Multi-source remote sensing image matching based on contourlet transform and Tsallis entropy

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Abstract: There are a lot of differences in multi-source remote sensing images from various sensors about the same scene. Maximization of mutual information can be used for the multi-source image matching, but the accuracy and efficiency of image matching need to be further improved. Therefore, an algorithm for multi-source remote sensing image matching was proposed in this paper, based on contourlet transform, Tsallis entropy based mutual information and improved particle swarm optimization. Firstly, the target image and reference image were decomposed to the low resolution image using contourlet transform, respectively. Then, a new image similarity measure criterion, the Tsallis entropy based mutual information, was used to achieve the global optimization. Meanwhile, a modified extremum disturbed and simple particle swarm optimization algorithm was applied to match the lowest resolution remote sensing images. Based on the preliminary result, the matching between the higher resolution images could be implemented stepwise up to the full resolution images. The experimental results show that, compared with those of other existing remote sensing image matching methods, the proposed algorithm has the high accuracy, strong robustness and requires much fewer operations.

Key words: multi-source remote sensing image matching, contourlet transform, Tsallis entropy, particle swarm optimization

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1 INTRODUCTION

Image matching, one of the key technologies in image understanding and computer vision, has a wide application prospect in many fields, such as the vehicle cruise guidance, moving object tracking and recognition, aerial photogrammetry, video motion estimation, image retrieval and so on. In remote sensing image processing, image matching technology is applied to positioning and registration (Brown, 1992; Barbara & Jan, 2003; Zhang et al., 2005; Li et al., 2006). The region in reference image which corresponds to target image is determined by calculating the similarity. Usually, image matching methods are divided into two categories, pixel-based matching and feature-based matching. Due to the different imaging principles of multi-source remote sensors, the gray scale gap among the images of the same scene becomes large. If using the normalized cross-correlation which has high requirement on gray correlation, the matching result can hardly be satisfied, and is vulnerable to noise. If using the feature-based matching algorithm by exacting the image edges, it will generate matching errors, or even can not match for homogenous region, such as water area, because of the inconsistent edges and contours.

Since 1994, mutual information measure criterion has been used in medical image registration, and has received a wide range of research and application. It doesn’t need to make any assumption about the relationship of image gray scale. No pretreatment is required. Because of the high precision and strong robustness, mutual information measure criterion is suitable for multi-modal image matching, and therefore it is considered to apply to multi-source remote sensing image matching. Cole-Rhodes et al. (2003) introduced a multi-resolution registration of remote sensing imagery by optimization of mutual information using a stochastic gradient. The experimental results show that mutual information is more suitable than cross-correlation for multi-source image matching. Tian et al. (2006) adopted the similarity of regional mutual information in matching algorithm, to solve the issue of weak correlation among the gray spectrum. However, when applying mutual information to image matching, the precision needs to be further improved. Furthermore, estimation of mutual information, which is iteratively required, is a time-consuming process.

In view of the matching precision, Tsallis entropy (Martin et al., 2001; Furuichi, 2006; Waleed & Ben, 2009) based mutual information is considered to solve the problem. The system...
description of conventional Shannon entropy is extensive, yet practical systems have time and space correlation more or less, which are nonextensive. As a result, Tsallis proposed nonextensive entropy, namely Tsallis entropy, which is more universal, accurate and effective than Shannon entropy. According to this, we use Tsallis entropy based mutual information as similarity measure criterion, to further improve the matching precision, instead of conventional mutual information based on Shannon entropy.

