Color-based Registration of Point Cloud Data by Video Camera for Electromagnetic Simulation

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Abstract: Radio propagation simulation is a valuable tool to predict the propagation channel characteristics for system design and service-cell planning. In the simulation, the accurate environment model is needed to improve the prediction accuracy of the site-specific channel. Recently, the ability of smartphones makes remarkable progress, and the point cloud data of the environment can be obtained by the video camera output of the smartphone. However, because of the memory size limitation of those devices, it is necessary to repeat the measurement and combine the several point cloud datasets to model the large-volume environment. In this paper, we proposed the color-based registration method by extending the fast descriptor algorithm. We applied our proposed algorithm to the point cloud data taken by the video camera of the smartphone, and proved that the calculation time was reduced by 70% in the office scenario. The work is expected to be utilized for the radio propagation simulation in actual environments.

Keywords: Color moment, Gray scale variation, Indoor environment, Point cloud registration, Radio propagation simulation

Classification: Antennas and propagation

References

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1 Introduction

To assist with the cell planning of the wireless communication system, the site-specific radio propagation simulation and its prediction accuracy improvement have been actively researched throughout the years. One vital input is the environment model, which should be as close to the actual environment as possible to achieve good prediction performance. It can be manually drawn by commercial software like computer-aided design (CAD) or SketchUp. However, it is very cumbersome and the small details could be occasionally missed, which degrade the prediction performance.

Therefore, to reflect the environment accurately, obtaining the point cloud by the laser scanner, which is a set of points in 3D space presenting the geometry of objects, is an effective way. Recently, the ability of smartphones makes remarkable progress, and using video camera of smartphone to generate the point cloud data becomes a practical solution. However, because of the memory size limitation of those devices, they are not suitable for obtaining the large volume environment at once. Therefore, it is necessary to scan the environment multiple times and register several point clouds to a common coordinate system. The registration is normally done by finding the points from two different sets of point clouds that correspond to the same physical location. These points are called correspondences. After that, these point cloud sets can be combined by using those correspondences as references. Thus, the accuracy of correspondences detection is vital for obtaining a decent registration result.

The fast descriptor algorithm [1] is one of the most popular existing techniques of point cloud registration. In this algorithm, the seed correspondence is found in the initial matching step. Subsequently, more correspondences are estimated based on that seed correspondence. This algorithm has proven to have a good accuracy. However, many seed correspondences derived from the initial matching step are incorrect. This leads to an increase in computation time due to the useless propagation matching of those incorrect correspondences. Thus, this paper aims to improve computation time by introducing the color-based filter to remove improper correspondences.

2 The Proposed Registration Method

2.1 Overview

The goal of point cloud registration is to estimate the transformation matrix between the two sets of point clouds data from a set of seed/point correspondences. Here the correspondence represents a set of points that can be identified or projected in both point cloud data by using transformation matrix. The proposed modification of the fast descriptor algorithm is shown in Fig. 1. In a nutshell, while the conventional descriptor relies only on the geometry of point clouds to initialize the point correspondences, our modification introduces the use of point cloud’s color properties to refine the point correspondences after initial matching. As a result, the number of points is drastically decreased as well as the computation time in the propagation.
matching and latter processes where the detailed procedures are provided in [1].

2.2 Color Moment Descriptor
Because the video camera outputs the color properties of the point in addition to its geometry information, utilizing the color property is an effective way to find good correspondences. According to [2], the color moment is an index describing a distribution of color intensity among three color channels; red (R), green (G), and blue (B). Intuitively, the true correspondences between two sets of point clouds, though taken from a different perspective, should have similar color distributions because both are corresponding to the same physical object. In other words, a set of potential incorrect correspondences between two point clouds could be detected and easily filtered out by considering the statistical difference from a color moment. Suppose the color moment of a particular point cloud \( x \) at \( k \)-th color channel is characterized as the center of a sphere surrounded by a bunch of neighboring points \( x_i \) and spanned with radius \( r(l) \), three statistical measurements can be described as follows

\[
\begin{align*}
\mu^{l,k} &= \frac{1}{|S(l)|} \sum_{i \in \{j|x_j \in S(l)\}} c_{ik}, \\
\sigma^{l,k} &= \left( \frac{1}{|S(l)|} \sum_{i \in \{j|x_j \in S(l)\}} (c_{ik} - \mu^{l,k})^2 \right)^{1/2}, \\
\gamma^{l,k} &= \left( \frac{1}{|S(l)|} \sum_{i \in \{j|x_j \in S(l)\}} (c_{ik} - \mu^{l,k})^3 \right)^{1/3}
\end{align*}
\]

(1)

where \( S(l) = \{ x_i \mid \| x_i - x \| \leq r(l) \} \), \( k \in \{ \text{R, G, B} \} \), \( c_{ik} \), \( \mu \), \( \sigma \) and \( \gamma \) represent color index, mean, standard deviation and skewness, respectively.
For the \( l \)-th layer of radius, the 9-dimensional vector of color moment corresponding to the point \( x \) is defined as

\[
c_l = \left[ \mu_{l,R}, \mu_{l,G}, \mu_{l,B}, \sigma_{l,R}, \sigma_{l,G}, \sigma_{l,B}, \gamma_{l,R}, \gamma_{l,G}, \gamma_{l,B} \right]^T.
\] (2)

