I_029

拡散過程による自動画像地図照合ための共通特徴の抽出

Extracting Common Feature for Automatic Image-Map Registration Using Diffusion Process

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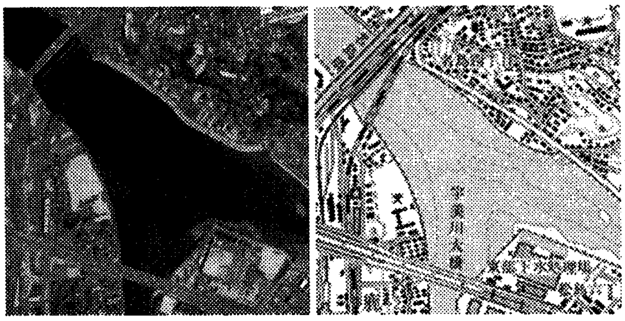
1 Introduction

Over the years, Geographic Information System (GIS) technologies have developed in the area of remote sensing. That is to update GIS via revising the digital map by using the aerial image. Because the scene in the image is quite different from that in the map, the central problem of it is how to extract common features between image and map. Figure 1 shows a digital map and an aerial image of the same scene in urban area. They are quite different form each other in presentations. The major differences in presentations between them can be concluded as follows: 1)Most objects such as bridge, railway, buildings and etc. in the image are modelled to corresponding signs in the map; 2)Some symbols are added to the map for noting the names of streets and buildings. These symbols can be viewed as noise. 3)Several objects visible in the image such as moving cars and trees are not represented in the map.Therefore, a common feature can overcome these differences in presentations between image and map for image-map registration is highly required.

Considering the differences described above between the image and the map, points or edges are more appropriate feature than colors, patches, regions and etc. in our task. However, because the points or edges extracted by using conventional measure such as Canny edge detector [1] cannot overcome the differences, the traditional procedure for registering image and map requires the manual extraction of tie points. Automation of the registration procedure requires the replacement of manual method with automatic one [2]. To solve this problem, we propose a novel new feature named Diffusion Geodesic Path (DGP) for image-map registration in this paper. In order to extract DGP, edges in the image and the map extracted serval times through a diffusion process by any edge detector. Then, each edge point in the initial time will be given a weight depending on the extracted (appeared) times during the diffusion process, and we can construct two new edge images from the image and the map using the obtained weights. The diffusion process makes the new edge images overcome the differences in representation between the image and the map. After that, paths between two feature points (such as corner points) are extracted from the new edge images using geodesic distance. Finally, a part of reliable paths are selected and can be used for registration using any similarity measure such as Hausdorff distances [3] and Hilbert scannning distance [4] .



(a) (b)

Figure 1 The image and the map of the same scene.

In summary, the major contribution of this paper is to use the diffusion process in physics to overcome the differences in presentations between image and map, and extract the new feature DGP. This feature makes the automatic image-map registration possible. It is shown that the new feature is a common and robust feature between and map, and the registration result using the proposed framework is better than those using conventional corner points or edges in the experiment.

The rest paper is organized as follows. First, we present the new feature DGP and the whole framework for automatic image-map registration in detail in Section 2. Section 3 is about the experimental results using DGP and comparisons with conventional features for image-map registration. We conclude this paper in the last section.

2 Diffusion Geodesic Path

In this section we first describe how to construct new images using diffusion process and then discuss how to extract the DGP from the new construct images [6, 7, 8, 9]. Finally, how to automatically select reliable paths for image-map registration is presented.

2.1 Constructing Images Using Diffusion

Recently year, diffusion has widely been used in image process and computer vision fields. For a given image $I(x)$, first we treat it as an isolated temperature function field $T(x,t)$ in initial status $t = 0$ and get $T(x,0) = I(x)$. From the heat diffusion equation,

$$\frac{\partial T}{\partial t} = \frac{\partial^2 T}{\partial x^2} \tag{1}$$

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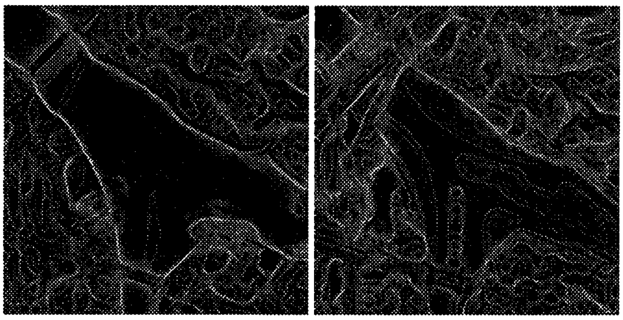


