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Graphic Matching Based on Shape Contexts and Reweighted Random Walks

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ABSTRACT

Graphic matching is a very critical issue in all aspects of computer vision. In this paper, a new graphics matching algorithm combining shape contexts and reweighted random walks was proposed. On the basis of the local descriptor, shape contexts, the reweighted random walks algorithm was modified to possess stronger robustness and correctness in the final result. Our main process is to use the descriptor of the shape contexts for the random walk on the iteration, of which purpose is to control the random walk probability matrix. We calculate bias matrix by using descriptors and then in the iteration we use it to enhance random walks' and random jumps' accuracy, finally we get the one-to-one registration result by discretization of the matrix. The algorithm not only preserves the noise robustness of reweighted random walks but also possesses the rotation, translation, scale invariance of shape contexts. Through extensive experiments, based on real images and random synthetic point sets, and comparisons with other algorithms, it is confirmed that this new method can produce excellent results in graphic matching.

Keywords: Image matching, shape context, reweight random walks, feature correspondence.

1. INTRODUCTION

Graphic matching has been applied in many fields such as graphics analysis [1,2], pattern recognition [3], computer vision [4], and so on. It demands to determine whether two graphs are the same or similar with each other, measure the similarity between them and finally report the value of the matching degree. The similarity between these two graphs should be measurable and easy to be calculated. Besides, the judgment based on the matching algorithm should be consistent with human intuition.

The main objective of our paper is to propose a more rational and highly robust algorithm. And an accurate graphical registration result can be obtained in polynomial time. Our goal is to establish feature correspondences against significant clutter and deformation from arbitrary images. Our method can be used to effectively register the two maps, which automatically come to the results we want.

The Graphic matching is mainly divided into rigid matching and non-rigid matching. At present, the non-rigid matching problems are still in large quantities and quite difficult to be solved. For the non-rigid matching problem of shape, the most common method is to use the geometric properties of the graph to find a descriptor, which transforms the problem of graphic matching into a comparison between descriptors.

The point pattern matching is also a significant and fundamental problem. Point pattern matching algorithm can be divided into two categories [5]. The first category is the solving algorithm based on transformation relationship, namely, estimating the spatial transformation parameters between the point patterns and using the parameter to restore or simulate the transformation between the point patterns, so that the point pattern matching problem can be solved. Therefore, it is also called an algorithm based on transformation parameter estimation. The main algorithms for this type are ICP [6], Soft assign [7], probabilistic statistics algorithm [8] and so on. The second one refers to the solving algorithm based on matching relationship. It utilizes characteristics of extraction points within the point set and the matching recognition method to obtain the matching relationship among all these characteristics of two point sets and thus to solve the point graphic matching problem, or more likely, a feature-based matching algorithm. This category of algorithms mainly includes shape context [9, 10], fast point feature histograms [11], spectral correspondence [12,13,14] and so on.

We know that the absolute distance between two points may change significantly under nonrigid deformation but the neighborhood structure of a point is generally well preserved due to physical constraints. The rough structure of a shape is typically preserved, otherwise, even people cannot match shapes reliably under arbitrary large deformation. Such constraints may be represented as the distribution of points on a graphical model. We form a graphical model through the

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points and associated structure between points. Graphical models are often used to encode pairwise matching problems. In this, each feature can be matched only once, so they can easily represent the relationship between matches. In this paper the geometric information of the graphics model will be used. For example, the bias matrix of this paper is based on the graphic model. We believe that the graphical models can provide very robust geometric information, so we can improve the accuracy of our algorithm as a whole.

The main contribution of this paper is a shape matching method that is robust to deformation and outliers in the shape. Our approach significantly improves the accuracy of the algorithm, and has achieved good results in the real images and synthetic images experiments.

The algorithm in this paper employs the combination of shape context descriptor and reweighted random walk algorithm [15].The shape context descriptor is a very popular shape description, which is widely used for object recognition. It adopts a feature description method based on local point cloud. Each shape context is a log-polar histogram of the coordinates of other point sets. Since it takes full advantage of context information, it possesses a better robustness. This feature extraction method allows the computer to measure the similarity between various shapes and to obtain point correspondences on the registration shape. As a mathematical statistical model, random walk has been widely used in the field of image processing and achieved good results. The basic idea of Random Walks for Graph Matching is to solve the graph matching problem by using the random walks algorithm in the association graph constructed by two graphs. The graphic matching between two graphs is formulated as node selection on an association graph in which the nodes represent the candidate correspondences between these two graphs. The reweighted random walks not only preserves the original affinity relations but also implements the two-way matching constraints.

