A Method of Line Matching Based on Feature Points

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***Abstract*--This paper proposes a method for line matching based on invariance of feature points. Firstly, feature points are roughly matched by Normalized Cross Correlation (NNC) and Average of Square Difference (ASD). Additionally, feature points obtained from the two views are grouped into matched point pairs. Finally, curve segments between matched point pairs are matched by dynamic programming algorithm with edge potential functions (EPF) taken as the measure. The proposed method makes full use of feature points, the relationship between feature points and the curve, and space information of the gray image.**

***Index Terms*--Feature Point; Dynamic Programming; Edge Potential Functions; Curve Potential Function; line matching.**

I. INTRODUCTION

Feature matching plays an important role in many applications, such as image registration, 3D reconstruction, object recognition and video understanding. In feature matching, point matching has received much attention and various approaches have been proposed [1, 2, 3, 4]. Line matching is another challenging task because of the deficiencies in extracting lines and the inaccuracy of line endpoint locations. And we cannot directly exploit the epipolar geometry as a global geometric constraint. In the case of points (corners), correspondences must satisfy the epipolar constraint.

However, in the past years there are various approaches proposed. The existing approaches to line matching can be grouped by two types [5]: matching individual line segments; and matching groups of line segments. Individual line segments are generally matched on their geometric attributes such as orientation, length, grayscale, extent of overlap. Schmid and Zisserman [6, 7] take the epipolar constraint of line endpoints for short baseline matching, and one parameter family of plane homographies for wide baseline matching. Grouping matching strategy [8] are available for removing ambiguities because of more geometric information, and it is able to cope with more significant camera motion. However, it often has high computational complexity and is sensitive to line topological connections or inaccuracy of endpoints. Herbert and Vittorio [9] exploit the complementary information of line segments and regions to deal with a broader range of scenes for man-made environments with homogeneous surfaces. Wang [10] proposes mean-standard deviation line descriptor (MSLD for short) for automatic line matching without any prior knowledge. MSLD has two major appealing characteristics: it is purely image content-based and can work without any other possible constraints; it is applicable to general scenes for only constructing descriptor on a single scale and not scale-invariant. Wang and Liu [11] propose the line descriptor (HLD), which can be used for automatic wide-baseline stereo matching. Woo and Park [12, 13] present a line matching method for the reconstruction of 3D line segment based on geometric and intensity information, and a stereo matching method of 2D line segments for the detection of 3D line segment. Pascal Vasseur [14] presents a method for catadioptric line matching across multiple images. A line matching algorithm [15] is presented based on the line intersection context feature, and it can especially work in poorly textured indoor scenes. The class of scenes addressed in this paper is typically general scene like flowers. Despite of occlusion, these scenes often contain points which can be used as additional features. Points convey locations of occlude, whereas curve segments convey amount of important geometrical and topological information about the constitution of the scene. Using both types of features allows exploiting their complementary information for line matching.

The approach presented in this paper matches feature points roughly, and then matches lines based on matching feature points. Our approach exploits not only the perspective invariance of feature points but also the appearance similarity of pairs of curves, the topological relations among all curve segments, and gray space.

The remainder of this paper is organized as following. Section 2 introduces the definition of Edge Potential Functions (EPF for short) and fundamental concepts. Section 3 describes our approach based on feature points to matching curves exploiting dynamic programming. The paper concludes with a discussion of the limitations and future work in Section 4.

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II. FUNDAMENTAL CONCEPTS

In this paper, matching lines is composed of two main steps: points matching and lines matching. So we firstly introduce the concepts of point matching and lines matching in this section.

A. Concepts about Matching Feature Points

1) Normalized Cross Correlation

For two feature points x_{1i} and x_{2j} to be matched, Normalized Cross Correlation calculates the brightness mean and the variance of two sliding windows whose central points are x_{1i} and x_{2j} respectively ($2m+1$, $2n+1$ are the length and width of the two windows). The NCC is defined as following [16]:

$$NCC(x_{1i},x_{2j})=\sum_{k=-m}^{m}\sum_{l=-n}^{n}\frac{[I_1(x_{1i}+k,y_{1i}+l)-\overline{I_1(x_{1i},y_{1i})}]\times[I_2(x_{2j}+k,y_{2j}+l)-\overline{I_2(x_{2j},y_{2j})}]}{(2m+1)\times(2n+1)\times\sigma(x_{1i},y_{1i})\times\sigma(x_{2j},y_{2j})} \tag{1}$$

$$\overline{I(x,y)}=\frac{1}{(2m+1)(2n+1)}\sum_{k=-m}^{m}\sum_{l=-n}^{n}I(x+k,y+l)$$

$$\sigma(x,y)=\sqrt{\frac{\sum_{k=-m}^{m}\sum_{l=-n}^{n}I^2(x+k,y+l)}{(2m+1)(2n+1)}-\overline{I^2(x,y)}} \tag{2}$$

