A new 6D ICP algorithm with color segmentation-based adaptive sampling

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ABSTRACT
In ICP-based algorithms, the closest points are considered as the corresponding points. However, this method fails to find matching points accurately when the initial position of the point clouds is not sufficiently close. In this paper, we propose a new method to solve this problem using six-dimensional (6D) distance, which consists of color information and three-dimensional (3D) distance, and color distribution matching. First, before finding the corresponding points using this method, a Gaussian filter is applied on the input color image. A color based image segmentation is done on that image and then n number of samples are randomly chosen from each segment. This process is applied in order to improve the computational time and performance. Second, corresponding point candidates are searched by solving a local minima problem using 6D distance. Then the color distribution matching is applied on these candidates to find the final corresponding point. Several experiments are conducted to evaluate the proposed method and the experimental results prove it has improved over the conventional methods.

Keywords
Iterative Closest Point(ICP), Point-to-Plane ICP, 3D registration, Color segmentation

1. INTRODUCTION
3D registration is a computer vision technique of aligning multi-view range images with respect to a reference coordinate system. Various 3D registration algorithms have been introduced in the past few decades. Iterative Closest Point (ICP) algorithm introduced by Besl and McKay [Besl92a] is one of the vastly used 3D registration algorithm, which got various modification later on. But ICP like algorithms have the local minima problem which is hard to solve. Many alternative algorithms have been introduced throughout the past few years to solve this local minima problem such as probabilistic and color ICP methods. Among these methods, Point-to-Plane method, which was introduced by Chen and Medioni [Chen91a], minimizes the cost function value between the estimated point cloud and improves the performance by combining 3D surface information. However, Point-to-Plane algorithms also consider the closest points as the corresponding points and, as a result, there could exist some performance drawbacks as well as repeated iterations.

Considering these facts, in this research, we have introduced a new 6D ICP algorithm which manages to increase the matching performance by using the color information to find more accurate corresponding

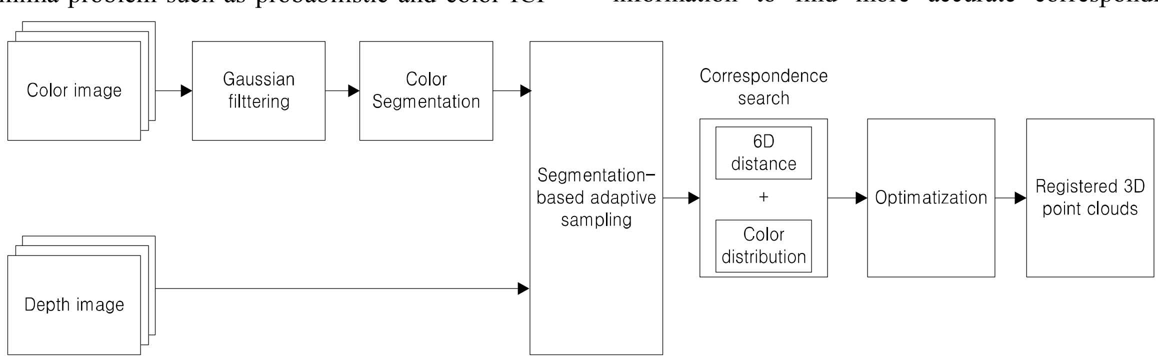

Figure 1. Flow chart of the proposed algorithm.

points. Johnson and Kang introduced a 6D color ICP algorithm [Johnson99a], which manages to find the matching information by implementing location information as well as color information. The introduction of finding corresponding points using color information contributes to solving the local minima problem that cannot be solved only using 3D information. However, the performance of this method deteriorates when the repeated identical color patterns exist.

In order to overcome this drawback and also to improve the performance of the algorithm, this paper uses 6D distance information as well as color distribution similarities while searching for corresponding points. Section 2 describes how to use 6D distance and color distribution similarity to find corresponding points, whereas Section 3 describes the use of the color segmentation-based adaptive sampling to improve the computation time and performance. Section 4 verifies the performance of the proposed method through experimental results and Section 5 gives the conclusion of the paper.

