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A new navigation approach of terrain contour matching based on 3-D terrain reconstruction from onboard image sequence

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This article presents a passive navigation method of terrain contour matching by reconstructing the 3-D terrain from the image sequence (acquired by the onboard camera). To achieve automation and simultaneity of the image sequence processing for navigation, a correspondence registration method based on control points tracking is proposed which tracks the sparse control points through the whole image sequence and uses them as correspondence in the relation geometry solution. Besides, a key frame selection method based on the images overlapping ratio and intersecting angles is explored, thereafter the requirement for the camera system configuration is provided. The proposed method also includes an optimal local homography estimating algorithm according to the control points, which helps correctly predict points to be matched and their speed corresponding. Consequently, the real-time 3-D terrain of the trajectory thus reconstructed is matched with the referenced terrain map, and the result of which provides navigating information. The digital simulation experiment and the real image based experiment have verified the proposed method.

terrain contour matching, vision-based navigation, 3-D reconstruction, control points, key frame registration, optimal local homography

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Vision-based navigation obtains the position, pose and velocity by processing the images taken by the onboard camera. The technique is widely used in the field of self navigation of UAV and other aerial vehicles for its passive imaging, self-sufficiency, little disturbance, light weight, and small energy consumption. As one of the major means in the vision-based navigation, image matching is based on the corresponding relation between the topographical features and geographical positions, and it generally falls into imagery matching and terrain contour matching (TCM).

Navigation method based on the imagery matching registers the real image of the scene to the reference image with high accuracy; the navigation method based on TCM matches the real-time contour map to the reference map. At present, the contour map is measured mostly by radar or laser ranger. The reliability of the imagery matching method decreases as the imagery of the scene is affected by season, weather, and the duration of the shooting time, but the terrain contour is comparatively stable and thereafter the TCM navigation is more robust [1]. The conventional terrain measuring sensor is radar or laser ranger, which is likely to be detected and attacked when active. In addition, it has the disadvantages of heavy mass, huge energy consumption, and the less measurement data production [2].

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To solve the aforementioned problems, the terrain estimating method by a passive imaging sensor has been researched and found its application in autonomous vehicles. Lopez and Hrabar et al. calculated the depth map of the scene by means of optical flow during the flight planning and the obstacle avoiding, which requires the vehicle's velocity as a necessity [3, 4]. The 3-D reconstruction from image sequence is another focus of vision-based navigation researches. Templeton et al. researched the 3-D terrain reconstructing method based on planar parallax algorithm, which was employed in the terrain map generating and UAV navigating [5, 6]. Johnson et al. proposed a method of the reconstruction of terrain in the automatic landing of UAV, which needed the camera pose and transform information between the imaging [7]. They also researched the rinciple of the terrain selecting during the navigation [8]. Stevens et al. studied how to get navigating information by matching the reconstructed terrain map with the reference terrain map [9]. To their method, the information of the vehicle velocity, reconstruction of a large terrain map, and the particular off-line processing of the referenced map were indispensable. So far in the research on the terrain matching navigation based on 3-D terrain reconstruction from image sequence, the reliable automatic registration of the feature points of images with long distance and the real-time terrain reconstruction are the bottleneck.

This article presents a real-time and automatic vision-based navigation method for terrain matching by reconstructing 3-D terrain from image sequence. To achieve automation and simultaneity of the image sequence processing, we propose an image sequence processing method which tracks the sparse control points through the whole sequence to obtain the correspondence to solve the relation geometry. It estimates the optimal local homography from the control points to assist the feature points matching, by which the computation is reduced considerably. Consequently, the 3-D terrain of the trajectory is reconstructed in a real-time manner. It can be matched against the referenced terrain map directly and thereafter the navigating information is obtained.

1 Principle and key technique of the TCM navigating based on 3-D reconstruction from onboard image sequence

The principle and key technique of the TCM navigating based on 3-D reconstruction from onboard image sequence are as follows. First, the onboard camera takes the images along the trajectory continuously, and then the real-time 3-D terrain map is reconstructed from the overlapped images. Second, the reconstructed map is matched against the reference terrain map to provide the navigating information. As the basis of the TCM is the correspondence between the terrain and its position, it is necessary that the terrain should be of fluctuation. This article assumes that the rough relative position and pose of the camera are known, so the reconstructed terrain map is conformed with the referenced map, and the matching method TCM can be used directly [1, 10].

