Precise and Robust Color Point Cloud Registration with Correntropy-based ICP Algorithm

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***Abstract*—The paper proposes a variant of the Iterative Closest Point (ICP) algorithm for point cloud registration that addresses two main issues with existing ICP-based algorithms: the lack of precise and complete color information and the lack of robustness to noise and outliers. The proposed algorithm introduces a color distance metric based on the L*a*b* color space and a correntropy-based objective function to enhance the accuracy and robustness of the algorithm. Simulation experiments on an RGB-D object dataset show that the proposed algorithm outperforms existing ICP-based methods in terms of accuracy and robustness.**

***Index Terms*—Point Cloud Registration, ICP, L*a*b* Color Space, Correntropy**

I. INTRODUCTION

Point cloud registration is a transformation prediction problem to align two point clouds collected from the same object or scene. Point cloud registration has been widely used in many computer vision fields, such as 3D reconstruction, pose estimation, and self-localisation and mapping (SLAM) [1]. With the development of 3D sensors such as LiDAR and RGB-D cameras, point cloud registration has attracted more and more attention and many research works have been proposed in this field.

The Iterative Closest Point (ICP) [2] algorithm is one of the most popular point cloud registration algorithms for rigid body cloud registration. The basic idea of the ICP algorithm can be divided into two steps. The first step is to find the corresponding point pairs between the two point clouds through the closest point search. The second step is to solve the rigid transformation between the two point clouds by minimizing the objective function of point cloud alignment. The standard ICP algorithm lacks support for color information in point clouds, and is not robust enough to noise and outliers. To enhance the ICP algorithm with robust assistance of color information, many improved methods have been proposed based on the standard ICP algorithm. For example, the Hue-assisted ICP algorithm [3] introduces hue value in the HSV color space to resolve the ambiguity problem and improve computational efficiency.

However, the above ICP-based algorithm still has two problems as the following. First, the assistance of color information is not precise and complete enough. Only the hue value in HSV color space is integrated into the closest point search process, which builds a gap between the registration result and the human-friendly visual perception effect. Second, the algorithm still lacks robustness to noise and outliers. Especially, the introduction of color information also brings more noise, which further reduces the robustness of the algorithm.

To address the above problems, we propose a variant of the ICP algorithm that can combine human-friendly perception of color information and robust performance with noisy data. Specifically, the proposed method consists of improvements in the following two aspects. The first aspect of the improvement focuses on introducing more complete and human-friendly color information. We propose a color distance metric based on the L*a*b* color space, and integrate it into the closest point search process to obtain more accurate corresponding point pairs. The second aspect of the improvement focuses on enhancing the robustness of the algorithm. We introduce a correntropy-based objective function in the iterative optimization process, and maximize the correntropy criterion to reduce the influence of noise and outliers, thereby improving the robustness of the algorithm.

In summary, the main contributions of this paper are three-fold:

1) A variant of the ICP algorithm is proposed, which introduces more complete and human-friendly color information and enhances the robustness of the algorithm.
2) The color distance metric in the L*a*b* color space is proposed, which reflects more precise color information. The correntropy-based objective function is introduced to deal with outliers and noises in the registration process.
3) Simulation experiments are conducted on the RGB-D object dataset with various initial conditions. The results show that the proposed algorithm outperforms existing ICP-based methods in terms of accuracy and robustness.

II. RELATED WORK

ICP-based algorithms are a class of point cloud registration algorithms that have been widely used in real applications. They mainly achieve the registration of two rigid point clouds through two steps: corresponding point pair search and iterative optimization. Since the standard ICP algorithm [2] was proposed, enormous research has been conducted to improve its accuracy, robustness and computational efficiency [4]. According to the improvement of different steps, the focus of current ICP-based methods can be divided into two categories, i.e., the corresponding point search method and the iterative optimization objective function.

