SEMI-RIGID REGISTRATION OF REMOTE SENSING AIRBORNE SCANNER IMAGES

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ABSTRACT

This communication addresses the problem of automatic registration of raw images issued from an airborne multispectral imaging scanner with the aid of reference ortho-images available by classical aerial photography. We develop the proposed model, which accounts for a scan line shift process, in order to compensate for the roll motion of the aircraft, in addition to a RST deformation. The estimation of the model parameters is performed by using a PDE-based approach for the maximization of the mutual information between the source and the target image, starting from an initial estimate of the scan line process. We assess the robustness of this method and show an example of application to aerial image data.

1. INTRODUCTION

Automatic pixel-based registration of images has now become an essential tool for the enhancement of information in multimodal image processing systems, and particularly in the fields of medical imaging [1], [2] and remote sensing [3]. Historically, the research in image registration started by considering rigid deformation models such as RST (*rotation, scale, translation*), often involving cross-correlation (in Cartesian co-ordinates for translation and/or (log-)polar co-ordinates for rotation and scale [4]) between images acquired by identical or similar sensors. However, this rather robust approach is of little interest when :

- one wishes to automatically register images acquired by different image sources (visible, infrared, etc.),
- the deformation model is complex and cannot be reduced to a global and rigid one such as RST.

Several answers exist to manage these difficulties, sometimes within a joint framework. Firstly, it is well-known that Shannon's information theory is able to account for the inhomogeneity of information sources [5], by adopting the mutual information shared by two image data of different nature as a comparison criterion. Secondly, the increasing development and use of PDE-based and variational approaches in image processing and analysis allows to consider complex deformations by means of regularized displacement fields [1] [6] [7].

In this communication, we propose a tool for the automatic registration of images acquired by airborne remote sensors working in a line scanning mode. Such devices (like CASI, AISA or AVIRIS) allow to capture a single scene in several spectral bands and produce 'data cubes' which convey both spatial (two-dimensional) and spectral (one-dimensional) information. Whilst one spatial dimension corresponds to an instantaneous scan line, the other spatial dimension is subject to the aircraft's attitude (roll, pitch and yaw), among which the roll motion is prominent. Registration of such raw image data onto reference images thus make it necessary to introduce an adequate deformation model, as well as to account for the multi-modality of image acquisition.

In Section 2, we first present the deformation model which combines a rigid RST model and a scan line shift process. In Section 3, we derive the estimation of the parameters of the inverse transform, and its setting by a PDE approach. We assess the robustness of this method in a synthetic case and show an example of application to CASI image data in Section 4. Finally, we conclude in Section 5.

2. DEFORMATION MODEL

The automatic registration of a raw image acquired by a multispectral scanner onto a reference image requires a precise modeling of the deformation processes which are involved. In the present case, if we assume in a first place only a uniform translation of the aircraft at given altitude and in a given direction, the first contribution of mis-alignment with respect to a reference image (namely a georeferenced image) is a rigid RST deformation: the acquired image can be superimposed on the reference image up to a positive similitude. In a second place, the attitude data (roll, pitch, yaw) can be taken into account. However, in order to reduce the dimensionality of the parameter estimation, and observing that the roll motion is prominent in most available airborne scanner data, we have considered that raw images are also altered by a relative scan line shift process. To summarize, we have chosen the following deformation model :

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$$\mathcal{D}(\alpha, \rho, \mathbf{t}, \mathbf{l}) = \mathcal{L}(\mathbf{l}) \circ \mathcal{T}(\mathbf{t}) \circ \mathcal{S}(\rho) \circ \mathcal{R}(\alpha) \quad , \qquad (1)$$

where $\mathcal{R}, \mathcal{S}$ et $\mathcal{T}$ are respectively the transformations of rotation by angle α, scaling by factor ρ (both applied at the image center) and translation by vector $\mathbf{t}$, and $\mathcal{L}$ is the application of a set of relative shifts $\mathbf{l} = [l_0 \ldots l_{i_{\max}-1}]^T$ between the scan lines (see Fig. 1). Resolving the registration problem thus requires the optimization of the parameter $\Theta = [\alpha, \rho, \mathbf{t}, \mathbf{l}^T]^T$:

$$\Theta^\star = \arg\min_\Theta C(I_r, I_d \circ \mathcal{D}_\Theta^{-1}) \quad , \qquad (2)$$

where $I_r(\mathbf{s}), \mathbf{s} = (i, j) \in \Omega = \Omega_i \times \Omega_j$ is the reference image (which we shall refer to as the target), $I_d(\mathbf{s})$ is the original raw deformed image (the source image to align), and $C(.,.)$ is a criterion for the comparison between two images, i.e. a mis-alignment cost functional.

