so that the complex wavelet \( \psi_f(t) = \psi(t) + j\psi'(t) \) is almost analytic. The \( \psi'(t) \) is similar to the Hilbert transform of \( \psi(t) \)

\[
\psi'(t) = \mathcal{H}\{\psi(t)\}
\]

3. The robust SOFM neural network is utilized to recognize and extract the features. This can be done by training and simulating the network for the resultant coefficients (approximation and detail) of each level of MR and CT images.

(i) For small random values, first of all initialize the weights \( W_{jk} \) (1 \(< j < n; 1 < k < m)\), where \( m \) specifies that the total number of nodes, shown in Fig. 3. And simultaneously set the neighborhood of the node \( j^* \) as \( NE_{j^*}(t) \).

(ii) Input \( X = \{X_1(t), X_2(t), X_3(t), \ldots, X_n(t)\} \). And the sum of the input \( X \) is \( S_x \). Here \( X_i(t) \) is nothing but the \( t^{th} \) input to the neighborhood of the node \( j^* \), its each neuron is in parallel at time \( t \) and the sum of neighborhood code \( W_{jk} \) is \( S_{wk} \).

\[
S_x = \sum_{k=0}^{m-1} x_l
\]

\[
S_{wk} = \sum_{k=0}^{m-1} y_l
\]

(iii) Compute the distance \( d_j \) between the inputs \( X_i(t) \) and node \( W_{jk}(t) \).

\[
d_j = \sum_{l=1}^{n}(X_i(t) - W_{jk}(t))^2
\]

Use \( j^* \) to determine the minimum distance \( d_{j^*} \).

\[
d_{j^*} = \min_{1 \leq j \leq n-1} \left\{ \sum_{l=1}^{n}(X_i(t) - W_{jk}(t))^2 \right\}
\]

(iv) The distortion between \( x_i \) and \( W_{jk} \)

\[
d(x_i, W_{jk}) \geq \left( S_x - S_{wk} \right)^2 / m
\]

The minimum distortion \( d_{min} \) can be defined as

\[
\left( S_x - S_{wk} \right)^2 \geq MD
\]

\[
d(x_i, W_{jk}) > d_{min}
\]

Where \( MD = k \times d_{min} \)

(v) To eliminate distance calculations, (8) and (9) should be satisfied, and then the neighborhood code \( W_{jk} \) can be excluded. So, the new weights for \( j^* \) in \( n_{j^*}(t) \) is defined as

\[
W_{jk}(t + 1) = W_{jk}(t) + \alpha(t) \left[ \frac{1}{n_{j^*}} \sum_{d_{j^*}} X_i(t) - W_{jk}(t) \right]
\]

\( \alpha(t) \) and \( \cdot NE_{j^*}(t) \) are controlled to decrease in \( t \). And \( t \) is the number of iterations. \( \sum d_{j^*} X_i(t) \) is the sum of the \( k^{th} \) component of the training vectors. and to converges, the range of \( \alpha(t) \) should be \((0, 1)\).

(vi) The above process achieved the maximum numbers of iterations stop the process, else repeat step (i) to (iii).

4. By using the fusion technique, merge the approximation and detail coefficients.

5. Apply IDTCWT to the fusion result to get the final fused image \( I_f \).

5. Result and Discussion

Quantitative evaluation results demonstrate that the proposed method gives better performance for multiclass object classification in comparison to other state-of-the-art methods. Experiment results show that the PSNR of the fusion method based on DT-CWT with Robust SOFM is better than the fusion methods of DWT, FDCT, NSCT, and DTCWT, shown in Fig. 5. Table 1 describes that the PSNR of fused images are compared with the PSNR of both MR and CT images of different transform methods, shown in Fig. 6 and Fig. 7 respectively.

**Peak Signal to Noise Ratio (PSNR):** To get better fusion results, the PSNR value will be high.

\[
PSNR = 20 \log_{10} \left[ \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{I_f(i,j) - I_{j}(i,j)}{L^2} \right]
\]

Where \( L = \) No. of gray levels in the image.
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Fig. 5. (a) MR images; (b) CT images; Fused Images (c) DWT; (d) FDCT; (e) NSCT; (f) DT-CWT; (e) DTCWT-SOFM
6. Conclusion

In medical image processing applications, specifically in MRI and CT images, the edge preserve is an important in complementary details of input images. DT-CWT is implemented using two real wavelet transforms. Robust SOFM networks can be parallel processed to improve the speed of the operation and for the characteristics of automatic identification. Thus, the fused image contains a more accurate and more suitable for human visual. Through the results, as compared with the DWT, FDCT, NSCT and DTCWT fusion methods we found that image fusion method DTCWT with Robust SOFM gives better PSNR value.

References