This papers' graph matching algorithm generally consists of the following three processes. The first process is the extraction of partial graphics features (edge angle normal, etc.). The second one is to calculate the matching matrix based on the internal characteristics of the graph. All possible matching correspondences are established in accordance with local features of graphs and then, the compatibility coefficient between the points of registration graph is generated. Thirdly, the global image matching is achieved by combining the compatibility coefficients with the iterative matrices of reweighted random walks.

2. OUR METHOD FOR GRAPH MATCHING

Firstly, the shape context algorithm is used to calculate the histogram of each feature point. After that, the Euclidean distance is employed to calculate the matching similarity of each pair of feature points between two images to be registered. Euclidean distance can reflect the absolute difference of individual numerical characteristics. From perspectives of association graph of reweighted random walks as shown in Figure 1, each nodes represent candidate correspondences between the two graphs. Therefore, the shape context histogram is firstly used to obtain the similarity between these nodes. Then, registration constraint value between the point pi to all other points in the association graph of reweighted random walks is calculated by

$$g = \sum m,n \exp(-(\text{costmatrix}(pi,qm) + \text{costmatrix}(pj,qn))), \tag{1}$$

Where, costmatrix(pi,qm) denote the cost of matching these two point sets, the pi is on the first shape and qm is on the second shape. Finally, the registration constraint value of each node pi in the association graph is further normalized.

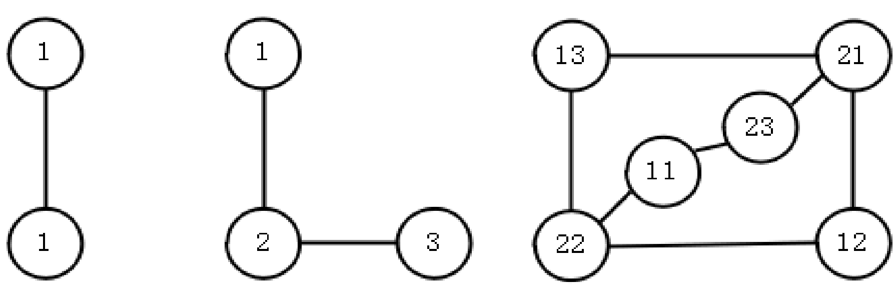


Figure 1. Point sets G1(left) and G2(middle). The right graph is association graphs used in reweighted random walks.

In the weighted random walk, in order to preserve the affinity between points, the algorithm changes the traditional random walk process. That is, the affinity between points is added to the traditional random walk and the affinity-preserving random walk is created. Thus, the similarity between the registration points exerts great guiding effects on random walks. In order to preserve the bidirectional registration constraint of the random walk algorithm, this method adopts a jump in the random walk which strengthens the effects of reliable nodes on random walks. That means the random walker moves by passing an edge with probability a or by performing a jump to some constrained nodes with probability 1-a. In order to make the jump matrix more reasonable and improve the accuracy of the registration after two-way normalization, we combine the similarity between the registration points, that is, the shape context distance. In summary, the bias vector g has been added into two respects. The first is the similarity between points. The second is the constraint of the reweighted jump. Thus, the method can be formulated as follows:

$$x = (a(x+g)^{T} + (1-a)(f(x^{*}W))^{T})P, \tag{2}$$

Where, f() represents the inflation and bistochastic normalization function.

In each iteration, the new random walk probability matrix can be obtained by adding the registration constraint value calculated by shape context and the random walk probability x obtained by the last iteration; the starting probability x is uniform. And then, the inflation and bistochastic normalization function is performed to reduce the unreliable correspondences and enhance the accuracy of two-way constrain. The new method based on shape contexts and reweighted random walks is described in Algorithm.1.

