Research Article

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Oil exploration oriented multi-sensor image fusion algorithm

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Abstract: In order to accurately forecast the fracture and fracture dominance direction in oil exploration, in this paper, we propose a novel multi-sensor image fusion algorithm. The main innovations of this paper lie in that we introduce Dual-tree complex wavelet transform (DTCWT) in data fusion and divide an image to several regions before image fusion. DTCWT refers to a new type of wavelet transform, and it is designed to solve the problem of signal decomposition and reconstruction based on two parallel transforms of real wavelet. We utilize DTCWT to segment the features of the input images and generate a region map, and then exploit normalized Shannon entropy of a region to design the priority function. To test the effectiveness of our proposed multi-sensor image fusion algorithm, four standard pairs of images are used to construct the dataset. Experimental results demonstrate that the proposed algorithm can achieve high accuracy in multi-sensor image fusion, especially for images of oil exploration.

Keywords: Oil exploration, Multi-sensor image fusion, Dual-tree complex wavelet transform, Priority map, Hilbert transform

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1 Introduction

Oil and gas exploration is a very complicated process, which involves a wide range of different disciplines and applications [1]. Therefore, it is of great importance to introduce computer science in oil and gas exploration. It is very significant to utilize computers to save, manage and use a large number of valuable professional information in the process of oil exploration, and then design new exploration and production methods [2, 3]. With the rapid popularization of information techniques in the petroleum industry, how to promote the management efficiency of petroleum enterprise is a key issue for us to solve [4].

With the development of the petroleum seismic exploration technology, especially the development of multi wave seismic exploration technology, people can easily obtain information about the fissures, cracks and other information about oil and gas [5, 6]. As the information obtained by various methods is influenced by many factors, the uncertainty may be high. [7]. Utilizing an effective data fusion method to fuse the information in oil exploration, the fracture and fracture dominance direction can be estimated with high accuracy [8].

In recent years, image fusion has become an important issue in the image processing community. The target of image fusion is to generate a composite image by integrating the complementary information from multiple source images of the same scene [9]. For an image fusion system, the input source images can be acquired from either different types of imaging sensors or a sensor whose optical parameters can be changed, and the output fused image will be more suitable for human or machine perception than any individual source image [10]. The fused image is able to describe multiple properties of source images, which makes it more suitable for the aim of human visual perception and computer processing tasks [11, 12]. Multi-sensor image fusion means a new branch of research which contains sensors, signal processing, image processing, and artificial intelligence. Image fusion technique has been widely employed in many applications such as computer vision, surveillance, medical imaging, and remote sensing [13].

In this paper, we propose a novel oil exploration oriented multi-sensor image fusion algorithm, and main innovations of it lie in the following aspects:

(1) we introduce DTCWT in data fusion and divide an image to several regions before image fusion.

(2) DTCWT is exploited to divide features of the input images and generate a region map, and then normalized
Shannon entropy of a region is used to implement the priority function.

The rest of the paper is organized as follows. Related works about multi-sensor image fusion are provided in section 2. In Section 3, we illustrate the dual-tree complex wavelet transform theory. Section 4 proposes the region-based multi-sensor image fusion algorithm based on DTCWT. In section 5, experiments are conducted to make performance evaluation for the proposed algorithm. In the end, the whole paper is concluded in section 5.

2 Related works

Multi-sensor image fusion belongs to information fusion, which denotes the synergistic integration of various sources of sensory image into one image. The information to be fused may be collected from various sensors of the same object or scene, or from the same sensor of different imaging manner, or from different images of different time period. In this section, we provide and analyze related works about multi-sensor image fusion.

Wang et al. proposed a new approach based on non-subsampled shearlet transform and multi-scale top-hat transform to fuse the Synthetic Aperture Radar (SAR) images, infrared image and visible light image. Particularly, three original images are decomposed into low frequency sub-band coefficients and the band pass direction sub-band coefficients by the proposed algorithm. Furthermore, this reduces the negative influence of noises of SAR and infrared image on the image after fusion [14].

