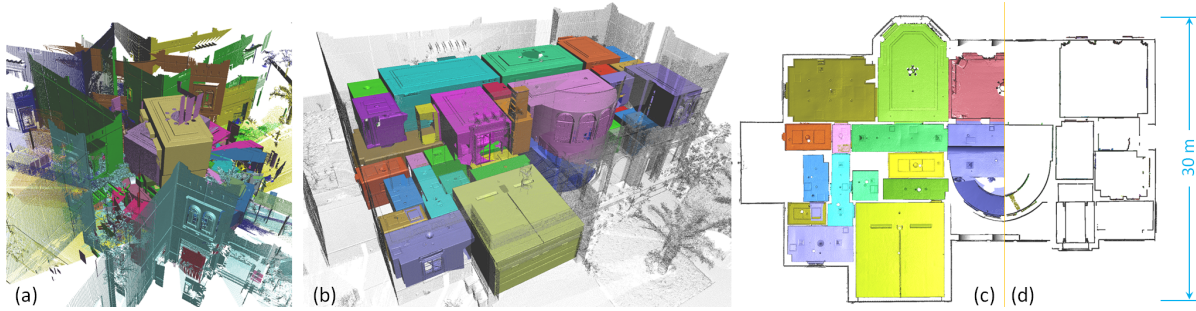


# Block Assembly for Global Registration of Building Scans

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**Figure 1:** Our method can register individual scans of isolated rooms (e.g., bedrooms, bathrooms, etc.) of a building along with scans of the building's exterior into a single point cloud. (a) The input scans rendered with different colors. (b) Our registration result. The rooms are rendered with distinct colors and the exterior of the building is down-sampled and rendered in a uniform gray color. (c) A top view of the registered rooms in the first floor. (d) A cross section of the registered data in (b) at 2.0m from the ground.

## Abstract

We propose a framework for global registration of building scans. The first contribution of our work is to detect and use portals (e.g. doors and windows) to improve the local registration between two scans. Our second contribution is an optimization based on a linear integer programming formulation. We abstract each scan as a block and model the blocks registration as an optimization problem that aims at maximizing the overall matching score of the entire scene. We propose an efficient solution to this optimization problem by iteratively detecting and adding local constraints. We demonstrate the effectiveness of the proposed method on buildings of various styles and we show that our approach is superior to the current state of the art.

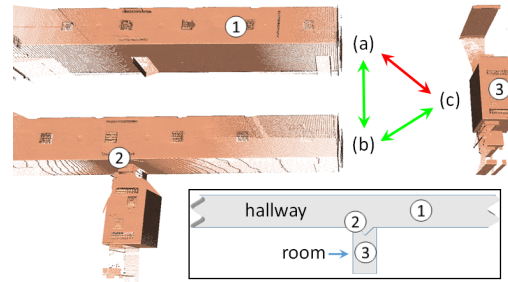
**Keywords:** registration, reconstruction, assembly, building, indoor, laser scanning, point cloud

**Concepts:** •Computing methodologies → Matching; Reconstruction;

## 1 Introduction

Acquiring 3D buildings is an important prerequisite for applications such as simulation, navigation, virtual reality, and entertainment. In this work, we are interested in scanning architectural structures at a larger scale, e.g. office buildings, sports centers, classrooms, or complete residential buildings including their exterior. One possible approach for scanning building interior is to use a hand-held scanner [Chen et al. 2013; Zhou and Koltun 2013; Choi et al.

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**Figure 2:** Registration is sensitive to scanner positions. The inset shows the 2D layout of the scene consisting of a long hallway and a room. Scans (a), (b), and (c) are obtained at positions 1, 2, and 3, respectively. Traditional methods can register (a) to (b), and (b) to (c), but cannot register (a) to (c) because there are large flat regions and not enough features.

2015; Kahler et al. ] that can provide very good results for scenes consisting of a small set of rooms. However, since existing hand-held scanners have narrow fields of view, many frames have to be captured to ensure reasonable coverage even for a small scene (e.g., an office). This often leads to severe drift or failure in registration of these frames. In addition, hand-held scanners have restricted range limits. For example, the Microsoft Kinect sensor range is  $[0.6m, 4m]$ , which is not appropriate for scanning large indoor scenes or the exterior of buildings. Therefore, we employ a static scanner to scan large buildings and we optionally use hand-held scanners to capture individual rooms. The technical problem we address in this paper is to register a set of individual scans obtained by one or multiple scanners.

Registration of building scans is challenging because of the following reasons. Firstly, in contrast to hand-held scans that adjacent frames are spatially close, scans obtained by a static scanner are further apart. Therefore, registration of these scans becomes a global matching problem. Secondly, unlike general objects (e.g., statues, mechanical parts) where rich geometric features can be extracted, buildings mainly consist of piecewise planar regions, so fewer features can be extracted for registration. For example in

Figure 2, scan (a) cannot be registered to (c) because they can slide due to insufficient constraints. Thirdly, sufficient overlaps required for registration [Matterport 2016] cannot be always guaranteed during the scanning. One can easily introduce extra scanning positions to create overlaps for building interior or exterior, but extra scans may not help when registering interior scans to exterior scans of a building (see Figure 4 (a) for an example). Note that introducing extra scans leads to a larger number of scans, but the extra scans usually do not provide additional information describing the scene geometry. Lastly, multiple users could be involved to perform uncoordinated scanning in parallel for large scenes, which makes it harder to guarantee sufficient overlap between neighboring scans.

