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Multiple point sets registration based on Expectation Maximization algorithm☆

Yiqiong Zhou[a], Siyu Xu[a], Congcong Jin[a], Ziyi Guo*,[b]

[a] School of Software Engineering, Xi'an Jiaotong University, Xi'an, China
[b] School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China

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ABSTRACT

Many methods have been proposed and improved to deal with multi-view point cloud registration. Most of them are based on the classical method, namely Iterative Closest Point(ICP), which is fast and accurate in most cases. However in the presence of noise and outliers, the equal weights ICP assigned to all correspondences would lead to unsatisfactory registration results. To address this issue, this paper proposes a new automatic multi-view registration method based on Expectation Maximization(EM). A Gaussian distribution on representing the relationship between point-sets according to their distance was introduced first. Then EM is brought in to optimize the likelihood function formulated with above Gaussian distribution. Through an iterative method the multi-view registration results can be obtained at last. The experimental results demonstrate accuracy and robustness of our methods over four state-of-the-art algorithms, especially when noisy data exist.

1. Introduction

Among enormous problems in computer vision such as image retrieval, object recognition, image dehazing [1,2] and etc., point cloud registration is a fundamental issue which aims at recovering the original 3-D object from many point sets that obtained from different views. This technology can be applied to many fields, like 3-D reconstruction [3], robotics [4], computer graphics [5], etc.

A point cloud is a set of data points in a three-dimensional coordinate system. It describes the objects in the world around us like images. To achieve Point cloud registration, pair-view registration needs to be completed first, which can obtain the transformation between two separate point cloud coordinate systems. The method always being adopted to handle the pair-wise registration is Iterative Closest Point(ICP) [6]. Based on the pair-view registration methods, multi-view registration can be solved by using them iteratively [7].

Much progress has been achieved in point cloud registration in recent years. In the problem of pair-wise registration, a lot of variants of ICP was proposed [8,9]. Besides, other methods based on genetic algorithm(GA) [10] and particle filter [11] were invented as well. All of them improve the efficiency and accuracy to some degree. In the multi-view registration problem, Govindu and Pooja [12] applied the motion average algorithm to tackle it. Mateo et al. [13] casted the problem into the Bayesian framework.

However, current multi-view registration algorithms always fail in achieving satisfactory results, due to the accumulation of the different pairwise errors and limitations of methods. Pairwise errors partially result from noise in point data. Those noise would lead to wrong correspondences, thus harm the efficiency, accuracy and robustness directly.

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* Corresponding author.
E-mail addresses: yiqiongzhou.cd@gmail.com (Y. Zhou), ziyiguo94@gmail.com (Z. Guo).

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Aiming at reducing the influence of the noise and enhancing the robustness, this paper proposes an automatic multi-view registration method based on Expectation Maximization(EM), which treats all points unequally by assigning different weights to different points and achieves better registration results without feature extraction. It first introduces a Gaussian distribution to assign the noise points with lower weights, then utilizes EM to solve the objective function. Moreover, an iterative solution is used to obtain the transformation of multi-view registration.

As an extended version of [14], this paper introduces more related methods and includes more details. Another set of experiment about the comparison with ground-truths was conducted. Besides, one more novel approach is added to the comparison to indicate the superiority of our method.

The rest of this paper is organized as follows: Brief history of research works in registration problem is given in Section 2. Section 3 introduces the Iterative Closet Point(ICP) algorithm. Section 4 illustrates our proposed approach in detail. Section 5 presents the experimental results and Section 6 concludes the paper.

2. Related work

The registration problem can be divided into two categories according to the number of scans to be registered: pair-view registration and multi-view registration. The most classic technique to achieve pair-view registration is ICP [6], which consists of two iterative steps: assigning the correspondences according to the nearest-neighbor relationship and determining the motion with Singular Value Decomposition(SVD). The greedy and iterative ICP method is simple but have a requirement of proper initial parameters. In addition, false correspondences would lead to the decrements of accuracy and robustness. To obtain better correspondences, some methods represent point-sets as probability density functions(PDF). For example, in the work of Tsin and Kanade [15], two point-sets were modeled as kernel density function.

