The Registration of UAV Down-Looking Aerial Images to Satellite Images with Image Entropy and Edges

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Abstract. In this paper, we propose a novel and efficient image registration algorithm between high resolution satellite images and UAV down-looking aerial images. The algorithm is achieved by a composite deformable template matching. To overcome the limitations of environment changes and different sensors, and to remain image information, we fuse the image edge and entropy features as image representation. According to the altitude information of the UAV, we can get the scales of the down-looking aerial images relative to the satellite images. In the following, we perform an effective search strategy in the satellite images to find the best matching position. Different experimental results show that the proposed algorithm is effective and robust.

Keywords: image registration, deformable template match; entropy image; image edge.

1 Introduction

Image registration has found applications in numerous real life applications such as remote sensing, medical image analysis, computer vision and pattern recognition [1]. Given two, or more images to be registered, image registration estimates the parameters of the geometric transformation model that maps a given image to the reference one. Geo-registration is a very useful technique, which can be widely used in UAV (Unmannered Aerial Vehicle) to navigate, or to geo-locating a target, or even to refine a map [2].

Feature-based registration methods have made great progress in dealing with aerial images [3,4,5] and aerial image sequences [6,2]in recent years. Tuo et al. [3] perform registration after modifying the images to fit a specified brightness histogram. The features are then detected and aligned. Yasein and Agathoklis [4] solve only for a similarity transformation, but use an iterative optimization where the points are weighted according to the current residual. Xiong and Quek [5] perform registration up to similarity transformations without explicitly finding correspondences. After detecting features in both images, an orientation is computed for each feature and all possible correspondences are mapped into a histogram according to the orientation

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differences. The peak in the histogram is chosen as the rotation between the images. Scale is determined through the use of angle histograms computed with multiple image patch sizes and selecting the highest peak from the histogram. Niranjan et al. [6] build upon the work of Xiong and Quek in order to register images in an image sequence up to a homography. Lin et al. [2] concentrate on registering consecutive aerial images from an image sequence. They use a reference image (such as a map image) in order to eliminate errors that accumulate from local methods. Their two-step process first performs registration between images and then uses this as an initial estimate for the registration with the reference image.

Various works have been presented for the UAV pose estimation using a camera. A localization method matching digital elevation maps with aerial images has been suggested [7], and relative and absolute UAV localization methods by matching between satellite images and down-looking aerial images have been studied [8]. Caballero estimates a relative position of the UAV by calculating hymnographies among down-looking aerial scenes with the assumption that the ground is a plane[9][10]. Kil-Ho Son develops an UAV global pose estimation algorithm by matching the forward-looking aerial images with the satellite images [11].

The paper is organized as follows. In Section 2, we introduce the background of the proposed image registration algorithm. Then we describe the novel deformable template matching method in Section 3. The experimental results are presented in Section 4, which is followed by some conclusions in Section 5.

2 Background

Access to high resolution images for many areas of the world does not represent a problem any longer. So, it is feasible that we regard the high resolution satellite images provided by the up to date Google Earth software as the geo-referenced image. Beside, the UAV is equipped with down-looking vision systems and the laser altimeter. The viewpoint of the vision system is similar to that of the satellite, so we assume that the motion between satellite images and down-looking aerial images agrees to affine transformation model in Equation 1. This is convenient to the following matching.

$$\begin{bmatrix} x_s \\ y_s \end{bmatrix} = A \begin{bmatrix} x_u \\ y_u \end{bmatrix} + T = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_u \\ y_u \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} \tag{1}$$

Where (x_s, y_s), (x_u, y_u) are the coordinates in satellite image and down-looking aerial image respectively, A is the deformation matrix, T is the translation vector.

The laser altimeter can give the UAV altitude relative to the ground. The altitude can give a cue to calculate the scales of the down-looking aerial images relative to the satellite images. This is very important information for us. Scaling is performed converting the aerial image to the resolution of the reference image. The scale factor s is calculated using Equation 2 and it is different in x and y direction of the image plane since the aerial images used do not have squared pixels.

$$\begin{bmatrix} s_x \\ s_y \end{bmatrix} = \begin{bmatrix} \frac{1}{f_x} \\ \frac{1}{f_y} \end{bmatrix} H \times I_{res} \tag{2}$$

H is the altitude of the UAV relative to the ground given by the laser altimeter. I_{res} is the resolution of the reference image provided by the Google Earth.