Where $\overline{I(x,y)}$ and $\sigma(x,y)$ denote the brightness mean and variance of all pixels in sliding window centered feature point (x,y) respectively.

Formula (1) indicates that the range of NCC is $[-1,1]$. The larger value indicates that the feature of two sliding windows is more similar, and vice versa. NCC is very effective measure for matching feature points, and it is invariance for the linear change of image brightness and has a very good distinction for the windows of different areas.

2) Average of Square Difference (ASD for short)

Average of Square Difference is the most direct way for the similarity measure between the two neighboring windows, which uses mean root square of absolute difference of corresponding pixels' brightness value between the two sliding windows as the metric. The smaller value indicates that the feature of two sliding windows is more similar; on the contrary, the larger value indicates that the similarity of two sliding windows is smaller. For the same configuration with the previous two sliding window, ASD is defined as the formula (3)

$$ASD(x_{1i},y_{1j})=\sqrt{\frac{1}{(2m+1)\times(2n+1)}\sum_{k=-m}^{m}\sum_{l=-n}^{n}[I_1(x_{1i}+k,y_{1i}+l)-I_2(x_{2j}+k,y_{2j}+l)]^2} \tag{3}$$

B. Concepts about Matching Lines

The idea of applying the electrical potential to model different physical domains has been applied successfully in other situations. O. Khatib [19] presents an artificial potential field to drive a robot in a complex environment using the field generated by objects as attraction (target) and repulsion (obstacles) forces. The potential model proposed by Minh Son Dao [17] is tailored to the context of image matching and it can be used to attract a template of the searched object or a sketch drawn by a user in the position where a similar shape is present in the image and the concept of edge potential functions (EPF). In fact, the more similarity the two shapes take, the higher total attraction can be gendered by the edge field. In this section, we give the concept of curve potential function according to EPF.

1) Edge Potential Function (EPF for short)

In the image, the coordinates of the ith edge point is (x_i,y_i), which is assumed to be equivalent to a point charge $Q_{eq}(x_i,y_i)$, contributing to the potential of all image pixels.

$$EPF(x,y)=\frac{1}{4\pi\varepsilon_{eq}}\sum_i\frac{Q_{eq}(x_i,y_i)}{\sqrt{(x-x_i)^2+(y-y_i)^2}} \tag{4}$$

Where ε_{eq} is a constant that measures the equivalent permittivity of image background, taking into account the extent of attraction of each edge point. That is, ε_{eq} influences the spread of the potential function which makes it more steep or smooth depending on its magnitude.

3) Curve Potential Function (CPF for short)

In our approach, the points in curve is taken as the field points, and the pixels in the surrounding area of the curve are looked as source charges (the area around the curve segment can be taken as support for the border region as shown in Figure. 1). The difference value of pixels gray between points in the curve and the surrounding area of the curve is the quantities of charge. The curve potential energy is:

$$CEPF(L)=\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{I(x_j,y_j)-I(x_i,y_i)}{\sqrt{(x_j-x_i)^2+(y_j-y_i)^2}} \qquad (5)$$

Where (x_i, y_i) and (x_j, y_j) are the coordinates of the *i*th point in the curve and the *j*th point in the range $l\times k$ surrounding the *i*th point respectively. $I(x_j, y_j)$ and $I(x_i, y_i)$ are their gray values, *n* and *m* are the numbers of points in the curve and the range $l\times k$ respectively.