(a) (b)

Figure 2 The constructed images from image and map

we obtain a unique solution

$$T(x,t) = T_0(x) * \phi(x,t) \quad (2)$$

by giving initial condition $T_o(x)$

$$T(x,0) = T_0(x) \doteq I(x) \quad (3)$$

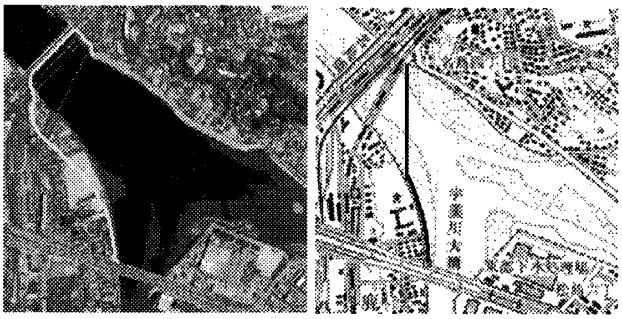
where $*$ means convolution process and $\phi(x,t)$ is the diffusion kernel. In our paper, we use Gaussian kernel defined as:

$$\phi(x,t) = (2\pi t^2)^{-n/2} exp(-\frac{1}{2t^2})x'x$$

where n is the dimension of $I(x)$ and t is referred to as the time parameter. For an image and a map, $T(x,t)$ can be viewed as a process of diffusion to overcome the differences between them and makes them similar. In this way, edge extraction can benefit from diffusion process and major edge points can be obtained from both the image and the map. Now we are arriving at how to construct new images using the diffusion process. Suppose that in the initial time t_0, a point sets extracted by any edge detector named initial edge points is $A = \{a_1, \ldots, a_l\}$ from the diffused image. After all initial edge points are located, tracking for voting during the diffusion process is introduced to our work. The voting times of A is $V_A = \{v_{a1}, \ldots, v_{al}\}$. Note that in the initial time t_0, all voting times for each point is 1. When it is diffused, if an initial edge point in A appears again at a sample time, the voting times of it will be updated by adding 1 to it. After the diffusion process is finished, we find the maximum voting times m_A from V_A and normalize the voting weights $\Omega_A = \{\omega_{a1}, \ldots, \omega_{al}\}$ as $\omega_{ai} = \frac{v_{ai}}{m_A}$, where ω_{ai} and is the voting weight for ith point in A . Here, we can obtain two new edge images using the weights as their intensities. The voting weight represents the importance of an edge point. An initial edge point with large weight means that this point is a major feature point through the diffusion process. Figure 2 show the new constructed images from the image and the map in Figure 1. From Figure 2, we can see that the new image from the image is similar to that from the map.

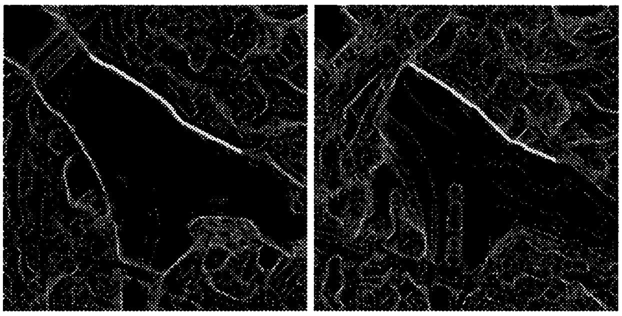
2.2 Geodesic Path

For a surface given parametrically by $x = x(u,v)$, $y = y(u,v)$, and $z = z(u,v)$, the geodesic can be found by minimizing the arc length



(a) (b)

Figure 3 The geodesic paths in the original image and map.



(a) (b)

Figure 4 The geodesic paths in the new constructed images.

$$l = \int s = \int \sqrt{dx^2 + dy^2 + dz^2} \quad (4)$$

As mentioned previously, it can be computed using level set method by fast marching algorithm on images. We have tried to extract paths on the original image and map directly, and the results are shown in Figure 3 (the white curve in image and the black curve in map). We found that the extracted paths between two same corner points are quite different from each other.

For extracting paths on new constructed edge images, first we need to extract some candidate points for computing the geodesic path between these points on images. In our case, we extract corner points by Harris corner detector [5] from original image and map. Since edge in the new constructed images are from the original image and map, that we can locate the candidate points using the detected corner points from the original image and map. Notice that we extract geodesic path from the constructed new images not the original images.