The flowchart of the navigation system is shown in Figure 1, which includes a 3-D terrain reconstruction and a terrain contour matching.

1.1 Method for key frame image selection

Key frames are selected from the image sequence, and they are the input to the 3-D reconstruction. An adequate overlapping area as well as a right intersecting angle should be guaranteed for the key frames selecting [11].

Based on the rough flight velocity and height known, the key frames are determined by the transforming information. We assume the followings: the optical axis is vertically downward, the height is h, the imaging focal is f, the angle of field is α, the displacement between the two imaging positions is Δs, the scale of the overlapped area along the flight direction is L, and the overlap ratio is r. The relationship is shown in Figure 2.

1) Requirements for key frames overlapping

The overlapping ratio r is the ratio of the overlapping area of two images to the total area of the individual image. When the whole strip is reconstructed from more than one couple of key frames, $r>r_{\min}$, where $r_{\min}$=0.6 is generally taken.

The relationship between the overlapping area and the flying distance, as illustrated by Figure 2, is

$$L = 2h\tan(\alpha/2) - \Delta s. \qquad (1)$$

From eq. (1), we can derive the relationship between the overlapping ratio and the flying distance as

$$r = L/[2h\tan(\alpha/2)] = 1 - \Delta s/[2h\tan(\alpha/2)]. \qquad (2)$$

After the ratio r is determined, the distance between the two positions where the images are taken can be computed by

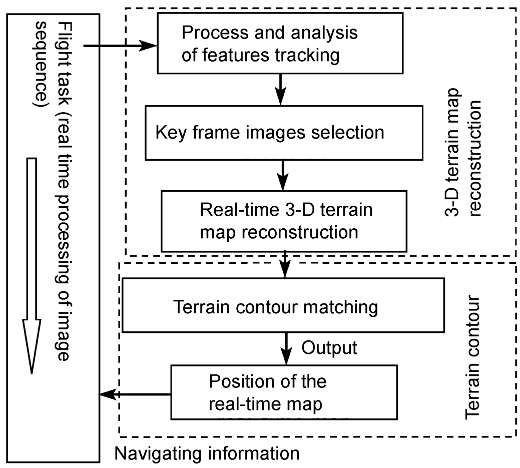

Figure 1 Flowchart of navigation based on the 3-D terrain reconstruction from image sequence.

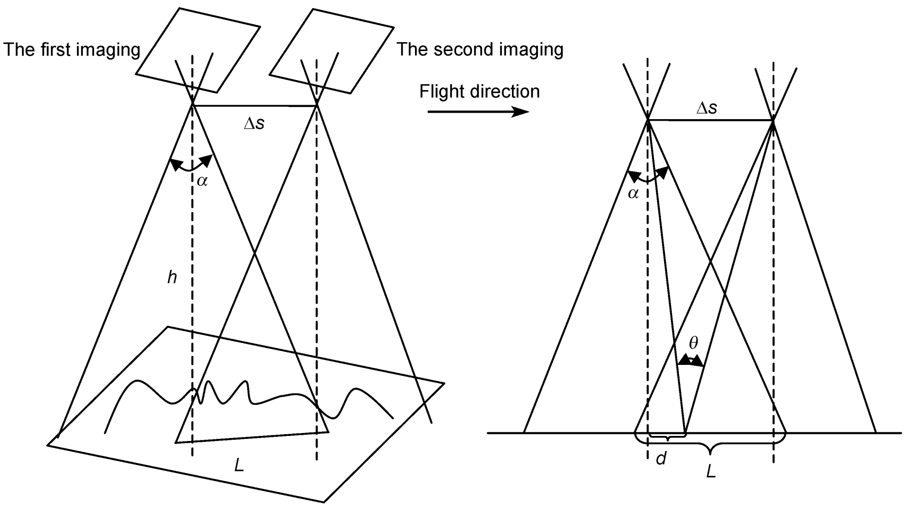

Figure 2 Working principle of key frames determination.