2. 6D DISTANCE AND COLOR DISTRIBUTION SIMILARITY

Algorithm 1 represents the pseudo code of the standard ICP algorithm. Modified ICP algorithms, such as Point-to-Plane ICP or Generalized ICP [Segal09a], increase the performance by improving the error minimization function represented in line 11 of the Algorithm 1 Even though the error minimization function is different in these methods, most of them use the same nearest neighbor algorithm in line 4 to search the corresponding points. This nearest neighbor algorithm consumes less computational time for correspondence search as the closest point is considered the corresponding point. However, there is a limitation on solving the local minima problem as a reason of finding the corresponding point only using the 3D distance [Rusinkiewicz01a].

input: Two point clouds: A=$\{a_1, \dots, a_n\}$, B=$\{b_1, \dots, b_n\}$

An initial transformation: T_0

output: The Correct transformation: T

1: $T \leftarrow T_0$
2: while not converged do
3: for i ← 1 to N do
4: $m_i \leftarrow$ FindClosestPointInA($T \cdot b_i$);
5: if $\|m_i - T \cdot b_i\| \leq d_{max}$ then
6: $w_i \leftarrow 1$;
7: else
8: $w_i \leftarrow 0$;
9: end if
10: end for
11: $T \leftarrow argmin_T \left[\sum_i w_i \left\|T \cdot b_i - m_i\right\|^2\right]$
12: end while

Algorithm 1. Standard ICP

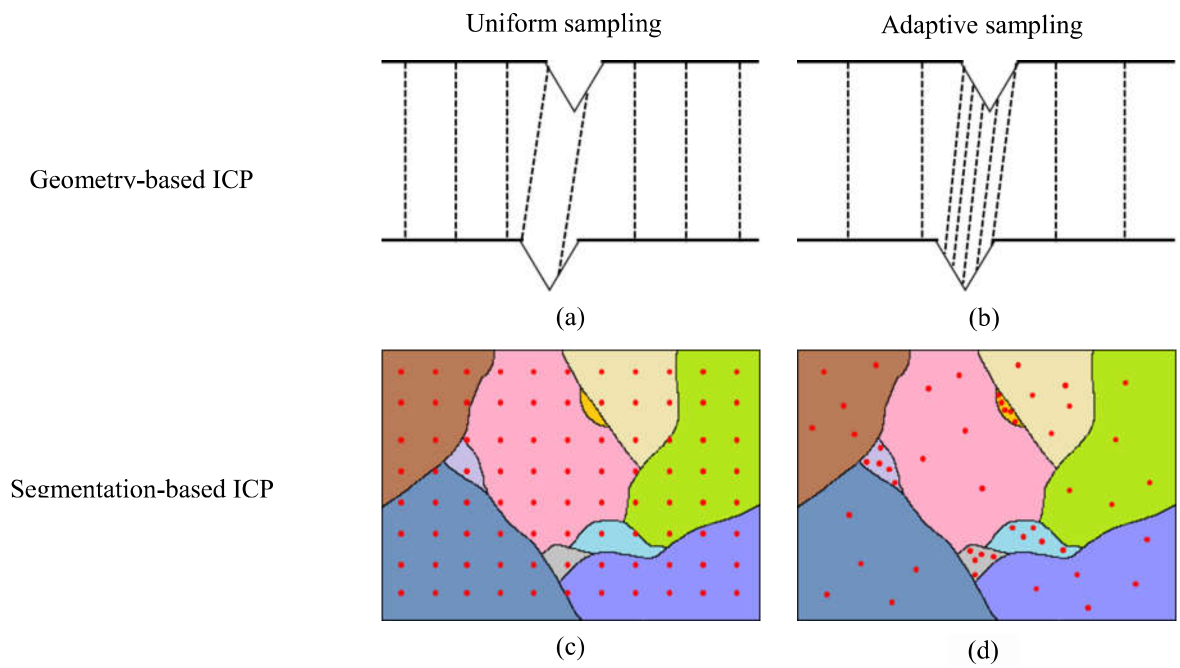

Figure 2. Two different sampling method used for corresponding point search in Geometry-based ICP and Segmentation-based ICP

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In this paper, we improve the corresponding point searching method using the three-dimensional distance with the color information. Corresponding point search method proposed in this paper can be summarized in two steps. In the first step, corresponding point candidates are searched using 6D distance. In the second step, the color distribution of each candidate's neighboring points is matched with the query point's color distribution. The best matching candidate is selected as the final corresponding point.

