A MULTI-TEMPORAL IMAGE REGISTRATION METHOD BASED ON EDGE MATCHING AND MAXIMUM LIKELIHOOD ESTIMATION SAMPLE CONSENSUS

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ABSTRACT:

In the paper, we propose a newly registration method for multi-temporal image registration. Multi-temporal image registration has two difficulties: one is how to design matching strategy to gain enough initial correspondence points. Because the wrong matching correspondence points are unavoidable, we are unable to know how many outliers, so the second difficult of registration is how to calculate true registration parameter from the initial point set correctly. In this paper, we present edge matching to resolve the first difficulty, and creatively introduce maximum likelihood estimation sample consensus to resolve the robustness of registration parameter calculation. The experiment shows, the feature matching we utilized has better performance than traditional normalization correlation coefficient. And the Maximum Likelihood Estimation Sample Conesus is able to solve the true registration parameter robustly. And it can relieve us from defining threshold. In experiment, we select a pair of IKONOS imagery. The feature matching combined with the Maximum Likelihood Estimation Sample Consensus has robust and satisfying registration result.

1. INTRODUCTION

Remote sensing imagery change detection has gain more and more attention in academic and research society in near decades. Image Registration, relative radiometric rectification and change detection strategy are most frequently discussed in published papers. Researchers have made use of calculation variogram to discuss the registration accuracy (Dai XL,1998). And they draw conclusion that only sub-pixel accuracy achieved will not have an adverse impact on final change detection result. In this paper, we focus on multi-temporal image registration. Image registration is the most critical steps in change detection. It seeks to remove the two-date images geometric position inconsistent, making the same image coordinates reflect the same objects

The registration difficulty comes from the change detection image characteristics. The imagery pair have following characteristics：1) The actual change exists between image pair. If change between pair is massive, it is extremely difficult for computer to search the same feature; 2) radiometric difference exist. So the same object has the different spectrum value. These reasons cause the registration framework to select stability characteristic as matching element, simultaneously should not be sensitive to the illumination change.

Based on above analysis, we propose a newly registration framework. Comparing with published method, the framework not only solves feature matching problem, but also concerns on how to robustly calculate registration parameters. To be specific, the framework contains two aspects. The one focuses on feature matching. In this stage, we utilize stable feature in two-data imagery pair and design matching rule non-sensitive of illumination change. This enables us to obtain the initial set of points, we call it ***U***. It is noted that ***U*** will contain wrong matching points (outlier correspondence). The least square wouldn't solve correct registration parameter if outliers occupy majority. So in the second stage, we pay attention on how to calculate registration parameter robustly. These will make us robustly calculate registration parameter successfully, even outliers occupies the majority. Above two has guaranteed the matching success. The paper organizes four parts: in Introduction section, we introduce the paper's motivation. And in section 2, we introduce the edge matching ideas, in section 3, we outline the MLESAC method. In section 4, we utilize a pair of multi-spectral IKONOS data analyze our framework.

2. EDGE FEATURE MATCHING

Comparing with point feature, edge feature in the two images is more stable. Therefore, in feature matching stage, we choose edge as matching element and select canny operator to detect edge. And at the same time, we regard the correspondence edge should satisfy "the edge gradient angle's difference and edge distance weighted sum is minimum". The strategy is expressed by the following equation(1):

$$
\begin{aligned}
P &= a \times d + b \times \left|\theta_{t1} - \theta_{t2}\right| \\
a &= 1 / d_{\max} \\
b &= 1 / r_{\max}
\end{aligned}
\tag{1}
$$

Where d: is two-data imagery edge point's distance;
θ_{t1},: t1 imagery edge gradient angle；
θt_2,: t2 imagery edge gradient angle；
$a=1/d_{max}$: d_{max} is maximum distance between correspondence edge point;
$b=1/r_{max}$： r_{max} is maximum gradient angle difference between correspondence edge point.