In the following, we perform a novel deformable image matching between geo-refernced image and down-looking aerial image to find the UAV position, and give the values of affine parameters.

3 Novel Deformable Template Matching

The geo-referenced and the video camera image are generally taken at different time. It can be months or years, the illumination conditions will differ. Therefore, it is necessary to choose the features which are robust to the illumination changes. A Sobel edge detector is applied to both the geo-referenced image and the image taken from the on-board video camera. The choice of using edge features derives from the fact that the edges are quite robust to environmental illumination changes.

Another important factor to be considered is the altitude of the UAV from the ground. The higher the UAV flies, the more structure from the environment can be captured. It means that image registration is more reliable at higher altitude. Considering that small details change quite fast (e.g. car moving on the road) while large structures tend to be more static (e.g. roads, buildings...), flying at higher altitude makes the registration more robust to small dynamic changes in the environment. Besides, the geo-referenced and the aerial image are captured with different sensors. We must find the features which are insensitive to many issues in multi-sensor matching while retaining much image information. The entropy image is the best selection, which is proved by Clark F. Olson in [12]. The entropy image is also invariant to the illumination changes, which is a strong support to the edge feature. But the obtained entropy image is influenced by the window size. The edge feature can overcome this drawback.

In this paper, we fuse the edge and entropy of the template as its representatives, the both features are complementary, which are robust to environment changes, different sensors and retain image information. We aim to maximize the normalized correlation between high resolution satellite images and down-looking aerial images to find the best matching position. In our proposed algorithm, there are two terms in the deformable template matching function, as shown in Equation 3. The flowchart is shown in Fig. 1.

$$NCC_{total} = (NCC_{edge} + NCC_{entropy}) / 2 \tag{3}$$

In general, the deformable template matching involves rotating and rescaling the aerial image according to the pose parameters. The scale parameter can be estimated in Section 2. We can obtain the rotation parameter with the best matching position by searching in the geo-referenced image.

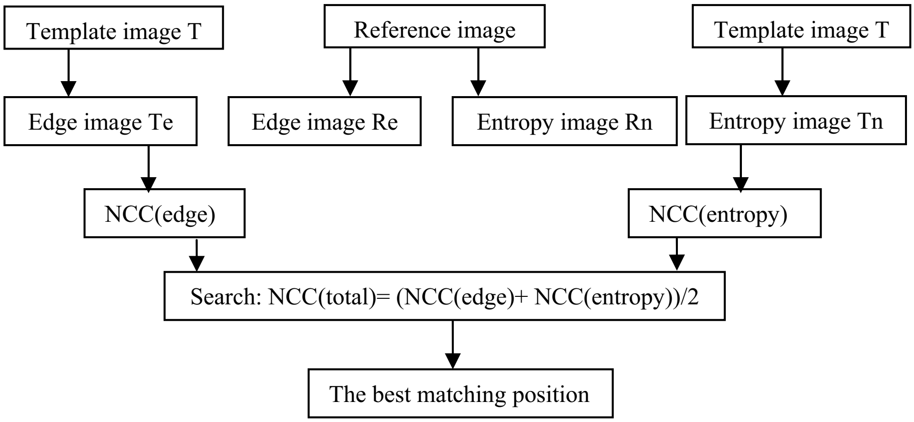


Fig. 1. The flow chart of our proposed deformable template matching algorithm

3.1 The Edge Operation

After the color aerial images are converted to the gray images, a median filter is applied to remove small details which are visible in the aerial image but not visible in the reference one. It is also capable of preserving the edges sharp when removes the details. After filtering, the Sobel edge detector is applied. Then scaling is performed converting the aerial image to the resolution of the reference image. The calculation of the scale parameters refers to the method in Section 2. According to the reference image, it is converted into gray images, and the Sobel edge detector is applied. The aerial and reference edge images are saved for the following deformable template matching.