Previous work on the corresponding point search method mainly focuses on improving the matching strategy of corresponding points between point clouds, such as SparseICP [5] and NICP [6]. The SparseICP algorithm matches only a small number of representative key points in the point cloud, which improves the computational efficiency of large-scale point cloud registration and reduces the requirement for dense point cloud sampling. The NICP algorithm introduces normal information to constrain the correspondence between point clouds, which can better utilize the non-uniform surface features. It uses a Gaussian distribution model to represent the error distribution between point clouds and improves the robustness to noise and uncertainty.

Previous work on the iterative optimization objective function mainly focuses on improving the objective function in the iterative calculation process, such as Point-to-Plane ICP [7] and PLICP [8]. The Point-to-Plane ICP algorithm uses the distance metric between point and plane to calculate the optimization function between point clouds. Compared with the traditional point-to-point error metric, it is closer to the registration problem in the real physical world and has a faster convergence speed when the point cloud contains more plane structures. However, it also brings higher computational complexity. The PLICP algorithm uses the distance metric between point and line and uses the shortest vertical distance from point to target line segment as the optimization function, which achieves better accuracy and robustness in point cloud registration problems containing line structures.

The proposed method focuses on improving both the corresponding point search strategy and the iterative optimization objective function. In terms of corresponding point search, a color distance metric based on the L*a*b* color space is proposed and integrated into the closest point search process to obtain more accurate corresponding point pairs. In terms of the objective function, a correntropy-based objective function is introduced to reduce the influence of noise and outliers, thereby improving the robustness of the algorithm.

III. Preliminary

In this section, we give a formal definition of the point cloud registration problem and take a brief review of the basic ICP algorithm.

Given two point clouds, including the data point cloud $\{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$ and the model point cloud $\{\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_m\}$, the goal of point cloud registration is to find an optimal transformation $\mathbf{T}$, so that the transformed data point cloud $\{\mathbf{T}(\mathbf{x}_1), \mathbf{T}(\mathbf{x}_2), \cdots, \mathbf{T}(\mathbf{x}_n)\}$ can be close to the model point cloud $\{\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_m\}$, thereby achieving the fusion of these two point clouds.

In the standard ICP algorithm, it is assumed that the transformation from the data point cloud to the model point cloud is a rigid transformation $\mathbf{T}(x) = \mathbf{R}\mathbf{x} + \mathbf{t}$, where $\mathbf{R} \in \mathbb{R}^{3\times 3}$ is a rotation matrix and $\mathbf{t} \in \mathbb{R}^3$ is a translation vector. Generally, the initial $\mathbf{R}_0$ and $\mathbf{t}_0$ can be estimated according to the spatial relationship between the point clouds. The standard ICP algorithm iteratively performs the following two steps. For the k-th ($k \geq 1$) iteration, firstly, the closest point pair search method is used to calculate the correspondence between the data point cloud and the model point cloud. Specifically, for each point in the data point cloud, its corresponding point is calculated as the closest point in the target point cloud after transformation:

$$c_k(i) = \arg\min_{j=1,\cdots,m} \|(\mathbf{R}_{k-1}\mathbf{x}_i + \mathbf{t}_{k-1}) - \mathbf{y}_j\|_2^2, \quad (1)$$

Secondly, the Euclidean distance between the corresponding point pairs of the data point cloud and the model point cloud is minimized by the least squares method to calculate the transformation parameters at this iteration:

$$\mathbf{R}_k, \mathbf{t}_k = \arg\min_{\mathbf{R},\mathbf{t}} \sum_{i=1}^{n} \left\|(\mathbf{R}\mathbf{x}_i + \mathbf{t}) - \mathbf{y}_{c_k(i)}\right\|_2^2 \quad (2)$$

These steps are repeated until the distance between the corresponding point pairs of the data point cloud and the model point cloud converges to a predefined small value. Finally, the rigid transformation can be solved to register the two point clouds.