Li et al. proposed a fast mutual modulation fusion algorithm for multi-sensor images. In this paper, two source images are magnified by factors that are obtained from the ratio of the corresponding pixel energy. Afterwards, an offset term achieved by calculating statistical parameters of source images is given [15].

Heideklang et al. proposed a new algorithm framework to enhance the detection of near-surface defects in magnetizable and conductive specimens by integrating the measurements of eddy current, magnetic flux leakage and thermography testing. The main contribution of this paper is to design different signal processing approaches for data normalization with the pixel level [16].

Furtado et al. aimed to compare performance of two different image classification methods, that is 1) synthetically fused optical and SAR images, and 2) multi-sensor classification of paired SAR and optical images. Utilizing the multi-sensor and image fusion technique, the author found that optical-based classifications performed better than SAR-based classifications [17].

Jung et al. compared the fused images obtained from various scaling factors and tested the performance of the proposed algorithm at urban and rural test areas. Experimental results demonstrated that that the proposed algorithm can merge the spatial resolution and the temperature information of image with high accuracy [18].

Abdikan et al. investigated quality-assessment algorithms of multi-sensor data fusion. Particularly, three SAR data-sets from different types of sensors and optical data from SPOT-2 (a type of satellite) were applied.

Furthermore, this work provided a comparative study of multi-sensor fusion approaches, which is the intensity-hue-saturation, Ehlers, and Brovey techniques, through utilizing various statistical analysis techniques [19].

Yang et al. proposed a new discrete wavelet transform based multi-sensor image fusion approach, which is designed by setting various fusion schemes for low frequency and high frequency coefficients. Particularly, the wavelet coefficients of the approximant and detail sub-images are fused using a variance based policy and a wavelet entropy based policy [20].

Wang et al. proposed a tunable-Q contourlet transform (CT) for multi-sensor texture-image fusion. In this work, the authors exploited a multi-scale pyramid to decompose an image into frequency channels which have the same bandwidth on a logarithmic scale. Experimental results proved that image fusion based on the tunable-Q CT is able to effectively extract texture details from high-resolution images [21].

Apart from the above works, other techniques have been used to fuse images obtained from multiple sensors, such as blind source separation [22], PCA and lifting wavelet transformation [23], pulse-coupled neural network [24], and wavelet transforms [25].

In contrast to the above works, in this paper, we integrate the Dual-tree complex wavelet transform theory and region based policy together to fuse images which are obtained from various visual sensors.

3 Dual-tree complex wavelet transform theory

It is well known that a wavelet series denotes a representation of a square-integrable function by a certain orthonormal series that is generated by a wavelet [26]. Furthermore, wavelet transformation means one of the time frequency based transformations [27]. The structure of the dual-tree
complex wavelet transform is illustrated in Fig. 1 and Fig. 2.

![Figure 1: Decomposition process of the dual-tree complex wavelet transform](image1)

![Figure 2: Reconstruction process of the dual-tree complex wavelet transform](image2)

Dual-tree complex wavelet transform (denoted as DTCWT) is a new type of wavelet transform, it aims to tackle the issue of signal decomposition and reconstruction through two parallel transforms of real wavelet [28, 29]. Particularly, each tree in DTCWT contains the following filters, that is, a) low-pass filter (represented as \( h_0 \) and \( g_0 \)) and b) high-pass filter (represented as \( h_1 \) and \( g_1 \)) [30]. However, the parallel wavelet filter bank trees are designed to calculate thee coefficient of the complex wavelet. In order to use decomposition coefficients of the trees, filters within a tree may give delays [31, 32].