In order to reduce the scope of the feature search and less image rotation impact, before edge matching, we select three to four correspondence points manually and apply initial registration. So in equation (1), $d_{\max}$ and $r_{\max}$ is decided by manually registration result. For example, if after rough registration, distance residual error is 10 pixel and rotation angle residual error is 0.001 radian, the $d_{\max}$ = 10, and a= 0.1, the $r_{\max}$ = 0.001, and b=1000. The edge matching strategy is proposed firstly by T.D.Hong (Hong T D, 2005). He applied the strategy in multi-mode imagery matching. We draw reference from the method and apply it in multi-temporal registration. In Section 4, we will compare the edge matching method with normalization correlation coefficient method.

3. MAXIMUM LIKELIHOOD ESTIMATION SAMPLE CONSENSUS

No matter what the matching method selected, the initial matching set ***U*** will always contain mismatching correspondence points. So the development of a robust registration parameters solving method is meaningful.

In the majority of the literature, the traditional Least Squares method（LS）method is adopted. If the true correspondence points occupy majority in ***U***, the LS is able to smooth out the mismatching correspondence points. When condition is reverse, the LS can't remove gross error and the registration parameters' result is questionable. So in the following, we adopt Maximum Likelihood Estimation Sample Consensus(MLESA）to remove gross error and calculate registration parameters. MLESAC is proposed by P.H.S Torr (P.H.S.Torr,2000) to solve machine learning problem and within the scope of author's reading, it is firstly introduced in image registration.

MLESAC origins from Random Sample Consensus（RANSAC）. RANSAC (Martin A.Fischler, 1981) is representative way in robust estimation theory. Because it is simple in principle and has strong anti-gross error capacity, in the field of remote sensing applications, the researchers pay growing attention on it. T.Kim(T.Kim,2005) propose to registration two-date imagery using RANSAC and Normalization Correlation Coefficient.

The standard RANSAC algorithm needs to determine two important parameters artificially: threshold *t* and repeat assumptions' number *k*. The choice of threshold *t* relates to the success or failure of RANSAC algorithm. The threshold value chooses has been small or oversized, may make RANSAC algorithm will be unable to correctly select correct parameter θ* from parameter space. To solve the problem, this paper introduces the MLESAC algorithm to estimate two images registration parameters. Compared with RANSAC, MLESAC support function's calculation way is calculation every registration parameter established posterior probability, and we regard the greatest posterior probability as the final parameters. The most important step is how to model the probability of residual error and calculation of the statistical parameters of the model.

3.1 Ransac

Before introduce MLESAC, we briefly review RANSAC algorithm. The algorithm input is the observation data set ***U***. In initial matching set ***U***, part of data conforms to the correct parameter; we call these data inliers or true correspondence points. Moreover in ***U***, there is another part of data which doesn't conform to the correct parameter data; we call these data outliers or gross error. The RANSAC algorithm goal lies in discovering correct parameter θ* from the parameter space Θ, and in retention inliers simultaneously rejection outliers.

The algorithm divides in two steps:1) assumption generation step; and 2) assumption certification step. These two steps iterate until the iteration number equal to predefined *k*. In step 1), from ***U*** we randomly select *m* matching points, and calculate parameters θ_k according to application. In step 2), following parameters θ_k and predefined support function *J*(x), we can calculate the parameter θ_k*'s* support. In standard RANSAC. The support function is the amount which is consistent with parameters θ_k. When iteration reaches predefined *k*, we select the θ* which has greatest support as correct solution.