IV. Our Method

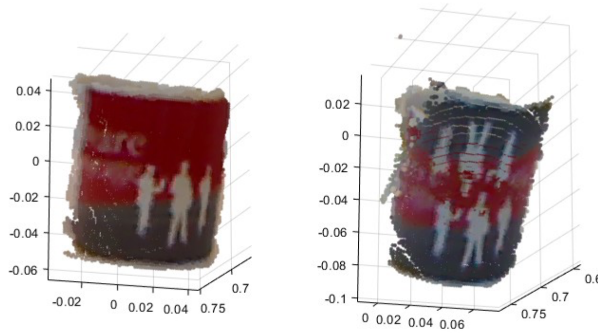
A. Problem Statement

Color point cloud registration is the registration of two point clouds with additional color information. In the color point cloud, each point contains the coordinates not only in the spatial space, but also in the color space. Denote the colored data point cloud as $\{(\mathbf{x}_1, \mathbf{p}_1), (\mathbf{x}_2, \mathbf{p}_2), \cdots, (\mathbf{x}_n, \mathbf{p}_n)\}$ and the colored model point cloud as $\{(\mathbf{y}_1, \mathbf{q}_1), (\mathbf{y}_1, \mathbf{q}_2), \cdots, (\mathbf{y}_m, \mathbf{q}_m)\}$, where $\mathbf{x}_i, \mathbf{y}_j$ are the spatial coordinates, and $\mathbf{p}_i, \mathbf{q}_j$ are the color coordinates.

There are mainly two challenges in color point cloud registration: the integration of color information and the influence of noise and outliers. Firstly, the standard ICP algorithm only uses the spatial coordinates of the point cloud to calculate the corresponding point pairs, while ignoring the color information. Secondly, the introduction of the color information also brings more noise and outliers, which will further reduce the robustness of the algorithm. These challenges make the registration algorithm easily fall into local optima, which leads to a failure of the standard ICP algorithm as shown in Fig. 1.

B. Method Overview

In this paper, we propose a variant of the ICP algorithm to integrate human-friendly color information and the robustness of the algorithm. Specifically, the proposed method consists of two steps. At the first step, the closest point search process is guided by more complete and human-friendly color information, where a color distance metric based on



(a) Groundtruth result (b) ICP registration result

Fig. 1: The registration result of the standard ICP algorithm.

the L*a*b* color space is proposed and integrated to obtain more accurate corresponding point pairs. At the second step, a correntropy-based objective function is introduced in the iterative optimization process, and maximizes the correntropy criterion to reduce the influence of noise and outliers, thereby enhancing the robustness of the algorithm.

C. Human-friendly Color Distance Metric

To introduce the color information into the point cloud registration, we propose a human-friendly color distance in the L*a*b* color space and enhance the closest point pair search with a comprehensive distance metric including both spatial and color differences.

To calculate the color difference between two points, the color attributes of the colored point need to be mapped to a suitable color space to calculate the Euclidean distance. The color data captured by the camera is usually in the form of 3 channels in the RGB color space. However, the RGB color space is not perceptually uniform. Therefore, the Euclidean distance in RGB space cannot well measure the perceived color difference between point pairs [9]. In contrast, the L*a*b* color space is a perceptually uniform color space, where the uniform change in coordinates corresponds to the uniform change in color perception [10]. The L*a*b* color space can simulate the nonlinear response of the human eye to color signals, and thus the Euclidean distance in this space can better reflect the perceived color difference and guide the registration algorithm to perform more accurate and human-friendly correspondence between color point clouds.