Ideally, one option to greatly simplify the registration problem is to exploit high precision positioning techniques. However, existing positioning techniques, such as GPS, can only roughly position individual scans of outdoor environments (with positioning errors larger than 3.5m [GPS.gov 2015]). For indoor scanning, the accuracy becomes even worse due to the attenuation and occlusion of satellite signals. Other well-developed indoor positioning techniques, mainly WiFi positioning systems, require a lot of additional work to create the setup. Their accuracy highly depends on the number of access points, and even the state-of-the-art accuracy is still too low (1–5m) for registration purposes [Dardari et al. 2015]. So in engineering, markers are usually required and are carefully placed in the scene before scanning, and manual work is required to obtain the registration. Our work aims to lower the requirements for the scanning process, so we assume that scans are given without additional positioning or marker information.

We propose two novel methods to tackle the problem of global registration of building scans. The first method improves the local registration, and the second one improves the global registration. Firstly, we make use of common building characteristics and observe that buildings usually contain quite a few portals (e.g., doors, windows) between neighboring blocks. These portals are natural connectors that can provide promising hints for connecting isolated scans. This observation inspires us to use the portals as additional information for local registration complementing traditional registration methods based on features in overlapping regions. Experiments on large scenes indicate that portals are valid and effective features for registering scans without overlapping areas and scans capturing both exterior and interior of buildings.

Secondly, we observe that the registration of isolated scans is similar to solving a jigsaw puzzle. This observation inspires us to formulate the global registration as a combinatorial optimization problem. Unfortunately, related work on solving similar problems indicates that an exploration of the entire search space is actually impractical [Huber 2002; Huang et al. 2006] because the problem is NP hard. For scenes consisting of a few (e.g., 5) isolated scans one may manually align them with reasonable accuracy, but this strategy becomes very time consuming if the number of isolated scans becomes larger (e.g., 10). To tackle the global registration problem, we propose a novel formulation based on linear integer programming, which enables us to make use of various strategies to prune the search space available in the state-of-the-art solvers. However, this approach is still too slow for large problems. As a solution, we propose an acceleration strategy based on iteratively adding constraints instead of exhaustively enumerating them at the beginning of the optimization.

In the results we compare our method with four competing algorithms to demonstrate the effectiveness of our approach. Figure 1 shows a registration result of a two-floor residential building consisting of 29 rooms captured by 37 individual scans.

The main contributions of our work are:

- the *first* global registration framework that can handle scans of isolated rooms, and scans capturing both exterior and interior of buildings based on portals extracted from the scans.
- a novel formulation of global registration based on constrained combinatorial optimization, and an efficient solution by iteratively adding constraints.
- reliable registration results for building scans in cases where existing state-of-the-art methods fail.

## 2 Related Work

In this section, we review recent work on acquisition planning, pairwise registration, global registration, and block assembly.

**Acquisition planning.** To ensure sufficient coverage for scanning, various acquisition planning methods have been proposed to guide the scanning and reconstruction of physical objects [Scott et al. 2003; Wu et al. 2014]. Recent methods [Yan et al. 2014; Xu et al. 2015] propose to modify the environment to access occluded parts of the scene. Acquisition planning aims at strategically positioning of the scanner to achieve improved coverage of a physical object. By contrast, we assume multiple scans of a complex building as input, and we focus on effectively registering them into a consistent single scan.

**Pairwise registration.** Given two scans, pairwise registration computes a rigid or non-rigid transformation between the two input scans. Typical pairwise registration algorithms are the well known Iterative Closest Point (ICP) [Besl and McKay 1992] and its variants [Rueckert et al. 1999; Rusinkiewicz and Levoy 2001; Li et al. 2008; Segal et al. 2009]. These registration methods rely on correspondence information of two scans (e.g., point-to-point, point-to-surface) and thus they require that two input scans have a large portion of overlap. Gelfand et al. [2005] extract key points and their descriptors from the input scans, then they establish sparse correspondences between the key points based on their descriptors. The registration is obtained using a branch-and-bound algorithm to find the optimal set of correspondences, followed by an ICP refinement step. The 4PCS registration scheme proposed by Aiger et al. [2008] is robust to noise and outliers. However, it requires reasonable overlaps to query 4-points wide bases and it is computational inefficient for scans of large buildings. Based on pairwise registration, the KinectFusion technique and its variants [Newcombe et al. 2011; Izadi et al. 2011; Whelan et al. 2012; Roth and Vona 2012; Nießner et al. 2013], and many successive techniques [Chen et al. 2013; Zhou and Koltun 2013; Choi et al. 2015; Kahler et al. ] can incrementally fuse depth data into a single surface model. These methods are suitable for capturing relatively small scenes, but usually fail for large scenes where overlap and common features between individual scans cannot be guaranteed (see Section 1). For a more comprehensive survey of both rigid and non-rigid registration methods, please refer to [Tam et al. 2013].

**Global registration.** Global registration methods, which are usually built on top of pairwise registration algorithms, take as input multiple point clouds and try to minimize the accumulated matching error introduced by the pairwise registration methods. Brown and Rusinkiewicz [2007] generate correspondence hypothesis among multiple scans based on a locally weighted ICP, and then obtain the optimal locations of the feature points by minimizing the change in their relative distances computed in a neighborhood. Finally, thin-plate splines are computed based on the optimized feature correspondences to warp each of the scans. To register

multiple non-rigid frames, Huang et al. [2011] focuses on the alignment order of the scans to reduce the accumulated drift during incremental registration. They propose a graph structure for global alignment based on frame-to-frame surface tracking for pairwise registration. Then temporally consistent registration can be achieved by minimizing the overall non-rigid transformation based on graph optimization. Zhou and Koltun [2013] estimate a rough camera trajectory using RGB-D SLAM (simultaneous localization and mapping) and detect the points of interest from a density map of the scene. To tackle the registration error accumulated along the scanning trajectory, they construct a pose graph with its edges representing the relative pose for each pair of consecutive frames. Then the poses of all frames are optimized using a weighted non-linear least squares formulation.