3.2 MLESAC

MLESAC is advance algorithm of RANSAC. We assume that initial match point set is ***U***,***U*** contain *n* initial matching points, and（$x_{1i},y_{1i},x_{2i},y_{2i}$）represents the *i*th initial matching point's coordinates. If the point is true correspondence, the coordinates' residual error obeys normal distribution with zero mean. We can represent the right matching point's probability density as $p_1(e_i)$:

$$p_1(e_i)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp(-\frac{e_i^{\,2}}{2\sigma^2}) \tag{2}$$

If the *i*th matching point is wrong matching, in MLESAC, we can assume the coordinates residual error obeys uniform distribution, with –v/2…+v/2 being the pixel range within which outliers are expected to fall(for feature matching this is dictated by the size of the search window for matches). Therefore we derive the residual error probability distribution as $p_r(e_i)$:

$$p_r(e_i)=r\frac{1}{\sqrt{2\pi\sigma^2}}\exp(-\frac{e_i^{\,2}}{2\sigma^2})+(1-r)\frac{1}{v} \tag{3}$$

The residual error is modelled as a mixture model of Gaussian and uniform distribution. Therefore the MLESAC's support function is :

$$Js(\theta_k)=p(\boldsymbol{U}\,|\,\theta_k)=\left(\frac{1}{\sqrt{2\pi}|\sigma_k|}\right)^n\prod_{i=1..n}[r_k\times\exp(-\frac{e_i(k)^2}{2\sigma_k^2})+(1-r_k)\frac{1}{v}] \tag{4}$$

Where θ_k is a generative registration parameter,
n represents the number of matching points in ***U***,
r_k is mixing coefficient. σ_k^2 is normal distribution covariance.

To estimate *r*, using Expectation Maximization (EM).a set of indicator variables needs to be introduced: η_i,i=1…n,where η_i = 1 if the *i*th correspondence is true matching correspondence (inlier), and η_i = 0 if the *i*th correspondence is wrong matching (outlier). The EM algorithm proceeds as follows treating the η_i as missing data:

(1) generate a guess for *r*
(2) estimate the expectation of the η_i from the current estimate of *r*
(3) make a new estimate of *r* from the current estimate of η_i and go to step(2).. In more detail for stage (1) the initial estimate of r is 0.5. For stage (2) denote the expected value of η_i by z_i then it follows that $\Pr(\eta_i=1|r) = zi$. Given an estimate of r this can be estimated as：

$$p_r(\eta_i = 1 \mid r) = \frac{p_i}{p_i + p_0} \tag{5}$$

$p_r(\eta_i=0|r)=1\text{-}zi$. Here p_i is the likelihood of a datum given that it is an inlier:

$$p_1(e_i) = r \times \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{e_i^2}{2\sigma^2}) \tag{6}$$

And p_0 is the likelihood of a datum given that it is an outlier:

$$p_0(e_i) = (1-r) \times \frac{1}{v} \tag{7}$$

For stage (3)

$$r = \frac{\sum_{i=1}^{n} z_i}{n} \tag{8}$$

4. TRANSFORMATION FUNCTION

For scenes captured by high altitude imaging satellites with narrow angular field of view of a relatively flat terrain, the mathematical relationship between the coordinates of conjugate points in the reference and input images can be described by an affine transformation. (Rami AI-Ruzouq, 2004). Since this paper focuses on the registration of remotely sensed imagery (IKONOS), affine transformation functions will be used to establish the mathematical relationship between conjugate elements of the involved image pair.

$$\begin{aligned} X2 &= M0 + M1 \times X1 + M2 \times Y2 \\ Y2 &= N0 + N1 \times X1 + N2 \times Y2 \end{aligned} \tag{9}$$

5. EXPERIMENT

For comparing matching performance, we adopt normalization correlation coefficient (NCC) principle to get correspondence points. The NCC principal isn't sensitive to illumination change. If illumination change is linear, NCC will run well. In principal it is perfect for change detection, because in most published paper, researcher regard two-data imagery's illumination change is linear. So in experiment, we apply the edge matching strategy and the NCC principal respectively on the same test pair.

(a) 2003 IKONOS Red Band Imagery

(b) 2004 IKONOS Red Band Imagery

Figure1. Multi-temporal Imagery Pair

We select two-data multi-spectral IKONOS imagery as test pair in figure 1.

