THE PRACTICE OF AUTOMATIC SATELLITE IMAGE REGISTRATION

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ABSTRACT: In this paper, a new algorithm for satellite image registration was developed. The main characteristic of the algorithm is to align two images automatically, without requiring either control points or sensor's parameters. Two kinds of models, characterising the image variability between images, were utilised. One is projective model, accounting for geometrical variation . The other is the polynomial illumination change model, accounting for the variation in illumination at different time. These two model parameters can be simultaneously estimated via the intensity matching, using the Levenberg-Marquardt minimisation framework incorporated with multi-resolution and multiple model strategy. The algorithm has been verified by an intensive experiment on a great number of real images, taken by satellite, digital and frame camera. The Experimental result demonstrates the robustness, efficiency and accuracy of the algorithm.

1. INTRODUCTION

Satellite Image registration is a crucial underlying process for application such as mosaicking, change detection, cloud removal and digital elevation model reconstruction. Commercial software, such as ErDas, utilises control points or sensor's information to implement image registration. However, information on the control points or sensor's information may not be readily available or accurate enough, the registration based on such information is therefore limited and may even be inaccurate. Another disadvantage of using control points for image registration is that too much manual work is involved. It is indeed a tedious work for user to input so many correspondences on both of the images via an interactive way. Therefore, the functionality of automatic satellite image registration is much required.

Although the automatic registration techniques have been well developed for the application of video mosaick (Gregory D al 1998 , LG Brown 1992, P.Anandan 1988, R.Szeliski al. 1997), a challenge was faced when these techniques are applied for registration of aerial photograph or satellite image, due to the following reasons. In the first place, since the satellite images to be aligned are usually taken at different time (or even different day) and different location, the brightness constancy assumption, which underlies the common intensity matching approach, is violated. Therefore, we have to take the illumination change into account for successful registration of two satellite images containing illumination variations. Although the generalised brightness model to account for uniform photometric variation (i.e. $\alpha I+\beta$, where α and β are the illumination multiplication and bias factors) was widely used in video/image processing, this model cannot however account for spatially varying change of illumination existing in satellite image pair. Secondly, because satellite images are taken at different time, there may be some environment change during the interval. For instance, the cloud may be present when the first image was captured, and it may have disappeared when the second image was taken. In such a case, the algorithm should have certain kind of mechanism to detect automatically which pixel is an outlier (corresponding to cloud), and which pixel is an inlier, in order to do a successful registration.

To overcome these problems, a generalised dynamic image model is used in the paper, which assumes the illumination multiplication and bias factor to be functions of location. We assume that these two illumination factors are slowly varying functions of location, thus they can be well approximated by low-order polynomials of position variables. The satellite image registration is then formulated as an energy minimisation problem to estimate the projective transformation parameters accounting for the image variability caused by position change of camera, as well as illumination polynomial coefficient accounting for variation in illumination at different time. The framework and new algorithm for estimating such a set of parameters were developed. In order to increase the speed of estimation, the multi-resolution and multi-model scheme was implemented. In addition, the robust estimation framework was integrated in the algorithm so that the erroneous measurement (or the measurements not consistent with majority) is treated as outliers and their influence on estimation is reduced. In this way, the algorithm has the capability of dealing with partial occlusion and multiple motion. The experimental results demonstrated that the algorithm is of robustness, efficiency and accuracy.

2. THE FORMULATION OF IMAGE REGISTRATION

The conventional image registration algorithms, in particular image intensity matching approach, are based on the brightness constancy assumption given as follows:

$$g(x', y') = f(x, y) \tag{1}$$

Where f and g are the image intensity functions at time t_1 and t_2 respectively. Some previous work utilised a generalised brightness model to account for uniform photometric variation, i.e.,

$$g(x', y') = \alpha \times f(x, y) + \beta \tag{2}$$

Note that the constants α and β are the illumination multiplication and the bias factors respectively. However, this model cannot account for spatially varying illumination variations. To overcome this restriction, a generalised dynamic image model is proposed (S. Negahdaripour, 1998) by assuming the illumination multiplication and bias factor (α and β) to be functions of location (*x,y*). In this paper, we assume these two illumination factors are slowly varying functions of location, thus they can be well approximated by low-order polynomial of position variables (*x,y*) as follows.