If N corner points are extracted, we can construct $N * (N-1)/2$ paths. Because registration can be done by few paths and constructing too many paths is computational expensive, there is no necessary to extract too many corner points in our case, . Hence, we specify the minimum possible distance between corner points when extracting them. Figure 4 show the geodesic paths between two corner points in the new constructed images. We can see that the geodesic paths are very similar although the original image and map are different.

2.3 Selecting Path

Registration is a computational expensive work. If too many paths are used for registration, the cost time is oppressive. On the other hand, using too many paths may not work better than using some few reliable paths and too many paths may deteriorate the registration contrary. Moreover, not all paths between two points can be extracted successfully by using the fast marching algorithm. Hence, selecting a part of reliable paths is necessary in our registration work.

How to select reliable paths in our paer is based on two major criterions:

- **The length of the path:** The longer path is favored in our work, because longer path can provide more common features between the image and the map.
- **The overlapped rate on major edge points:** First, if a point on a geodesic path is overlapped with a point of the new constructed image with intensity larger than a predefined intensity I_0, we treat it as an overlapped point. If the number of points (pixels) on a path is m, and the number of overlapped points on this path is m', the overlapped rate r can be easily computed as $r = \frac{m'}{m}$.

As mentioned previously, the intensity of a point in the new constructed image can present the importance of it, so the selection can also preserve important paths for registration. Based on these two criterions, for a path, if both its length L and overlapped rate r are larger than two thresholds L_0 and r_0 predefined, we select this path as a candidate for registration. The selection also makes a tradeoff between the speed and accuracy.

3 Experimental Results

We will describe our experiments using the proposed DGP for image-map registration in this section. We have two different experiments. First, we compare the overlapped ratio of DGP with other features. The second experiment studies the performance of our DGP for image-map registration.

3.1 Overlapped Ratio

In the first experiment, we compare the overlapped ratio between image and map using different points features including edge points, corner points, and DGP points. Figure 5 show these features.

Suppose two point set P from image and Q from map are given, we compare the number of points of them, and choose the smaller one n as the divisor for computing the ratio. This ratio can express how common the feature is. Then, we adjust them to the optimal position that they are registered and count how many points are overlapped with each other. Here, an point in image is treated as a overlapped point of another point in map when the pixel distance between them less than a threshold T. If n' points are overlapped, the ratio can be computed as n'/n. Figure 6 shows the overlapped ratio change as the T increases. We can see that the ratio of DGP is much better than the edge or corner points in small T. Although, the ratio of DGP is smaller than that of edge points when $T > 2$, this phenomenon cannot present the edge points is more common than our DGP. The reason is that edge points is much denser than DGP, and when T increasing the ratio should increase rapidly.

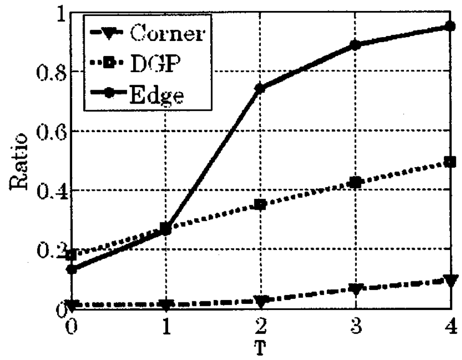


Figure 6 Overlapped ratio.