Aiming at the operation efficiency, improved algorithms have been proposed in succession recently. Some (You & Bhattacharya, 2001; Yamamura et al., 2007) reduced the computation load through compressing searching space, for example, multi-resolution structure based on wavelet transform was used to match from coarse to fine. Some (Prachya et al., 2001; Xu et al., 2005; Yang & Zhang, 2006; Zhang et al., 2008) accelerated the matching speed by various optimization algorithms, and one of the most typical methods was genetic algorithm (GA), which was a non-ergodic optimization search strategy. Contourlet transform, proposed in recent years (Donoho & Vetterli, 2005), has the characteristics of multi-resolution, localization, critical sampling, directionality and anisotropy. Thus, we can use these characteristics in image matching, especially multi-resolution. As for the latter, basic genetic algorithm has poor ability of local optimization, and parameters have a great impact on the results. Particle swarm optimization (PSO) achieves swarm intelligence optimal search by studying and updating (Sjahputera & Keller, 2005; Li & Ji, 2007). Compared with genetic algorithm, PSO is simple and easy to implement, and is a highly efficient parallel search algorithm which needs less adjustable parameters. Therefore, it is expected to reduce the computation time significantly.

Taken together, a multi-source remote sensing image matching algorithm based on contourlet transform, Tsallis entropy and improved particle swarm optimization was introduced. The algorithm mainly contains the following aspects: (1) Decompose the target image and reference image to low resolution with contourlet transform, respectively. Match the lowest resolution remote sensing images. Based on the preliminary result, the matching between the higher resolution images can be implemented stepwise up to the full resolution images. (2) For two same size images, target image and the sub-reference image, use Tsallis entropy based mutual information as similarity measure criterion to advance the matching precision. (3) Apply a modified extremum disturbed and simple particle swarm optimization algorithm (mtsPSO) to image matching, so that the operation speed can be further improved.

2 PRINCIPLE OF CONTOURLET TRANSFORM, PSO AND MUTUAL INFORMATION

2.1 Contourlet transform

Discrete Contourlet transform, also called Pyramidal Direction Filter Bank (PDFB), mainly has two stages: subband decomposition and directional transform. The Laplacian Pyramid is first to capture the point discontinuities, and then followed by a directional filter bank to link point discontinuities into a coefficient. Fig.1 shows the decomposition scheme of contourlet transform. The original image is decomposed into a lowpass image and several high frequency components, which distributed on multiple scales and multiple directions.

![Contourlet filter bank](image)

Fig. 1 Contourlet filter bank

2.2 Basic particle swarm optimization algorithm

For an n-dimensional search space, the position and velocity of the i-th particle are represented as $X_i=(X_{i1},X_{i2},\ldots,X_{in})$ and $V_i=(V_{i1},V_{i2},\ldots,V_{in})$, respectively. The former stands for the solution of the problem, and corresponds to the objective function value which is used to evaluate the fitness of particles. The latter denotes the new velocity of a particle from the current position to its next position. At first, initialize the particle swarm; and then search for the optimal solution by iterating. Suppose that, in the $t$-th iteration, $p(t)$ is the best previous position of the $i$-th particle, named individual extremum; $g(t)$ is the best previous position discovered by the whole swarm, named global extremum. In the $(t+1)$-th iteration, the particles are manipulated according to the following equations:

$$V_i(t+1) = wV_i(t) + c_1r_1(p(t) - X_i(t)) + c_2r_2(g(t) - X_i(t))$$

(1)

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

(2)

where $c_1$ and $c_2$ are two acceleration constants that regulate the relative velocities with respect to the best global and local positions, respectively. In this paper, $c_1=c_2=2$; $r_1$ and $r_2$ are random variables drawn from a uniform distribution in the range (0,1); $w$ is the weight coefficients, which is usually reduces linearly as interaction time:

$$w = w_{\text{max}} - t \times \frac{w_{\text{max}} - w_{\text{min}}}{t_{\text{max}}}$$

(3)

where $w_{\text{max}}$ and $w_{\text{min}}$ denote the maximum and minimum inertia weight, respectively; $t_{\text{max}}$ stands for the total iteration time. In the iteration update process, the velocity is restricted to the range $V_i \in [V_{\text{min}},V_{\text{max}}]$, the position is limited in permissible range, the final output $g$ is the global optimal solution.