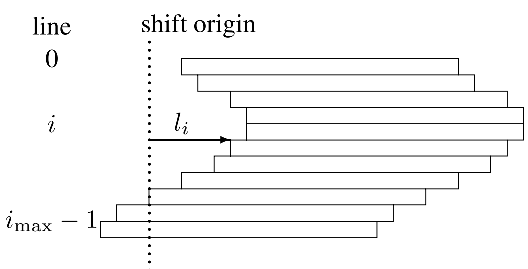

Fig. 1. Scan line shift modeling.

3. MODEL PARAMETER ESTIMATION

In the case of source and target images issued from the same imaging device, the choice of the Sum of Squared Differences (SSD) or the Correlation Ratio (CR) criteria are the most natural ones [4] [8]. However, for different sensors and/or in the case of multi-date acquisition and/or in the case of other target images (aerial, satellite, digitized maps, etc.) which can be used for registration, these criteria do not apply. In such cases, the use of the mutual information between the source and target image is recommended [9]. We have used this criterion, considering the minimization of the following criterion:

$$\mathcal{J}_{\mathcal{MI}}(\Theta) = -\mathcal{MI}(I_r, I_d \circ \mathcal{D}_\Theta^{-1}) \quad , \qquad (3)$$

where the mutual information between registered and reference images is given by:

$$\mathcal{MI}(I_r, I_d \circ \mathcal{D}_\Theta^{-1}) = \int_{\mathbb{R}^2} f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}(i_1, i_2) \log \frac{f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}(i_1, i_2)}{f_{I_r}(i_1) f_{I_d \circ \mathcal{D}_\Theta^{-1}}(i_2)} di_1 di_2 \quad . \qquad (4)$$

$f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}$ represents the joint pdf of the target and registered images, f_{I_r} is the pdf of the target image and $f_{I_d \circ \mathcal{D}_\Theta^{-1}}$ is the pdf of the registered image.

3.1. Optimization using PDEs

We have performed the optimization of the joint RST and line shift process $\mathbf{l}$ by approaching the solution of the Euler-Lagrange equation by a gradient descent. RST parameters were not subject to any regularization of the solution, while the solution for $\mathbf{l}$ was regularized using a low-pass filtering which was specified and performed in the frequency domain, in a similar manner than the one described in [6]. More precisely, the gradient descent writes:

$$\left\{ \begin{array}{lcl} \alpha_t & = & \int_\Omega W_\Theta(\mathbf{s}) \nabla_\alpha I_d \circ \mathcal{D}_\Theta^{-1}(\mathbf{s}) \, d\mathbf{s} \\ \rho_t & = & \int_\Omega W_\Theta(\mathbf{s}) \nabla_\rho I_d \circ \mathcal{D}_\Theta^{-1}(\mathbf{s}) \, d\mathbf{s} \\ \mathbf{t}_t & = & \int_\Omega W_\Theta(\mathbf{s}) \nabla_{\mathbf{s}} I_d \circ \mathcal{D}_\Theta^{-1}(\mathbf{s}) \, d\mathbf{s} \\ \mathbf{l}_t & = & \left[\int_{\Omega_j} W_\Theta(\mathbf{s}) \nabla_j I_d \circ \mathcal{D}_\Theta^{-1}(\mathbf{s}) \, dj \right] \circledast \mathbf{g} \\ \Theta(t=0) & = & \Theta_0 \end{array} \right. \qquad (5)$$

where

$$W_\Theta(\mathbf{s}) = -\frac{1}{\mu(\Omega)} \left[\psi \star \frac{\partial L^{\mathbf{\Theta}}}{\partial i_2} \right] (I_r(\mathbf{s}), I_d \circ \mathcal{D}_\Theta^{-1}(\mathbf{s})), \qquad (6)$$

$$\frac{\partial L^{\mathbf{\Theta}}}{\partial i_2} = \frac{1}{f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}(i_1, i_2)} \frac{\partial f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}(i_1, i_2)}{\partial i_2} - \frac{1}{f_{I_d \circ \mathcal{D}_\Theta^{-1}}(i_2)} \frac{\partial f_{I_d \circ \mathcal{D}_\Theta^{-1}}(i_2)}{\partial i_2} \quad , \qquad (7)$$