In addition, ICP doesn't fit the situation where the model shape and data shape are partially overlapped. To address this issue, Chetverikov et al. [8] proposed the Trimmed Iterative Closet Point (TrICP) algorithm. It introduces an overlapping percentage and only registers the trimmed scans. Based on that, Xu et al. [16] proposed the scaling and trimmed ICP to tackle the scaling registration problem of partially overlapping point sets. In 2016, Zhu et al. [17] assigned different weights to overlapping area and non-overlapping area based on the ration of bidirectional distances to obtain a robust registration result of partially overlapping clouds.

Later, Granger and Pennec [18] proposed EM-ICP in 2002, which matches a set of model and scene points, then updates correspondences and the registration transformation simultaneously. It improves the efficiency and robustness to some extent. Afterwards, Tamaki et al. [19] came up with the method which is implemented on GPU to speed up the EM-ICP and assigned weights to each correspondence to cope with noise, but the alignment was still unsatisfactory.

Besides, correntropy was introduced into ICP algorithm to solve the pair-wise registration problem by maximizing the correntropy between two point clouds [20]. Although it addresses the rigid registration problem with noises and outliers, its robustness need to be further improved in the case of cloud pairs with low overlapping percentage. In 2015, Probabilistic ICP(PICP) was proposed by Du et al. [21]. It introduces a Gaussian distribution and utilizes EM to solve the pair-wise registration problem.

To build a full 3-D model, a set of transformations that used to align multiple scans in a single references frame need to be found. The representative algorithm in solving the multi-view registration was proposed in 1992 by Chen et al. [7]. Two main steps, which are registering two scans and then merging them into one scan, are alternately processed in the algorithm. However, the sequential strategy suffers from drift accumulation due to the chain-based optimization.

Then, Govindu and Pooja [12] proposed the motion average algorithm, which obtains a better accuracy by making use of the redundant information. However, it suffers from partially overlapping scans, since it adopts ICP to obtain the relative motions. Furthermore, an automatic multi-view registration approach was proposed by Fantoni et al. [22], which needs to extract some features of scans, like RoPS feature, to achieve registration. But it's not realistic to obtain these features every time. What's more, Zhu et al. [23] extended the TrICP algorithm to deal with the multi-view registration by iterations.

The method based on low-rank decomposition of a large matrix was introduced in the work of Arrigoni, et al. [24]. With respect to two scans with high overlapping percentages, their transformation is concatenated into a large matrix and can be estimated by approximating a low-rank data matrix. The method performs well in the presence of outliers and missing data.

3. The ICP algorithm

Suppose there are two scans, a data shape $D = \left\{\vec{d}_i\right\}_{i=1}^{N_d}$ $(\vec{d}_i \in \mathbb{R}^3)$ and a model shape $M = \{\vec{m}_j\}_{j=1}^{N_m}$ $(\vec{m}_j \in \mathbb{R}^3)$, the goal of registration is to find the optimal transformation $\{\mathbf{R}, \vec{t}\}$, with which D can be in the best alignment with M. According to the ICP algorithm, the problem can be formulated as below:

$$\begin{aligned} &\min_{\mathbf{R}, \vec{t}, j \in \{1,2,\dots,N_m\}} \sum_{i=1}^{N_d} \left\| \left(\mathbf{R}\vec{d}_i + \vec{t}\right) - \vec{m}_j \right\|_2^2 \\ &s.\ t \quad \mathbf{R}^T\mathbf{R} = \mathbf{I}_{3\times 3}, \ \det(\mathbf{R}) = 1 \end{aligned} \tag{1}$$

where N_d denotes the number of points in D, N_m is the number of points in M, $\mathbf{R} \in \mathbb{R}^{3\times 3}$ represents the rotation matrix, $\vec{t} \in \mathbb{R}^3$ is the translation vector.