2.3 Shannon entropy based mutual information

Mutual information usually describes the statistical correla-
tion between two systems, which can be expressed by entropy. Shannon entropy of system $A$ is defined as,
\[ H(A) = -\sum_a p_A(a) \log p_A(a) \]  
(4)
The joint entropy of system $A$ and $B$ is given as
\[ H(A, B) = -\sum_{a,b} p_{A,B}(a,b) \log p_{A,B}(a,b) \]  
(5)
where $a \in A$, $b \in B$; $p_A(a)$ denotes the probability density of system $A$; $p_{A,B}(a,b)$ is the joint probability density of system $A$ and $B$. If $H(A|B)$ denotes conditional entropy of $A$, when system $B$ is known. The mutual information of two systems is described as:
\[ I(A, B) = H(A) + H(B) - H(A, B) = H(A) - H(A|B) \]  
(6)
Use generalized distance of probability distribution to estimate the mutual information,
\[ I(A, B) = \sum_{a,b} p_{A,B}(a,b) \log \frac{p_{A,B}(a,b)}{p_A(a)p_B(b)} \]  
(7)

3 REALIZATION PROCESS OF THE PROPOSED ALGORITHM

A novel image matching algorithm for multi-source remote sensing images based on contourlet transform, Tsallis entropy and improved particle swarm optimization is proposed. In the algorithm, images are matched from coarse to fine, using the multi-resolution of contourlet transform; and Tsallis entropy based mutual information is introduced as a new image similarity measure criterion; meanwhile, the mtsPSO is used to overcome the shortcomings of bPSO, such as relapsing into local extremum, slow convergence velocity and low convergence precision in the late evolutionary. The detail realization process of the proposed algorithm is as following:

1. The target image and reference image are decomposed by contourlet transform. Where, we use “9-7” pyramid filter, since the linear phase and approximate orthogonality make it more suitable for image signal processing. We choose “pkva” directional filter, and the number of directional subbands in each scale is 4. The decomposition levels are determined by the variables of the particle position, which avoids the defects caused by particle velocity, such as relapsing into local extremum, slow convergence velocity and low convergence precision in the late evolutionary. Meanwhile, it accelerates the particles to overstep the local extremum, and improves the practicability of the particle swarm optimization. The update process of the algorithm is given as following:
\[ X_i(t + 1) = w X_i(t) + c_1 \eta_1 \left[p_{r_h \rightarrow r} p_i - X_i(t)\right] + c_2 \eta_2 \left[p_{r_h \rightarrow g} g - X_i(t)\right] \]  
(11)
where $t_0$ and $t_g$ stand for the numbers of stagnation steps of individual extremum and global extremum, respectively. $T_0$ and $T_g$ represent the thresholds of stagnation steps when the individual extremum and global extremum need to be disturbed. $r_{t_0 \rightarrow T_0} = \begin{cases} 1 & t_0 \leq T_0 \\ U(0,1) & t_0 > T_0 \end{cases}$ and $r_{t_g \rightarrow T_g} = \begin{cases} 1 & t_g \leq T_g \\ U(0,1) & t_g > T_g \end{cases}$ are uniform random numbers with condition. $U(0,1)$ denotes random variables drawn from a uniform distribution in the range $(0,1)$. Let $T_0 = T_g = 10$. 

In particular, Tsallis entropy converges to Shannon entropy, as $q \rightarrow 1$.

Deprive Tsallis entropy based mutual information as following:
\[ I_q(A, B) = S_q(A) - S_q(A|B) = \frac{1}{1-q} \sum_a p_A(a)^q \sum_b p_B(b)^q - \frac{1}{1-q} \sum_a p_A(a)^q \sum_b p_B(b)^q \]  
(12)
(13)
Considering Eq.(8) and Eq.(9), we can get
\[ I_q(A, B) = \frac{1}{1-q}[1 - \sum_a p_A(a)^q - \sum_b p_B(b)^q] = \sum_a p_A(a)^q \sum_b p_B(b)^q \]  
(10)
Considering large inertia weight is benefit to the ability of global search, when small inertia weight is benefit to the ability of local search, mtsPSO proposed in this paper is modified based on the extremum disturbed and simple particle swarm optimization (Hu & Li, 2007). Inertia weights achieve the best balanced inertia factors adaptively, using the strategy of decreasing inertia weight (Chen et al., 2006):

$$w = (w_{\text{start}} - w_{\text{end}}) \left( \frac{t}{t_{\text{max}}} \right)^2 + (w_{\text{end}} - w_{\text{start}}) \left( \frac{2t}{t_{\text{max}}} \right) + w_{\text{start}} \quad (12)$$

