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Iterative Point Matching via multi-direction geometric serialization and reliable correspondence selection

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ABSTRACT

Point matching aims at finding the optimal matching between two sets of feature points. It is widely accomplished by graph matching methods which match nodes of graphs via minimizing energy functions. However, the obtained correspondences between feature points vary in their matching qualities. In this paper, we propose an innovative matching algorithm which iteratively improves the matching found by such methods. The intuition is that we may improve a given matching by identifying "reliable" correspondences, and re-matching the rest feature points without reliable correspondences. A critical issue here is how to identify reliable correspondences, which is addressed with two novel mechanisms, Multi-direction Geometric Serialization (MGS) and Reliable Correspondence Selection (RCS). Specifically, MGS provides representations of the spatial relations among feature points. With these representations, RCS determines whether a correspondence is reliable according to a reliability metric. By recursively applying MGS and RCS, and re-matching feature points without reliable correspondences, a new (intermediate) matching can be obtained. In this manner, our algorithm starts with a matching provided by a classical method, iteratively generates a number of intermediate matchings, and chooses the best one as the final matching. Experiments demonstrate that our algorithm significantly improves the matching precisions of classical graph matching methods.

1. Introduction

Point matching plays an important role in computer vision applications such as 3D reconstruction, object classification, and video analysis. A popular approach to this problem is to construct a graph model whose nodes represent the feature points and whose edges represent the relations between feature points. Consequently, the matching between two sets of feature points (in a template point set and a deformed scene point set) is accomplished by matching two graphs (namely, a template graph and a deformed scene graph), which provides pairwise correspondences between feature points.

Conventionally, graph matching is formulated as a quadratic assignment problem minimizing a so-called energy function [18,33]. However, the quadratic assignment problem is NP-complete [5,28], implying that there is no theoretical guarantee that the globally optimal matching can always be found. While this is a bad news for theorists, it sheds some light on the possibility of further improving classical methods in practice. Intuitively, improvements on the matching precision can be achieved by re-matching those feature points whose correspondences are highly likely to be incorrect (i.e., unreliable), but this leads to a critical issue: how to identify reliable or unreliable correspondences.

In this paper, we propose two novel mechanisms, Multi-direction Geometric Serialization (MGS) and Reliable Correspondence Selection (RCS), to address the above issue. For each point set, MGS generates multiple ordering representations of feature points by projecting feature points onto different vectors. For example, after being projected onto a vector, the feature points of a given point set can be serialized and represented as an ordering. By collecting together different ordering representations obtained on different vectors, MGS provides abundant ordering representations for each point set, which describes the relative spatial relations among feature points from different perspectives.

With abundant ordering representations given by MGS, RCS quantitatively evaluates each correspondence in the original matching, which determines whether the correspondence can be accepted or not. More specifically, let $C^{\mathcal{T}}$ be an ordering representation of the template, $C^{\mathcal{S}}$ be an ordering representation of the scene, and $(C^{\mathcal{T}}, C^{\mathcal{S}})$ is called a representation pair. To evaluate whether a given correspondence $[\mathbf{p}, \mathbf{q}]$ is reliable, RCS checks the ordering violation of the correspondence $[\mathbf{p}, \mathbf{q}]$ against other correspondences on each representation pair, and the violation

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information with respect to multiple representation pairs together determines a reliability metric of the correspondence. Using this metric, the correspondences with the highest reliability are accepted while the rest correspondences are abandoned. The cooperation of MGS and RCS identifies those reliable correspondences, and the rest feature points without reliable correspondences will be re-matched by a classical matching method. MGS and RCS, together with the re-matching mechanism, generate a new matching that could be better than the initial one.

With the MGS and RCS proposed in this paper, we devise a novel algorithmic framework called Iterative Point Matching (IPM) which starts with the initial matching provided by a classical graph matching method, generates and records a new intermediate matching at each iteration. After a fixed number of iterations, it takes the intermediate matching with the lowest energy as the final matching. The proposed IPM is orthogonal to classical graph matching methods, as it is independent of classical methods, and can be utilized to improve the matching found by many classical methods. In empirical evaluations of the IPM, we use several state-of-the-art matching methods to provide initial matchings for the IPM, and observe that the IPM significantly improves the matching precision over various datasets.

Our main contributions are three-fold. First, we propose to characterize geometric relations among feature points by projecting the points onto vectors. The obtained ordering representations can precisely characterize the relations given a sufficient number of projection vectors. Second, we propose to iteratively re-match the feature points without reliable correspondences instead of simply abandoning them, which effectively improves the matching quality. Third, the proposed IPM can adapt to many different matching methods to enhance the matching precision, since the IPM is independent of any concrete matching method.

The rest of this paper proceeds as follows: Section 2 presents some related work. Section 3 describes details of the IPM. Section 4 reports the experimental results. Section 5 concludes the whole paper.

