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Probability iterative closest point algorithm for *m*-D point set registration with noise

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ABSTRACT

This paper proposes probability iterative closest point (ICP) method based on expectation maximization (EM) estimation for registration of point sets with noise. The traditional ICP algorithm can deal with rigid registration between two point sets effectively, but it may fail to register point sets with noise. In order to improve the registration precision, a Gaussian model is introduced into the traditional rigid registration problem. At each iterative step, similar to the original ICP algorithm, there are two parts of the proposed method. Firstly, the one-to-one correspondence between two point sets is set up. Secondly, the rigid transformation is solved by singular value decomposition (SVD) method, and then the Gaussian model is updated by the distance and variance between two point sets. The proposed method improves the precision of registration of point sets with noise significantly with fast speed. Experimental results validate that the proposed algorithm is more accurate and faster compared with other rigid registration methods.

1. Introduction

In pattern recognition and computer vision, various features are applied widely [1,2], especially the point set representing position is a common feature. Therefore, point set registration has become a very important and basic research topic for its wide application. The goal of registration is to find the corresponding relationship between two point sets and compute an appropriate transformation with which the shape point set can register to the model point set. The typical method is the iterative closest point (ICP) algorithm which offers a good solution to the point set registration [3–5]. The ICP algorithm has been widely used in many fields for its advantages of high speed and precision. Moreover, some scholars have also extended the rigid registration to the non-rigid case, including scale [6], affine [7] and nonlinear registration [8].

In the past few decades, many researchers have devoted great efforts to rigid registration of traditional point sets, especially on the speed and robustness. To speed up the ICP algorithm, Xu et al. [9] introduced five constraint conditions of registration point pairs, and Kim et al. [10] proposed two acceleration techniques: hierarchical model point selection and logarithmic data point search. A combination of ICP variants was able to align two range images in a few tens of milliseconds, but it needed a good initial guess for high speed [11]. The Levenberg–Marquardt algorithm which was general-purpose non-linear optimization was adopted to accelerate the ICP [12]. Jost et al. [13] proposed a solution combining a coarse to fine multiresolution approach with the neighbor to speed up the ICP. Meanwhile, there were also many researchers studying the robustness of ICP. Almhdie et al. [14] presented an enhanced implementation of the popular ICP algorithm for the registration of 3D free-form closed surfaces, which was based on the use of a look up matrix for finding the best correspondence pairs. Zhang et al. [15] presented a more robust ICP approach for 2D point set registration and an inequality constraint of the rotation angle was introduced into the registration model which was solved by an extended ICP algorithm. Invariant features decreased the probability of being trapped in a local minimum [16]. Lee et al. proposed a matrix which represented the reliability of the rotation components of ICP [17]. Biunique correspondence [18] was introduced to enhance the performance of ICP by searching multiple closest points and the algorithm could find the correct rigid transformation with the existence of large non-overlapping area and poor initial alignment. Silva et al. [19] introduced a new hybrid genetic algorithm technique and evaluation metric based on surface interpenetration to improve the robustness.

It should be pointed out that the above mentioned approaches could not handle the point sets with a large number of outliers and

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noise which exist widely in application. To solve the registration of point sets with outliers, many researchers made great efforts. Some matched corresponding points based on overlapping percentage. The trimmed ICP algorithm which incorporated an overlapping percentage into a least square function to trim outliers was proposed [20]. Nevertheless, the algorithm was time-consuming. Hence, the fractional ICP which simultaneously computed the best transformation and the overlapping percentage could identify and discard outliers, and achieved fast speed [21]. However, this method depended greatly on the parameter. Thus, Du et al. [22] proposed a novel objective function which could automatically compute rigid transformation, correspondence, and overlapping percentage without influence of a parameter. Meanwhile, the distance threshold was also discussed. Rodriguez-Losada [23] presented a technique to improve the data association in the ICP based on a distance-filter adopting the idea of a coarse estimation of the correct solution, which could be used to test each single association and robustly discard wrong ones. A modified ICP method was proposed to ameliorate the performance of laser scan alignment by applying dynamic distance error threshold [24]. Ridene and Goulette proposed a variant of ICP based on an adaptive dynamic threshold and a RANSAC method was used to remove outliers [25].