In this paper, we set $w_{\text{start}}=0.95, w_{\text{end}}=0.4$.

(6) Iteration. Let $t=t+1$. Check whether it meets the end of the condition: If $t=t_{\text{max}}$ or satisfy the terminating criteria which is problem-dependent, stop iterating and output the best solution, else go to step (3).

(7) According to the position of the best solution $g_t$, the best offset in low resolution image $\Delta x_L, \Delta y_L$ can be determined and output.

(8) In the scale of $L-1$, continue to search in the neighborhood of point $(2\Delta x_L, 2\Delta y_L)$, and find the best offset position $(\Delta x_{L-1}, \Delta y_{L-1})$ in the current scale. Repeat the process, until the best offset position $(\Delta x_0, \Delta y_0)$ in full resolution image is found.

4 EXPERIMENTAL RESULTS AND ANALYSIS

We carried out the experiments on 200 groups of remote sensing images, and chose three of them to illustrate, that were SPOT image (256×256, Fig. 2(a)) and TM image (50×50, Fig.2(b)), visible image (256×256, Fig.2(d)) and SAR image (50×50, Fig.2(e)), visible image (256×256, Fig.2(g)) and infrared image (5×50, Fig.2(h)). The platform used for the experiments was Matlab 7.1 on a PIV-based 2.78GHz PC with 512M memory. The results are shown in Fig.2(c) (f) (i).

4.1 Comparison with the experimental results for different decomposition levels $L$

The decomposition level $L$ is determined by target image. Take the experiments on the above images, and run the program 50 times, compute the average values as matching points. The results are shown in Table 1, where point coordinates are subject to the left corner coordinates of matching images.

<table>
<thead>
<tr>
<th>$L$</th>
<th>Matching position</th>
<th>Matching error</th>
<th>Average time/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>(122,80)</td>
<td>(-4, -2)</td>
<td>10.47238</td>
</tr>
<tr>
<td>1</td>
<td>(126,82)</td>
<td>(0, 0)</td>
<td>5.99021</td>
</tr>
<tr>
<td>2</td>
<td>(126,82)</td>
<td>(0, 0)</td>
<td>3.38824</td>
</tr>
<tr>
<td>0</td>
<td>(37,46)</td>
<td>(0, 0)</td>
<td>10.01475</td>
</tr>
<tr>
<td>1</td>
<td>(37,46)</td>
<td>(0, 0)</td>
<td>3.22392</td>
</tr>
<tr>
<td>2</td>
<td>(37,46)</td>
<td>(0, 0)</td>
<td>3.40373</td>
</tr>
<tr>
<td>0</td>
<td>(114,120)</td>
<td>(-1,2)</td>
<td>10.75026</td>
</tr>
<tr>
<td>1</td>
<td>(115,118)</td>
<td>(0, 0)</td>
<td>6.10187</td>
</tr>
<tr>
<td>2</td>
<td>(115,118)</td>
<td>(0, 0)</td>
<td>3.40373</td>
</tr>
</tbody>
</table>

Table 1 shows that, when $L$ gets smaller, there exists minor matching errors and is quite time-consuming; when $L$ gets larger, fewer operations are needed. However, due to the less information that low resolution image contains, when the number of decomposition levels increases, there will be error matching.