$$\Delta s = 2h(1-r)\tan(\alpha/2). \tag{3}$$

The request for the minimal ratio is $r_{\min}$, so the maximal distance $\Delta s_{\max}$ can be expressed by

$$\Delta s_{\max} = 2h(1-r_{\min})\tan(\alpha/2). \tag{4}$$

2) Requirement for interacting angle

When the intersection method is adopted to compute the 3-D coordinates of the points, the interacting angle should satisfy $\theta>\theta_{\min}$. In practice, it generally takes $\theta_{\min}$=10°, which should be larger if the restriction of the overlapping ratio permits. This article studies the angle of the interacting rays on the plane determined by the two optical axes (as shown in Figure 2). The target point that has a distance d to the projecting point of the first optical axis has an interacting angle θ, which is expressed as

$$\theta = \arctan\left(d/h\right) + \arctan[(\Delta s - d)/h]. \tag{5}$$

In the overlapping area with length of L in the flying direction, the minimal interacting angle of the object point is expressed as eq. (6),

$$\theta_{\min}^{L} = \arctan(\tan(\alpha/2) - L/h) + \arctan((L+\Delta s)/h - \tan(\alpha/2)), \tag{6}$$

which gets the minimal value under the condition that $d = h\tan(\alpha/2) - L$. When eq. (1) is substituted into eq. (6), the minimal interacting angle is expressed as

$$\theta_{\min} = \theta_{\min}^{L} = \alpha/2 - \arctan\left(\tan(\alpha/2) - \Delta s/h\right). \tag{7}$$

According to eq. (7) the minimal distance between the imaging positions of key frames is represented by

$$\Delta s_{\min} = h(\tan(\alpha/2) - \tan(\alpha/2 - \theta_{\min})). \tag{8}$$

3) Requirement of key frames for imaging and key frame selecting method

The condition to obtain key frames from image sequence is $\Delta s_{\min} \leqslant \Delta s_{\max}$. Based on eqs. (4) and (8), the configuration for the onboard imaging system is

$$(2r_{\min} - 1)\tan(\alpha/2) - \tan\left(\alpha/2 - \theta_{\min}\right) < 0. \tag{9}$$

To satisfy the requirement of the overlapping ratio and interacting angle for the flight distance Δs, the key frames are selected under the condition that the displacement Δs is supposed to take a value as large as eq. (10) permits.

$$\Delta s_{\min} \leqslant \Delta s \leqslant \Delta s_{\max}. \tag{10}$$

1.2 Corresponding feature points matching of key frames based on control points tracking

1) Problem in corresponding feature points matching and solution

The robust and highly accurate matching of the feature points between the key frames is critical in the 3-D reconstruction from image sequence. When applied to vision navigation, the matching must be implemented in a real-time and automatic manner. In a world scene, the view angle is large, so the geometric and radiant changes of the corresponding points are relatively large. As a result, the reliability of matching is decreased and the time consumption is increased [12].

However, the image sequence is acquired on a temporal basis during the flight, so the feature points tracking and automatic matching are facilitated by the small disparity, little change of image character and imaging angle of the adjacent images captured onboard thanks to their continuity in time and overlapping in imaging areas. Therefore, a feature points matching method is proposed by tracking the control points which are consequently used as corresponding points in the estimation of multi-view geometry.

2) Quasi uniform selection and application of control points

The control points tracked through the whole image sequence should be relatively uniform because they serve as the input data for the multi-view geometry estimation. In order to avoid the case where the distribution of the detected feature points by feature extracting algorithm is too arbitrary, a features extracting method is proposed which employs the region information. The method includes two steps.

Step 1. To divide the whole image into to $I\times J$ sub regions.

Step 2. To calculate the pixel's interesting value (IV) of each sub-region. In the area where the IVs are large enough, n features of the largest IV are selected and finally the control points of the sub-region are composed.

Forstner feature extracting algorithm is employed for its accuracy and computing speed. The corresponding points between the key frames are obtained by tracking all the control points through the whole image sequence.

1.3 Dense points matching based on the optimal local homography determined by the control points

1) Problem in dense points matching of key frames and its solution

The control points distribute in the whole image, but they are not suitable for terrain contour matching for their sparseness. So it is necessary to match and reconstruct the dense points, which takes large amount of computation. To meet the challenge of real-time reconstruction, we propose a dense points matching method that is guided by the optimal local homography derived from the control points.