**Block assembly.** Researchers have studied the problem of assembling different pieces of an object [Cutler 1978; Huber 2002; Huang et al. 2006; Huang et al. 2012; Fu et al. 2015]. Cutler [1978] is the first to propose computational assembly of interlocking burr puzzles, which was proven to be NP-hard in later work of [Huber 2002]. In Cutler’s experiments, exhaustive search is employed which is too slow to explore the configuration space for structures consisting of only six-pieces. By assuming continuous sharp feature curves, Huang et al. [2012] compute an ambient vector field that extrapolates these curved features and this field is used to guide the alignment of two distinct parts. To register fractured object pieces, Huang et al. [2006] first classify the object faces into original and fracture faces by roughness analysis. Then using patch-based surface features, potential matches are computed to perform a pairwise matching among all fractured faces. To eliminate errors in the pairwise matching step, a multi-piece registration is performed in a greedy manner which incrementally merges the pieces based on penetration and consistency checks. This method relies heavily on the rich geometric features of the fractured surfaces, which rarely exist between scans of different building blocks. To register multiple point clouds, Huber and Hebert [2003] encode pairwise matchings using a graph structure and they obtain a globally consistent registration by computing a minimum spanning tree of the graph. Using a similar graph structure, Sharp et al. [Sharp et al. 2004] obtain global registration by merging the individually optimized subgraphs of neighboring scans. This method requires that the neighborhood for each scan exists. Their optimization of subgraphs inspires us to explore more of the local registrations. The difference is that, instead of seeking out good local alignments, we integrate the most unlikely local alignments as constraints in an optimization framework that ensures a globally optimal alignment of all the scans.

All the above registration approaches require that reasonable overlaps exist among the input scans. Thus, they are neither applicable for indoor scenes when isolated regions are prevalent in the input, or scans capturing both interior and exterior of buildings. To register such scans, we rely on *portals* as the connectors and we globally register all scans based on a combinatorial optimization formulation.

### 3 Overview

Given a set of separately scanned point clouds representing a building, our goal is to consistently register them into a global coordinate frame. Our method consists of the following parts:

**Preprocessing.** In the preprocessing step, we abstract each scan as a block by detecting the largest connected component of each scan. These blocks are the inputs to our system. However, since our global registration framework is general, we also discuss possible inputs of other types (see Section 4.1).



**Figure 3:** Three different devices used for capturing the input data to our system. From left to right, a Leica ScanStation C10 static laser scanner, a FARO Freestyle X hand-held scanner, and a Microsoft Kinect One depth camera.

**Portal detection.** We automatically extract walls and portals (i.e., doors, windows) from the blocks based on heuristics. We optionally allow the user to remove and add portals to improve the automatic results (see Section 4.2).

**Graph construction.** The portals and blocks are encoded using a graph with its edges representing all potential pairwise alignments. We assign each edge in the connection graph a weight representing the matching score of the two portals or two blocks connected by this edge (see Section 4.3).

**Block assembly.** Then globally consistent registration is achieved by solving a combinatorial optimization problem. We propose a linear integer programming formulation that maximizes the overall matching score among all the blocks (see Section 4.4).

**Acceleration algorithm.** For efficiency, we introduce an acceleration algorithm based on the idea of iteratively adding constraints starting with the most unlikely local alignments (i.e., conflicting alignments). Instead of finding a complete set of conflicting alignments, we only detect locally conflicting matches of very few scans. Thus, the global registration turns out to be a constrained linear integer programming problem that can be efficiently solved (see Section 4.5).

## 4 Methodology

### 4.1 Input and preprocessing

We experimented with a variety of input data from a static laser scanner (Leica ScanStation C10), a hand-held scanner (FARO Freestyle X), and a consumer level depth camera (Kinect One) (see Figure 3) with an effective operating range of 100m, 3m, and 1.5m, respectively. Thus, large rooms and the exterior of the buildings are scanned with the static scanner. The remaining interior is scanned by a combination of the three scanners. For the Kinect sensor, we use it to scan small rooms with KinectFusion [Izadi et al. 2011].

Due to occlusions, each point cloud from the above scanners may contain a large number of disconnected parts, and several relatively small parts are not helpful for the subsequent registration and some of them are actually outliers. Thus, we extract the most dominant part (we call it a *block* in our paper) from each point cloud. To this end, we build a graph where pairs of points are connected by edges if their distance is smaller than a threshold (20cm in our implementation). Then, the largest connected component is extracted as the representative block of the scan. The blocks (optionally down sampled) of all the scans are used as the input to our method.

## 4.2 Portal detection

Given the blocks that may not be directly connected with overlapping regions, we rely on portals to build the connections between them. We consider two types of portals: door portals and window portals. Figure 4 (a) shows an example of door portals that we use to connect the interior and exterior scans of a building. One encouraging characteristic of the portals is that, unlike other objects that suffer from occlusions (such as chairs), portals are residing in walls so their shapes are usually clearly captured by the scanner (see Figure 4 (b)). This provides us promising hints for registering the interior scan to the exterior scan of a room (see Figure 4 (c)). Given these properties of the portals, we propose a portal detection algorithm based on heuristics.