ψ is the kernel used for the computation of the Parzen-Rosenblatt estimate of the joint pdf $f_{I_r, I_d \circ \mathcal{D}_\Theta^{-1}}$, $\circledast$ is the circular convolution operator and the vector $\mathbf{g}$ represents the impulse response of an ideal frequency (non causal) low-pass filter:

$$g(i) = 1 + 2 \sum_{k=1}^{K} \cos \frac{2\pi k i}{i_{\max}} \, , \quad i = [0 \ldots i_{\max} - 1] \qquad (8)$$

3.2. Initialization of the scan line shift process

In order to avoid starting the gradient descent in Eq. 5 with an initial guess of $\mathbf{l}$ too far from the solution, we propose to compute a rough estimate of this line shift process in an unsupervised way by the use of the spatial correlation between successive lines. Specifically, we try to align successive lines of the raw image by computing their cross-correlation, and store the locations of the cross-correlation maxima into a vector $\mathbf{c} = [c_0 \ldots c_{i_{\max}-1}]^T$. Next, $\mathbf{c}$ is sum-cumulated and the result is low-pass filtered to provide an initial estimate of the line shift process, that is:

$$\hat{\mathbf{l}} = [c_0\ ,\ c_0 + c_1\ ,\ \ldots \sum_{i=0}^{i_{\max}-1} c_i] \circledast \mathbf{f} \tag{9}$$

Fig. 4 shows an example of unsupervised scan line shift compensation with this simple technique. Obviously, this method tends to align successive scan lines thanks to the most highly contrasted and vertical linear features which are present (e.g. roads), which may not always be the case in practical situations. Nevertheless, its advantage is to easily remove from the initial estimate 'high frequency' shift variations in the scan line process. In our experiments, we have chosen an ideal frequency low-pass filter $\mathbf{f}$ with 15 coefficients.

4. EXPERIMENTAL RESULTS

4.1. Assessment of parameter estimation

In order to assess the proposed algorithm, we have applied the deformation model in Eq. 1, and a reversal of gray level values to a reference image to obtain a deformed image (see Fig. 3). The parameters of the RST model are given in Table 1. The line shift process is given by $l_i = 10\cos(2\pi i/256) - 5\cos(4\pi i/256)$.

We have computed these parameters in two situations, each time applying 500 iterations of the descent (5). In each case, we did not use the initial guess of the scan line shift. The first case makes use of the optimal line shift process model, i.e. its expression in the spectral domain requires three independent coefficients ($K = 2$ in Eq. 8). The second case corresponds to an over-estimation of the filter order with four independent parameters ($K = 3$). The results obtained are given in Table 1 for the RST model parameters, with $\mathbf{t}$ in pixel units. Estimates of the scan line shift processes are shown in Fig. 2. The results show that the algorithm converges to the expected solution, even for RST parameters when the filter order is over-estimated. A larger over-estimation of this order ($K = 4$ or 5) yields a poor estimate of the model parameters. From a practical viewpoint, the selection of the optimal filter order can be made by comparing the mutual information $\mathcal{MI}(I_r, I_d \circ \mathcal{D}_\Theta^{-1})$, or the joint entropy $\mathcal{H}(I_r, I_d \circ \mathcal{D}_\Theta^{-1})$ for different values of K.

Table 1. Estimation of deformation model parameters

RST parameters	α	ρ	$\mathbf{t}$
true	20^o	1.2	$(5, 5)$
regul. $K = 2$	19.62^o	1.196	$(4.99, 5.28)$
regul. $K = 3$	20.22^o	1.187	$(5.50, 5.53)$

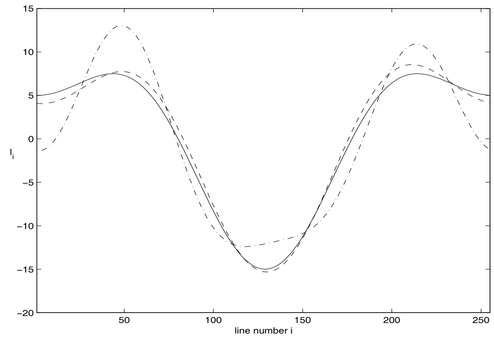

Fig. 2. Scan line shift estimation: (—) true ; (- -) estimate using $K = 2$; (-.-) estimate using $K = 3$.