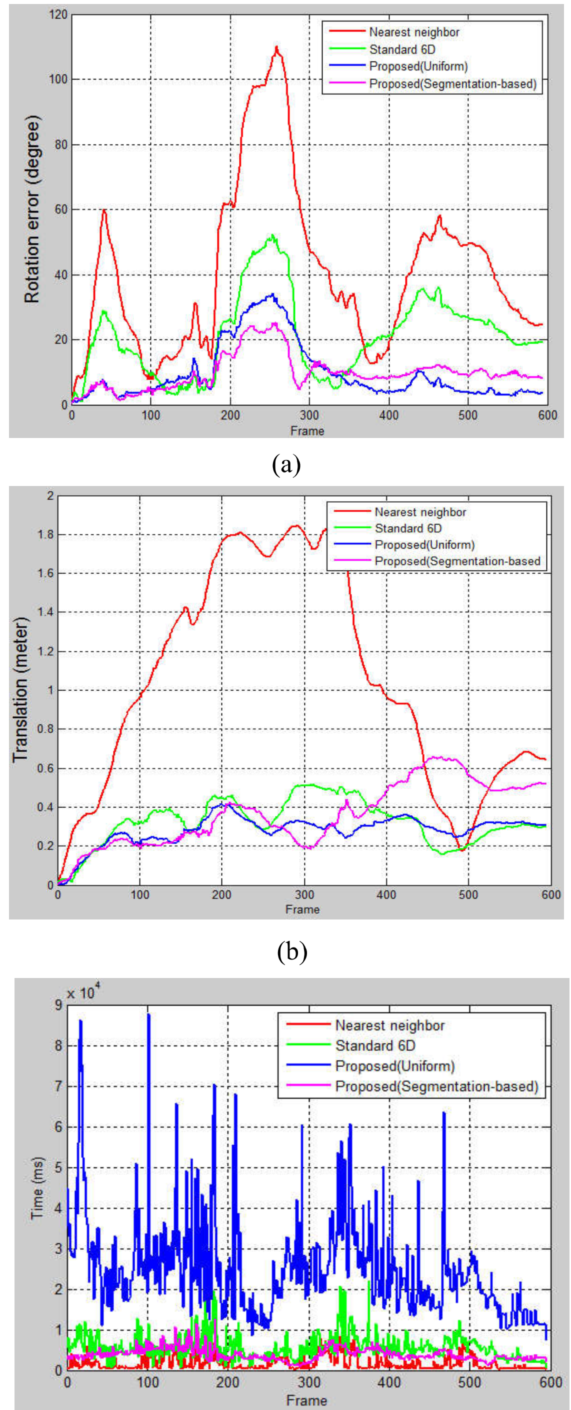
First, we assume there are two point clouds A $= \{a_i\}_{i=1,\dots,n}$ and B$= \{b_i\}_{i=1,\dots,m}$. Then, for each query point (a_i) on the cloud A, we search k number of candidate corresponding points $(b_{i0},\dots,b_{ik})$ from point cloud B using the 6D distance defined in equation (1).

$$d_6 = \sqrt{\begin{matrix}(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2 \\ +\alpha_1(r_1-r_2)^2+\alpha_2(g_1-g_2)^2 \\ +\alpha_3(b_1-b_2)^2\end{matrix}} \qquad (1)$$

Here, $x_i, y_i, z_i (i = 1,2)$ represents the 3D position of the selected two points while $r_i, g_i, b_i (i = 1,2)$ represents the corresponding RGB color values. α_i $(i = 1,2,3)$ is a experimentally determined weight coefficient for each RGB component.

In order to select the final corresponding point out of all the candidate points, the color distribution of the neighboring area of the candidate point (b_{ij}) and query point (a_i) is compared. Comparison of the color distribution is done by finding the first three eigenvectors and eigenvalues through the PCA (Principal Component Analysis) for each candidate's neighbors. If one of the calculated eigenvalues is too high compared to other two, that candidate point is considered as an outlier and excluded from the candidate corresponding points list. The reason is that, if one eigenvalue is excessively higher compared to others then the color of that point is very similar to surrounding area. Deciding the final corresponding point in such areas is difficult.