Homography, an important parameter in the two-view geometry, is induced by a 3-D plane. Image points of the 3-D plane are corresponded to image points in a second view by a planar homography. The relationship of the corresponding image points $\boldsymbol{x}$ and $\boldsymbol{x}'$ of the two views associated with homography is described as $\boldsymbol{x}'=\boldsymbol{H}\boldsymbol{x}$, where the homography matrix $\boldsymbol{H}$ is a 3×3 matrix, which can find a linear solution from 4 or more groups of matched points [13]. A homography matrix $\boldsymbol{H}$ solved from any 4 groups of matched points accords with a 3-D plane if and only if the homography matrix $\boldsymbol{H}$ is compatible with the fundamental matrix $\boldsymbol{F}$, namely the matrix $\boldsymbol{H}^{\mathrm{T}}\boldsymbol{F}$ is skew-symmetric, which is described as [13, 14].

$$\boldsymbol{H}^{\mathrm{T}}\boldsymbol{F}+\boldsymbol{F}^{\mathrm{T}}\boldsymbol{H}=\boldsymbol{0}. \tag{11}$$

A dense point matching method is proposed on the basis of the compatible property. It employs the epipolar and optimal local homography constraints and takes the advantage that the optimal local homography gives a correct correspondence forecasting. The local plane is a 3-D plane passing the correspondence around the point to be matched, whose corresponding homograph is called local homography. All the quaternary-correspondence groups of the correspondence adjacent to the matching point can be recognized as either correspondence groups which belong to the local plane or groups which do not. Figure 3 explains the correspondence groups, where the quaternary-correspondence groups (x_1, x_2, x_3, x_4) and (x_1, x_2, x_5, x_6) are correspondence groups belonging to local planes, but the groups (x_1, x_2, x_3, x_5) and (x_1, x_2, x_3, x_6) are not. The optimal local homography is the homography which can give a to-be matched point a predicting position with the highest accuracy. The algorithm to estimate the optimal local homography is described as follows.

Step 1. To acquire candidate correspondence groups by compatible condition. Each group belongs to a local plane where 4 control points are located.

Step 2. To predict the corresponding points of the points to be matched according to each local homography, and then calculate the correlations between the point to be matched and its predicting points which are regarded as the measurement of the local homography.

Step 3. To choose the local homography with the biggest correlation as the optimal local homography of the area where the to-be matched point is located.

In Figure 3, the predicting points determined are p_i' by local homography $\boldsymbol{H}_i$, and p' by $\boldsymbol{H}$. Considering that the correlation between p and p' is the greatest, $\boldsymbol{H}$ is accepted as the optimal local homography.

Compared with the method proposed in ref. [15] that uses the local homograhy decided by the correspondence nearest to the point to be matched, our method which introduces the verifying information by the matching image yields more accurate correspondence.

2) Points matching guided by the optimal local homograhpy

The matching method includes two parts as follows.

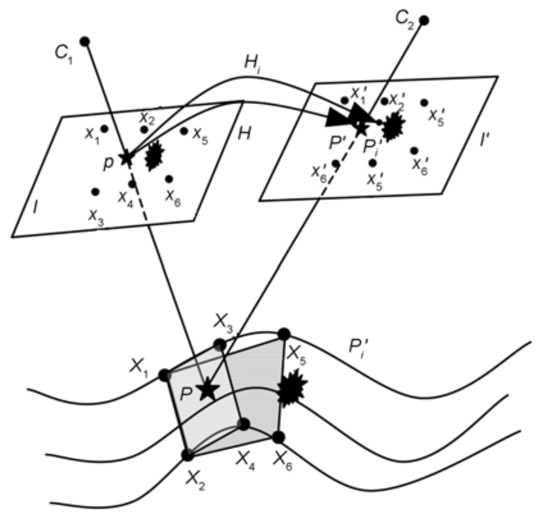

Figure 3 Feature matching by the guide of the optimal local homography.