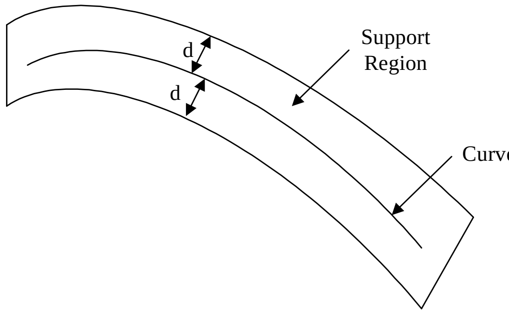


Figure 1. Support Region of Curve

3) Similarity Measure based on Curve Potential Function (CPF for short)

For the right and left views $I(x,y)$ and $I'(x,y)$, *L* and *L'* are the corresponding curves of the right and left views. The formula for the matching metric is:

$$\rho(L,L')=\left|\overline{CEPF(L)}-\overline{CEPF(L')}\right| \qquad (6)$$

$\overline{CEPF(L)}$ and $\overline{CEPF(L')}$ are the average potential energies of the curves *L* and *L'* respectively

$$\overline{CEPF(L)}=\frac{CEPF(L)}{n} \qquad (7)$$

Where $CEPF(L)$ and n respectively denote curve potential and the number of points in the curve. The value of ρ is very small but greater than 0, and the two curve segments are more similar. By the formula (5), (6) and (7), we know that the segment matching based on the potential energy of a curve not only makes use of gray-scale characteristics of a support region, but also exploits the length of a curve and the geometric relationship between pixels, so it has a good similarity measure for a curve segment.

III. THE CURVE MATCHING METHOD

Firstly, our method marks the crossing points of image contour, and then detects feature points of curves with the feature point marked simultaneously. So each marker is the endpoint of one or more curve segments. Based on these markers we present a new matching method of curve segment. The main idea of the method is to use NCC and the brightness variance of ASD for matching markers roughly, the two view markers set is divided into many-to-many matching point sets, and then adopt dynamic programming algorithm for matching curve segments among matching points using curve potential as similarity measure.

A. Point Matching

Marker sets of two views are divided into many-to-many matching point sets by gray information of marker points and the correlated method. The similarity between marker points *p* in image *I* and marker point *q* in image *I'* is calculated according to formula (1). To increase speed of searching and accuracy of matching, For the 3×3 rectangular area taking *p* as the central point in image *I*, we find a $\frac{1}{4}W\times\frac{1}{4}H$ rectangular area in image *I'* (*W* and *H* are the width and height of image *I'* respectively) and central point of this area has the same coordinates as *p*. According to formula (1), the similarity NCC between marker *p* and *q* can be calculated (if $NCC>\varepsilon$, then *p* and *q* match):

$$P=\left\{q_j \,\middle|\, NCC(p_i,q_j)\ge\varepsilon\right\} \qquad (8)$$

Where *P* is the feature points set in the image *I'* that match with the feature point *p* in the image *I*. Similarly, feature points in the image *I'* can search matching feature points set in the image *I*.

B. Curve Segment Matching

1) The Idea of Curve Segment Matching

Because of contour segment based on marked points (feature points and crosses), each marked point is endpoints of one or more curve segments. We assume that curve segments set $\{PL\}$ is made up of curves whose endpoints are the marker point p_i and p_i is a starting point and points of the set $\{P_j\}$ are ending points in the image *I* (Figure.2 (a)). The feature points set $\{P_i'\}$ in image *I'* is made up of points matching the feature point p_i in image *I*. Assume $p'_{i,k}\in\{P_i'\}$, then curves set $\{PL'\}$ is made up of curves whose starting and ending points are points set $\{P_i'\}$ and $\{P_j'\}$ respectively, as shown in Figure 2 (b).

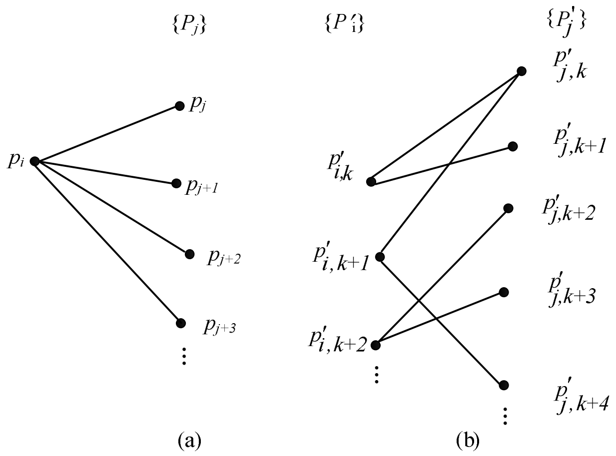


Figure 2 (a) Line segments starting at feature point p_i in image *I*,, (b) Line segments starting at feature points in image I' matching with p_i in image *I*