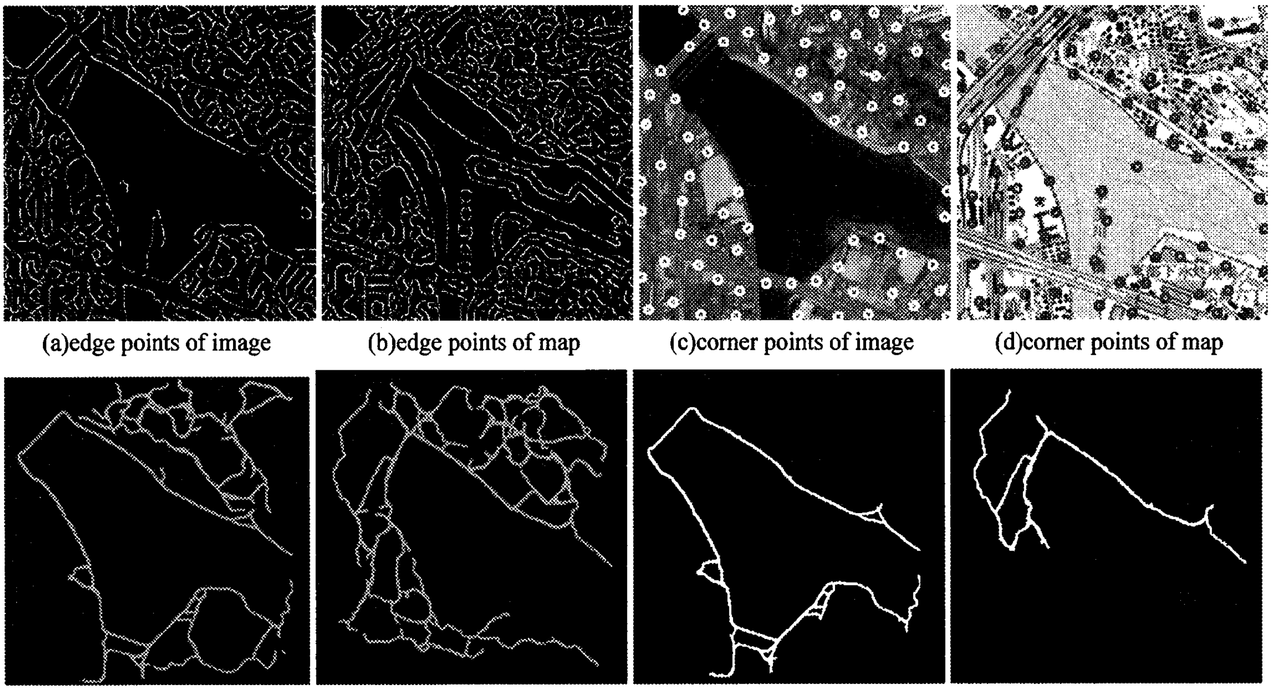
3.2 Image-Map Registration

After extraction and selection of path, the image-map registration problem becomes the point pattern matching problem in our case. As mentioned previously, many similarity measures such as Hausdorff distances and Hilbert scanning distance can be used for this problem. Our work concentrates on how to extract and select DGP, hence, the similarity measure is not important in our work, and we choose the Hilbert scanning distance as the similarity measure in our paper. On the other hand, with the same reason, it is no differences between using different transformation forms (such as affine or only translation) in our paper. In the experiment, we only consider the translation between image and map in the experiments for simplicity. Then, the registration problem is that to find the optimal translation using the Hilbert scanning distance. Without loss of generality, we fix the image and allow only map to translate. The translation of a map point $[x\ y]^T$ to an image point $[x'\ y']^T$ can be written as follow:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

where the translation is $[t_x,\ t_y]^T$. In the experiment, we treat the map as the model and the image as reference image. We recommend readers to [3] to read more about the matching portions of the model and image for details. Our test sets are an image of 256×256 pixels and also a 256×256 pixels map as shown in Figure 1. We compare the registration results by using different features including: 1)Edges directly extracted from original image and map by Canny detector as shown in Figure 5(a) and (b); 2)Corner points extracted from original image and map by Harris detector as shown in Figure 5(c) and (d); 3)The selected DGP as shown in Figure 5(g) and (h).

We compute the registration error in this experiment by



(a)edge points of image (b)edge points of map (c)corner points of image (d)corner points of map

(e)DGP of image (f)DGP of map (g)selected DGP of image (h)selected DGP of map

Figure 5 The different features for registration.

Table 1 The registration results.

	RMS (Translation)
Edge points	22.5 (9,1)
Corner points	18.4 (6,-3)
DGP	1.0 (-11,-7)

the root-mean-square value (RMS) defined as

$$RMS = \sqrt{(t_x - t_{x_0})^2 + (t_y - t_{y_0})^2}$$

where (t_{x_0}, t_{y_0}) is the best registration position. Here the best registration position is (-12,-7) and we let the translation range be $[-20, 20]$ for both x and y. The RMS results using different feature in this experiment are shown in Table 1. The RMS is only 1.0 by using DGP where as 22.5 and 18.4 by using edge points and corner points, respectively. Form the table, it is easily understood that the RMS using DGP is obviously smaller than that of other measures.

4 Conclusions

In this paper, we propose a novel new feature named Diffusion Geodesic Distance (DGP) and a framework use it for automatic image-map registration. The major contribution of our work is that DGP can remove the differences in presentations between image and map using the physical diffusion process. In the framework, we also select a reliable part of the extracted paths using two criterions. The experimental results show that our DGP is a common and robust feature for image-map registration and the registration using the proposed framework achieves better performance than using conventional features such as edge points or corner points.

The future studies will aim at automatically setting the parameters for extracting and selecting DGP. More complicated transformation between the image and the map should also be validated.

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