Fig. 3. Registration of synthetic images: (left) Source image ; (middle) Target image ; (right) Registered source image for $K = 2$.

4.2. CASI image registration

We have applied this technique and assessed its robustness in several experimental cases, using real raw data (non corrected for roll motion and non georeferenced) issued from the CASI multispectral scanner available in our laboratory. These images were acquired in 1998 over a coastal zone in Brittany, France, and we tried to align them onto ortho-images acquired in 2003 by the French National Geographic Institute (IGN). Fig. 4 shows an example of a target image and a registered result. 300 iterations of the gradient descent were performed, using a frequency filter with $K = 10$ coefficients and the scan line shift estimate $\hat{\mathbf{l}}$ as the initial condition for the line shift process. The registration in this example is satisfactory, even if a vestigial line shift remains at the bottom of the rectified image. This occurs due to the fact that the line shift process in our model is constrained to be a periodic function of the i variable, which is obviously not the general case. Mis-alignment at the top left of the image is mainly due to the topography and cannot be removed with the present model.

5. CONCLUSION

In this communication, we have presented a method for semi-rigid registration of images acquired by an aerial scanner device, using ortho-images as reference. This technique is based upon an adequate, simplified deformation model which accounts for the relative motion of the scan line. It uses the mutual information criterion in a PDE-based approach to estimate the model parameters. We have shown on some examples that this technique provides satisfactory results ; we stress that it can be used in an automatic fashion with little parameterization for the georeferencing the and mosaicking of aerial image data. Moreover, it is very easily extensible to more complex (non rigid) deformation models such as polynomial warping in place of the RST model, which could allow to correct raw images for variations of the local topography. The assessment of the present approach with the automatic geocorrection of CASI images using GPS and real time aircraft's attitude data is presently under study.

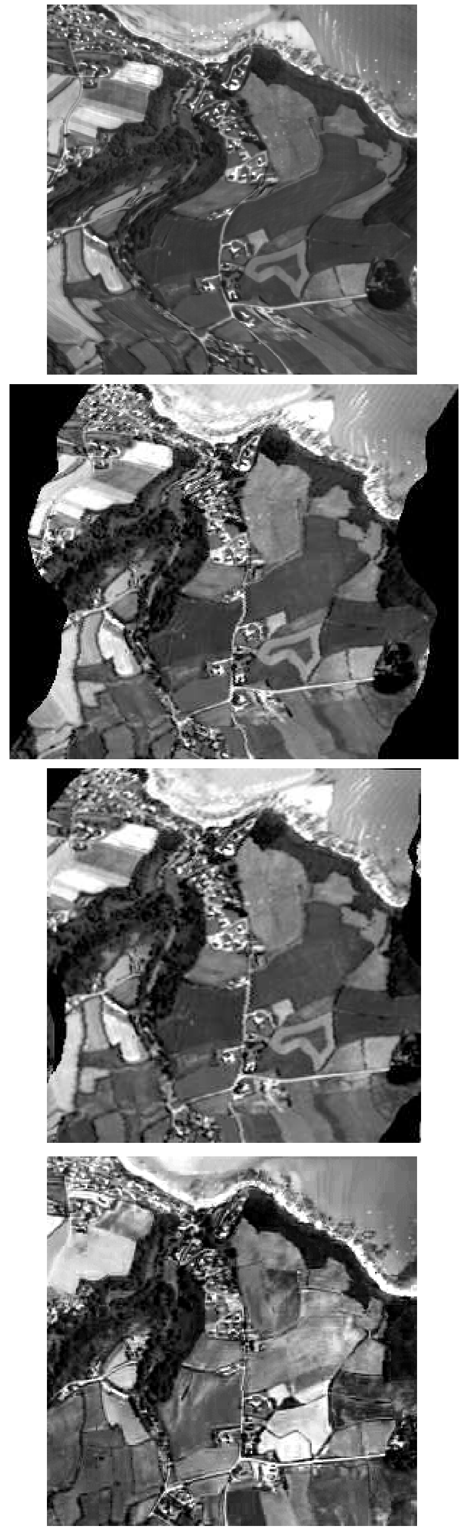

Fig. 4. Registration of aerial image. From top to bottom: Original raw CASI image ; Roll-corrected image ; Registered CASI image ; IGN target ortho-image.

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