Thus, the color moment matrix \( C \) with \( L \) layers can be represented by,

\[
C = \begin{bmatrix}
  c_1 & c_2 & c_3 & \ldots & c_L
\end{bmatrix}.
\] (3)

2.3 Gray Scale Variation Descriptor

The color moment descriptor alone is not enough to select the correct correspondences because there still exist multiple objects having a similar color distribution. Therefore, in this paper, we introduced the novel descriptor called the gray scale variation to assist the registration process. This descriptor assumes that correspondences between two sets of point clouds should share a dominant direction of gray scale variation \( o^* \) because they are exposed to the same light intensity. Assuming a unit vector from a particular point \( x \) to the \( i \)-th neighboring point is \( x'_i = x_i - x \), the optimal dominant direction of gray scale variation is determined by the following

\[
o^* = \arg \max_o \sum_{x \in S(l)} w_i \left[ x'_i^T o \right]^2.
\] (4)

where \( w_i = |I[x_i] - I[x]| \), and \( I[\cdot] \) indicate an amplitude variation of gray scale and the function to derive a gray scale value. The problem in Eq. 4 can be easily solved via Singular Value Decomposition (SVD). Let \( o^*_i \) be the gray scale variation at \( l \)-th layer, the gray scale variation matrix \( O \) of \( x \) can be written as,

\[
O = \begin{bmatrix}
  o^*_1 & o^*_2 & o^*_3 & \ldots & o^*_L
\end{bmatrix}.
\] (5)

2.4 Filtering Rule

In fast descriptor algorithm, the correct correspondences between a two set of point clouds \( x \) and \( y \) are determined based on the similarity of normal vector \( n_l \) and variance within the area of \( l \)-th layer. In our modified descriptor algorithm, however, \( O \) and \( C \) are additionally included as additional parameters to effectively filter out the non-correspondences before the propagation matching step as shown in Fig. 1. Specifically, only a pair of \( x \) and \( y \) whose parameters meet all following conditions at all \( L \) layers will be selected as correspondences

\[
\begin{align*}
  \left| \mu_{l,x} - \mu_{l,y} \right| &< \chi_\mu, \\
  \left| \sigma_{l,x} - \sigma_{l,y} \right| &< \chi_\sigma, \quad l = 1, \ldots, L, \quad k \in \{ R, G, B \}, \\
  \sigma_{l,x} \cdot \sigma_{l,y} &> 0, \\
  \left| \gamma_{l,x} - \gamma_{l,y} \right| &< \chi_\gamma
\end{align*}
\] (6)
where \( \theta^l = \cos^{-1}(n_l, a_l) \). \( \chi_\mu \), \( \chi_\sigma \), and \( \chi_\theta \) are the filter rule thresholds of three statistical measurements of certain point.

3 Experiment Procedure

In this measurement, point clouds data from two scenarios, office desk, and poster, as shown in Fig. 2 were captured using iPad with Structure Sensor device [3]. Then, these data were processed offline by MATLAB installed on local machine with Intel i7-7700 and 16 GB of memory. The office desk scenario is more complicated than the poster because it contains plenty of complicated components such as corners and edges.

In the experiment, point clouds data were captured at the same position twice, and one point cloud dataset was intentionally rotated by random angle. We applied the fast descriptor algorithm and our proposed algorithm to register those two datasets and evaluated the rotation error of the estimated transformation matrix and calculation time. The thresholds in the filtering rule were determined where \( \chi_\mu \), \( \chi_\sigma \), and \( \chi_\theta \) were set to 10, 10, and 15, respectively.

![Image](image.png)

(a) Office Desk  
(b) Poster

**Fig. 2:** Two Scenarios of Measurement

4 Experiment Result

The result is shown in Fig. 3. In both scenarios, the proposed algorithm achieved similar accuracy to the conventional algorithm. However, the computation time was drastically decreased, especially in the office scenario. The proposed method was 70% faster than the conventional algorithm. The reason why the improvement was significant in the office scenario is that there are numerous correspondences such as corners and edges of structures. But the proposed algorithm could filter the non-correspondence effectively by combining the color properties. In contrast, the improvement of computation time was rather moderate in the poster scenario because the structures were relatively simple, and the correct correspondences were obtained without the color information.
The results are interpreted that the proposed method is effective in improving the calculation time, and the improvement is expected to be significant in the large-volume environment with the presence of complex structures.

(a) Office Desk: Accuracy

(b) Office Desk: Complexity

(c) Poster: Accuracy

(d) Poster: Complexity

Fig. 3: Evaluation Result

5 Conclusion

This paper aimed to improve the computation time of the conventional fast descriptor algorithm during point cloud registration. The proposed algorithm introduced the color filter to reject incorrect correspondences. The filter contained two types of color descriptors namely color moments and gray scale variation. The result illustrated that, with the effect of color descriptors, the complexity of point clouds registration has been reduced by around 70% in office scenario while maintaining the same level of accuracy. On the contrary, the computation time was marginally decreased in the case of poster scenario due to the simple environmental structure.

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