3D Registration with Maximal Cliques

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Link	https://arxiv.org/pdf/2305.10854.pdf
Completed	@August 1, 2023
Publisher	CVPR 2023
Status	Done

Abstract

- Imagine you have two sets of points in 3D space, and you want to find the best way to align, or match, these two sets of points together.
- Imagine you have two clouds of colorful confetti (point clouds), and you want to figure out the best way to place one cloud on top of the other so that the confetti dots line up perfectly.
- They use a graph to represent the relationship between points in the two sets. Think of this graph like a map that shows which points are more similar to each other.
- To do this, they create what they call a "compatibility graph." It helps to figure out which points in the two sets are likely to match or align with each other.
- Once the authors have constructed the compatibility graph, they look for something called "maximal cliques" in the graph. A "maximal clique" is a group of points in the graph where each point is connected to every other point in that group. So, it's like a tightly-knit team of points that all agree with each other.
- These maximal cliques have a special property - they represent a "consensus set." This means that the points within each maximal clique are considered to be strong candidates for matching or aligning with each other. In other words, the points in a

maximal clique are likely to belong to the same object or have a close relationship in the 3D scene.

- They perform something called "node-guided clique selection," which means they carefully pick the best teams of points (maximal cliques) based on how strong the connections are between the points in each team. The connections between points are represented by "graph weights" (a measure of how well they fit together).
- Next, for each of the selected teams (maximal cliques), the authors calculate what they call "transformation hypotheses." This is like figuring out different ways to rotate, translate, and scale the points in the team to match them with the other set of points.
- They use a mathematical algorithm called "SVD" (Singular Value Decomposition) to calculate these transformation hypotheses. It helps find the most accurate ways to move and rotate the points in the team to make them fit as well as possible with the other set of points.
- Finally, they pick the best transformation hypothesis out of all the calculated ones. This is like choosing the best way to move and rotate the points in the team so that they align perfectly with the other set of points.
- Once they have this best transformation hypothesis, they use it to perform the registration process. Registration is like putting the two sets of points together in the right position and orientation, so they fit together like puzzle pieces.

3.2

- strengthens the weight values of compatible correspondences and weakens the weight values of incompatible ones
- 0.7, 0.4, 0.2, 0.9 —> 0.37, 0.17, 0.062, 0.765

3.3

- In the context of 3D point cloud registration, RANSAC (Random Sample Consensus) is a popular algorithm used to estimate the transformation (such as rotation and translation) between two point clouds with noisy and possibly outlier correspondences. The algorithm randomly selects a minimal set of correspondences, called a sample, and then computes a transformation based on this sample. It then evaluates the number of inliers (correspondences that are consistent with the transformation) that fall within a certain tolerance. This process is repeated multiple times, and the transformation with the highest number of inliers is considered the best estimate.

- The degeneracy of a graph is a measure of how sparse the graph is. In the context of the paper's compatibility graph, the degeneracy (denoted by d) represents the maximum number of edges that can be removed from the graph before it becomes disconnected. A graph with low degeneracy is more sparse and has relatively fewer edges compared to its number of nodes.

3.4

- SVD stands for Singular Value Decomposition, and it is a powerful mathematical technique used in various fields, including linear algebra, data analysis, and signal processing. In the context of the paper's point cloud registration method, SVD is utilized to obtain sets of 6-DoF (Degree of Freedom) pose hypotheses for each consistent set of correspondences found in the maximal cliques.
- Here's an explanation of SVD in simple terms:
- Singular Value Decomposition (SVD) is a method to break down a matrix into three separate matrices, representing its essential components. Given a matrix A, SVD factorizes it into three matrices:
- A = U * Σ * V^T

Where:

- A is the original matrix (e.g., a matrix representing the correspondences' geometric information).
- U is an orthogonal matrix (its columns are orthogonal unit vectors).
- Σ is a diagonal matrix with non-negative real numbers (singular values) on its diagonal.
- V^T is the transpose of an orthogonal matrix V.

The key points to understand about SVD are:

1. Orthogonal matrices: The matrices U and V are orthogonal, which means their transpose is equal to their inverse ($U^T = U^{-1}$, $V^T = V^{-1}$). Orthogonal matrices represent rotations in space, which is crucial for finding the pose of an object.
2. Diagonal matrix Σ: The singular values on the diagonal of Σ provide valuable information about the scaling or importance of the columns of U and V. The singular values are ordered, and the largest ones represent the most significant variations or components of the original matrix A.