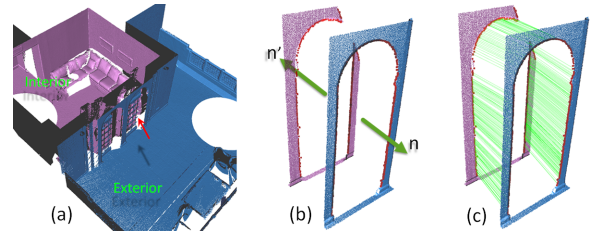
Our portal detection starts with extracting walls from the blocks. We first extract planes from each block using RANSAC [Schnabel et al. 2007]. Then, large vertical planes are labeled as walls. To identify the ground, we require the upright orientation of the scans, which in principle could be automatically computed by analyzing the data [Fu et al. 2008; Ghanem et al. 2015]. However, we mainly use the upright orientation information provided by the scanners, or let the user select the ground plane to define the upright orientation.

Next, we extract the clearly captured boundaries of the portals that will then be used to match one block with others in the assembly step. Without ambiguity, we optionally call these boundary points a *portal* in the following of the paper. There are multiple ways for extracting the boundaries from a point cloud. One idea is to perform a line sweeping algorithm along both horizontal and vertical directions. Then the gradient extrema in the point distribution along the sweeps give extracted horizontal and vertical lines, as done in [Nan et al. 2010]. This is simple and effective for detecting rectangular shape boundaries from a planar point cloud. To ensure robust matching between portals, more general shapes of portals (e.g., a door with an arc on the top) should also be considered. Another idea is by analyzing the surface variations in the point cloud proposed by [Pauly et al. 2003]. It works very well for scans of free-from surfaces with a moderate level of noise, but it is not suitable for our data as most surfaces are planar and higher-level noise exists. Considering that portals are 2D shapes lying on the walls, we propose to detect the boundaries by projecting the points onto the supporting planes of the walls, followed by sequentially applying two image morphological operations: dilation and erosion. After that, portals are defined as the 3D points whose projection are within a threshold to the images boundaries (10 pixels in our implementation). Figure 4 (b) shows the portal detection result of the two doors.

In the unlikely cases where automatic detection fails, we allow the user to remove and add portals to improve the automatic results. For a manual correction, the user only needs to roughly mark the region containing a false positive (non-portal detected as a portal) or a false negative (a portal not being detected). Note that we do not even require all portals to be correctly detected, because the subsequent block assembly step can tolerate some errors.

## 4.3 Graph construction

Once the portals are extracted from the blocks, we construct a connection graph that encodes the possible pairwise matching of the portals of all the blocks. Specifically, each node of the graph represents a portal of a block, and each edge in the graph connects a pair of portals from two different blocks. To cope with scans that demonstrate overlap and sufficient correspondences, we also encode all the blocks as nodes in the graph, but we only connect pairs of blocks by an edge if they have sufficient common key points



**Figure 4: Portal detection and matching.** (a) Two individual scans capturing the interior (purple) and exterior (blue) of a room. The red arrow indicates two door portals, one on each side of the door. (b) The extracted portals (red points). (c) The matching of the two portals. Green lines indicate the correspondences of the points.

to be registered with each other. More details on the key point extraction and matching are described in [Gelfand et al. 2005]. Note that when constructing the graph, we only connect scan pairs if they do not penetrate into each other (see Section 4.5). This penetration test will prune a large number of false local registrations. After the connection graph being constructed, we assign each edge a matching score (encoding a distance measure) and a transformation (encoding the relative position and orientation) between the two blocks. The computed transformation will then be used for aligning the two blocks in the subsequent block assembly step.

The matching score and transformation between pairs of portals or pairs of blocks are computed as follows:

- **Pairwise portal matching.** We first roughly align the points of the two portals using PCA [Liu and Ramani 2009]. Then, we represent the data of the two portals with Gaussian Mixture Models (GMMs) and compute a non-linear registration by finding the alignment between the two GMMs [Jian and Vemuri 2011]. The  $L_2$  distance between the registered GMMs gives us a distance measure of the portal pair. Note that by computing a non-rigid transformation, our portal matching algorithm is robust to imperfections (i.e., noise, outliers, possible occluded boundaries, and non-linear distortions) in the detected portals. As can be seen in Figure 4 (c), although the upper part of the portal in the interior scan is occluded by a curtain during the scanning, our algorithm based on non-linear registration successfully extracts dense correspondences between them. From these correspondences, we can compute a unique rigid transformation (rotation and translation) as an initial alignment of the two blocks. Note, since the supporting planes (e.g., the walls where the portals reside) of the two blocks are parallel, we compute the transformation such that it conforms to this parallelism constraint. Specifically, the constrained transformation can be computed by solving the following optimization problem.

$$\begin{aligned} \min_{\mathbf{R}, \mathbf{t}} \quad & \sum_{i=1}^n \|\mathbf{q}'_i - \mathbf{R}\mathbf{q}_i - (\mathbf{t} + t_{wall}\mathbf{n})\|^2 \\ \text{s.t.} \quad & \mathbf{n}' + \mathbf{R}\mathbf{n} = 0 \end{aligned} \quad (1)$$

where  $\mathbf{Q} = \{\mathbf{q}_i\}$  and  $\mathbf{Q}' = \{\mathbf{q}'_i\}$  are the  $n$  pairs of corresponding 3D points.  $\mathbf{n}$  and  $\mathbf{n}'$  denote the normals of the two supporting planes (see Figure 4 (b)), and  $\mathbf{R}$ ,  $\mathbf{t}$  are the rotation and translation to be computed. Here, we assume the walls of a building have a uniform thickness  $t_{wall}$  that is specified by the user for both interior and exterior walls. Our ICP-based refinement step after block assembly will correct minor deviations from this assumption. This is a quadratic programming problem under linear equality constraint. We



solve it using an iterative active set method (i.e., the QP-BLEIC solver provided by [Bochkanov 2015]).