3.2 The Entropy Image

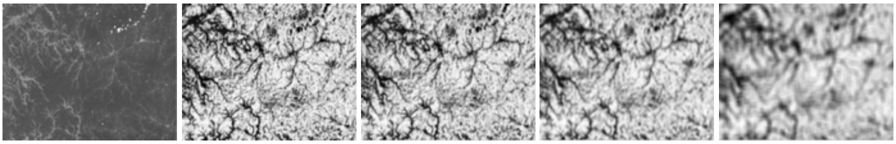
For a discrete random variable A, with the marginal probability distribution $p(A)$, the entropy is defined as

$$H(A) = -\sum_{A} p(A) \log p(A) \tag{4}$$

Note that $0 \times \log 0$ is taken to be zero, since

$$\lim_{x \to 0} x \log x = 0 \tag{5}$$

We apply an entropy transformation to both the aerial image and reference image as follows. For each image location (x, y), we examine the intensity values in an image window centered (x, y) with the size $k \times k$. The intensities are histogrammed and the entropy for the window is computed according to the Equation (4). In practice, it is useful to smooth the histogram prior to using the Equation (4). For efficiency, we use a histogram with 128 bins and smooth the histogram using a Gaussian window.



(a) (b) (c) (d) (e)

Fig. 2. Entropy images at different scales. (a) The original image (b)By 5*5window (c)By 7*7window (d)By 11*11window (b)By 21*21 window.

Fig. 2 shows an example of the entropy images generated at different scales. We can see that the entropy transformation retains the amount of local variation information in image. As the size of the window increases, the local entropy is spread and smoothed over a larger area, which provides an important basis for the following deformable template matching.

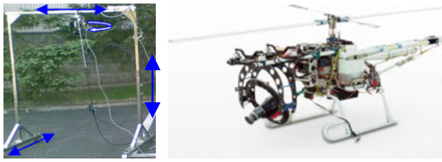
3.3 The Efficient Search

In order to get the optimism matching between the aerial image and the reference image, we use the FFT to quickly determine the normalization values for each translation of the aerial image. The search strategy is as follows.

According to the deformable template matching, we only know the scale of aerial images in the reference image, the rotation is unknown. We can search in the reference image to find the suitable angle with the best matching. The range of the rotation belongs to $[0, 2\pi)$, we divide the range equally into 36 parts, that is, θ_i = 0°, 10°, 20°….35°. With the obtained scale, each angle θ_i corresponds to a template T_i, in the following, we find the best matching position of the template T_i in the reference image, and give the normalized correlation value NCC_i. We calculate the average of the adjacent normalized correlation values: NCC_{i-1}, NCC_i, and NCC_{i+1}. The maximum of the average values is the optimism matching with the interval $[\theta_{i-1}, \theta_{i+1}]$. The interval $[\theta_{i-1}, \theta_{i+1}]$ is subdivided into smaller sections recursively to get the interval closer to the optimism matching position. The operation is repeated until the interval converges to a small neighborhood.

4 Experiments

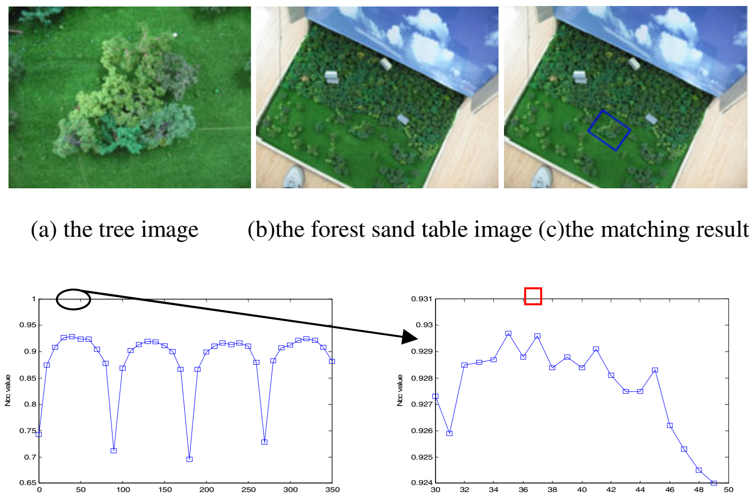
In this section, the performance of the proposed algorithm is evaluated for the different reference images and the down-looking aerial images. The high resolution satellite images from the Google earth are as the reference images in this paper. The UAV aerial images with the altitude information are provided. In order to calculate the scales, we calibrate the used camera with the calibration toolbox of Matlab beforehand. In the first experiment, the aerial images are obtained by the simulation motion platform of the UAV vision system (shown in Fig. 3(a)). In other experiments, the aerial images are captured by video camera fixed on the UAV (shown in Fig. 3(b)).



