

State of the Art Point cloud registration algorithms are normally classified into two major categories: global (coarse) and local (refinement). For the purpose of this work we can classify point cloud registration algorithms into two major categories: point-to-point and point-to-model. The approaches that do not work with point cloud data or 3D models, but are still related to the registration problem, are also included. [H] [width=]images/Classification.jpg Classification of the State of the Art.

Figure ?? shows an overview of the papers reviewed.

Point-to-point registration

Global methods

RANSAC [?] can also be used to perform the registration task but is time-consuming due to the randomness of the sampling. Following the same line, S. Quan and J. Yang [?] propose a method that helps the RANSAC algorithm sampling the best transformation. Another less common approach for coarse registration is proposed by Sakakubara et al. [?]. This coarse registration method uses a neural network to attempt to solve the global registration problem. This is the case for Sarode et al. [?] present a registration framework that also use the PointNet to extract feature from the point cloud. Ding and Feng [?] present another deep learning method called DeepMapping, whose main structure is constituted by a neural network. More recently, Huang et al. [?] propose a learning method that can be trained in a semi-supervised or unsupervised manner.

Local methods

Besl and N. D. McKay [?] propose the Iterative Closest Point (ICP) algorithm to perform registration between point clouds. According to Segal et al. [?], the ICP algorithm can be summarized in two main steps: the computation of correspondences and the minimization of a cost function. ICP and its variants are still the standard algorithms for point cloud registration because of their simplicity.

Hybrid methods

The results of the global methods can be refined with the use of a local method, most of the time a variation of the ICP algorithm. Go-ICP is a branch-and-bound (BnB) based approach proposed by Yang et al. [?] to address the susceptibility of ICP to local minima. The approach proposed by Jun Lu et al. [?] obtains a consistent four-point set by using Super4PCS [?], then it creates a local registration. Because of the increasing success of Deep Learning in 2D applications, there have been attempts to use deep neural networks for point cloud registration. Another approaches does not use a neural network to solve the complete point cloud registration problem but a partial registration.

Point-to-model registration

Sampling methods

In order to register a 3D model with a point cloud, the simplest idea is to sample points from the 3D model to generate a point cloud. Kim et al. [?] register a 3D CAD model of a construction site with a point cloud by sampling points from the 3D model. Kim et al. [?] is an extension of their previous work [?] In this approach, they just add a noise filter step to the previous work.

Local methods

Other approaches work directly with the information provided in the 3D models to perform the registration task. Li and Song [?] propose two extensions to the most popular local registration method, the ICP algorithm, to be able to handle non-rigid point clouds. In the specific case of CityGML, Goebbels et al. [?] propose an extension of the well-known ICP to perform point-to-model registration. Another approach by Goebbels et al. [?] explores the possibility to find features that help to perform the registration. An extension of the work in [?] has been made by Goebbels et al. [?], where the steps to perform the registration are automated. Others There are other approaches that attempt to solve different matching problems with or without correspondences. Breuel [?] proposes the use of matchlist-based BnB techniques to solve geometric matching problems without correspondences. Bazin et al. [?] present an approach that combines Linear Programming and BnB procedures to achieve global optimality. Brown et al. [?] extend the idea of the two previous approaches and present a 2D-3D registration method that does not require correspondences. Windheuser et al. [?] propose the use of Integer Linear Programming to find correspondences between non-rigid 3D point clouds. Limitations of previous work ICP and its variants provide simple and easily-implemented iterative methods, but they are not globally optimal. RANSAC and its variations cannot guarantee any global optimality in their final results [?]. According to [?], RANSAC is not suitable for point-to-model registration. The globally optimal methods such as Linear programming and BnB based methods are very time-consuming. The last years, there has been a boom in the use of neural networks and deep neural networks to solve 2D problems. In general, one thing that can be noticed is that none of this methods offers a direct solution for the coarse registration.