- **Pairwise block matching.** For a pair of blocks, we first extract a set of key points using a variant of the Harris key point detector [Harris and Stephens 1988] and compute their Point Feature Histograms (PFH) descriptors at each key point [Rusu and Cousins 2011]. Since the number of the key points is significantly smaller than the total number of points in a block, this enables us to perform very efficient matching between the two blocks. To do so, we exploit a RANSAC-based alignment of the two sets of key points followed by an ICP refinement step. Since the scans we are dealing with contain only rigid transformations, we randomly choose three pairs of key points that have the same relative distances. Then, the distance between the two blocks is defined by the average point-wise distance between the two blocks after ICP refinement. We then compute the transformation between the two blocks from the corresponding key points using the method described in [Horn 1987].

We normalize the two types of distances separately both into the range of  $[0, 1]$ . Then the score  $s_i$  assigned for the  $i_{th}$  edge in the connection graph is defined as  $s_i = 1 - d_i$ , where  $d_i$  is the aforementioned normalized distance.

#### 4.4 Block assembly

Now we detail our framework for the global assembly of the blocks based on the connection graph. We first introduce the energy terms and then the objective function is a weighted sum of these terms. In the next section, we will introduce an acceleration algorithm to efficiently solve the optimization problem.

Our block assembly algorithm is designed to choose an optimal set of the pairwise matchings representing a globally consistent alignment of all the input blocks. As each pairwise matching is encoded as an edge with a matching score in the connection graph, the solution to our block assembly problem is equivalent to selecting a subset of the edges of the graph such that the overall matching confidence is as high as possible, while all the nodes in the graph remain connected and a unique transformation of each block can be computed with respect to an arbitrarily chosen reference block. To this end, we formulate the block assembly as a combinatorial optimization problem based on linear integer programming.

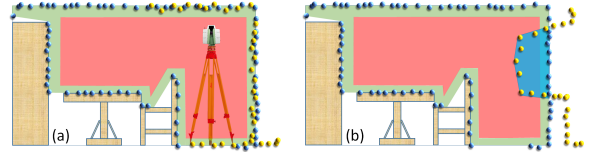
Let  $\mathbf{B} = \{b_1, \dots, b_M\}$  denote the  $M$  input blocks, and  $\mathbf{X} = \{x_1, \dots, x_N\}$  denote the binary labels for both pairwise portal matchings and pairwise block matchings encoded in the connection graph, then our objective function is defined as the sum of two energy terms: matching confidence and connectivity.

- **Matching confidence.** The matching confidence term  $E_m(\mathbf{X})$  measures the overall alignment quality of the final registration. It is defined as the average matching score of all the pairwise matchings.

$$E_m(\mathbf{X}) = \frac{1}{N} \sum_{i=1}^N (s_i \cdot x_i), \quad (2)$$

where  $s_i$  is the matching score associated on the  $i_{th}$  edge. The variable  $x_i$  encodes if an edge is chosen (1) or not chosen (0). Thus, this term encourages the final alignment of all the blocks to be tight.

- **Connectivity.** To favor as many as possible blocks to be registered, we encourage more of the edges (pairwise



**Figure 5:** Non-conflicting local registration (a), and conflicting local registration (b) of two scans. The blue and yellow dots represent two scans to be registered. The red region indicates the free space of the blue scan. In the corresponding octree structure, the free space was shrunk by 10cm (the green region) in order to tolerate noise. The magnitude of the conflict in the right example was measured by the volume of the blue region.

matchings) to remain in the final registration. Thus, we introduce a connectivity term  $E_c(\mathbf{X})$  that is defined as the portion of the edges remaining for aligning pairs of portals or blocks.

$$E_c(\mathbf{X}) = \frac{1}{N} \sum_{i=1}^N x_i. \quad (3)$$

To ensure global consistency, we add two types of exclusiveness constraints to the optimization problem. The first type is that one portal in a block cannot be aligned with multiple portals. The second type forbids points penetrating into the free space of other blocks. Figure 5 (a) illustrates the free space. In our implementation, we use an octree constructed on each block to approximate the space and to query if points are transformed into the empty space of other blocks. To distinguish the two types of constraints, we call the latter *conflict* constraint in the following of the paper. Our global registration optimization can be formulated as

$$\begin{aligned} \max_{\mathbf{X}} \quad & E = \lambda_m E_m + \lambda_c E_c \\ \text{s.t.} \quad & \begin{cases} \sum_{i \in \mathcal{N}(p_j)} x_i \leq 1, & p_j \in \mathbf{P} \text{ and } 1 \leq i \leq N \\ C_k = \emptyset, & C_k \in \mathbb{P}, \\ x_i \in \{0, 1\}, & 1 \leq i \leq N \end{cases} \end{aligned} \quad (4)$$

where  $\mathbf{P}$  denotes all the portals and  $i \in \mathcal{N}(p_j)$  denotes the edges connecting portal  $p_j$  with its neighboring portals in the connection graph. Thus,  $\sum_{i \in \mathcal{N}(p_j)} x_i$  counts the number of portals connected with  $p_j$ . This constraint ensures that each portal is only connected to one or zero other portals. The set  $\mathbb{P}$  denotes the power set of all possible alignments, which can be obtained by traversing all the sub-graphs of the connection graph and check if there exist points transformed into the free space of other blocks in the sub-graph. Thus, the conflict constraint  $C_k = \emptyset$  ensures that no point is penetrating into the free space of other blocks. The  $\lambda_m$ , and  $\lambda_c$  are two weights that balance between the two competing terms.

