A Fast Algorithm for Matching Remote Scene Images

LIU Jin  YAN Li

Abstract  An iterative algorithm to calculate mutual correlation using hierarchical key points and the search space mark principle is proposed. An effective algorithm is designed to improve the matching speed. By hierarchical key point algorithm and mutual correlation coefficients of the matching images, the important points can be iteratively calculated in the images hierarchically, and the correlation coefficient can be obtained with satisfactory precision. Massive spots in the parameter space which are impossible to match can be removed by the search space mark principle. Two approximate continuities in the correlation image matching process, the image gray level distribution continuity and the correlation coefficient value in the parameter space continuity, are considered in the method. The experiments show that the new algorithm can greatly enhance matching speed and achieve accurate matching results.

Keywords  image correlation matching; fast algorithm; iterative algorithm

CLC number  P237

Introduction

In many applications of image recognition, correlation matching is used for measuring the similarity of two image patterns. Correlation is not affected by the linear transform of both contrast and brightness of the matching images, and this stability feature makes it usable in many applications such as remote scene matching\(^1\), train number recognition\(^2\), object recognition, etc. In practice, the real time images may be translated, scaled or rotated versions of the template image, which determines the complex of the matching process\(^3-7\). When the real time image becomes bigger, or better matching precision is required, it is important to find a fast correlation matching algorithm.

Two approximate continuities can be considered in the matching process: the gray level distribution in the image and the correlation distribution in the search space. Based on these two continuities, the hierarchical key point algorithm and the search space marking technique are suggested in this paper and are found to accelerate the matching process greatly.

1 Fast correlation matching algorithm

The correlation between two images is defined as

\[
\rho(f_0, f_1) = \frac{\sum_{i,j} (f_0(x_i, y_j) - \bar{f}_0)(f_1(x_i, y_j) - \bar{f}_1)}{\sqrt{\sum_{i,j} (f_0(x_i, y_j) - \bar{f}_0)^2 \sum_{i,j} (f_1(x_i, y_j) - \bar{f}_1)^2}}
\]  

(1)

Suppose \(f_0(x,y)\) is the template image in Eq.(1) and \(f_1(x,y)\) is the sub-image in the big real time
image. The template image can be normalized as \( f_0(x, y) \) beforehand because it is invariant in the searching process.

\[
\rho(f_0, f_1) = \frac{\sum_{(x, y)} f_0(x, y) f_1(x, y)}{\sqrt{\sum_{(x, y)} (f_1(x, y) - \bar{f}_1)^2} \sqrt{\sum_{(x, y)} (f_0(x, y) - \bar{f}_0)^2}}
\]

where

\[
f_0(x, y) = \frac{f_0(x, y) - \bar{f}_0}{\sqrt{\sum_{(x, y)} (f_0(x, y) - \bar{f}_0)^2}}
\]

\[
(2)
\]

2 The hierarchical key point algorithm

According to the behavior of human vision, the center of the matching region has a greater effect on the edge of the region. For an observer, the detailed difference among the nearby pixels is much weaker than the macrograph distribution of the image. The traditional correlation calculation samples pixels line by line, which may not strengthen the importance of the center and the macrograph distribution of the region. A hierarchical key point algorithm is suggested, which hierarchically samples the pixels by a reasonable order as shown in Fig.1. It can be seen that the key points are distributed by a fractal shape from top to bottom in each level, and the higher hierarchical has a higher density distribution. Based on the key points of levels 0 ~ n−1, the point order of level n is not very important. The order of each sample point is marked in Fig.2.

As shown in Fig.1, the distribution of the first n-level key point maintains a proportional \( (2^{n+1} - 1) \times (2^{n+1} - 1) \) sample. Some representative sample points corresponding to each point in Fig.1 in the template and the real time image are selected in order to carry out a fractional correlation calculation. There are \( 2^n (3 \times 2^k - 2) \) points in level n. The hierarchical key point can be obtained for any \( M \times N \) image. When the step of the row direction is less than or equal to 1, row interpolation should be stopped while column interpolation continues until the step of the column direction is less than or equal to 1 so that all pixels can be scanned.