i) To recognize the control correspondence groups

Given point $p(x,y)$ to be matched on the first image, quaternary-correspondence group of correspondence is selected in turn by its distance to the point. The homography matrix $\boldsymbol{H}_i$ of the selected group is calculated, and the homography of a group is considered the candidate local homography if $\boldsymbol{H}_i$ meets the compatible property condition. Otherwise, new quaternary correspondence group is selected by increasing the distance to the to-be matched point and calculated until $\boldsymbol{H}_i$ is recognized. The same process is done to recognize the next local homograhpy, until k groups are selected. Experiments show that it is adequate to forecast the correspondence when k is 3.

ii) Point matching guided by the local homography

For all points $p_i(x,y)$ in the area of the local control points on the first image I, their initial corresponding points $p_i^j(x,y)$ on the second image I' are predicted by using the homography $\boldsymbol{H}_j\,(j=1,\ 2,\ldots,\ m)$, and m predicting points are obtained. The correlations between points $p_i(x,y)$ and $p_i^j(x,y)$ are calculated by the image correlation with the corresponding image area. The homography which gives the predicting point with the maximal correlation is selected as the optical local homography, and point $p_i^j(x,y)\big|_{\max \mathrm{Cor}}$ is the final predicting point.

The matching guided by the optimal local homography is to calculate the predicting point on the second image using the homography, then to search the accurate position of the corresponding by least square matching (LSM) [16, 17].

The control points around the point to be matched form an average homography, which can give a predicting position for matching. Compared with the average homography, the optimal homography has the advantage that the point has a co-plane with the control point defining the homography and the predicting point is the most coherent with the point. As far as the terrain image matching is concerned, it is more accurate to predict points by the optimal local homography. In addition, it yields a better result when applied to dense point matching.

2 Implementation of the navigation based on the 3-D terrain reconstruction from image sequence

2.1 3-D terrain reconstruction of temporal image sequence

The 3-D terrain reconstruction of the temporal image sequence is a key process to the navigation. It includes key frames selection, key-frame feature point extraction and registration, and 3-D estimation.

In the application of navigation, key frames are selected by the proposed method. The control points are tracked through the whole sequence, and they are used as the correspondence in the relative geometry solving of the key frames. Then the optimal local homography is estimated, which guides the dense point matching in 3-D terrain reconstruction.

After the relative position and the pose parameter are introduced, the reconstructed terrain can be transformed to the coordinates consistent with the reference digital terrain map. Multiple couples of frames are used to connect the reconstructed local 3-D terrain together when a single couple is not sufficient for terrain matching.

This article adopts a two-view image method to reconstruct key-frame images. First, the fundamental matrix is solved from the tracked points by RANSAC algorithm; second, the motion parameters and the projection matrix are retrieved by introducing the interior parameters of the camera, and the projection matrixes in two cases are formed; third, the strip dense points are matched and reconstructed by triangular interaction.

In order to get a robust and accurate result, the algorithm combining weighted solution and RANSAC estimation is applied. In the final stage of the 3-D resolution, the optimal procedure is introduced to refine the result.

1) Fundamental matrix solution

The relationship of the corresponding points $\boldsymbol{x}\rightarrow\boldsymbol{x}'$ and the fundamental matrix $\boldsymbol{F}$ is expressed as $\boldsymbol{x}'^{\mathrm{T}}\boldsymbol{F}\boldsymbol{x}=\boldsymbol{0}$. Given no less than 8 groups of correspondence, the $\boldsymbol{F}$ matrix can be computed linearly [13]. This article chooses 8 groups of correspondence randomly to compute the $\boldsymbol{F}$ matrix iteratively with RANSAC algorithm, and then selects the optimal solution with the most supporting correspondence. The matching measurement is used as the weighting value in matrix $\boldsymbol{F}$ solution to increase the accuracy.

2) Solution and optimization of relative motion between image pairs

The essential matrix $\boldsymbol{E}$ in the two-view geometry can be derived from the equation $\boldsymbol{E}=\boldsymbol{K}^{\mathrm{T}}\boldsymbol{F}\boldsymbol{K}$, where matrix $\boldsymbol{K}$ is the camera's interior parameter. The rotation parameter $\boldsymbol{R}$ and translation parameter $\boldsymbol{t}$ are obtained by decomposition of matrix $\boldsymbol{E}$, which are refined to get the accurate solution by the L-M optimizing.

According to the displacement between the imaging positions of the key frames, the parameter $\boldsymbol{t}$ is adjusted to its true scale, so the motion parameter is consistent with the real value.

