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A robust coherent point drift approach based on rotation invariant shape context

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ABSTRACT

Point set matching is a common problem in many domains, such as medical image analysis, object recognition, 3D reconstruction, and motion tracking. Coherent point drift (CPD) appears as an efficient algorithm to align two point sets. It treated point set matching as a problem of Gaussian mixture density estimation. But there are four drawbacks in the CPD method: outlier ratio given manually, equal prior probability for the mixture model, lack of shape information and failure for large rotation transformations. To deal with these limitations, we propose a robust CPD approach based on rotation invariant shape context. First, a rotation invariant shape context (RISC) is constructed for each point of the two sets to keep the rotation invariance of shape features. Then an adaptive prior probability and outlier ratio are computed based on RISC. For each Gaussian mixture model (GMM) component, the prior probability is linked to the number of the sample points derived from this component. Finally, the correspondence and transformation are achieved through expectation-maximization (EM) process. The results on synthetic and real data show that our method is a robust and effective non-rigid point matching approach.

1. Introduction

Point set matching is a fundamental problem in many domains, such as medical image analysis [1], object recognition [2,3], 3D reconstruction [4], and motion tracking [5]. The goal of matching is to find the meaningful correspondence between two point sets and estimate the spatial transformation based on the found correspondence. The locations of points, which are the simplest form of the feature, are usually extracted to construct the point sets.

The application of point set matching is impacted by two factors. One is the robustness to degradations, for instance, noises, outliers and occlusion points stemming from image acquisition and feature extraction. Another is the capability of processing high dimensional point sets. There are two general problems in point set matching: unknown correspondence and unknown transformation. If one of the two problems is fixed or known, it is easy to obtain another one, so they are two coupled problems.

Since decades, many methods have been proposed to solve this coupled problem. Iterative closest point (ICP) [6–8] is the commonly used rigid point set matching method. It iteratively determines the correspondence based on L2-norm distance and obtains spatial transformation related to the point sets. Because of the one-to-one correspondence in each iteration, ICP is easy to get stuck in local minimum. Besides, ICP needs a good initial transformation to assign two point sets.

Compared with rigid transformation, there are many non-rigid transformations all over the real world, such as soft tissue deformation in the cranio-maxillofacial surgery, deformable motion tracking, and surgical planning and evaluation. Several variants [9–17] of ICP have been introduced to solve non-rigid point set matching problem. There are two common iterative steps in these methods: (1) finding the current correspondence between two point sets; (2) building the new transformation based on the current correspondence. Robust point matching (RPM) [12] is one of them. In contrast to ICP, RPM adopts soft assignment and deterministic annealing to improve matching performance. However, RPM is not really a probability method. In the E-step of expectation maximization (EM) [18], RPM does not attain truly the posterior probability.

Recently, some non-rigid point set matching algorithms based on probability have been proposed, especially on the Gaussian mixture model (GMM). This type of methods can be classified into two categories. One category is that the matching problem is treated as