2. Related work

Point matching has been studied in various contexts [8,14,17] for its important applications. Besl and McKay proposed a classical algorithm [3] that heuristically corresponds each point in the template to its closest point in the scene. 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 [29]. Myronenko and Song represented the template points by a Gaussian mixture model such that the matching problem is tackled as a probability density estimation problem [24]. Li et al. reconstructed the location of each feature point by the coordinates of its neighbor points [22], which enables their algorithm to match via linear programming techniques [18]. Zheng and Doermann corresponded points using the similarity of their neighborhood structures, and their algorithm is robust in the presence of non-rigid deformations [32]. Scott and Nowak enforced an order preserving constraint in a contour matching method to regularize the matching process [27]. The above algorithms all exploited the geometric information of feature points.

To leverage more information about the set of feature points, it is a popular approach to build a graph model which is a concise yet informative representation for capturing multiple characteristics of a set of feature points. So, the point matching problem can be solved as a graph matching problem [9]. In general, the graph matching is formulated as a quadratic assignment problem which is known to be NP-complete [5,28]. Hence, many algorithms aim at tackling this problem more efficiently and precisely [25]. Progressive Graph Matching [7] first matches two small active graphs, and then progressively expands the matching via a probabilistic voting process. Graduated Assignment [15] takes advantage of Taylor's formula [1] to expand the energy function of the quadratic assignment problem and uses the softassign to gradually obtain the final matching result. Reweighted Random Walk Matching [6] introduces a random walk view on the graph matching problem. The above methods, however, are often trapped by local minima of their energy functions, suggesting that there are still spaces to further improve the matching quality.

So far there have been a number of strategies to improve the matching quality. The statistical robust regression methods, such as LMedS (Least-Median of Squares) [26] and M-estimator [16], try to emulate popular statistical methods, while avoid to be unduly affected by outliers or other small departures from model assumptions. The case diagnostics methods check the influence of putative correspondences on model estimation to reject unreliable correspondences directly. The sampling methods, for example, Random Sample Consensus [13], estimate the parameters of a predefined model by sampling such that correspondences which do not cohere with the estimated model are abandoned. Li and Hu proposed to regularize the correspondence function to remove unreliable correspondences [23]. Zhao et al. proposed to use a robust method for vector field learning to identify reliable correspondences [31]. However, previous approaches do not re-match points without reliable correspondences to further improve the matching precision.

In this paper, we propose a new algorithmic framework, the IPM, to improve the matching using the geometric information of points. Our study is substantially different from the above studies, because the IPM not only identifies reliable/unreliable correspondences, but also re-matches points that are identified to be unreliable.

3. Methodology

In this section, we elaborate the algorithmic flow of the IPM. We first present the general problem formulation. Then we introduce respectively two novel mechanisms integrated in our IPM framework, namely, Multi-direction Geometric Serialization (MGS) and Reliable Correspondence Selection (RCS), by which reliable correspondences are identified. We also describe the re-matching process where reliable correspondences are exploited to re-match the rest feature points. Finally, we summarize the whole IPM flow.

3.1. Problem formulation

Suppose the template $\mathcal{T}$ is composed of n_t feature points and a deformed scene $\mathcal{S}$ is composed of n_s feature points. Let $G_{\mathcal{T}} = \{\mathbf{p}_i\}_{i=1}^{n_t}$ and $G_{\mathcal{S}} = \{\mathbf{q}_j\}_{j=1}^{n_s}$ be the sets of feature points in $\mathcal{T}$ and $\mathcal{S}$ respectively, where $\mathbf{p}_i \in \mathbb{R}^d$ is the i-th template feature point and $\mathbf{q}_j \in \mathbb{R}^d$ is the j-th scene feature point.

It is a common practice to match some feature points to dummy points to improve the robustness against outliers. Without loss of generality, n_s dummy points are induced into $G_{\mathcal{T}}$ and n_t dummy points are induced into $G_{\mathcal{S}}$. Hence, $G_{\mathcal{T}}$ and $G_{\mathcal{S}}$ are further extended such that $G_{\mathcal{T}} = \{\mathbf{p}_i\}_{i=1}^{n_{ts}}$, and $G_{\mathcal{S}} = \{\mathbf{q}_j\}_{j=1}^{n_{ts}}$ where $n_{ts} = n_t + n_s$. Consequently, every feature point in $G_{\mathcal{T}}$ or $G_{\mathcal{S}}$ is matched to one point (real or dummy feature point) in the other set of points.

Let $M(\cdot)$ be a matching function which maps every template feature point $\mathbf{p}_i$ to its corresponding feature point. $M(\cdot)$ can be effectively represented by a set of binary variables, more specifically, a matrix X in this paper. Each entry of the matrix is a binary variable:

$$X_{ij} = \begin{cases} 1, & \text{if } M(\mathbf{p}_i) = \mathbf{q}_j \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where X_{ij} is the variable of X at the i-th row and j-th column. When