$$g(x', y') = \alpha(x, y) \times f(x, y) + \beta(x, y) \tag{3}$$

Where $\alpha(x, y)$ and $\beta(x, y)$ are the low-order polynomial functions with the coefficients represented by $\vec{\alpha} = (\alpha_0, \alpha_1, \cdots \alpha_{p-1})$ and $\vec{\beta} = (\beta_0, \beta_1, \cdots \beta_{p-1})$ respectively. In our implementation, for simplicity, we employed a bilinear model for the illumination multiplication function and a constant function for the illumination bias. In this simple case, $\vec{\alpha} = (\alpha_0, \alpha_1, \alpha_2)$ and $\vec{\beta} = (\beta_0)$. It can be readily extended to a more complicated case. The coefficients of these two polynomial functions can be determined simultaneously with the geometric transformation parameters.

The geometric transformation in the image matching for planar objects can be strictly represented by a projective transformation. For projective transformation, The position relationship between a pair of corresponding points can be written as:

$$x_i' = \frac{m_o x_i + m_1 y_i + m_2}{m_6 x_i + m_7 y_i + 1}; \; y_i' = \frac{m_3 x_i + m_4 y_i + m_5}{m_6 x_i + m_7 y_i + 1} \tag{4}$$

Where $\vec{m} = \{m_0, m_1, \cdots m_7\}$ is the parameter vector for a projective model.

The error function between two frames after projective transformation will be represented as:

$$\sum_i | g(x_i', y_i') - \alpha(x_i, y_i) f(x_i, y_i) - \beta(x_i, y_i) |^2 \tag{5}$$

The alignment of two images is to find such optimal parameters $\vec{m}, \vec{\alpha}, \vec{\beta}$ that minimise a weighted sum of errors, i.e.,

$$E = \sum_i w_i (g(x_i', y_i') - \alpha(x_i, y_i) f(x_i, y_i) - \beta(x_i, y_i))^2 \tag{6}$$

It should be noticed that w_i is the weight associated with the data constraint computed at the location (x_i, y_i). The weighting allows us to incorporate robust estimation into our minimisation framework, which is accomplished by dynamically adjusting the weight for each constraint appropriately based on its residue. Since equation (6) is a non-linear minimisation problem, we have to use the iterative non-linear minimisation algorithm, say Levenberg-Marquardt algorithm, to obtain the optimal values of $\vec{m}, \vec{\alpha}, \vec{\beta}$. As we know, in order to make the algorithm to converge to global minimum, the initial estimate of $\vec{m}, \vec{\alpha}, \vec{\beta}$ should be close to the solution. In our approach, the initial parameters is obtained by pseudo simulated annealing approach incorporated with multiresolution and multiple model strategy, it is then refined via Levenberg-Marquardt algorithm based on intensity-based match.

3. THE DESCRIPTION OF THE ALGORITHM

3.1 Robust estimation Via Dynamic Weighting

Since images may contain partial occlusion, multiple motion and perturbation noise, robust estimation technique was used in the paper. In the robust estimation approach, the quadratic function of residue used in least-squares estimation is replaced by a ρ-function, which assigns small weights for the constraint with larger residues. There are a few member of ρ-functions used in image processing, we used Lorentzion function in the paper, which is given as follows:

$$\rho_{LO}(x,\sigma) = \log(1+\frac{x^2}{2\sigma^2})$$

where x is the residue of data constraint and σ is the scale parameter. When using the ρ-function for model fitting, the influence for each data constraint to the solution is characterised by an influence function, which is the derivative of the ρ-function. If we take the derivatives of the above function, we can obtain the influence function as follow

$$\psi(x,\sigma) = \frac{2x}{2\sigma^2 + x^2}$$

The influence function decrease as the magnitude of the residue increases. For the least-square estimation, the influence function is linearly increasing as the magnitude of the residue increases. Therefore the least-square estimation is more sensitive to outliers than the robust estimation. To use robust estimation in our minimisation framework, we can simply replace the quadratic function in (6) by above ρ-function, This yields the following new objective function

$$E(\vec{m}, \vec{\alpha}, \vec{\beta}) = \sum_i w_i \rho_{LO}(r_i, \sigma) = \sum_i w_i \rho_{LO}(g(x_i', y_i') - \alpha(x_i, y_i) f(x_i, y_i) - \beta(x_i, y_i), \sigma) \quad (7)$$