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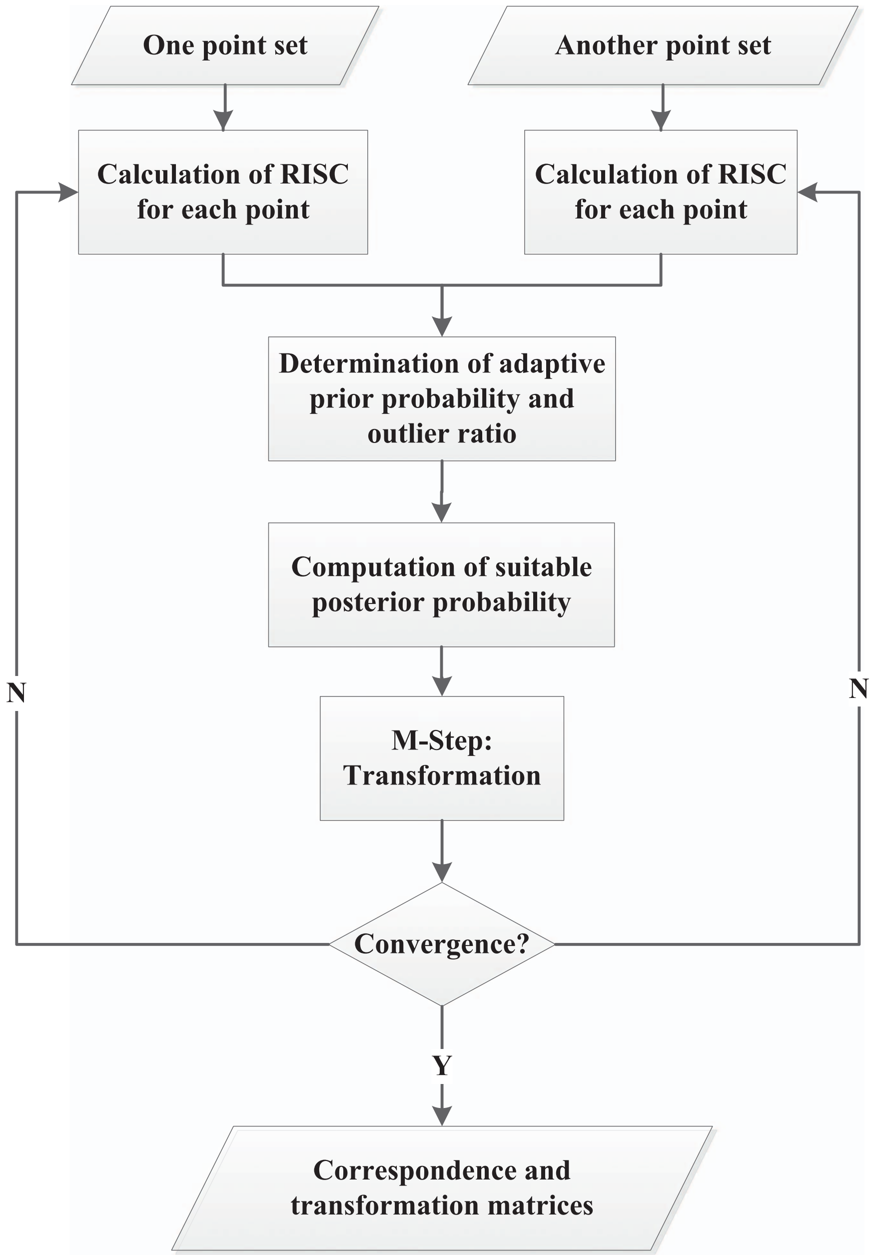

Fig. 1. Flowchart of the robust CPD based on rotation invariant shape context (SCCPD).

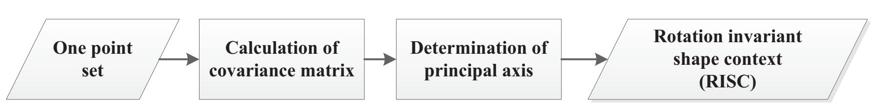

Fig. 2. Scheme of calculating the rotation invariant shape context (RISC).

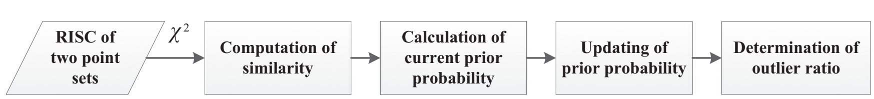

Fig. 3. Scheme of determining the adaptive prior probability and outlier ratio.

the maximum similarity problem of two distributions, and both of the two point sets are represented as GMM centroids. The representative method is Kernel correlation (KC) based point set matching approach [19], and its cost function is expressed as KL-divergence between two distributions. The drawback of KC-based methods is that it can only get the transformation.

The other category is the methods that represent one point set as GMM centroids and the other set as sample points from this component of GMM. So the point set matching problem is regarded as a mixture density estimation problem. Coherent point drift (CPD) [20,21] is the representative method. The method can deal with high dimensional point sets and appears robust to outliers. To handle the outliers in the point set, a uniform distribution is added to express the distribution of outliers.