Therefore, we choose to use the L*a*b* color space to model the color information of the point cloud, and use the colorful components a* and b* to represent the color vector of each point in the point cloud $\mathbf{p}_i, \mathbf{q}_j \in \mathbb{R}^2$. Thus, the color difference of point pair $\mathbf{p}_i, \mathbf{q}_j$ can be calculated by the Euclidean distance in the L*a*b* color space:

$$\Delta E_{ij} = \sqrt{\|\mathbf{p_i} - \mathbf{q_j}\|_2^2} \tag{3}$$

Considering the importance of color difference in point cloud registration, we add the Euclidean distance in the L*a*b* space to the closest point search process, and introduce a weight parameter α to balance the spatial distance and the color distance. The improved correspondence mapping is calculated as follows:

$$c_k(i) = \arg\min_j \left\{ \|(\mathbf{R}_{k-1}\mathbf{x}_i + \mathbf{t}_{k-1}) - \mathbf{y}_j\|_2^2 + \alpha \Delta E_{ij}^2 \right\} \tag{4}$$

For $\alpha = 0$, the proposed method degenerates to the standard ICP algorithm. By introducing the color distance term ΔE, the improved correspondence mapping explicitly guides the algorithm to focus on the color information contained in the color point cloud, thereby achieving more accurate and precise registration results.

D. Correntropy-based Objective Function

To reduce the influence of noise and outliers on the registration results of color point clouds, we introduce a correntropy-based objective function to improve the iterative optimization process of the standard ICP algorithm and enhance its robustness.

At the iterative optimization process, the standard objective is to minimize the Euclidean distance between the corresponding point pairs, i.e., to minimize the sum of L_2 objective function in Eq. (2). However, the noise and outliers in the point cloud data usually cause abnormally large L_2 errors, which impose too much effect on the overall objective function and may mislead the iterative optimization process. To reduce the influence of noise and outliers on the optimization process, we introduce a correntropy-based objective function, in which the widespread Gaussian kernel is used as the kernel function. The objective function is calculated as follows:

$$\mathbf{R}_k, \mathbf{t}_k = \arg\max_{\mathbf{R},\mathbf{t}} \sum_{i=1}^{n} \exp(-w(i)) \tag{5}$$

$$w(i) = \frac{\left\|(\mathbf{R}\mathbf{x}_i + \mathbf{t}) - \mathbf{y}_{c(i)}\right\|_2^2}{2\sigma^2} \tag{6}$$

where σ is a hyperparameter to control the kernel width. The correntropy-based objective function is calculated by the sum of the negative exponential term $\exp(-w(i))$. For those noise and outlier points, although the distance $w(i)$ may become much larger, the negative exponential term $\exp(-w(i))$ will be close to zero, which reduces the influence of noise and outliers on the optimization process. Therefore, the correntropy-based objective function is enabled with more robustness to noise and outliers than the standard L_2 objective function.

V. Experiment

To verify the performance and robustness of the proposed ICP algorithm, we design and conduct simulation experiments on the public point cloud dataset.

A. Experiment Settings

1) Dataset: In the simulation study, we select the RGB-D Object dataset [14] for evaluation. The RGB-D Object dataset contains 51 categories of common household objects, where both RGB images and depth images of each object are

TABLE I: Error results on the coffee mug dataset in three different initial conditions. The best results are emphasized in **bold**.

Method	Rotation = 15°		Rotation = 30°		Rotation = 45°	
	$E_{\mathbf{R}}$	$E_{\mathbf{t}}$	$E_{\mathbf{R}}$	$E_{\mathbf{t}}$	$E_{\mathbf{R}}$	$E_{\mathbf{t}}$
ICP [2]	2.8105	1.4002	1.8168	0.8859	0.1597	0.0707
CICP [11], [12]	0.1719	0.0869	0.2815	0.1397	0.3359	0.1626
HCICP [13]	0.1716	0.0867	0.2784	0.1384	0.3286	0.1599
ICP + L*a*b*	0.0540	0.0077	0.0540	0.0076	0.0543	0.0077
Ours	**0.0113**	**0.0049**	**0.0117**	**0.0049**	**0.0113**	**0.0049**