3) 3-D terrain reconstruction

The projection matrixes, $\boldsymbol{Q}_1=\boldsymbol{K}(\boldsymbol{I}\ \ \boldsymbol{0})$ and $\boldsymbol{Q}_2=\boldsymbol{K}(\boldsymbol{R}\ \ \boldsymbol{T})$, which are used to solve coordinates of a 3-D point, are derived from the camera motion parameters $\boldsymbol{R}$ and $\boldsymbol{T}$. The target point $\boldsymbol{X}$ is reconstructed from the matched point set by triangular intersection according to the imaging relation:

$$\begin{cases}\mu x_1=\boldsymbol{Q}_1\boldsymbol{X},\\ \mu x_2=\boldsymbol{Q}_2\boldsymbol{X}.\end{cases} \tag{12}$$

The variable $\boldsymbol{X}$ denotes the coordinates of the 3-D point in the camera coordinate system $X_cY_cZ_c$. Therefore, they should be transferred to the coordinate system $h_t\text{-}x'y'$ according to the camera pose $\boldsymbol{R}_0$ by

$$\boldsymbol{X}(x', y', h_t) = \boldsymbol{R}_0\boldsymbol{X}(x_c, y_c, z_c), \tag{13}$$

where h_t is the vertical direction, and $x'y'$ denotes the horizontal plane.

2.2 Terrain contour matching

The reference terrain map is the terrain height function $h_m(x, y)$ about the point absolute position (x, y), and it is stored in the digital format. The terrain contour matching provides positioning information by matching the real-time trajectory terrain map $h_t\text{-}x'y'$ with the reference map $h_m(x, y)$.

This article adopts the COR correlation algorithm in terrain matching. It determines the correlation coefficients between the real-time map and the points around the initial position of the reference map, and then carries out accurate positioning by quadrically fitting the correlations. The searching area is decided according to error value of the airborne inertial guidance system.

2.3 Implementation of the navigation based on 3-D terrain reconstruction from image sequence

In light of the aforementioned principle and the techniques, the navigation process based on 3-D terrain reconstruction from image sequence works as follows.

To extract and track the control points, estimate the distance between the imaging positions → To select the key frames from the image sequence → To solve the relative geometry of the key frames → To recognize the optimal local homography from control points and match the dense points guided by the homography → To introduce the relative distance and to solve 3-D points' coordinates → To introduce the reference pose parameter and transfer the reconstructed real-time 3-D terrain → To match the real-time terrain with the reference terrain map and obtain the navigation information.

3 Experimental results analysis

3.1 Analysis of the simulated data for 3-D reconstruction from image sequence

Figure 4 is the simulated digital terrain map, where the rectangle shows the region to be reconstructed. The simulating conditions are described as follows. The flying vehicle carrying the camera at the height of 200 m, the focus is 600 pixels, and the image is of 512×512 pixels. The motion of the camera is along the horizon, and the optical axis is vertical; the key frames are selected from the image sequence.

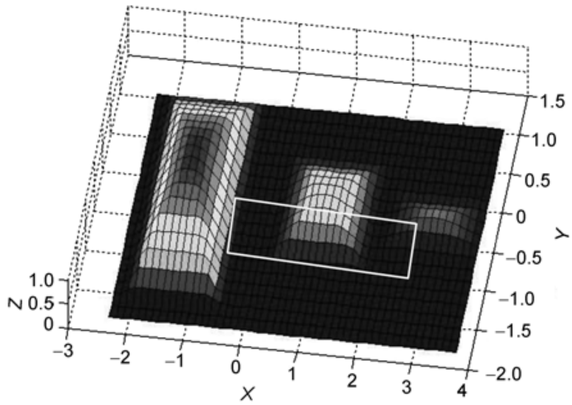

Figure 4 Simulated 3-D terrain.

In the experiment, the 3-D terrain was reconstructed from the simulated images, and the precision was verified by matching the reference map with the reconstructed terrain which was used as the real-time map.

The reconstructed local terrain map worked as the real-time map in the application of navigation. With the addition of positioning Gaussian noise of the image points to the 3-D reconstruction, the accuracy and the distribution of the COR correlations for the terrain matching were testified.