It can be observed from Fig. 1 and Fig. 2 that the key issue of dual-tree complex wavelet transforms is to design the decomposition process and reconstruction process. To tackle the multi-sensor image fusion task, signal \( f(x, y) \) of an image is decomposed based on a complex scaling function, which is illustrated by the following equation.

\[
f(x, y) = \sum_{l \in \mathbb{Z}^2} A_{j_0, l} \phi_{j_0, l}(x, y) + \sum_{k \in a} \sum_{j=1}^{j_0} \sum_{l \in \mathbb{Z}^2} D_{j, l}^k \psi_{j, l}^k(x, y)
\]

where \( j_0 \) is the number of decomposition level, and \( A_{j_0, l} \) and \( D_{j, l}^k \) mean the scaling coefficients and wavelet coefficients respectively. Moreover, \( \phi_{j_0, l}(x, y) \) refers to the scaling coefficients, and \( \psi_{j, l}^k(x, y) \) represents the wavelet functions which are oriented at different directions.

2D wavelet \( \varphi(x, y) \) is equal to \( \varphi(x) \cdot \varphi(y) \), and \( \varphi_{h}(t) \) is almost equal to the Hilbert transform of \( \varphi_{h}(t) \). Based on the above definitions, wavelets are defined as follows.

\[
\varphi_1(x, y) = \frac{1}{\sqrt{2}} \cdot (\varphi_{1,1}(x, y) - \varphi_{2,1}(x, y)), \quad i \in \{1, 2, 3\}
\]

\[
\varphi_{i+3}(x, y) = \frac{1}{\sqrt{2}} \cdot (\varphi_{1,1}(x, y) + \varphi_{2,1}(x, y)), \quad i \in \{1, 2, 3\}
\]

## 4 Region-based multi-sensor image fusion algorithm based on DTCWT

We suppose that there are \( N \) 2D source images \( I_1, I_2, \cdots, I_N \) of \( K \times L \) pixels, and we also suppose that \( T_\Theta : I \rightarrow I' \) refers to a transformation. Moreover, the symbol \( T_\Theta \) means the transformation which is parameterized by \( \Theta \). Assume that \( R_\Phi : I \rightarrow (R_{I_1}, R_{I_1}, \cdots, R_{I_n}) \) is defined as a transformation, and image \( I \in I_1 \) is satisfied. For a given image \( I_i \), it is segmented to \( n \) region in the process of transformation. Moreover, a region \( R_i \) can be converted to vector \( V(R_i), \quad i \in \{1, 2, \cdots, n\} \). We define the transformation process as follows.

\[
W_\Phi : V_{R_i} \rightarrow \overline{V}_{R_i}
\]

where \( \overline{V}_{R_i} \) denotes a weighted region vector of image \( I_i \), and our proposed image fusion algorithm is based on dividing an image to several regions. Parameter \( W_\Phi \) is the transformation which is weighted by \( \Phi \). For \( N \) registered images \( I_1, I_2, \cdots, I_N \), they are transformed by DTCWT as follows.

\[
[D_n, A_n] = \omega(I_n)
\]

where \( A_n \) refers to the approximation of the image at the highest level, and \( D_n \) is the textural information.
For an image which is obtained for a sensor, it is divided into several regions, that is, \( I_n = \{ R_1, R_2, \cdots, R_N \} \), where \( R_n = \{ r_{n,1}, r_{n,2}, \cdots, r_{n,T_n} \} \) \( n \in N \). Particularly, the map is down sampled to provide a segmentation map at each level of the transform. In the process of down sampling, the pixel priority is set higher for the smaller region. Furthermore, a priority map [34–36] is defined as follows.

\[
P_n = \{ p_{n,r_{n,1}}, p_{n,r_{n,2}}, \cdots, p_{n,r_{n,T_n}} \} \quad n \in N \tag{6}
\]

Next, we aim to select the region with highest priority to make a decision the coefficient to represent a region \( t \).

\[
M_t = \phi \left( p_{1,t}, p_{2,t}, \cdots, p_{N,t} \right) \tag{7}
\]

Based on the above steps, images from multi-sensors are fused by inverse transform as follows.

\[
F = \omega^{-1}(D_F, A_F) \tag{8}
\]

where \( \omega^{-1} \) means the inverse transform. As image segmentation process is very time consuming and weights of various image regions should be determined, in this work, we utilize normalized Shannon entropy of a region to be the priority function, which is defined as follows.

\[
P(r_{t_n}) = \frac{1}{|r_{t_n}|} \sum_{\forall \theta \in \mathcal{V} \cap \{x,y\} \in r_{t_n}} d^2_m(\theta, j)(x, y) \log d^2_m(\theta, j)(x, y) \tag{9}
\]

where \(|r_{t_n}|\) refers to size of region \( r_{t_n} \) in image \( n \), and \( d^2_m(\theta, j) \) is the detail coefficient of DTCWT in image segmentation process. Then, a mask \( M \) is obtained by determining which image region should be chosen from the fused image.