Algorithm.1 Graphic Matching Based on Shape Contexts and Reweighted Random Walks

1: Calculate shape context descriptors of every points
2: Using Euclidean distance get the costmatrix C
3: Prevent conflicting walks by setting Wia;jb=0, define reweight factor α , and inflation factor β
4: Set the maximum degree dmax = max ia$\sum$jbWia;jb, Initialize the transition matrix P =W/dmax
5: Calculate the bias matrix g by using C and the starting probability x
6: repeat
7: $x^{T} = (x+g)^{T}P$
8: $y^{T} = \exp(\beta x / \max x)$
9: bistochastic normalization scheme for (y+g)
10: $y = y/\sum yai$
11: $x^{T} = \alpha (x^{T}+g) + (1-\alpha)y^{T}$
12: $x = x/\sum xai$
13: until x converges
14: generate one to one matching results by discretizing x

3. EXPERIMENTS

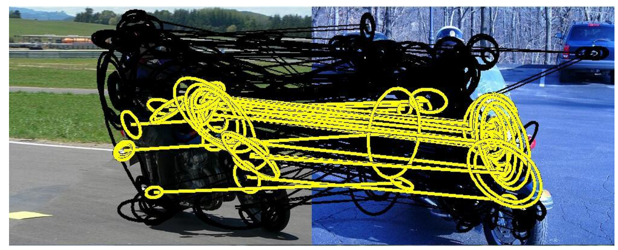
3.1 Real Image Matching

In this section, a series of experiments and comparisons with other methods were carried out. All methods were tested on 2.10 GHz Corei3 CPU, 8GB memory and implemented using MATLAB. The dataset of 30 image pairs were published in reweighted random walks for graph matching. The image pairs utilized the MSER detector and the SIFT descriptor to generate candidate correspondences. The images of dataset were collected from Caltech-101 and MSRC dataset.

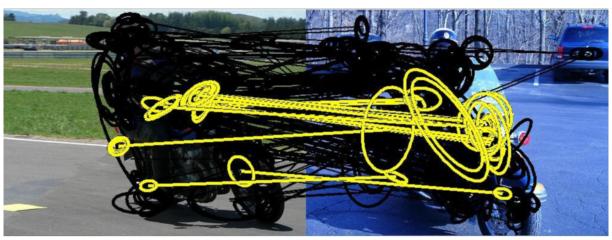
In the experiments, MaxIter, α and β were set as 300, 0.4 and 30, respectively and the method was tested in the real-world image matching. To test our algorithm, all matched graph pairs in the dataset were tested and compared with the SM and RRWM algorithms. The same affinity matrix and the Hungarian algorithm were adopted to get the last discrete result for the fairness of the experiment. It should be noted that our parameter settings were not the same as those of the original RRWM algorithm, especially in the α; when we increased shape context constraint weights, the algorithm could achieve better results. In the experiments, we used the same parameter settings for each pair of registration images. These settings allowed us to quantify the robustness and accuracy of all algorithms and conducted a fair comparison between them.

Some examples of real-world image matching are shown in Figure 2. In Figure 2, the yellow lines and black lines represent the right matching and the false matching, respectively. All the matching results are obtained by algorithms and the accuracy is derived from the percentage of our results in ground truth. Through analyzing some representative examples as shown in Figure 2, the conclusion that our method can achieve a significant result about the pattern matching problem is obtained. The accuracy and running time were calculated and compared with SM and RRWM. Figure 3 presents all experimental results. According to Figure 3, we can get that our method in the average matching result on the 30 pairs of images gets a good result. Experiments show that our algorithm provides the best accuracy in the real image matching problems.

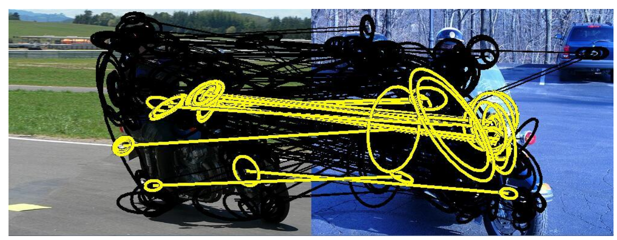
(a)The Matching Image



(b)OurMethod Accuracy:0.92(62/67)



(c)RRWM Accuracy:0.52(35/67)



(d)SM Accuracy:0.52(35/67)

(e)The Matching Image

(f)OurMethod Accuracy:0.79(34/43)

(g)RRWM Accuracy:0.48(21/43)

(h)SM Accuracy:0.55(24/43)

Figure 2. Some results of our experiments in real image matching.

