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Geodesic-like features for point matching

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ABSTRACT

Point matching problem seeks the optimal correspondences between two sets of points via minimizing the dissimilarities of the corresponded features. The features are widely represented by a graph model consisting of nodes and edges, where each node represents one key point and each edge describes the pair-wise relations between its end nodes. The edges are typically measured depending on the Euclidian distances between their end nodes, which is, however, not suitable for objects with non-rigid deformations. In this paper, we notice that all the key points are spanning on a manifold which is the surface of the target object. The distance measurement on a manifold, geodesic distance, is robust under non-rigid deformations. Hence, we first estimate the manifold depending on the key points and concisely represent the estimation by a graph model called the Geodesic Graph Model (GGM). Then, we calculate the distance measurement on GGM, which is called the geodesic-like distance, to approximate the geodesic distance. The geodesic-like distance can better tackle non-rigid deformations. To further improve the robustness of the geodesic-like distance, a weight setting process and a discretization process are proposed. The discretization process produces the geodesic-like features for the point matching problem. We conduct multiple experiments over widely used datasets and demonstrate the effectiveness of our method.

1. Introduction

It is a standard method to represent an image by extracting a set of key points from the image. Matching key points of two images is an important and fundamental problem in the field of computer vision. The application scope of matching key points broadly includes object recognition, 3D reconstruction, motion detection and so on.

In order to improve the matching precision, the spacial relations among key points are exploited by representing each set of key points with a graph model. Each node of the graph represents a key point and each edge of the graph represents the spacial relations between its two end nodes. Typically, the weights on edges are assigned according to the Euclidian distances among points, which is unsuitable for non-rigid deformations. For example, two key points are far from each other in one image while their counterparts can be deceptively close in the other image when the target object deforms non-rigidly. The target object is the object from whose surface the key points are extracted.

To tackle the point matching problem under non-rigid deformations, we notice that the surface of the target object is a manifold. As a distance measurement on a manifold, the geodesic distance is able to preserve the intrinsic geometry of the manifold and be robust to non-rigid deformations as demonstrated in [30]. This measurement can be valuable to handle non-rigid deformations between sets of points in the point matching problem. To apply the geodesic distance, the manifold, which is the surface of the target object, should be estimated firstly.

In this paper, we propose to estimate the manifold depending on the set of key points under the assumption that all the key points are extracted from a unique and connected surface of the target object. We use the “manifold” and the “surface” interchangeably. We evaluate the probabilities of points to be on the manifold according to their distances to key points. Points with high probabilities belong to the estimation of the manifold.

The resulted estimation of the manifold enable us to calculate the geodesic distance between key points. However, for computational efficiency, we represent the estimation by a graph model which is called the Geodesic Graph Model (GGM). In GGM, every node represents one key point in the point set. The geodesic distance between key points on the estimation is approximated by the geodesic-like distance defined on the GGM.

The geodesic-like distance is designed to imitate the geodesic distance. We calculate geodesic-like distances as suggested in [30].

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For two neighboring key points, their geodesic-like distance is well approximated by their Euclidean distance. For two faraway key points, their geodesic-like distance is approximated by adding up a sequence of short edges between neighboring key points. Similar to the geodesic distance, the geodesic-like distance is robust to non-rigid deformations of the manifold.

To further improve the robustness of the geodesic-like distances, we discretize their lengths. We represent the distribution of lengths of the geodesic-like distances by histograms. Then the sequence number of a histogram is a feature of all the lengths in the histogram. This feature is called the geodesic-like feature. In the meanwhile, we calculate the reliabilities of lengths of geodesic-like distances according to how well the geodesic-like distances approximate their corresponding geodesic distances. The Geodesic-like features and the reliabilities are exploited to tackle the point matching problem.

In order to evaluate our algorithm, we conduct several experiments on various datasets. Experimental results show the effectiveness of the proposed algorithm.

In summary, the main contributions of this paper are threefold:

1) To the best of our knowledge, we are the first to estimate the surface of the target object depending on the set of extracted key points. Under the assumption that all the key points are on the surface of the object, every point in the image is assigned a probability to be on the surface of the target object according to its distances to key points.
2) Based on our graph model GGM, we propose the geodesic-like distance as a new distance measurement between key points. Compared with conventional distance measurements, the geodesic-like distance is robust to non-rigid deformations of the target object.
3) To increase the robustness of our algorithm, we further propose to estimate the reliabilities of lengths of geodesic-like distances and come up with the geodesic-like features by exploiting a discretization process. The reliabilities and the geodesic-like features are applied in the point matching tasks to demonstrate their effectiveness.