After excluding the outliers, remaining candidate points and a_i is converted to quaternion in order to calculate the error through the vector calculus. If the dot product between a corresponding point candidate b_{ij} and the reference point a_i is closed to 1, then the color distribution of these two points are considered to be similar. The candidate point that has the highest dot product value is considered as the final corresponding point.



(a) (b) (c)

Figure 3. Estimated position between the ground truth and each algorithm of rotation error(a), translation error(b) and computational time(c) in the world coordinate.

3. COLOR SEGMENTATION-BASED ADAPTIVE SAMPLING

The proposed method requires a lot of computational time because it calculates the PCA for all points of the point cloud. Uniform sampling is generally used in order to reduce the computational time. However, uniform sampling is not suitable for point clouds, which have small features that are vital to determine correct alignment, such as in Fig 2. (a) and (b). Uniform sampling techniques (Fig. 2(a)) generally select only a few samples in these small feature areas. Computational time can be improved by doing dense sampling on feature areas and sparse sampling on the rest of the area as in Fig.2 (b).

A similar approach can be applied on the RGB-D image, which have both color and depth information. First, Gaussian filter is applied on the RGB image for minimizing the effect of motion blur. Then, a graph-based segmentation method [Felzenszwalb04a], which shows good performance and consume less time, is applied on the color image to do the color segmentation. Instead of doing uniform sampling such as in Fig.2 (c), an adaptive sampling technique, which selects same number of samples from each color segment as shown in Fig.2 (d), is used in our proposed method. This method makes dense sampling on small color segments, which are most like to be feature points, and sparse sampling on larger color segments, which are possibly not feature points. As a result, this method improves the computational time by reducing the total number of sample points and performance by increasing total number of samples on feature areas.

4. EXPERIMENT

In this section, we evaluate the performance of the proposed method using Freiburg dataset [Sturm12a] taken inside a general office environment. In the experiments, we evaluate for different corresponding point search methods; nearest neighbor, standard 6D, proposed method with uniform sampling, and proposed method with color segmentation-based adaptive sampling. Inside all these four methods, we use the same error minimization function, which is used in the Point-to-Plane ICP.

	Average rotation error (deg)	Average translation error (cm)	Time (sec/frame)
Nearest neighbor	1.12	1.45	1.74
Standard 6D	0.64	0.68	5.65
Proposed (uniform)	0.53	0.59	24.66
Proposed (segmentation)	0.54	0.71	3.89

Table 1. Average error of relative rotation and translation and computational time per frame

Fig.3 shows a comparison of the translation and rotation error of the proposed method with the conventional method in the world coordinate. Ground truth data provided with the Freiburg dataset is used to find the translation and rotation error of each four methods. Rotation error is calculated using the equation (2) and translation error is calculated by equation (3).

$$E_r = arccos\left(\frac{trace(\Delta R)}{2}\right) \quad (2)$$

$$E_t = \left\| t_e - t_g \right\| \quad (3)$$

Here, ΔR can be represented by equation $\Delta R = R_e R_g^{-1}$ where R_g is the ground truth rotation and R_e is the estimated rotation by each method. t_g represents the ground truth translation matrix and t_e represents the estimated translation matrix using the four methods.

Fig.3 and Table 1 shows that the rotation and translation error of the proposed method is less than the conventional nearest neighbor method and standard 6D method. The proposed method with uniform sampling takes considerably high computational time compared to other conventional methods. However, using the proposed segmentation based adaptive sampling, we were able to reduce the computational time up to a comparable level with other methods.

Fig.4 shows the registration results of the four methods on the 200th frame. This figure concludes that the proposed method shows more accurate aligning results than the nearest neighbor or standard 6D method.

5. CONCLUSION

This paper proposed a new corresponding point search method using 6D distance and color distribution matching. And also this method is improved using color segmentation-based adaptive sampling. In order to evaluate the performance of the proposed method, we compared it with conventional methods using verified data set and the results prove it has improved over the conventional methods. As a future work, we are planning to improve the performance of the proposed method to achieve more accurate results in less time.