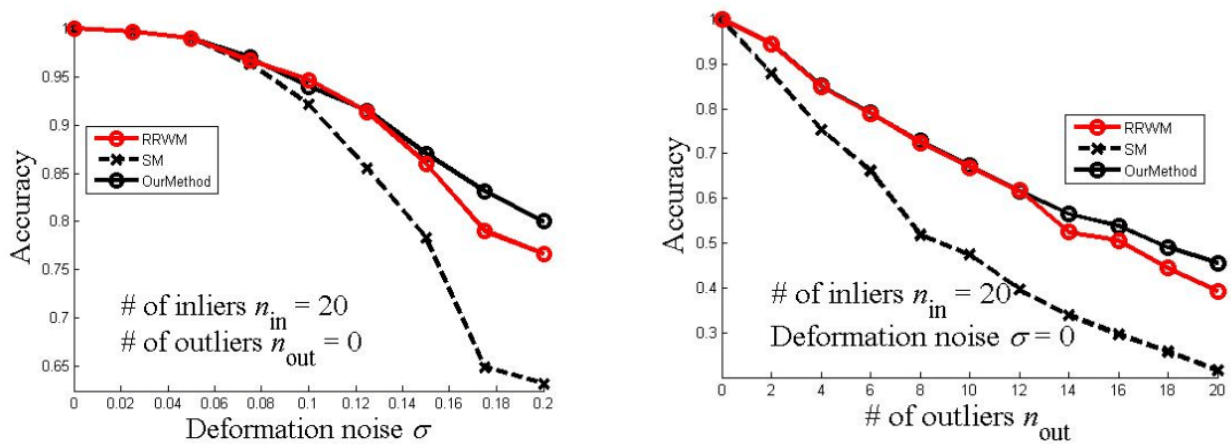
Methods	Accuracy(%)	Time(s)
RRWM	73.61	0.36
SM	64.45	0.04
OurMethod	74.65	0.21

Figure 3. The average matching result on the 30 pairs of images.

3.2 Matching on Random Synthetic Point Sets

In this parts, we did extensive point matching experiments on random synthetic point sets. Each point sets was consisting of n_{in} inlier nodes and the other outlier nodes. We then created a perturbed graph by adding noise between inlier nodes. The deformation noise was distributed using the Gaussian noise function. In order to build a fair comparison environment, the parameters and program running environment are similar to the experiments of real image matching.

In our experiments, we tested the performance of our algorithm at different deformation or outlier levels. We conducted a total of two types of tests. For each test we generated 30 pairs of random synthetic point sets. In the experiments of outlier, we fixed the inliers nin =20 and the number of outliers changed from 0 to 20, increasing by 2 each time. For the deformation experiment, we fixed the inliers nin = 20 and outliers nout = 0, and the deformation noise changed from 0 to 0.4 with increments of 0.05. The accuracy is measured by the number of detected true matches divided by the total number of ground truths. Our final average experimental results are shown in Figure 4. From the analysis of a and b in Figure 4, we can conclude that our algorithm has better experimental results in both deformation and outlier cases.



(a)Deformation experiments: accuracy

(b)Outlier experiments: accuracy

Figure 4. The random synthetic point sets experiments.

4. CONCLUSION

In this paper, a new graph matching method based on shape context and reweighted random walks is introduced. The experiments demonstrate that the accuracy of image matching in the complex situations extremely depends on the effective utilization of the matching constraints. Experiments show that the shape context has better constraint performance and the accuracy of the algorithm can be improved under certain weight constraints with shape context. The comparisons reveal that our method outperforms the existing methods in aspects of accuracy and time. Our approach is simple and easy to apply yet provides a accurate and quick conclusion.

For the method that proposed by us, we will use it in 3-dimensional point cloud registration. Due to the extreme complexity of the 3D point cloud, many algorithms can not achieve strong robustness, and the time complexity is also increasing dramatically, such as Belief Propagation algorithm [16]. Because of our algorithm in time and accuracy have achieved good results, so we can use this algorithm for the three-dimensional point cloud matching to provide an effective upgrade. We will use it flexibly in our future 3D point cloud registration.

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