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New iterative closest point algorithm for isotropic scaling registration of point sets with noise ☆

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ABSTRACT

This paper proposes a new probability iterative closest point (ICP) approach with bounded scale based on expectation maximization (EM) estimation for isotropic scaling registration of point sets with noise. The bounded-scale ICP algorithm can handle the case with different scales, but it could not effectively yield the alignment of point sets with noise. Aiming at improving registration precision, a Gaussian probability model is integrated into the bounded-scale registration problem, which is solved by the proposed method. This new method can be solved by the E-step and M-step. In the E-step, the one-to-one correspondence is built up between two point sets. In the M-step, the scale transformation including the rotation matrix, translation vector and scale factor is computed by singular value decomposition (SVD) method and the properties of parabola. Then, the Gaussian model is updated via the distance and variance between transformed point sets. Experimental results demonstrate the proposed method improves the performance significantly with high precision and fast speed.

1. Introduction

Point set registration is a fundamental problem of great importance that continues to attract considerable interest in pattern recognition and image processing, such as image retrieval [1–3], image registration and segmentation [4–6], 3D reconstruction and mobile visual search [7–10]. The goal of registration is to establish the corresponding relationship between two point sets, and recover the optimal spatial transformation which yields the best alignment. The Iterative Closest Point (ICP) algorithm is the most popular approach for its good performance and simplicity [11–13]. Moreover, many scholars studied the speed [14,15] and robustness [16,17] of the ICP algorithm.

In the past few decades, a great number of scholars make great efforts to improve the performance of ICP for registration of point sets with a large amount of outliers and noise which exist widely in practice. To handle the outliers, it has derived many methods. For instance, one simple way is to employ geometry constraint method [18], which often varied according to the shapes of the point sets, so it is not robust enough. Meanwhile, the distance threshold was also utilized [19–21]. Furthermore, the partial registration methods based on overlapping percentage are proposed for dealing with the outliers [22,23]. To improve the precision of the registration of point sets with noise, the probability was introduced to the registration algorithms. Based on expectation maximization (EM) principle, the EM-ICP algorithm [24] was proposed which was weighted by normalized Gaussian weights, and then Du et al. [25] proposed a probability ICP algorithm for accurate rigid point set registration with noise, but all of them did not take the scale into account.

In the meanwhile, the original ICP algorithm does not take the scale factor into consideration. To tackle with the isotropic scaling issue, Zinßer et al. [26] introduced integrated estimation of the scale factor. However, it requires a rough pre-alignment of the point sets. Therefore, Ying and Du et al. [27,28] instead proposed a novel approach named the Iterative Closest Point with Bounded Scale (ICPBS) algorithm which integrated a scale with boundaries into the traditional ICP algorithm for isotropic scaling registration with few outliers. Meanwhile, a lot of scholars extend the approach to varied cases. To improve the performance, Li et al. [29] introduced a sparse-to-dense hierarchical model in ICP algorithm to speed up the isotropic scaling registration. Moreover, Du et al. [30] extended it to deal with outliers by the scaling registration of partially overlapping point sets. However, it is lack of methods to deal with the scaling registration of point sets with noise to improve the precision.

For the purpose of taking the scale factor and noise into account, the coherent point drift algorithm (CPD) [31] is extended to the scaling registration, which adopts full correspondence

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relationship for all the points in the model point set and the shape point set. Therefore, it increases the computational complexity and the accuracy is limited for the small probabilities of incorrect point pairs which are assigned by full correspondence of CPD algorithm. To handle the problem of isotropic scaling registration with noise, we introduce the EM principle and the scale factor, and then one-to-one correspondence is employed which is for all the points in the shape point set only needing to find the closest points in the model set. The one-to-one correspondence is able to decrease the influence of the incorrect points and maintain the original information of point pairs without the interference of noise, which can achieve 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 dynamically, which results in the registration from coarse to fine. In the first stage, the variance is assigned to be a big value, so all the points are close to uniform distribution which is the coarse registration. As the variance decreases, the distribution becomes close to the real distribution of the registration error which is the fine registration. Experimental results on part B of CE-Shape-1, the Stanford 3D Scanning Repository databases and the real map mergence verify the proposed method has fast speed and high accuracy.

The rest of this paper is organized as follows. In Section 2, the ICPBS algorithm is briefly reviewed. Following that is Section 3, for the purpose of solving the isotropic scaling registration of point sets with noise, by introducing the Gaussian probability model, the probability iterative closest point algorithm with bounded scale is presented. A series of experiments demonstrate the effectiveness of our method in Section 4. Finally, the conclusion is drawn.

2. Iterative closest point with bounded scale

In the field of pattern recognition, training samples need to be aligned which can be accomplished by image registration methods. As points are basic features of images, point set registration is important in image registration. The ICP is the classical algorithm for the rigid registration of point sets. However, it cannot deal with the isotropic scaling registration problems which exist widely such as multi-resolution image registration. In practice, the isotropic scaling registration needs to be considered.