6. ACKNOWLEDGMENT

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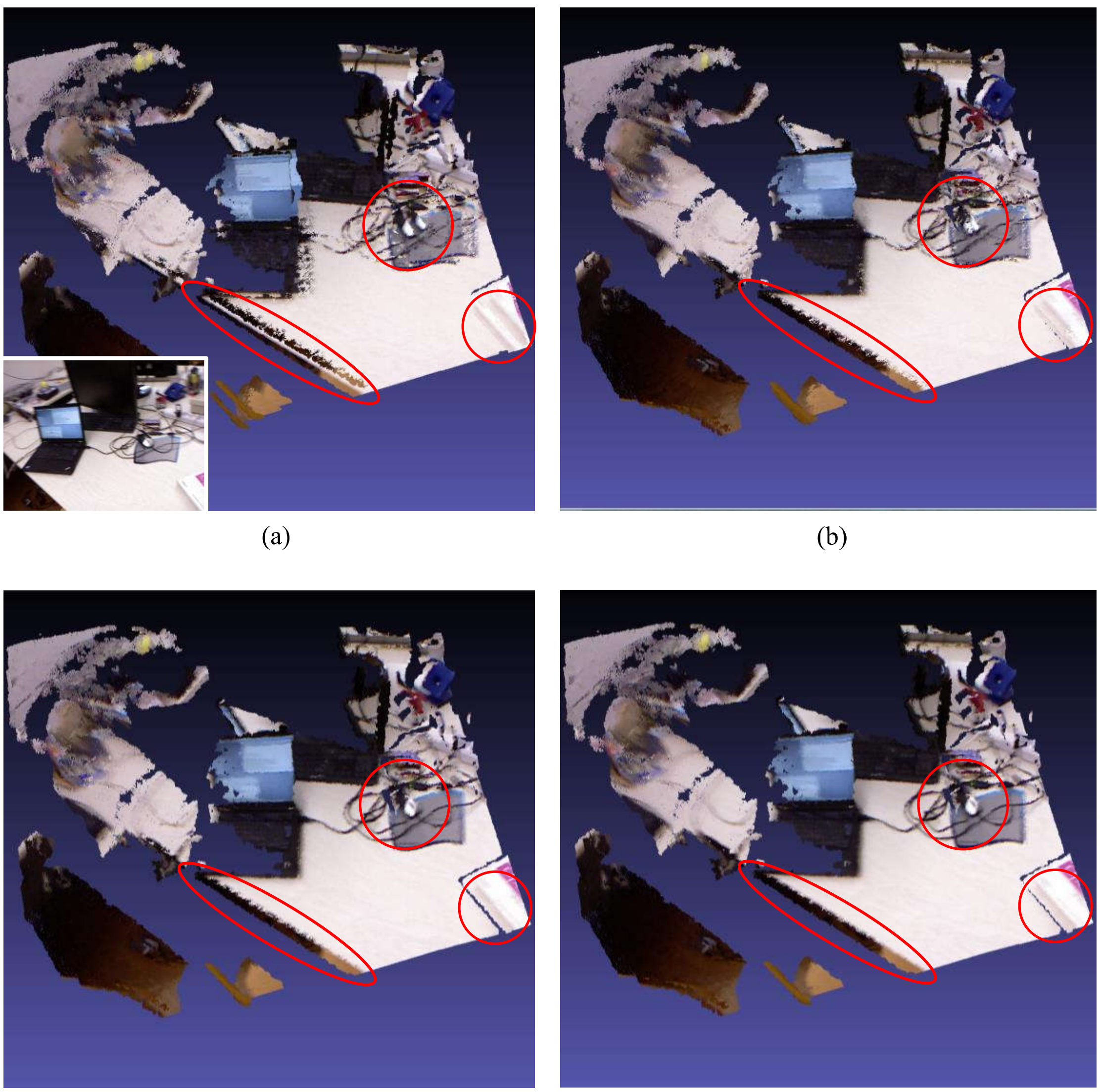

(a) (b)

(c) (d)

Figure 4. Registration results of the four method on the 200th frame sample. (a) Nearest neighbor (Reference image in bottom left corner). (b) Standard 6D. (c) Proposed method with uniform sampling. (d) Proposed method with segmentation-based adaptive sampling.

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