Search the point in set $\{P_j'\}$ matching with the points in set $\{P_j\}$, suppose $p_{j+l} \in \{P_j\}$. The curve segment is occluded if there is no matching point in $\{P_j'\}$, so there is no matching curve segment in set $\{PL'\}$. If only point $p'_{j,k+l}$ in set $\{P_j'\}$ matches with point p_{j+l} (on the other hand, only point p_{j+l} in set $\{P_j\}$ matches with point $p'_{j,k+l}$) and the curve segment only ends at point $p'_{j,k+l}$, then the curve segment $p_i p_{j+k}$ matches with $p'_{i,k} p'_{j,k+l}$. Two sets of curve segments will be composed by the ending points and their corresponding starting points in one of the following cases: 1) the points in $\{P_j'\}$ matching with point p_{j+l} are not unique; 2) point p_{j+l} matches only one point p'_{j+l} in $\{P_j'\}$, but p'_{j+l} may have more than one matching point in image *I*; 3) point p_{j+l} matches only one point p'_{j+l} in $\{P_j'\}$, but more than one curves end at p'_{j+l}. As shown in Figure 2, suppose points $p'_{j,k}$, $p'_{j,k+1}$ in $\{P_j'\}$ match with point p_j in $\{P_j\}$, then the curve which matches with $p_i p_j$ is included in set $\{p'_{i,k} p'_{j,k}, p'_{i,k} p'_{j,k+1}, p'_{i,k+1} p'_{j,k}\}$. So curve segments sets $\{PL\}$ and $\{PL'\}$, which take p_i and $\{P_i'\}$ as starting points respectively, are divided into some corresponding subsets which can be matched by dynamic programming. The curve segment and curve potential respectively are the matching unit and matching measure between the corresponding subsets of curve segments.

2) Dynamic Programming

Curve segments can be divided into several subsets by matching relationships among the endpoints of curve segments, and the intersection among these subsets cannot be empty. Using the potential energy of curve segments as the similarity measures, we know that the two curve segments match if the absolute value of the potential difference closes to zero.

m curves start at marked point p_i in image *I* and end at *m* marked points. If *n* points in image *I'* match with p_i, then there are *k* curve segments starting at these *n* points, which include matching curves with the *m* curves starting at p_i. Among the ending points of these *k* curves in image *I'*, we search the points which match with the ending points of the *m* curves in image *I*. Then a set can be made up of *c* curves that end at the matching points, and the *k* curves in image *I'* can be divided into *m* subsets EI_j' , $EI_j' = \{e_{jx}, x = 0,1,\ldots,z, z = c\}$, the intersection among which may not be empty. The *m* curves starting at p_i in the image *I* can be divided into *m* subsets which has one element ($EI_j = \{e_j\}$). The curves can be matched among corresponding sets EI_j' and EI_j by dynamic programming. Dynamic programming equation can be expressed as:

$$F(d) = \sum_{j}^{m} \min_{\substack{k \\ e_{jq} \neq e_{ip} \text{ if } i \neq j}} (d = |e_j - e_{jk}|) \tag{9}$$

$$d = |e_j - e_{jk}| = |\overline{CEPF(e_j)} - \overline{CEPF(e_{jk})}| \tag{10}$$

Where $e_j \in EI_j$, $e_{jk} \in EI_j'$, *m* is the number of the subsets, and *d* is the difference of the absolute value of average potential energy of two curves e_j, e_{jk}.

C. Experiment and Analysis

In order to verify the effect of the proposed method in this paper, we firstly rotate the images artificially, match the edges between the transformed images and the original ones, and analyze quantitatively the performance of the method by the match evaluation criteria (namely, the average repeatability [18]). Finally, we adopt images taken from different directions by a digital camera to verify the method. Figure 3 gives the schematic diagram of edge matching between the rotationally transformed image and the original one, and Figure 4 and Figure 5 respectively show the experiment results of complex and simple scene images taken from different directions.