The above-mentioned approaches are effective for outliers, but they are not suitable for dealing with point sets with noise which is always produced due to the precision of the acquisition equipment in the real application. The acquired data may have different precisions and random noise, so some researchers proposed to join probability into the ICP algorithm to improve the rigid registration precision [26–28], and the coherent point drift algorithm [28] extends to the non-rigid registration. Each of the point sets was represented by a mixture of Gaussians and the point set registration was treated as a problem of aligning the two mixtures [26]. A new method corresponded to ICP with multiple matches weighted by normalized Gaussian weights, gives birth to the EM–ICP using expectation maximization (EM) principle [27], which adopts full correspondence relationship for all the points in the model point set and the shape point set. Hence, it is time-consuming and the precision is limited due to the true correspondence being disturbed by the unimportant points which are the false corresponding points. To cope with this problem, we use the EM principle and adopt one-to-one correspondence which is for all the points in the shape point set only needed to find the closest points from the model set. The one-to-one correspondence is able to suppress the unimportant points and retain the original information of point pairs without the interference of noise, and therefore this method achieves high accuracy. However, the one-to-one correspondence may cause the proposed algorithm trapped into the local minimum, so the variance of Gaussian probability model is updated from large to small step by step, which makes the registration from coarse to fine. In the beginning the variance is given a big value, so all the points are approximate to uniform distribution which is the coarse registration. As the variance becomes small, the distribution gets close to the true distribution of the registration error which is the fine registration. As the proposed method adopts the one-to-one correspondence and the variance is updated from large to small, it achieves the fast speed and high accuracy.

This paper is organized as follows. Section 2 briefly reviews the process of the original ICP. Following that is Section 3, aiming at solving the rigid registration of point sets with noise, the Gaussian probability model is introduced and the probability iterative closest point algorithm is proposed. In Section 4, the validity and convergence property are analyzed. Experimental results on part B of CE-Shape-1 and the Stanford 3D Scanning Repository databases are present in Section 5. Finally, the conclusion is given in Section 6.

2. Iterative closest point algorithm

For the rigid registration of point sets, ICP is the typical algorithm proposed by Besl and McKay [3–5], which has been widely used in various research fields for its fast speed and high precision.

Given two point sets in $\mathbb{R}^n$: the shape point set $X=\{\vec{x}_i\}_{i=1}^{N_x}(N_x\in\mathbb{N})$ and the model point set $Y=\{\vec{y}_j\}_{j=1}^{N_y}(N_y\in\mathbb{N})$, in order to guarantee the consistency of the shape point set and the model point set in Euclidean distance space, the ICP algorithm is employed to solve the rigid transformation. For the registration of these two point sets, least square (LS) is used to measure and the formula can be expressed as follows:

$$\min_{\mathbf{R},t,j\in\{1,2,\cdots,N_y\}}\left(\sum_{i=1}^{N_x}\|(\mathbf{R}\vec{x}_i+t)-\vec{y}_j\|_2^2\right)$$
$$\text{s.t.}\quad \mathbf{R}^T\mathbf{R}=I_n,\det(\mathbf{R})=1 \tag{1}$$

The procedure of the ICP algorithm includes two steps. At each iterative step, correspondence is set up by finding the model points which are the closest to the shape point set, and then the rigid transformation is obtained. The main steps of ICP are summarized as follows:

(1) According to the obtained rigid transformation of $(k-1)$th step, the shape point set will be transformed by rotation matrix $\mathbf{R}_{k-1}$ and translation vector t_{k-1}. After transformation, correspondence between two point sets is established as follows:

$$c_k(i)=\underset{j\in\{1,2,\cdots,N_y\}}{\arg\min}\ (||(\mathbf{R}_{k-1}\vec{x}_i+t_{k-1})-\vec{y}_j||_2^2), i=1,2,\cdots,N_x \tag{2}$$

(2) For the shape point set $\{\vec{x}_i\}_{i=1}^{N_x}$ and the corresponding model point set$\{\vec{y}_{c_k(i)}\}_{i=1}^{N_x}$, we need to solve new rigid transformation between them as follows:

$$(\mathbf{R}_k,t_k)=\underset{\tilde{\mathbf{R}}_k{}^T\tilde{\mathbf{R}}_k=I_n,\det(\tilde{\mathbf{R}})=1,\tilde{t}_k}{\arg\min}\left(\sum_{i=1}^{N_x}||\tilde{\mathbf{R}}_k\vec{x}_i+\tilde{t}_k-\vec{y}_{c_k(i)}||_2^2\right) \tag{3}$$

Steps (1) and (2) are repeated until the iteration is convergent. As the method is a local convergent method, initial values of rotation matrix and translation vector are important. Good initial values not only guarantee the algorithm converges to the global minimum value, but also greatly improve the efficiency of computation. The selection of initial values also has a lot of methods [3,29,30], which is not detailedly analyzed here.

3. Probability iterative closest point algorithm

3.1. Problem statement

The traditional ICP algorithm can accomplish the rigid registration with good accuracy and fast speed, but it fails to register two point sets with noise named noisy point sets. The noise got by the sensor or produced by the image processing is called shape noise. Fig. 1 presents a registration result of 2D noisy point sets.

In Fig. 1, the red points show one shape without noise, while the blue points show the noisy point set. Through the ICP registration result, it is obvious to see that the noisy points on the edge will influence the result of registration significantly. Due to the interference of noise, the shape boundaries after registration will not be completely aligned, so Gaussian probability model is