#### 4.5 Acceleration algorithm

Theoretically, the optimal alignment of all the blocks could be obtained by solving the constrained optimization problem defined in Equation 4. This is a typical linear integer programming problem that can be efficiently solved given a moderate number of constraints. In our problem, however, enumerating the constraints requires exploring the power set of all possible alignments of the blocks, which is impractical for a larger number of scans [Huber 2002]. To accelerate our algorithm, we modify our optimization formulation in two aspects. First, instead of enumerating the

extremely large number of conflicts in the full power set, we only detect local conflicts in a small number (i.e., 4) of blocks. Second, we introduce another energy term ‘conflict tolerance’ that encodes the locally conflicting alignments as soft constraints. By making these modifications to the formulation, the optimal assembly of the blocks can be achieved by iteratively adding constraints and solving the modified optimization problem.

**Constraint set.** Considering that the number of locally conflicting alignments is much smaller than that of the power set, our acceleration relies on the fact that forbidding locally conflicting alignments can contribute to the consistency of the final global registration. These locally conflicting alignments will be encoded as exclusiveness constraints to discourage these local alignments in the subsequent optimization step.

**Conflict tolerance.** An exact conflict detection algorithm tends to be erroneous when high-level of noise or a large amount of outliers exist in the scans. There are two types of errors in conflict detection. First, conflicting local alignments of a few scans may be detected as non-conflicting. This does not affect much of the final block assembly because these conflicting local registrations usually have very low matching confidence. Since we are performing a global optimization, the matching confidence term will take the responsibility to ensure good matchings are chosen in the final registration. Second, good local alignments may be detected as conflicting. In such a case, these false positive conflicting local alignments will be forbidden in the final registration if they are encoded as hard constraints in the optimization. To prevent good matchings from being pruned in the final registration, we modify our objective function to tolerate some level of conflicts caused by noise and outliers, and we encode these conflicts as soft constraints in the objective function. For every pairwise alignment represented by an edge in the connection graph, we quantify its conflict as the volume of the conflicting regions. Thus, the conflict tolerance term can be defined as

$$E_t(\mathbf{X}) = \frac{\frac{1}{N} \sum_{i=1}^N (v_i \cdot x_i)}{\frac{1}{M} \sum_{j=1}^M vol(b_j)}, \quad (5)$$

where  $v_i$  is the volume of the conflicting region when aligning two blocks connected by the  $i_{th}$  edge in the connection graph, and  $vol(b_j)$  measures the volume of block  $b_j$ . The numerator defines the average conflicting volume, and the denominator represents the average volume of all the input blocks. In our implementation, the volume of a block is computed from its convex hull constructed using a down-sampled version of the block. Figure 5 (b) illustrates the conflicting volume.

Now the final constrained optimization formulation has the following form

$$\begin{aligned} \min_{\mathbf{X}} \quad & E = \lambda_m(1 - E_m) + \lambda_c(1 - E_c) + \lambda_t E_t \\ \text{s.t.} \quad & \begin{cases} \sum_{i \in \mathcal{N}(p_j)} x_i \leq 1, & p_j \in \mathbf{P} \text{ and } 1 \leq i \leq N \\ x_i \in \{0, 1\}, & 1 \leq i \leq N, \end{cases} \end{aligned} \quad (6)$$

where  $\lambda_t$  is the weight of the newly introduced conflict tolerance term that penalizes the overall volume of the conflicting alignments. Other symbols are the same as in Equation 4. Note that since we want to favor both matching confidence ( $E_m$ ) and connectivity ( $E_c$ ), we subtract them from one so that the problem is equivalent to the minimization of the new energy function. In our implementation, we set  $\lambda_m$ ,  $\lambda_c$ , and  $\lambda_t$  to be 1, 10, and 1, respectively.

With a considerably smaller number of exclusiveness constraints, our optimization problem defined in Equation 6 can now be solved

very efficiently (we use a solver provided by [Gurobi 2015]), which yields a consistent alignment of most of the blocks. In the very unlikely case where very few local alignments remain conflicting after each optimization step, we add them back to the constraint set and rerun the optimization. We iterate this process until a conflict-free registration is achieved. Finally, we refine the registration using an ICP step [Rusinkiewicz and Levoy 2001].

## 5 Results and Discussion

We have applied our block assembly algorithm to a variety of large indoor scenes and entire buildings. The rooms in all the example scenes are scanned with their doors in arbitrary positions, unless explicitly stated otherwise. Experiments demonstrate that portals are valid and effective features for augmenting local registrations, and by using the acceleration strategy our method is capable of registering a large number of scans.

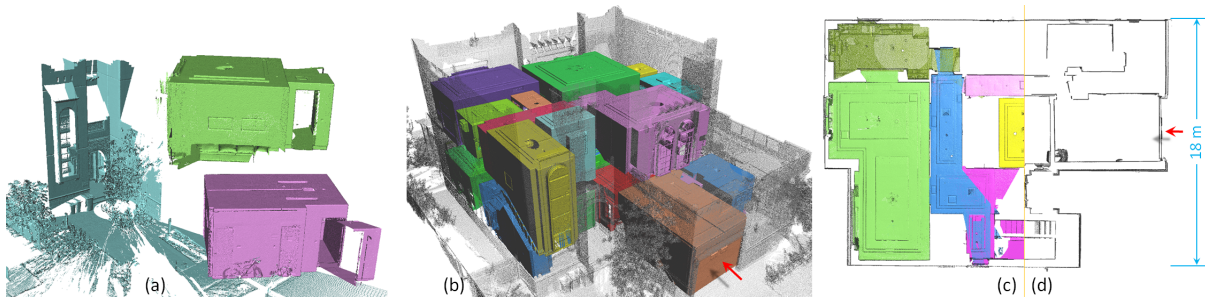
Figure 1 and Figure 6 show residential buildings with two floors where both the interior and exterior was scanned. The initial scans are captured using a combination of the static Leica scanner and the FARO hand-held scanner. The interior of the two buildings consists of multiple isolated rooms and we scanned them with their doors closed and thus each room is represented by a single scan. In contrast, the scans of the exterior of the buildings have significant overlapping regions. Our method successfully registers the non-overlapping scans of the rooms along with the building exterior into single consistent point clouds covering the entire buildings.