Furthermore, we allocate priority to image regions and exploit SSIM map between two adjacent images by the following equation.

\[
P(r_{t_n}) = SSIM_n(r_{t_n}) - SSIM_{n-1}(r_{t_n}) \tag{10}
\]

where \( SSIM_n(r_{t_n}) \) refers to the average SSIM value for the image region \( r_{t_n} \).

\section{5 Experiment}

In this section, experiments are conducted to test the performance of our proposed algorithm in oil exploration oriented image fusion.

\subsection{5.1 Experimental Dataset}

To compare algorithm performance with other methods, we choose four standard pairs of source images to construct the dataset, such as 1) Pepsi, 2) Clock, 3) Flower, 4) Leaf (shown in Fig. 3).

\subsection{5.2 Performance evaluation metric}

To evaluate the performance of various image fusion methods objectively, we should make quantitative evaluation for our proposed algorithm. As the visual diversity of images, it is very difficult to evaluate image fusion results. Therefore, we introduce several different performance metrics to make performance evaluation. In this subsection, we illustrate the performance evaluation metrics used in this experiment.

\subsection{5.2.1 Metric 1: Mutual information (MI)}

Mutual information is used to calculate the amount of information transferred from source image to the image after fusion, and it is defined as follows.

\[
MI(I_S, I_F) = H(I_S) + H(I_F) - H(I_S, I_F) \tag{11}
\]

where \( H(I_S, I_F) \) denotes the joint entropy between the source image \( I_S \) and the image \( I_F \) after fusion, and \( H(I_S), H(I_F) \) refer to the marginal entropy of \( I_S, I_F \).

\subsection{5.2.2 Metric 2: Cross entropy (CE)}

CE is defined as the cross entropy of images as follows.

\[
CE = \sum_{x=0}^{255} p_x^l \cdot \ln \left( \frac{p_x^l}{p_x^f} \right) \tag{12}
\]

where \( p_x \) denotes the probability distribution of pixels with the value equals of the whole number of pixels.
5.2.3 Metric 3: Amount of edge information

$Q_{AB/F}$ demonstrates the number of edge information which are successfully transferred from the input images into the image be fused, and it is defined as follows.

$$Q_{AB/F} = \frac{\sum_{x=1}^{M} \sum_{y=1}^{N} \left( (Q_{I_1} I_1 F(x, y) \cdot w_{I_1}(x, y)) + (Q_{I_2} I_2 F(x, y) \cdot w_{I_2}(x, y)) \right)}{\sum_{x=1}^{M} \sum_{y=1}^{N} (w_{I_1}(x, y) + w_{I_2}(x, y))}$$

(13)

where $Q_{I_1} I_1 F(x, y)$ and $Q_{I_2} I_2 F(x, y)$ denote values of edge and orientation at the point $(x, y)$, moreover, $w_{I_1}(x, y)$ and $w_{I_2}(x, y)$ mean weight of $Q_{I_1} I_1 F(x, y)$ and $Q_{I_2} I_2 F(x, y)$ respectively.

5.3 Experimental results and analysis

The performance of the proposed method is verified against existing multi-sensor image fusion algorithm, that is, 1) Average method (denoted as Av), 2) Select maximum method (denoted as Max), 3) PCA method (denoted as PCA), 4) Gradient Pyramid method (denoted as GP), 5) Laplacian Pyramid method (denoted as LP), 6) Curvelet method (denoted as CVT) [33]. Experimental results of the above four images using various performance evaluation metrics are shown in Fig. 4 to Fig. 7.