Furthermore, Eq.(2) can be changed to an iterative algorithm as follows:

\[
\begin{align*}
\rho_{n+1}(f_0, f_1) &= \frac{P_{n+1}}{\sigma_{n+1}^2} \\
P_{n+1} &= P_n + f_0(x_{n+1}, y_{n+1}) f_1(x_{n+1}, y_{n+1}) \\
\sigma^2_{n+1} &= \sigma^2_n + \frac{n}{n+1} f_1(x_{n+1}, y_{n+1}) - \bar{f}_1)^2 \\
\bar{f}_1 &= \frac{\{f_n(x_n, y_n)\} / (n+1)}
\end{align*}
\]

(3)

In Eq.(3), the initial values are \( P_0 = 0, \sigma_0^2 = 0 \), and the normalized template function \( \{f_0(x_{n+1}, y_{n+1})\} n \in \{0, \ldots\} \) can be calculated offline beforehand. By Eq.(3), we can always get a more precise correlation when obtaining a new hierarchical key point. When the level of the hierarchical key point is big enough, the correlation will remain constant and the algorithm can be stopped. Because the local high level key point is an interpolation of the low level key point, it will have a much smaller effect on the correlation.

3 Marking the search space

The method of marking the search space is based on the continuity of correlation distribution in the
search space. The process of matching the template and the real time sub-image can be abstracted as a process of searching for matching points in a parameter space. Suppose we are searching a \( m \times n \) template in a big \( M \times N \) real time image, the matching sub-image may be scaled by \( k \in [1-k, 1+k] \), that is, by searching a parameter point in an approximate \((M-m)\times(N-n)\times2k\) cube. Each matching point \((x, y, k)\) corresponds to a correlation value \( \rho_{x,y,k}(x, y, k) \), and the function \( \rho_{x,y,k}(x, y, k) \) has two continuity features as follows:

If \( \rho_{x,y,k}(x, y, k) \) is big enough, \( \rho_{x,y,k}(x, y, k) \rightarrow 1 \), there exists a small neighborhood of \((x, y, k_m)\) which has a bigger correlation.

\[
\rho_{x,y,k}(x, y, k) \rightarrow 1 \quad \& \quad (x, y, k) - (x, y, k_m) \rightarrow \zeta \rightarrow \rho_{x,y,k}(x, y, k_m) > \varepsilon
\]

If \( \rho_{x,y,k}(x, y, k) \) is small enough, there exists a small neighborhood of \((x, y, k_m)\) which has a smaller correlation.

\[
\rho_{x,y,k}(x, y, k) \rightarrow \zeta \rightarrow \rho_{x,y,k}(x, y, k_m) < \varepsilon
\]

The correlation reflects the confidence of the matching. In most cases, the correlation of a matching parameter point is small and its neighborhood ball region is masked, which means that its neighborhood will not be searched again. The radius of the mask ball may become adequately bigger with a decrease in its center correlation \(|\rho_{x,y,k}(x, y, k)|\). This masking space can be implemented by using a masking array, and both line scan and genetic algorithm can be implemented.

### 4 Experiments

Some experiments are carried out to verify the feasibility and the efficiency of the algorithm. Fig. 3(a) is a remote image of west Beijing. Its resolution is 764×685. Figs. 3(b), 3(c) and 3(d) are sub-image (templates) to be searched in Fig.3(a). Both the hierarchical key point algorithm and marking the search space technology are used in the experiment. As the template and the real time image are taken at different times, there may exist differences in the brightness, the contrast, the scale and the rotational angle between the remote image and the three templates. Fig.3(c) may be scaled in relation to Fig(a) and Fig.3(d) may be both scaled and rotated \( \pm 2^\circ \) in relation to Fig(a). Fig.3(b) is the sub-image without scale and rotation. The resolution is 764×685. Fig.3(c) is the sub-image without rotation. The scale range is \([0.88,1.12]\); resolution is 99×105. Fig.3(d) is the sub-image with small rotation. The scale range is \([0.8,1.2]\); resolution is 92×87.