4.2 Comparison with the experimental results of different algorithms

To prove the superiority, we did some contrast experiments using different algorithms, that were: (a) image matching algorithm based on cross correlation and PSO (Sjahputera & Keller, 2005); (b) image matching algorithm based on mutual information and PSO (Li & Ji, 2007); (c) image matching algorithm based on wavelet transform, mutual information and GA (Yang & Zhang, 2006); (d) image matching algorithm based on wavelet transform, mutual information and PSO (Zhang et al., 2008); (e) image matching algorithm proposed in this paper, based on contourlet transform, Tsallis entropy based mutual information and mtsPSO. Where $L=2$, $q=0.8$, and each program of algorithm run 50 times. Only when matching error equals to (0,0), the solution is correct. The results are shown in Table 2, where correct matching ratio is defined as the number of correct solutions to total operation time ratio.

Since the resolutions of optimization algorithm, such as GA and PSO, have some uncertainty, we executed the programs for multiple times. It is seen that, algorithm (a) can hardly get the
correct matching position. Because of the different imaging principles of multi-source remote sensors, the gray scale gap among the images is large. As a result, the gray linear relationship can not be established and correct matching position can not be found based on cross-correlation. Compared with algorithm (a), algorithm (b) applies mutual information to similarity measure criterion, so that it overcomes the matching errors caused by gray scale to a certain extent. However, the search range is still too large to decrease the computational complexity efficiently. Algorithm (c) and (d) bring in wavelet transform based on algorithm (b), in order to accelerate the search speed while keep the accuracy. Algorithm (c) is more time-consuming than algorithm (c), due to the more steps of GA, such as crossover and mutation. Using contourlet transform, Tsallis entropy based mutual information and mtsPSO, the precision of algorithm (e) is obviously higher than that of other four algorithms, besides it has the best stability and the computation speed is above four times faster than algorithm (b), (c) and (d).

4.3 Anti-noise ability of algorithm

Add Gaussian noise into the given images, whose mean is 0, variance is 0.01. Matching results using the proposed algorithm are shown as Fig.3.

The matching positions are (126, 80), (38, 46) and (115, 118), with the matching errors (0, −2), (1, 0) and (0,0), respectively. The results show that, the proposed algorithm has a certain anti-noise ability. For the noisy images, it can still get accurate solution. It is proved by many experiments that, when target image gets larger, the anti-noise ability gets stronger. That’s because the larger image is, the more information it contains, and the stronger anti-noise ability it has.

5 CONCLUSION

An image matching algorithm for multi-source remote sensing images was proposed, based on contourlet transform, Tsallis entropy based mutual information and improved particle swarm optimization. The target image and reference image were firstly decomposed by contourlet transform, and Tsallis entropy based mutual information was applied to similar measure criterion. Meanwhile an extremum disturbed and simple particle swarm optimization algorithm was introduced to match the multi-resolution images from coarse to fine. We analyzed the results through different decomposition levels and different algorithms. The results show that, compared with those of other existing remote sensing image matching methods, the proposed algorithm has high accuracy, strong robustness and requires much fewer operations. Next we consider working on the image matching problem of large angle rotation.

REFERENCES

Li Q and Ji H B. 2007. Medical image registration based on maximization of mutual information and particle swarm optimization. 5th International Conference on Photonics and Imaging in Biology and Medicine, 6534: 5342—5344
Contourlet Tsallis

吴一全，陈　飒

摘要：Contourlet Tsallis

关键词：Contourlet Tsallis

1


Cole-Rhodes (Furuichi, 2006; Martin, 2001; Walced & Ben, 2009) Shannon Tsallis Shannon

(You & Bhattacharya, 2000; Yutaro)
Contourlet\footnote{Pyramidal Direction Filter Bank, PDFB}, PSO\footnote{Particle Swarm Optimization, PSO} (Sjahputera & Keller, 2005; Li & Ji, 2007)\footnote{Contourlet, Particle Swarm Optimization, PSO}. \end{par}