Figure 5(a) is the reconstructed terrain with added Gaussian noise of sigma 0.2 pixels in the image correspondence.

Figure 5(b) shows the correlation distribution of the terrain matching, and the correlation efficient has the maximal value at the correct position. Analysis of multiple groups with a registration error no more than 0.5 pixels show that the correlation distribution of the matching is like that of Figure 5(b). When the noise is relatively big, the extreme value of the correlation peak decreases, so does the sharpness. However, the correlation coefficients have a similar distribution with Figure 5(b), and the positioning error is restricted within 1 m.

3.2 Analysis of simulated experiments

The simulated experiments were carried out to examine the method proposed. The image sequence was taken by a hand-hold camera over a sand table, which was the simulation of the real terrain. The proposed method was used to process the images and implement the reconstruction and matching.

Figure 6(a) and (b) are a couple of adjacent key frames among the image sequence, Figure 6(c) shows the 3-D reconstruction of the strip region labeled on Figure 6(a) by a rectangle. For the experiment shown in Figure 6, the image resolution was 640 pixels×450 pixels, the equivalence focal was 659 pixels, the imaging distance was about 1.5 m and the terrain fluctuation scale about 20 cm. The correlation distribution between the reconstructed terrain and the reference terrain map is shown in Figure 7, which has a maximal

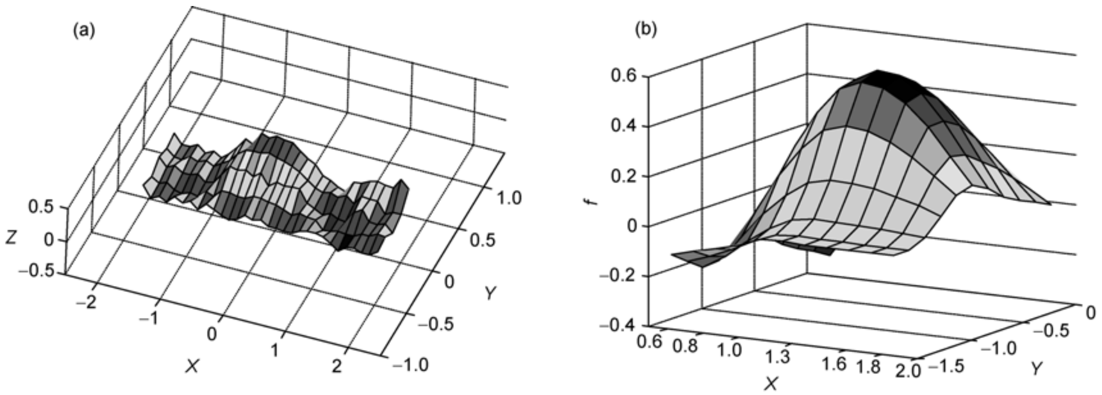

Figure 5 Reconstructed 3-D terrain and the correlation distribution of the terrain matching. (a) 3-D reconstruction of the simulated terrain; (b) correlation distribution of the matching between reconstructed strip and the reference map.

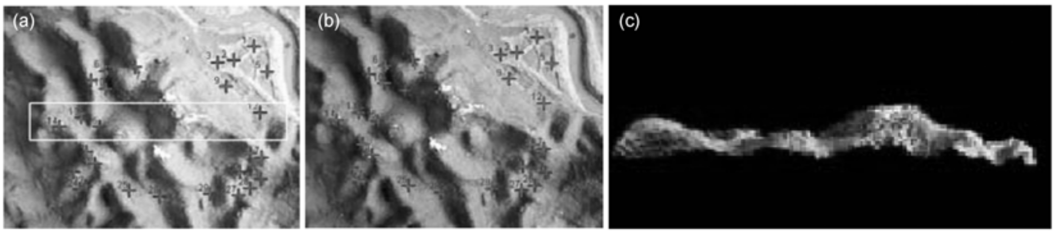

Figure 6 3-D reconstruction of the sand table in simulated experiment. (a) Key frame 1; (b) key frame 2; (c) 3-D reconstruction of the rectangle region.

correlation coefficient value of about 0.5, which has a good performance in locating the real-time terrain map due to the sharpness of correlation distribution. Results of the multiple experiments have shown that for a land form with the fluctuation scale of Δh, when taking the image sequence at the distance of $10\Delta h$, the locating deviation is within $0.1\Delta h$ by the method of 3-D reconstruction and terrain matching based on image sequence. The processing speed of the computer with the configuration of 3.0 GHz CPU and 1 GByte memory amounted to 15 frame/s or faster when tracking no less than 20 control points, and it took no more than 300 ms to reconstruct and match a strip with 100 points.