![Fig.3 The matching image and three sub-images with different brightness and contrast](image)

Four levels of key points are selected in the experiment to carry out correlation matching. When matching Fig.(b), only transformation is considered. When matching Fig.(c), both transformation and scale change \( k \in [0.88, 1.12] \) are considered. When matching Fig.(d), three changes are all considered—transformation, scale \( k \in [0.8, 1.2] \) and rotation deviation \( \pm 2^\circ \). The searching step of the scale is 0.01 and the searching step of the rotation angle is 1°.

In order to obtain an accurate matching result, a sub-pixel matching process is carried out in the \( 3 \times 3 \) pixel neighbor of the matching point after the fast matching algorithm. By the Chebyshev polynomial theorem\(^{[7]}\), the final matching result is the interpolation coordinate corresponding to the peak correlation obtained from the nine correlations in integral coordinates.

To compare the results using the traditional method—the same experiment which is also carried out by SSDA algorithm—the experimental differences are shown in Table 1 and Fig.4. The hierarchical key point algorithm and marking the search space technology can greatly improve the speed of the matching process without losing precision.
Table 1  The time cost between the suggested algorithm and common SSDA

|                      | Matching result | Cost time |                      | Matching result | Cost time |
|----------------------|-----------------|-----------|----------------------|-----------------|-----------|
|                      | Correlation     |           |                      | Correlation     |           |
|                      | 0.9907          |           |                      | 0.9907          |           |
|                      | Center coordinate |     | (221.00, 152.50)    | Center coordinate |     |
|                      | Scale=1,Rotation=0˚ | | 1.668s             | Scale=1, Rotation =0˚ | 34.78s |
| Fig.(b)              |                 |           |                      |                 |           |
|                      | Correlation     |           |                      | Correlation     |           |
|                      | 0.7863          |           |                      | 0.7861          |           |
|                      | Center coordinate |     | (610.86, 408.53)    | Center coordinate |     |
|                      | Scale=0.93, Rotation =0˚ | | 5.009s             | Scale =0.93, Rotation =0˚ | 93.61s |
| Fig.(c)              |                 |           |                      |                 |           |
|                      | Correlation     |           |                      | Correlation     |           |
|                      | 0.9171          |           |                      | 0.9168          |           |
|                      | Center coordinate |     | (500.95, 390.85)    | Center coordinate |     |
|                      | Scale=0.84, Rotation =2˚ | | 14.938s            | Scale =0.84, Rotation =2˚ | 368.85s |
| Fig.(d)              |                 |           |                      |                 |           |

CPU configuration Celeron2.4GHz

5  Conclusions

Based on two approximate continuities in the mutual correlation image matching process, the image gray level distribution continuity and the mutual correlation coefficient continuity in the parameter space, the hierarchical key point algorithm and marking the search space technology are presented in this paper. The algorithm enables us to obtain the matching result from a small number of hierarchical key points. Experiments show that the algorithm greatly accelerates the matching process.

References

[1] Flusser J, Suk T (1994) A moment-based approach to registration of images with affine geometric distortion[J]. *IEEE Trans on GeoScience and Remote Sensing*, 32(2): 382-387

[2] Liu Jin, Zhang Tianxu (2002) Train number recognition and reliability estimation. [J]. *Infrared and Laser Engineering*, 6, 31(3): 199-203

[3] Zhu Hong, Zhao Yigong (1999) Fast image correlative matching based on genetic algorithm[J]. *Journal of Infrared and Millimeter Waves*, 18(2): 145-150

[4] Li Feng, Zhou Yuanhua (1999) Study on image matching algorithm based on wavelet transform[J]. *Journal of Shanghai Jiaotong University*, 33 (9): 161-163

[5] Thevenaz P (2000) Optimization of mutual Information for multi-resolution image registration[J]. *IEEE Trans on Image Processing*, 12: 2083-2099

[6] Hutertas A (1986) Detection of intensity changes with subpixel accuracy using Laplacian Gaussian masks[J]. *IEEE Trans PAMI*, 8(5): 651-664

[7] Liu Jin (2005) Construction of feature invariants and its application in object recognition[D]. Wuhan: Huazhong University of Science and Technology

[8] Daniel I B, Harvey F (1972) A class of algorithms for fast digital image registration[J]. *IEEE Trans on Computer*, 21(2): 179-186