\noindent \textbf{2.2 Contourlet (bPSO)}

\begin{align}
V_i(t + 1) &= wV_i(t) + c_1r_1\left[p_i(t) - X_i(t)\right] + c_2r_2\left[g(t) - X_i(t)\right] \\
X_i(t + 1) &= X_i(t) + V_i(t + 1)
\end{align}

\begin{align}
\text{max} &\quad w = w_{\text{max}} - t \times \frac{w_{\text{max}} - w_{\text{min}}}{t_{\text{max}}} \\
\text{max} &\quad \sum_{i \in \{0, 1\}} V_i \in [V_{\text{min}}, V_{\text{max}}], \quad \sum_{i \in \{0, 1\}} g(t) \leq 1
\end{align}

\noindent \textbf{2.3 Shannon}\footnote{Contourlet, Shannon}\footnote{Tsalis}

\begin{align}
H(A) &= \sum_a p_A(a) \log p_A(a) \\
I(A, B) &= \sum_{a,b} p_A(a, b) \log p_A(a, b)
\end{align}

\begin{align}
I(A, B) &= H(A) + H(B) - H(A, B) \\
I(A, B) &= \sum_{a,b} p_A(a, b) \log \frac{p_A(a, b)}{p_A(a)p_B(b)}
\end{align}

\noindent \textbf{3 Contourlet}\footnote{Contourlet, Tsalis}
Contourlet

(1) \[ X(t+1) = wX(t) + c_1r_1[p_{t_0} - X(t)] + c_2r_2[t_{g} > t_{f} = T_g - X(t)] \] (11)

(2) \[ I_q(A, B) = S_q(A) - S_q(A \cap B) \]

(3) \[ I_q(A, B) = S_q(A) + S_q(B) - S_q(A \cap B) \]

(4) \[ p(x) \text{, Shannon} \]

(5) \[ X(t+1) = wX(t) + c_1r_1[p_{t_0} - X(t)] + c_2r_2[t_{g} > t_{f} = T_g - X(t)] \] (11)

(6) \[ w_{\text{start}} = 0.95, w_{\text{end}} = 0.4 \]

(7) \[ L - 1, 2 \Delta x, 2 \Delta y \]

(8) \[ L - 1, 2 \Delta x, 2 \Delta y \]
4 256×256 SPOT (2(a)) 50×50 TM (2(b)); 256×256 SAR (2(c)) (2(d)) 50×50 SAR (2(e)); 256×256 SAR (2(g)) 50×50 SAR (2(h)) Contourlet Tsallis L 7.1 Intel Pentium4 2.78GHz CPU 512M RAM MATLAB

4.1 L 3 1 × 3 (a) 4.99720 200 (b) 50.01207 6 (c) 19.38394 42 (d) 14.18557 40 (e) 3.38824 92

4.2 L 2, q=0.8, 50, ϒ=1, 2, 0, 8, 8, 8

表1 不同分解层时的匹配结果

<table>
<thead>
<tr>
<th>L</th>
<th>L</th>
<th>L/s</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>122.80</td>
<td>(−4, −2)</td>
<td>10.47238</td>
</tr>
<tr>
<td>1</td>
<td>126.82</td>
<td>(0, 0)</td>
<td>5.99021</td>
</tr>
<tr>
<td>2</td>
<td>126.82</td>
<td>(0, 0)</td>
<td>3.38824</td>
</tr>
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表2 不同算法的匹配结果

<table>
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<th>L</th>
<th>L/s</th>
<th>%</th>
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</thead>
<tbody>
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<td>(a)</td>
<td>4.66313</td>
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<td></td>
</tr>
<tr>
<td>(b)</td>
<td>50.69498</td>
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</tr>
<tr>
<td>(c)</td>
<td>18.85430</td>
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<td></td>
</tr>
<tr>
<td>(e)</td>
<td>3.40373</td>
<td>96</td>
<td></td>
</tr>
</tbody>
</table>

表3 取不同分解层时的匹配结果
REFERENCES


Li Q and Ji H B. 2007. Medical image registration based on maximization of mutual information and particle swarm optimiza-
tion. 5th International Conference on Photonics and Imaging in Biology and Medicine, 6534: 5342—5344
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