Given two point sets in $\mathbb{R}^n$: the shape point set $X = \{x_i\}_{i=1}^{N_x} (N_x \in \mathbb{N})$ and the model point set $Y = \{y_j\}_{j=1}^{N_y} (N_y \in \mathbb{N})$. Aiming to ensure the consistency of the shape point set and the model point set in Euclidean space, the ICPBS algorithm is employed to compute the isotropic scale transformation which can be expressed as the following least square (LS) problem:

$$\begin{aligned} &\min_{s,\mathbf{R},t,c(i)\in\{1,2,\dots,N_y\}} \left(\sum_{i=1}^{N_x} \|(s\mathbf{R}x_i + t) - y_{c(i)}\|_2^2 \right) \\ &\text{s.t.} \quad \mathbf{R}^T\mathbf{R} = I_n,\ \det(\mathbf{R}) = 1,\ s \in \cup_k [a_k, b_k] \end{aligned} \tag{1}$$

where $\mathbf{R}$ is a rotation matrix, t is a translation vector, and s is the scale factor whose lower boundary a_k and upper boundary b_k can be given manually or estimated according to the characteristics of the point sets, such as their covariance matrices.

The objective function can be solved by iteration. In each iteration, the correspondence between the shape point set and the model point set is built up, and then the scale transformation is solved. These two steps are given as follows:

Step 1, set up the corresponding relationship between X and Y with the $(k-1)$th scale transformation $(\mathbf{R}_{k-1}, t_{k-1}, s_{k-1})$:

$$c_k(i) = \underset{j\in\{1,2,\dots,N_y\}}{\arg\min} \left(\|(s_{k-1}\mathbf{R}_{k-1}x_i + t_{k-1}) - y_j\|_2^2 \right), \quad i = 1, 2, \dots, N_x \tag{2}$$

Step 2, solve the new scale transformation $(\mathbf{R}_k, t_k, s_k)$ according to the current correspondence $\{i, c_k(i)\}$:

$$(\mathbf{R}_k, t_k, s_k) = \underset{\substack{\mathbf{R}^T\mathbf{R} = I_n, \det(\mathbf{R}) = 1 \\ s \in \cup_k [a_k, b_k], t}}{\arg\min} \left(\sum_{i=1}^{N_x} \|s\mathbf{R}x_i + t - y_{c_k(i)}\|_2^2 \right) \tag{3}$$

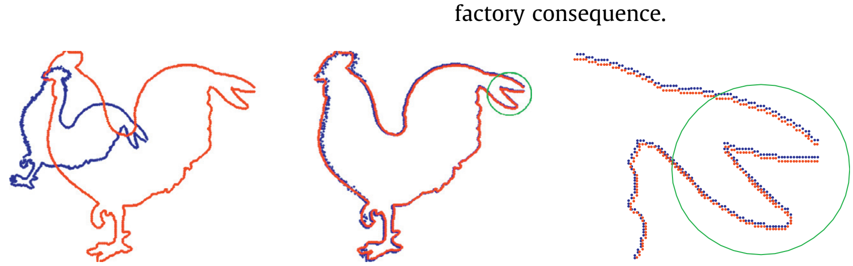
Steps 1 and 2 are repeated until the algorithm converges. As the algorithm is a local convergent method, good initial values of the rotation matrix and translation vector are urgently important, which not only drive the algorithm to converge, but also greatly reduce the computational complexity. There are also many methods [27,28] to cope with the selection of initial values, which are not concretely analyzed here.

3. Probability iterative closest point with bounded scale

3.1. Problem statement

In practice, the noise captured by the sensor or produced by the image processing exists widely in point sets which is called shape noise. Therefore, it is necessary to accomplish the isotropic scaling registration for point sets with noise. The ICPBS algorithm can yield the isotropic scaling registration with good accuracy and fast speed, but it could not register two point sets with noise preciously. Fig. 1 exhibits a registration result of 2D noisy point sets.

In Fig. 1, the red points represent one shape without noise, while the blue points show the noisy point set. The influence of noise on the ICPBS registration result can be clearly seen from the edge. Due to the disturbance of noise, the shape boundaries after registration are not completely overlapped, so we consider importing the Gaussian probability model. As the distances of noisy points are far, so the probabilities calculated by Gaussian model are small. Therefore, it assigns different importance to each point according to the probabilities, in this way, noisy points reduce the impact on the registration result which achieves satisfactory consequence.



(a) (b) (c)

Fig. 1. Isotropic scaling registration of 2D noisy point sets (red: the model point set without noise, blue: the shape point set with noise). (a) 2D Chicken. (b) Registration result of ICPBS. (c) Amplification result of the green area. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)