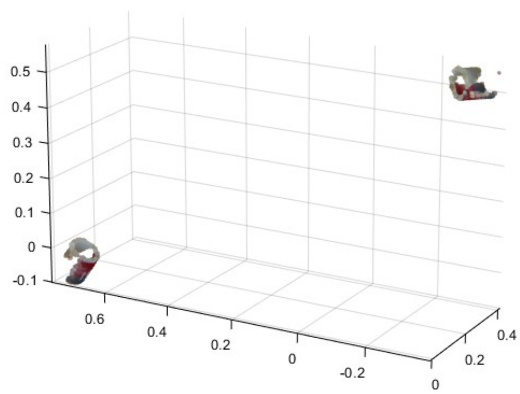


Fig. 2: The initial of the model and data point cloud.

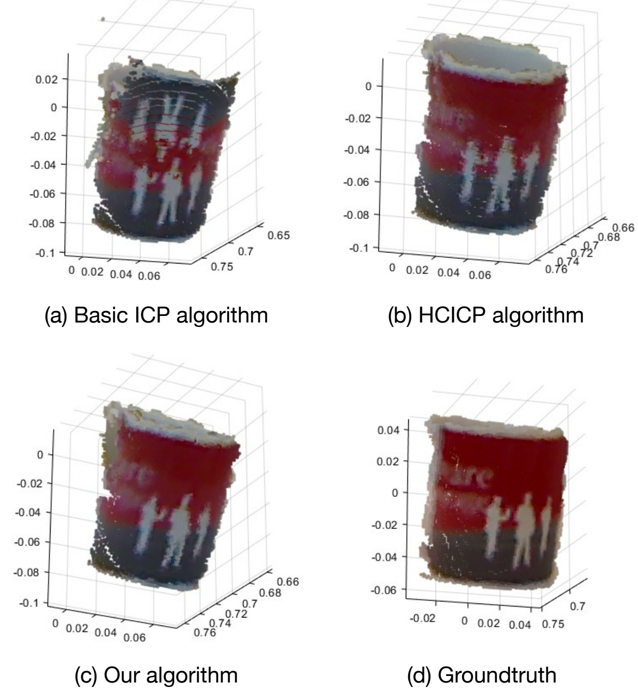


Fig. 3: The visualization of registration results.

collected with a Kinect-like 3D camera at the resolution of 640×480. The collected RGB-D images are then transformed into the color point cloud model by computing the 3D spatial coordinates of each pixel from the depth data and camera parameters. In the main experiments, the coffee mug from the RGB-D Object dataset is selected as the model point cloud.

2) Initialization Settings and Baselines: For each object, in order to simulate the scenario for point cloud registration, we translate the original point cloud and rotate it along the axis by different angles $(15°, 30°, 45°)$ to obtain the data point cloud. One initial position of the model point cloud and the data point cloud is shown in Fig. 2. The comparison baselines include the standard ICP [2], CICP [11], [12], and HCICP [13].

3) Evaluation Metrics and Implementation Details: For each algorithm and each object, the error between the solved rigid body transformation parameters $\hat{\mathbf{R}}, \hat{\mathbf{t}}$ and the ground-truth values $\mathbf{R}, \mathbf{t}$ is calculated as:

$$E_{\mathbf{R}} = \left\|\hat{\mathbf{R}} - \mathbf{R}\right\|_2, E_{\mathbf{t}} = \left\|\hat{\mathbf{t}} - \mathbf{t}\right\|_2 \tag{7}$$

The algorithms are implemented using MATLAB and the experiments are performed on PC with Intel Core CPU and 32G RAM.

B. Comparison with State-of-the-arts

We perform a comparison study of the proposed algorithm and the baselines on the coffee mug dataset. The experimental results are presented in Table I. From the comparison results, it is observed that:

(1) Compared with the baseline algorithms, the proposed algorithm achieves superior performances on all three conditions, with the improvement of 0.0228, 0.0225 and 0.0229 over the second-best results. This is mainly because the proposed algorithm introduces L*a*b* color space and maximum correntropy criterion. The introduction of L*a*b* color space makes the color information between point clouds correspond more accurately. The introduction of maximum correntropy criterion reduces the influence of noise and outliers and makes the optimization process more robust.