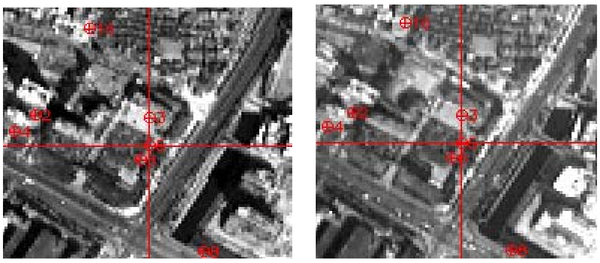
In NCC principal, we select Harris operator to extract feature point. In Harris operator, the Gaussian template's coefficient is fixed 0.5 and a is fixed 0.04, the extract window size is fixed 7 ×7. Because the pair is not large, it is not need to make pyramid search. After initial manual registration, we set the search window is 21×21. In edge matching method, we set parameters in equation (1): a =0.1(pixel), b=0.01(radian). Because both method can obtain many matching points (NCC principal can get 207 pairs of correspondence points, edge matching can get 12073 pairs of correspondence points), it is hard to compare so many pairs. Following matching degree, we order the two pairs of points, and choose the top 20 correspondence points. Analysis the 20 correspondence points matching correct rate, we can compare the two matching method.

For NCC method, although the test imagery pair doesn't contain massive change, the NCC performance is poor; it can only get 4 true correspondence points. It means that NCC has 20% correct rate in its top 20 matching correspondence pairs. For edge matching method, we analyze the matching result in Tabs1:

P	M	C	P	M	C
1	Y	N	11	N	Y
2	N	N	12	Y	N
3	Y	N	13	Y	N
4	Y	N	14	Y	N
5	Y	N	15	Y	N
6	Y	N	16	Y	N
7	Y	N	17	N	Y
8	Y	N	18	N	Y
9	Y	N	19	Y	N
10	Y	N	20	Y	N

Table 1. Top 20 Edge Matching Point Condition

In Table 1, the first row, P represents correspondence point serial number, M represents if the correspondence point is true matching pair or not, C represents the pair's location happen change or not. Y means yes, N means no. For example, the 1st correspondence point pair is true matching and there isn't change. From Table 1, we can calculate in the top 20 correspondence point pair, matching correct rate is 85%. The matching correct rate is higher than NCC. So the edge feature matching has higher probability than NCC to get matching point set. In figure 2, we superpose edge matching correspondence on two-date imagery, and zoom in the result.



(a)Superposition on 03 imagery (b) on 2004 imagery

Figure2. Edge Feature Matching Local Zoomed in

And we utilize initial edge matching points set ***U*** to analyze least square and MLESAC respectively. For the sake of simplicity, firstly we utilize the top 20 correspondence edge matching points in ***U*** to carry analysis. Then we gradually increase the number of wrong correspondence point. From two aspects —— capacity of removing wrong correspondence and ability of retaining right correspondence ——, we compare MLESAC with least square method. When utilize the top 20 correspondence edge matching points in ***U***, inliers occupy majority (ε=85%), least square method (LS) can smooth out wrong correspondences, and solve out right registration parameter. We list the result in Table 2:

	m1	m2	m0
LS	0.99	-0.02	58.46
MLESAC	0.99	-0.02	57.93
	n1	n2	n0
LS	0.02	1.00	23.03
MLESAC	0.02	1.00	22.58

Table 2 ε=85% LS and MLESAC Calculation Results

When ε=85%, LS regards the point pair 2,10,11,17 as wrong matching pair. MLESAC regards the point pair 1,2,10,11,12,17,20 as wrong matching pair. Compare the result with Table 1. We will find LS remove almost wrong matching pair, MLESAC remove wrong matching pair and some true matching pair. So the final RMSE obtained by LS is smaller than MLESAC's. We select five point pairs in test imagery and list them in Table 3. In Table 3, (X1,Y1) represent 2003 imagery point coordinate, (X2,Y2) represents 2004 imagery point coordinate. RX represents residual error in x direction, RY represents residual error in y direction, and RMSE represents the five point pairs' RMSE. It reflects the overall registration accuracy.