3.2 Optimisation Algorithm

Once the initial estimate of both projective and illumination model parameter were given, we can solve the minimisation problem of (7) by using Levenberg-Marquardt algorithm. The algorithm requires computation of the partial derivatives of r_i defined in (7) with respect to projective model parameters $\{m_0, m_1, \cdots m_7\}$ and illumination parameters $\vec{\alpha} = (\alpha_0, \alpha_1, \alpha_2)$ and $\vec{\beta} = (\beta_0)$. These are straightforward to compute. For example,

$$\begin{aligned} &\frac{\partial r_i}{\partial m_0} = \frac{x_i}{D_i}\frac{\partial g}{\partial x'}, \cdots\cdots, \frac{\partial r_i}{\partial m_7} = -\frac{y_i}{D_i}\left(x_i'\frac{\partial g}{\partial x'} + y_i'\frac{\partial g}{\partial y'}\right); \\ &\frac{\partial r_i}{\partial \alpha_0} = -f(x_i, y_i), \frac{\partial r_i}{\partial \alpha_1} = -x_i f(x_i, y_i), \cdots \frac{\partial r_i}{\partial \beta_0} = -1 \end{aligned} \quad (8)$$

Where $D_i = m_6 x_i + m_7 y_i + 1$ and $(\frac{\partial g}{\partial x'}, \frac{\partial g}{\partial y'})$ is the image intensity gradient of g at (x_i', y_i'). From these partial derivatives, we constructed the following iterative procedure based on the Levenberg-Marquardt algorithm:

1. Initialise model parameter $\vec{c}_0 = (\vec{m}_0, \vec{\alpha}_0, \vec{\beta}_0)$ based on initial value estimation procedure discussed later. The initial σ was selected to be large enough so that the robust estimation is very much like the least-squares estimators at beginning. Set the iteration index k=0;

2. Compute the residues r_i and the associated gradient vector $\vec{gad}_i = \frac{\partial r_i}{\partial \vec{c}}$ based on equation (8).

3. Compute the weight τ_i associated with each data constraint by $\tau_i = w_i \frac{\dot{\rho}(r_i)}{r_i}$

4. Form the weighted Hessian matrix and the weighted gradient vector $H = \sum_i \tau_i \vec{gad}\,\vec{gad}^T$, $\vec{b} = -\sum_i \tau_i r_i \vec{gad}$.

5. Update the motion parameter estimate $\vec{c}$ by an amount $\Delta\vec{c} = (H + \lambda I)^{-1}\vec{b}$, where λ is a time-varying stabilisation parameter.

6. Update the scale parameter $\sigma = \sqrt{\sum_i \tau_i r_i^2 / \sum_i \tau_i}$

7. Set $\vec{c}_{k+1} = \vec{c}_k + \Delta\vec{c}$ and k=k+1; if $\Delta\vec{c} = 0$, stop ; else go back to step 2

The advantage of using Levenberg-Marquardt over straightforward gradient descent is that it converges in less iteration.

3.3 Initial value estimation

In order to provide the algorithm with good stability and locking capabilities, a coarse-to-fine strategy is employed in which we construct a pyramid of spatially filtered and sub-sampled images. In our implementation, five-level of pyramid representation of image was constructed. At the coarse level, we used translation only model; at second, third and fourth level, we used affine model; and at original resolution of image, we used projective model. As in the figure 1.

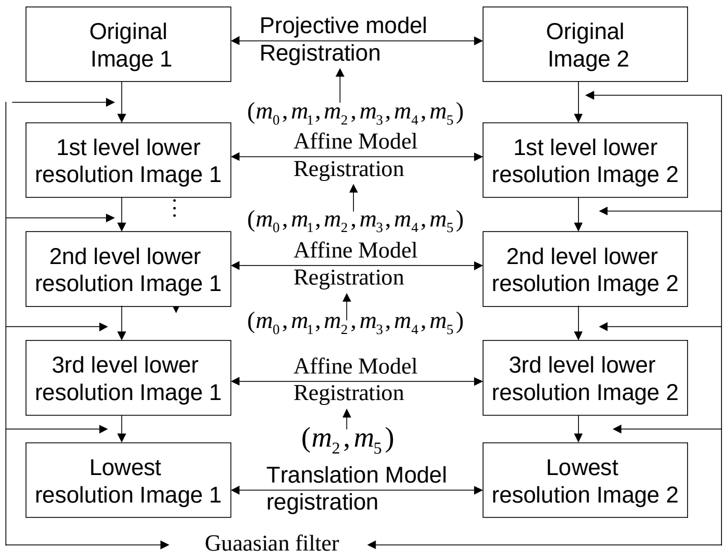

Figure 1. Multi-resolution and multiple model strategy for image registration

In the coarsest level, in order to estimate the translation terms m_2 and m_5 correctly, we used pseudo simulated annealing approach. The parameter space of m_2 and m_5 was divided into non-overlapping subspace. The parameter space of translation is limited by image size of that level, since it is impossible to find a translation that is larger than image size. In each subspace, the central point of the subspace is taken as initial value and running Gauss-Newton algorithm simultaneously, the optimal translation parameter is then obtained via search for the minimum energy among converged points of all the subspace.

