* 1. **Iterative Closest Point**

The iterative closest point (ICP) algorithm is an optimization technique used to find a rigid transformation which best aligns the reference cloud with the source pointcloud set. This method considers the closest corresponding points between two pointclouds (point to point?) and estimates a transformation to minimize the distance between them using a method of least squares [6]. By iteratively registering the reference cloud with the source cloud and applying rotation matrix R and a translation vector *t,* the source point set is expected to converge as the correspondences achieve alignment*.* This method however, has also been proven to be locally convergent, which means that the algorithm easily fails when the rotation angle between two point-sets is large [7]. For this reason, a good initial transformation is important such that it guarantees that the algorithm converges to the global minimum [7]. In this work, false correspondences from the environment scans are known to inhibit convergence. An implementation to reduce these false correspondences, such as RANSAC, is included.

The primary challenge in the localization stage is the selection of point clouds to use as inputs to the ICP algorithm [4],[7]. It has been shown and verified in this work that the success of the alignment process is highly dependent on the correspondence between input data sets. The existence of points in one cloud which are not represented in the other cloud can only add cost [6] to the alignment process. Further, significant amounts of outliers will cause the alignment to fail or perform poorly. Modifications to ICP and alternative algorithms have shown improved performance [4] [6] [17] in the presence of outliers, and methods are available (used in this approach) for automatic rejection of non-corresponding outliers []. However, the approach in this work addresses the problem by reducing the reference point cloud to a subset of the LiDAR cloud which contains a portion of the workpiece without the surrounding table or clamps.

One of the key issues with standard ICP is that it may not reach the global minimum of convergence which can be due to things such as false correspondences. These false correspondences cause poor initial alignment and therefore increase the chance of getting stuck in a local minimum [7]. Outlier rejection based on Random Sample Consensus (RANSAC) is one of the several methods including distance-based rejection, or duplicate target point rejection, that reduces the number of outliers in pointclouds. Furthermore, RANSAC may also be utilized to provide a good initial guess for the transformation estimation in ICP [6].

“Classical ICP” uses the point-to-point error metric.

The ICP method as described in [12], [4] is summarized here. Let be the reference point cloud set for representing the workpiece to be aligned with the source point cloud set for where , and where each point corresponds to the point with the same index (*i=k*). The reference set will come from a CAD model while the source cloud set will be collected from a data scan of the real environment. The mean square objective function using the point-to-point error metric (or point-to-plane [4][6]) to be minimized is,

(1)

where is an array that projects onto and that translates onto . If the correct correspondences are known, the correct relative rotation/translation can be calculated in closed form. A closed form implementation that can be found in the PCL library [16] is briefly described. The center of mass for the reference point cloud set and source point cloud set respectively is calculated for each set as,

(2)

The reference point cloud set and source point cloud set are shifted by their center mass such that they are distributed around zero as,

(3)

(3)

A cross-covariance matrix, is defined as

(4)

A singular value decomposition (SVD) of is given as

(5)

where D is a diagonal matrix containing the singular values, , ordered such that and are the left and right singular vectors of . When the , the rotation and translation minimizing are unique and given by:

(6)

and

(7)

In practice, the correspondences assumed in Eq. (1) are not truly known. Therefore, this process is performed iteratively[], by assuming a correspondence between the reference and source point cloud set based on a minimum distance between points. The source is corrected and the process repeats until convergence of the source and reference point cloud set occurs as given in the error .