P	x1	y1	x2	y2	Rx	RY
1	86.2	276.2	137.6	300.5	0.67	0.45
2	345.6	202.	396.9	231.2	0.34	0.74
3	266.3	388.8	313.9	417.6	0.42	0.50
4	17.2	194.2	70.2	217.60	1.40	0.026
5	195.5	125.5	250.0	152.0	0.22	0.44
RMSE：0.832						

Table 3 ε=85% LS Registration Accuracy

Combing Table 2 with Table 3, we draw a conclusion that when true matching feature is in the majority, LS can perform well. It can get sub-pixel registration accuracy. MLESAC perform a little worse than LS. Both algorithms can calculation right registration parameter with good initial matching pair.

In above experiment, we only select the top 20 matching degree correspondence points. But in practice, the matching degree is not always ensuring the pair is true correspondence. So we can't ensure how to select the point set's number, and we can't guarantee the true correspondence points occupy majority. Therefore, 85% correct rate in initial point set ***U*** is special case.

For investigation MLESAC robustness，we select 15 wrong correspondence pairs and true correspondence pairs from initial edge matching set ***U*** to form point set $\boldsymbol{U_2}$. We establish the serial number of 15 pairs of wrong correspondence points as 1-15， and establish the serial number of 20 true correspondence points as 16-35. Then in point set $\boldsymbol{U_2}$, true correspondence points account for 57.15%. We make use of LS and MLESAC remove the wrong matching points and solve registration parameter. We list the result in Table 4：

	m1	m2	m0
LS	1.00	-0.02	57.03
MLESAC	0.99	-0.02	58.23
	n1	n2	n0
LS	0.02	1.01	17.75*
MLESAC	0.02	1.00	23.04

Table 4 ε=57.15% LS and MLESAC performance

Compare Table 4 with Table 2，as point set $\boldsymbol{U_2}$ only contain 57.15% true correspondence points, LS is unable to solve the correct result. In aspect of removing wrong matching points, it take the 7th correspondence point pair as wrong matching pair；In aspect of solving registration parameter, LS result is far away from the true parameter listed in Table 2. But MLESAC demonstrates the good performance. MLESAC can remove all wrong correspondence matching points, and is able to solve the correct parameter. We also calculate the registration accuracy with the five selected correspondence pair and list the result in Table 5.

P	**x1**	**y1**	**x2**	**y2**	**RX**	**RY**	**REi**
1	**86.2**	**276.2**	**137.6**	**300.5**	**0.44**	**0.464**	**0.64**
2	**345.6**	**202.0**	**396.9**	**231.2**	**0.566**	**0.752**	**0.94**
3	**266.3**	**388.8**	**313.9**	**417.6**	**0.207**	**0.434**	**0.48**
4	**17.2**	**194.2**	**70.2**	**217.60**	**1.174**	**0.016**	**1.170**
5	**195.5**	**125.5**	**250.0**	**152.0**	**0.735**	**0.45**	**0.86**
RMSE: 0.818							

Table 5 ε =57.15% MLESAC Registration Result

Combing Table 4 with Table 5, we can conclude that when ε =57.15%, MLESAC is successful in calculating registration parameter and obtain sub-pixel registration accuracy.Figure3 is ε =57.15% registration visual result.

Figure3. MLESAC registration visual result

6. CONCLUSION

In this paper, we pay attention on multi-temporal image registration. Registration is critical step in change detection analysis and how to guarantee the registration accuracy is important. Firstly, we introduce edge feature matching in multi-temporal image matching. The edge feature matching performs well than normalization correlation coefficient in matching amount and matching correct rate. Secondly, we apply MLESAC in image registration. MLESAC operate well than least square method, even when matching point set contains a large number of wrong matching correspondences. The feature matching and MLESAC ensure the registration correct.

But it should be paid attention on urban building. In high resolution imager, urban building will cause projection difference. The proposed algorithm can't deal with the error. We need design change detection method to remove its error. And the author thinks the next step is applied the framework in large size imagery pair. And combine the method with pyramid search.

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