(a) (b)

Fig. 3. The UAV and its vision simulation motion platform

In the first experiment, the reference image is obtained by the Canon digital camera, which is about forest sand table from 1.7 meters. An image of a tree in forest sand table is as aerial image in this experiment from 0.24 meters. The two images are from different sensors and altitudes. The search process and the matching result are shown in Fig. 4. It is encouraging.



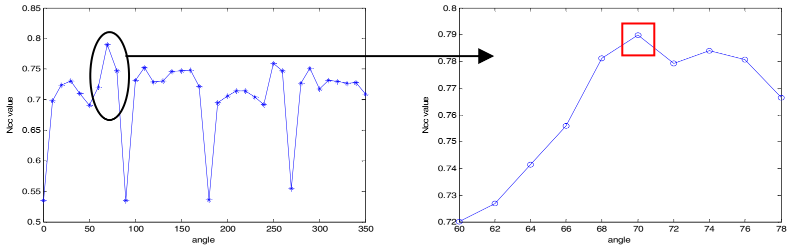
(a) the tree image (b)the forest sand table image (c)the matching result

(d) the result of the first search (e) the result of the further search

Fig. 4. A simulation experiment about forest sand table

A satellite image of Shenyang institute from the Google Earth is acquired from 300 meters above ground on Apr.2nd, 2009. The aerial image is obtained at 15 meters on Mar. 30th, 2010. s_x, s_y are gotten by Equation (2) with the help of the obtained camera internal parameters above. The two images are taken by different sensors and different environments. Firstly, we do the brute force search with the search strategy in Section 3.3. The normalized correlation values with different angles are shown in Fig. 5(d). The largest average of the normalized correlation values with the corresponding interval is at [60, 80]. The search continues until finding the suitable angle with the best matching, this is shown in Fig. 5(e). We can see from Fig. 5(c) that the experimental result of our proposed algorithm is satisfactory.

(a) the satellite image (b)the aerial image (c)the matching result



(d) the result of the first search (e) the result of the further search

Fig. 5. The matching result from the images of Shenyang institute

With the same aerial images and different satellite image, the satellite image is acquired from the higher altitude, so the scale s_x, s_y is calculated again. We can get another encouraging result of deformable template matching as shown in Fig.6

(a)another satellite image (b)the aerial image (c) different scale matching result

Fig. 6. The matching result from different scale satellite images of Shenyang institute

(a) (b) (c) (d)

Fig. 7. The matching results from different aerial images and same satellite image of Shenyang institute (a) the aerial image1, (b) the corresponding matching result from the aerial image1, (c) the aerial image2, (d) the corresponding matching result from the aerial image2

With the same satellite image in Fig.5 and different aerial image, another experiment is done to verify the robustness of the novel deformable template matching algorithm shown in Fig. 7.

From the above experimental results, we can see that our proposed algorithm is efficient and robust. Because, the viewpoint of the UAV camera is not completely down-looking and forward-looking, there are small errors in the matching. we will solve the problem in the future works.

5 Conclusions

In this paper, we develop a novel image registration algorithm between high resolution satellite images and UAV down-looking aerial images. The algorithm is achieved by a composite deformable template matching. The edge and the entropy of images are used to solve the problem brought by the changes of the illumination and different sensors. The combination of the edge the entropy also can retain most of the image information. The results of experiments on different types of images show that the proposed algorithm is effective and robust.

In the future, we will improve the efficient of our algorithm by updating the search strategy in composite deformable template matching, and extend the applications of the method for UAV pose estimation and UAV image mosaicing.

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