The criterion of average repeatability is the number of curve segments determined by feature points. In the original image, the number of curve segments in each of the transformed images is the same as the number of matched curve segments between the original and transformed images. It can be defined as:

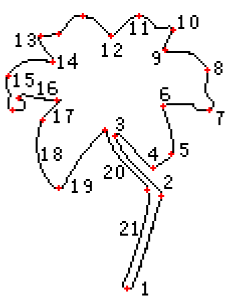
$$R_{avg} = \frac{N_m}{2}\left(\frac{1}{N_o} + \frac{1}{N_t}\right) \tag{11}$$

Where N_o and N_t are the numbers of curve segments in the original and transformed images respectively and N_m is the number of matched curve segments between them.

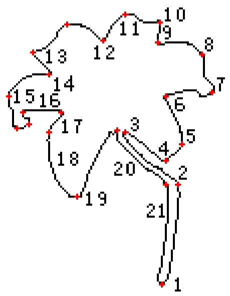
Figure 3 illustrates the curve matching between the edges of the original and transformed images. In Figure3, (a) is the original image, (b) is the transformed image obtained by rotating the original one by 10 degrees , (c) and (d) are the edges of (a) and (b) respectively. The curve segment labels are given in Figure3 (c) and (d), and curve segments with the same label are the match segments. Figure 3 (a) and (b) show that the edges of the two images are respectively divided into 24 curve segments according to feature points and the number of the matched curve segments is 21. The value of average repeatability R_{avg} is 87.5 percent according to formal (11). The experimental data shows that this method has a high degree of matching.

(a)

(b)



(c)



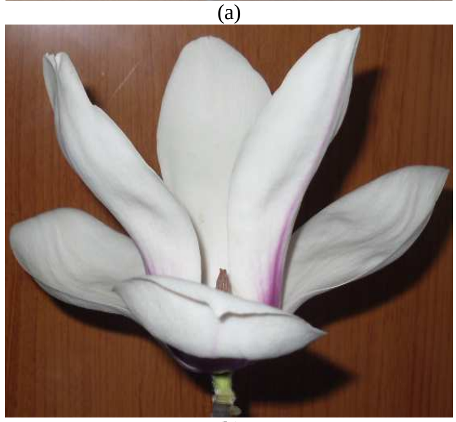
(d)

Figure 3. Curve matchless between the edges of the original and transformation images. (a) Original image, (b) Transformed image, (c) Edge of original image, (d) Edge of transformed image

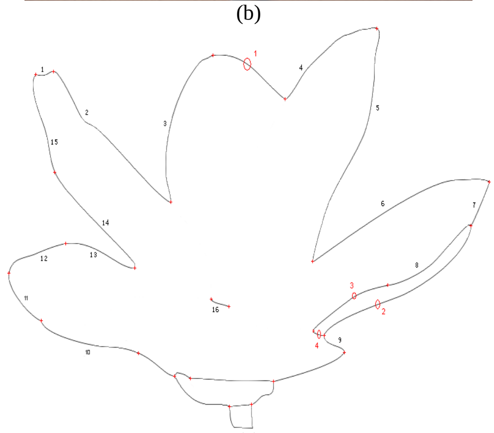
We apply the presented method to curve segment matching of a real word scene. As Figure 4 shows, images are taken from different directions by digital camera. (Figure 4 (a), (b) are the left and right views respectively). Figure 4 (c) and (d) depict the edges of the images in Figure 4 (a) and (b) respectively. The black marks in Figure 4 (c) and (d) are the matching curve segments, and the matching curve segments have the same labels, the red ellipses are used to highlight the incorrect matching of curve segments.

Figure 4 (c) and (d) show that there are some omissions of curve segment matching because of the error in feature point detection. For example, in Figure 4 (c) and (d), we can see that the curve segment marked by red ellipse and labeled by 1 in the left view does not match with the one marked by red ellipse and labeled by 1 in the right view. But in the original images shown in Figure 4 (a) and (b), the corresponding parts do really match by human observation. In Figure 4 (c) and (d), the curve segments, which are highlighted by red ellipses and labeled by 2, 3, 4, have no corresponding matching segments because of the occlusion of real word scene and the edge extraction. Comparing Figure 3 (c), (d) with Figure 4 (c), (d), we can see that the contour matching of real word scene images taken from different directions is less effective than the contour matching of original and theoretical rotation images, because there is no occlusion between them.