In Figure 7, a total number of 24 classrooms on the same floor are scanned using only the static Leica scanner. In this scene, the largest classroom was captured by two scans and the smaller classrooms were captured by one scan each. Note that the long hallways are captured by multiple scans with significant overlapping regions. As can be seen from the top view, our block assembly method can obtain a globally consistent registration of the entire floor.

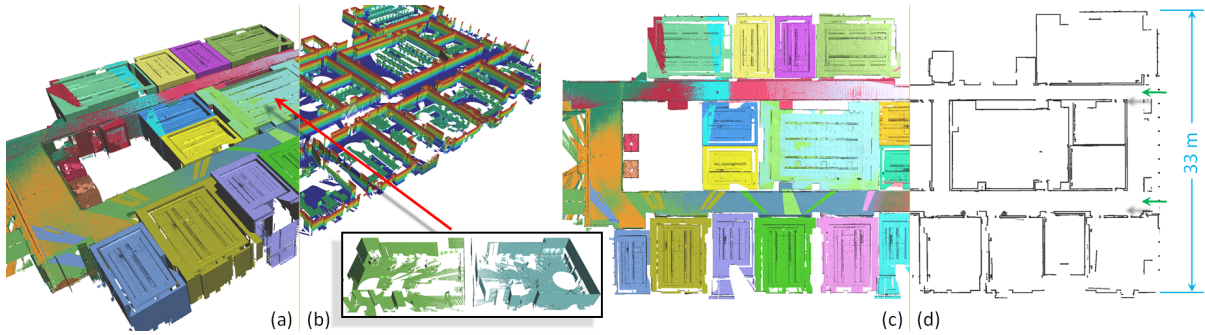
Figures 8 and 9 show the global registration results of two large sports centers. Note that the rooms in Figure 8 are positioned along a curved hallway and some rooms in these two buildings have curved walls. Since the curved walls are locally flat and clean, our automatic portal detection algorithm successfully detects most of their door portals (see Table 1). Using these portals along with the overlapping regions in the scans of the hallways, our method registers all the scans into a single consistent point cloud.

Figure 10 and Figure 11 show the registration results of two relatively small scenes. In Figure 10, the isolated rooms are scanned using the FARO hand-held scanner and the hallways using the static Leica scanner. Although there are no actual doors between individual rooms, the openings connecting rooms to the hallways turn out to be effective portals connecting the isolated rooms. The scene consisting of 4 rooms in Figure 11 is scanned using only the Kinect One scanner. We can see that although the initial scans are more noisy than the data from the other two scanners, our method still successfully extracts the portals to register the isolated rooms into a single point cloud. Since we are seeking a rigid global registration, the result is less accurate due to the noise and distortion (e.g., in the walls) in the input.

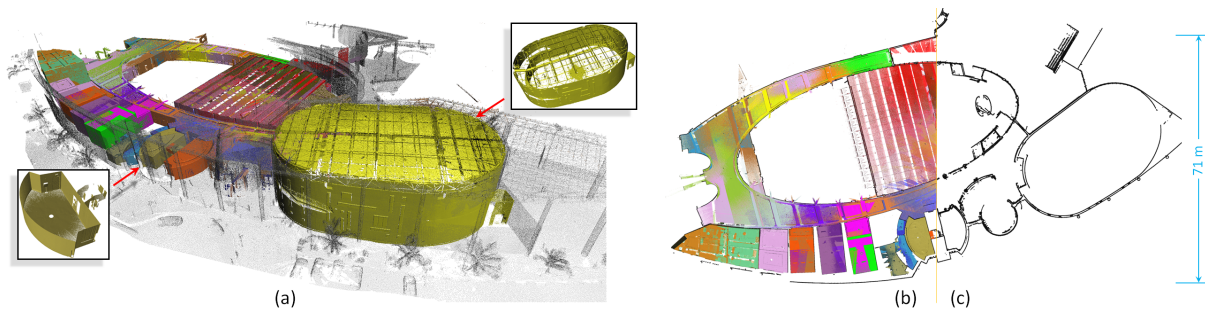
**Portal detection.** As can be seen from Table 1, our portal detection can automatically detect most of the portals requiring very few manual corrections. This is because portals usually do not suffer from occlusions and their boundaries can be clearly captured by the scanners. The performance of our portal detection algorithm can also be evaluated by computing precision and recall for each example, which is plotted in Figure 12.



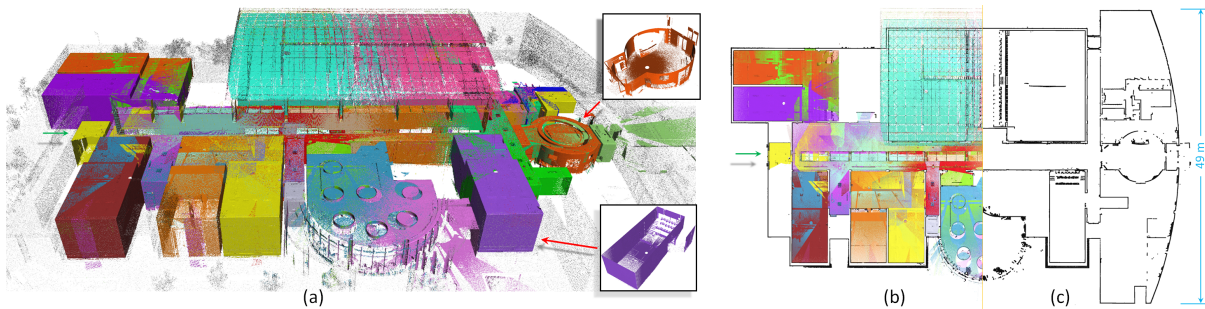
**Figure 6:** Global registration of a two-floor residential building consisting of 26 isolated rooms. (a) 3 out of the 31 input scans. (b) The registration result (isolated rooms are in different colors and the exterior of the building is down-sampled and rendered in dark gray). (c) A top view of the registered rooms in the first floor. (d) A cross section of the first floor at a height of 2.0m.