The next level in the pyramid is then processed. The initial estimates at this level are $(1,0,2m_2,0,1,2m_5)$. These parameter is further refined via LM algorithm decribed before. The output of this level for the optimal affine parameters is $\{m_0, m_1, m_2, m_3, m_4, m_5\}$. There is the same procedure for the third and fourth level.

Finally, the fifth level in the pyramid is processed (at original resolution of image). The initial estimated at this level is $\{m_0, m_1, 2m_2, m_3, m_4, 2m_5, 0, 0\}$. These values is again refined via LM algorithm at this level to output the final result of projective model parameters. That is what we required.

4. EXPERIMENTAL RESULT

Figure 2 shows an example of alignment of two images taken by aerial digital camera. The images were taken under different illumination condition. In addition, geometric variation between two images is quite large. The original dimension of the image is 1524x1012. For such kind of images, it is quite difficult to align them accurately by using conventional multiple model and multi-resolution algorithm, since initial parameter values of a model are far away from zero. By using our algorithm, the registration result is shown in figure 2 (c). The multiple model parameter value estimated at different resolution is shown in table 1. Although these two images contain large variation in geometry and illumination, the algorithm aligns them precisely.

Figure 3 shows an example of alignment of two SPOT satellite images. These two images come from Palm Springs, California. They are both SPOT panchromatic images with 10-meter resolution. Automatic registration of these two images involves two cascaded steps. In the first step, we got the projective parameter aligning first picture with second one. The result is {0.806762 0.073329 –187.650436 –0.064981 0.943515 58.386524 –0.000108 –0.000186}. Due to too much image variability between them, the transformed image (or warped image) is not well aligned with second image. Therefore, in the second step, we conducted alignment between the warped image and second one again. The estimated parameters is { 1.01095 –0.0217812 3.79294 –0.016141 1.033661 –5.222983 0.000124 0.00004}. Combining these two sets of projective model parameters together, we obtain the more accurate projective model parameters that brings the first image to be aligned with second one precisely. The result is shown in figure 3. (c).

5 . CONCLUSION

In the paper, a new algorithm for satellite image registration was developed. The algorithm has the following characteristics. (1). The registration process is totally automatic, without requiring either control points or sensor's parameters. (2). The robust estimation mechanism was incorporated into the algorithm, thus allowing partial occlusion and multiple motion; (3) Illumination model based on low-order polynomial functions used in our approach enhances the robustness of the algorithm against illumination changes. The Experimental result demonstrates the robustness, efficiency and accuracy of the algorithm.

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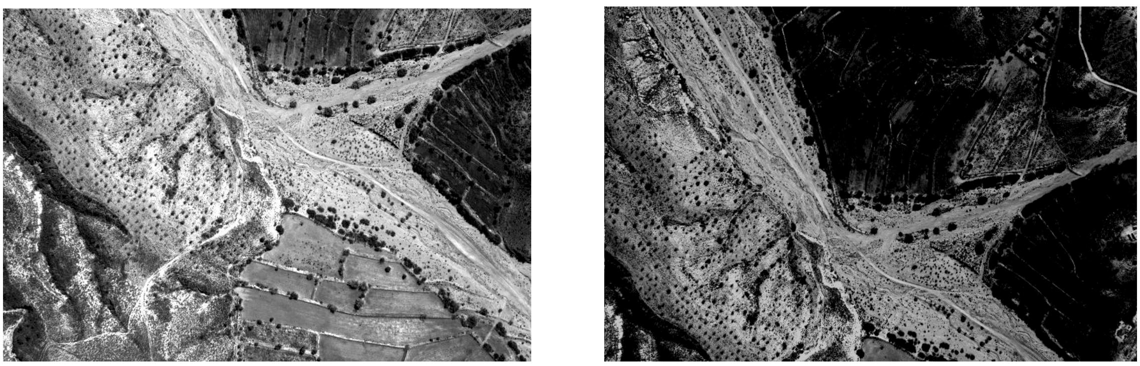
Table 1. Model parameter estimation at different level of pyramid