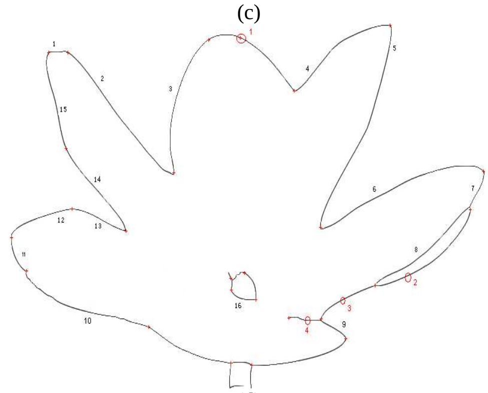
(a)



(b)



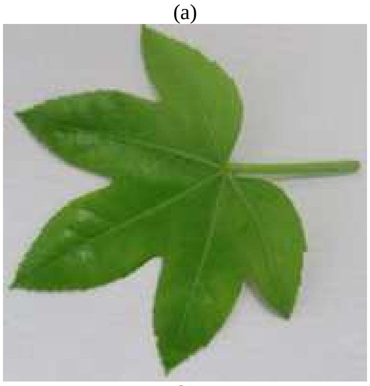
(c)

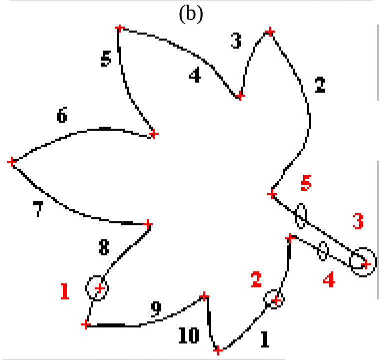


(d)

Figure 4. The curve segment matching of profile in the left and right views. (a) Left view, (b) Right view, (c) The edge of left view, (d) The edge of right view.


(a)


(b)


(c)

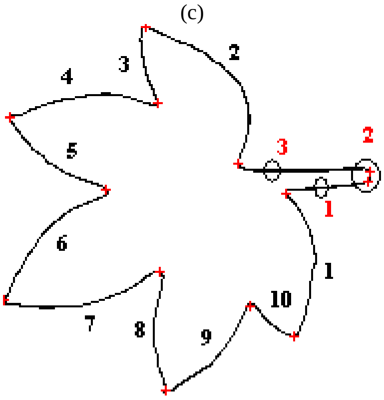

(d)

Figure 5 the curve segment matching of profile in the left and right views. (a) Left view, (b) Right view, (c) The edge of left view, (d) The edge of right view.

Figure 5 shows edge matching results of simple scene (leaf). Figure 5 (a), (b) are the left and right views respectively. Figure 5 (c) and (d) depict the edges of the images in Figure 5 (a) and (b) respectively. The black marks in Figure 5 (c) and (d) are the matching curve segments, and the matching curve segments have the same labels, the red marks ellipse. From Figure 5 (c), we know that the feature points marked by ellipses labeled by 1, 2 are the false detection points, but they don't influence edge matching because the potential of curve segment started them are big difference with other potential of curves. The curve segments marked ellipses labeled by 4, 2 in Figure 5 (c) have not corresponding match curves, but in the original images they should have, which is due to false detection points marked by ellipse labeled by 2 in Figure 5 (d). Comparing Figure 4 with Figure 5, we know that the method proposed in the paper has good effect for simple scene images.

For the images taken from different directions, the effects of curve segment match are influenced by edge and feature point detections which are differently affected by external environment (such as light) and occlusion. The method proposed in the paper firstly realize the rough match of feature points, so that curve segments of image contours can be divided into curve segments subsets according to the subset of rough match feature points. The curve segments will match between the corresponding subsets. Therefore the method greatly reduces the search space of matching, greatly improves the time complexity, and makes full use of the geometric relationships among the curve segments. Meanwhile, the method also take advantage of the spatial relationship among pixels around curve segments since the potential energy in ssupport region of curve is used in the measurement criteria of curve segments matches.

IV. CONCLUSION

The paper analyzes points feature, lines feature matching methods and their measurement criteria, and proposes a curve segment matching method based on the existing mature technology of points matching and the concept of the curve segment potential energy function. The main idea of the proposed method is that the key (corners and intersections) points are divided into subsets by rough match feature point subsets, and curve segments among corresponding subsets can be matched by using dynamic programming algorithm. The proposed method makes full use of feature points, the relation between feature points and curves, the geometric relationships among the curve segments and gray space. Through analysis, the proposed method has better matching accuracy and higher efficiency. However, images taken from different directions are affected differently by environment and have different occlusion, which affects edge detection, feature point detection and matching with various degrees.

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