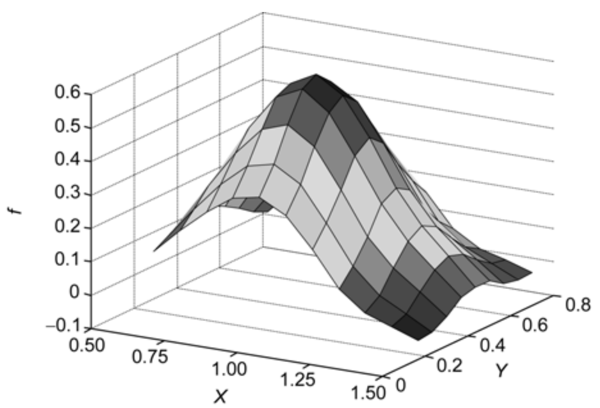

Figure 7 Distribution of the matching correlation coefficients of between the reconstructed sand table strip matched with the reference map.

In the experiment for sand table, obtaining correspondence of key frames based on the method of control points tracking spent 1/3 the time of the method based on points extracting and matching, and the ratio of the matching correctness improved by 20%. To the dense points matching, the method based on the guide of the optimal local homography gave an error less than 2 pixels for 90% of the predicting points, and this confirmed the automatic and speediness of the reconstruction.

3.3 Analysis of the real UAV image processing

We processed 3-D reconstruction of the real UAV image sequence with the proposed method. A hilly area was selected as the imaging area. Figures 8(a) and (b) exhibit a couple of key frames where the labeled points are the correspondence obtained by points tracking. Figure 8(c) shows the reconstructed strip terrain which is labeled in Figure 8(a) with a rectangle. The camera took image sequence from a fixed frontward-normal viewing angle, and the imaging resolution was about 0.3 m per pixel. According to the velocity information of the UAV, the base line of the key frame was obtained, and then the 3-D reconstruction of the absolute scale.

The corresponding relationship of the fluctuation with its position does not apply to a plain terrain, so the navigation based on the terrain contour matching is no longer valid. Therefore, our method integrates a preliminary planar judgment into the procedure of relation geometry solution.

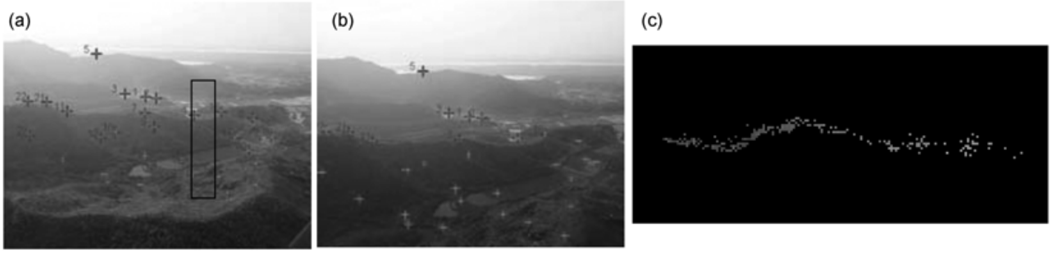

Figure 8 3-D reconstruction from a real UAV image sequence.

Only the area with fluctuation characteristics will enter the processing for the next reconstruction and matching. As to the navigation in a plain country, imagery-matching based method is a suitable choice, which is not the concern of this article.

4 Conclusions

This article proposes a novel navigation method of terrain contour matching by 3-D terrain reconstruction from the image sequence. It has distinct advantages over the conventional active terrain measurements with its passive imaging arrangement. To realize the real-time navigation, this article puts forward a method to obtain correspondence of key frame images by tracking control points and a method to guide dense feature points matching by estimating the optimal local homography according to control points. Both the reliability and simultaneity are achieved in the real-time terrain map reconstruction. Experimental results have proved the engineering practicability of our method.

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