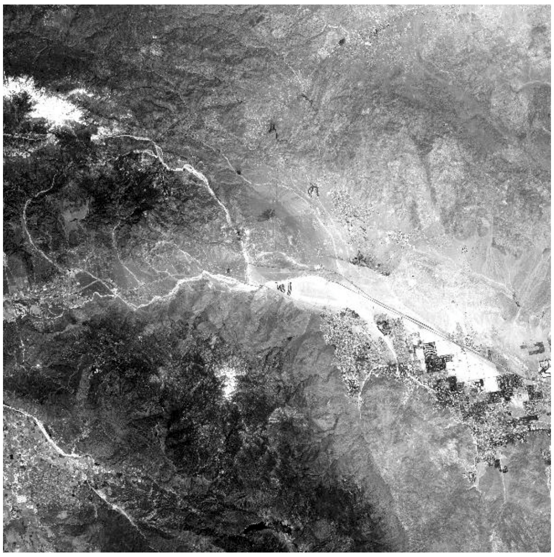
	m_0	m_1	m_2	m_3	m_4	m_5	m_6	m_7
Original Resolution	1.011485	0.005741	65.806	-0.00349	1.023697	366.91449	-0.00001	-0.000007
1st level lower Res.	1.009296	-0.00166	33.706211	-0.005312	0.973488	-179.128555		
2nd level lower Res.	1.007450	-0.002797	16.855967	-0.006308	0.966268	-89.183762		
3rd level lower Res.	1.003075	-0.00475	8.419368	-0.005961	0.961763	-44.089134		
Lowest Resolution			4.146406			-21.575346		



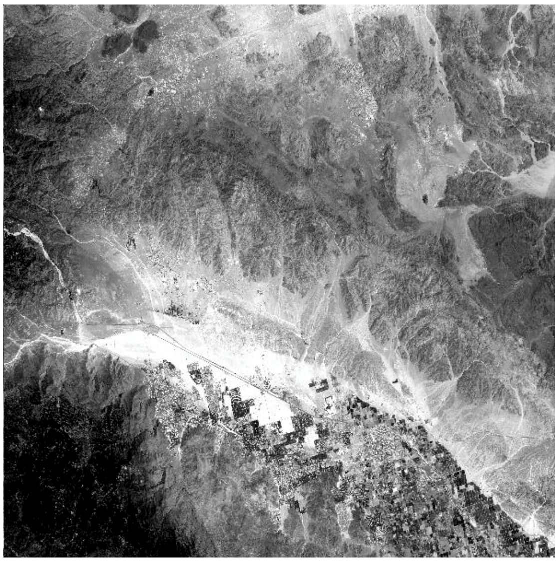
(a) (b)

(c)

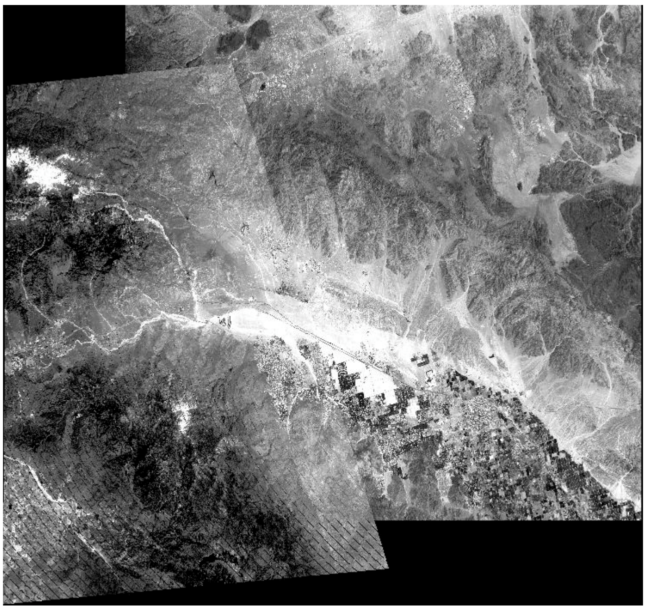
Figure 2. (a)(b) The original images, (c) The alignment of first image with second one



(a)



(b)



(c)

Figure 3. (a)(b) Two SPOT satellite images; (c) The alignment of first image with second one