The rest of this paper proceeds as follows: Section 2 discusses some related works. Section 3 details the procedure of building the GGM. Section 4 describes the method to obtain the geodesic-like features. Section 5 formulates the point matching as an energy minimization task. Section 6 reports the experimental results. The final section states our conclusions.

2. Related work

Point matching methods are applied in many situations. Pan et al. propose to establish the point correspondence between a 3D reference face and an input 3D face [24]. Sahbi et al. propose to recognize different logos via a point matching process [27]. Due to the wide application of the point matching problem, myriad studies dedicated to this problem [9,14]. The algorithms tackling this problem can be roughly categorized into two types: algorithms for rigid deformation matching problem and algorithms for non-rigid deformation matching problem [8].

Algorithms for rigid deformation matching problem demand the deformation type of the target object to be rigid. In spite of their strict assumptions, these algorithms can solve lots of matching problems. They are well studied and widely applied for their relative simplicity and robustness [7]. The RANSAC algorithm [12,25] samples the matching result to estimate the parameters of a predefined transformation model. The ICP algorithm [33] iteratively revises the transformation to minimize the distance from one point set to the other point set. However, they have difficulties in handling objects with non-rigid deformations.

In order to handle non-rigid deformations, algorithms for non-rigid deformation matching problem are extensively studied. Chui and Rangarajan propose the TPS-RPM [8] which uses the thin-plate spline [4] to parameterize the non-rigid deformations. Schnabel et al. propose the free-form deformations based on multi-level B-splines with multi-resolution optimization [28]. These methods focus on modeling the deformations between point sets.

In the meanwhile, another approach focuses on modeling the geometric structure of each point set [10,16]. Tsin and Kanade cast the matching problem as finding the maximum kernel correlation configuration of two point sets, where the kernel correlation is defined as a function of the entropy of the point set [32]. Myronenko and Song represent the template points by a gaussian mixture model such that the matching problem is tackled as a probability density estimation problem [22]. Jian and Vemuri propose to represent the input point sets using Gaussian mixture models such that a statistical discrepancy measure between the two corresponding mixtures is minimized [15]. Zhou and Torre propose to represent each point set by a graph model and handle non-rigid point matching problems from a graph matching [17] point of view [13,36]. Scott and Nowak enforced an order preserving constraint in a contour matching method to regularize the matching process [29].

Some researchers [18,34] note that the point set is a manifold [1,26,30] embedded in an image. The geometric structure of a point set can be described by methods which describe the geometric relations among data points on a manifold.

Inspired by the LLE algorithm [26] which is a manifold learning algorithm, Li et al. propose an object matching method [18] based on the fact that one point can be linearly reconstructed by its neighbor points. Their method keeps the reconstruction weights to describe the geometric relations among points. However, this method is not suitable for non-rigid deformations since the reconstruction weights of each point change largely under non-rigid deformations. Zheng and Doermann propose the PLNS algorithm [34] which has a similar idea with another famous manifold learning algorithm LPP [23]. Their method matches two points if the correspondence of one point's neighbor is a neighbor of its correspondence. This neighborhood relationship is much more robust during non-rigid deformations. However, this method discards all the geometric information between pairs of points that are far from each other, which abandons valuable information and limits the matching precision.

The achievements of the above mentioned algorithms show that it is fruitful to apply the methods which capture the geometric structure on a manifold to the point matching problem. The algorithm proposed in this paper is inspired by the Isomap algorithm [30] which is another popular manifold learning algorithm. Isomap represents the data points on a manifold with a graph model. This algorithm describes the geometric structure of data points depending on the geodesic distances between points. Since the geodesic distance is insensitive to non-rigid deformations, this distance measurement is a good choice for representing the geometric structure between key points in the matching problem. Elad and Kimmel propose an algorithm [11] which takes advantage of the geodesic distances and is used in the 3D object matching problem. This algorithm is a typical work using the geodesic distance to describe the spatial relations among key points.

To exploit the essence of the geodesic distance on 2D images, some studies come up with new measurements. Ling's inner distance method [19,20] for shape classification is the most famous