(2) Among the baseline algorithms, the standard ICP algorithm has the highest registration error. This is because it only uses spatial coordinate information and ignores color information. The improvements in CICP and HCICP algorithm can indeed reduce the registration error. This shows that adding correntropy criterion can enhance the robustness of the

TABLE II: Average Error$_{\pm \text{STD}}$ in the extensive study. The best results are emphasized in **bold**.

Method	Rotation = 15°		Rotation = 30°		Rotation = 45°	
	$\boldsymbol{E}_{\mathbf{R}}$	$\boldsymbol{E}_{\mathbf{t}}$	$\boldsymbol{E}_{\mathbf{R}}$	$\boldsymbol{E}_{\mathbf{t}}$	$\boldsymbol{E}_{\mathbf{R}}$	$\boldsymbol{E}_{\mathbf{t}}$
ICP [2]	$0.8170_{\pm 1.2344}$	$0.3671_{\pm 0.5620}$	$0.8372_{\pm 1.2251}$	$0.3557_{\pm 0.5279}$	$0.6894_{\pm 1.1354}$	$0.2657_{\pm 0.4488}$
CICP [11], [12]	$0.1156_{\pm 0.0714}$	$0.0498_{\pm 0.0332}$	$0.1750_{\pm 0.1292}$	$0.0746_{\pm 0.0600}$	$0.2653_{\pm 0.3266}$	$0.1231_{\pm 0.2035}$
HCICP [13]	$0.0847_{\pm 0.0742}$	$0.0375_{\pm 0.0332}$	$0.1088_{\pm 0.0975}$	$0.0479_{\pm 0.0447}$	$0.1269_{\pm 0.1404}$	$0.0563_{\pm 0.0656}$
Ours	$\mathbf{0.0819_{\pm 0.0707}}$	$\mathbf{0.0343_{\pm 0.0294}}$	$\mathbf{0.0829_{\pm 0.0714}}$	$\mathbf{0.0346_{\pm 0.0294}}$	$\mathbf{0.0835_{\pm 0.0728}}$	$\mathbf{0.0348_{\pm 0.0301}}$

registration result. Further introducing color information on this basis can well guide the algorithm to perform point cloud registration and reconstruction, but the distance measurement in the color space is still insufficient.

C. Visualization

For an intuitive and interpretable analysis of the algorithm performance, we visualize the registration results and the ground-truth of the coffee mug model, as shown in Fig. 3. It is observed that the proposed algorithm achieves a relatively more refined color point cloud registration effect. Our algorithm not only restores the overall geometric result and color pattern of the 3D point cloud model, but also effectively reduces the point cloud missing problem in the pattern. Contrastively, the standard ICP algorithm is unable to effectively stitch the pattern of the mug, and the restoration effect of the overall geometric structure is also poor. The HCICP algorithm can basically restore the overall geometric structure and color pattern of the mug model, but there are still many missing points in the pattern.

D. Extensive Study on All Categories of Objects

To obtain a comprehensive evaluation analysis, we conduct extensive experiments to cover all 51 categories of objects from the RGB-D Object dataset. The mean and standard deviation of registration errors over all objects are reported for each algorithm. The experimental results are presented in Table II. It is observed that our algorithm maintains robust superiority over the baselines on different kinds of objects from the entire dataset.

VI. Conclusion

In this paper, we propose a novel ICP algorithm for color point cloud registration. In the proposed algorithm, human-friendly color information is used to guide the point cloud registration, and the correntropy-based objective function is introduced to reduce the influence of noise and outliers. The proposed algorithm is evaluated on the RGB-D Object Dataset and the experimental results show that the proposed algorithm achieves the best registration result. In the future, we will further improve the proposed algorithm and apply it to more practical applications.

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