It can be observed clearly from Fig. 5 to Fig. 7 that for all images our proposed algorithm achieves highest value of MI and $Q_{AB/F}$, on the other hand, our proposed algorithm obtains lowest value of CE value among all test methods. That is to say, our proposed algorithm is able to preserve more effective and comprehensive information from source images, and then obtain a fused image with high accuracy.

Apart from the image fusion accuracy, we also want to test the computation cost for our algorithm. For the sake of fairness, program codes of all methods are implemented in MATLAB R2012a software on a 2.3 GHz Intel (R) Core(TM) CPU using 4GB RAM.

Table 1 illustrates that the time consumption of our proposed algorithm is only lower than CVT, and the computation efficiency of our algorithm is not satisfactory. As our algorithm can significantly promote the accuracy of multi-sensor image fusion, we still can say that the proposed is suitable to be used in multi-sensor image fusion.

Afterwards, to testify that the performance of our algorithm in the domain of oil exploration, we give two pairs of images (denoted as source image 1 and source image 2 respectively) in oil exploration and then provide the fusion

Figure 4: Performance evaluation for the image - Pepsi
Figure 5: Performance evaluation for the image - Clock

Figure 6: Performance evaluation for the image - Flower
Table 1: Computation efficiency for different methods

<table>
<thead>
<tr>
<th>Image fusion method</th>
<th>Pepsi</th>
<th>Clock</th>
<th>Flower</th>
<th>Leaf</th>
</tr>
</thead>
<tbody>
<tr>
<td>Av</td>
<td>0.127</td>
<td>0.127</td>
<td>0.122</td>
<td>0.126</td>
</tr>
<tr>
<td>Max</td>
<td>0.357</td>
<td>0.339</td>
<td>0.362</td>
<td>0.342</td>
</tr>
<tr>
<td>PCA</td>
<td>0.114</td>
<td>0.119</td>
<td>0.117</td>
<td>0.117</td>
</tr>
<tr>
<td>GP</td>
<td>0.358</td>
<td>0.358</td>
<td>0.366</td>
<td>0.355</td>
</tr>
<tr>
<td>LP</td>
<td>0.124</td>
<td>0.128</td>
<td>0.130</td>
<td>0.125</td>
</tr>
<tr>
<td>CVT</td>
<td>6.85</td>
<td>6.689</td>
<td>6.929</td>
<td>6.718</td>
</tr>
<tr>
<td>Our proposed algorithm</td>
<td>5.281</td>
<td>5.104</td>
<td>5.337</td>
<td>5.371</td>
</tr>
</tbody>
</table>

Figure 7: Performance evaluation for the image - Leaf

Figure 8: Image fusion results for images in Fig.3

result. Particularly, source image 1 and source image 2 refer to the seismic attribute diagram and the distribution map of fracture system respectively (shown in Table 2).

Table 2: Multi-sensor image fusion results for oil exploration

<table>
<thead>
<tr>
<th>Source image 1</th>
<th>Source image 2</th>
<th>Fusion result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pepsi</td>
<td>Clock</td>
<td>Flower</td>
</tr>
</tbody>
</table>

From Table 2, we can see that using the proposed algorithm, the most useful information of oil exploration is preserved in the final fused results, and our proposed method is able to preserve most important information and prune noisy data in the source images. Integrating all the above experimental results, the conclusion can be drawn that our proposed method can achieve high quality multi-sensor image fusion results.
6 Conclusion and future works

This paper aims to present a novel multi-sensor image fusion algorithm for oil exploration. We utilize dual-tree complex wavelet transform in multiple images fusion and separate an image to several regions before image fusion. In our work, DTCWT is exploited to segment the features of the input images and generate a region map, and the normalized Shannon entropy of a region is used to generate the priority function. Experimental results prove that the proposed algorithm is able to preserve the most important information of oil exploration after multi-sensor image fusion.

As the computation efficiency of our algorithm is not satisfactory to us, in the future, we will try to introduce parallel computing policy in our work, and then significantly promote computation efficiency.

References