**Figure 7:** Registration of 24 classrooms and 2 long hallways (see the green arrows) lying on the same floor. (a) The registered scans rendered with roofs. (b) The registered scene without roofs (color coded by Z-values). The inset shows the largest classroom captured by two scans. (c) A top view of this floor with roofs. (d) A cross section of the registered scans.



**Figure 8:** Registration result of a sports center consisting of 8 isolated rooms positioned along a curved hallway. (a) The registered scans. (b) A top view of the registration result. (c) A cross section of the registered scans. Individual scans are coded in different colors.

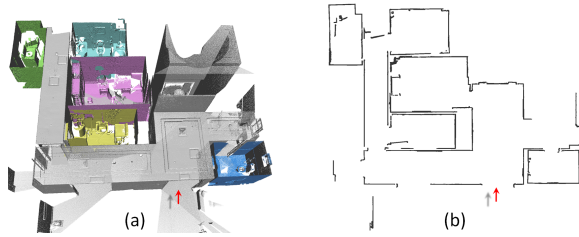


**Figure 9:** Registration result of another sports center consisting of 26 individual rooms. (a) The registered scans. (b) A top view of the registration result. (c) A cross section of the registered scans. Individual scans are coded in different colors.

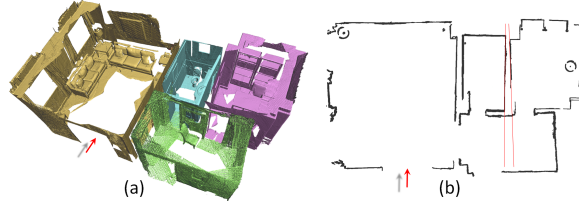


**Table 1:** A summary of the number of scans (#Scans), number of isolated rooms (#Rooms), number of portals detected by our method and the percentage of portals corrected for generating the result (#Portal / %Manual), number of edges connecting pairs of portals and the percentage of them selected in the final result (#E-portal / %Selected), number of edges connecting pairs of overlapping blocks and the percentage of them selected in the final result (#E-overlap / %Selected), runtime of the initial constraint detection (Constraint), runtime of the block assembly (Assembly), and the number of iterations taken in the optimization (#Iter) for each example.

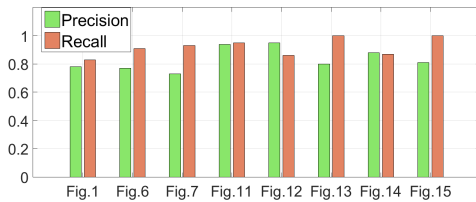
Figure	#Scans	#Rooms	#Portal / %Manual	#E-portal / %Selected	#E-overlap / %Selected	Constraint	Assembly	#Iter
1	37	29	78 / 3 %	671 / 5.2 %	14 / 93 %	55 sec	73 sec	5
10	8	5	15 / 0 %	67 / 9.0 %	1 / 100 %	0.3 sec	4 sec	1
11	4	4	10 / 0 %	7 / 42.8 %	0 / -	0 sec	4 sec	1
6	31	26	73 / 5 %	538 / 4.3 %	16 / 100 %	45 sec	51 sec	19
7	49	24	74 / 0 %	1100 / 5.5 %	31 / 74 %	132 sec	8 sec	1
8	67	11	87 / 4.6 %	487 / 5.7 %	52 / 99 %	51 sec	11 sec	1
9	73	26	152 / 6 %	1472 / 2.3 %	89 / 93 %	284 sec	25 sec	2
15	156	102	376 / 2 %	10528 / 1.7 %	65 / 95 %	263 min	33 sec	9



**Figure 10:** A scene with its rooms scanned using the FARO hand-held scanner. (a) Our registration result. The scans in gray color represent the hallway. (b) A cross section.

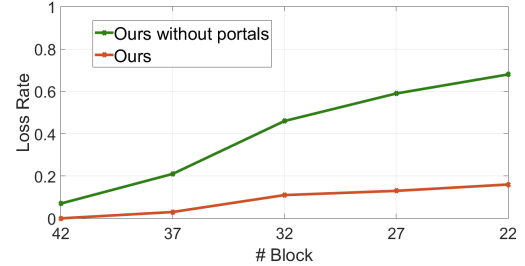


**Figure 11:** A scene consisting of 4 rooms purely captured by the Kinect One scanner. (a) Our registration result. (b) A cross section. Note that the Kinect scanner introduces challenging distortions, e.g., the red lines indicate two walls that should be parallel.



**Figure 12:** Precision and recall of the portal detection algorithm for each set of scans used in our experiments.

**Effect of portals.** From the percentage of edges selected by our optimization (Table 1), we can see that most of the feature-based matchings are valid. This is expected as geometric features are stable. In contrast, only a small portion of portal matchings are selected. This is because real scenes usually contain doors (or windows) having the same geometry and thus many pairs have high matching scores, but most of these portal matchings cause conflicts and thus they are forbidden by our global optimization. From the percentage of edges chosen to connect portals and the percentage



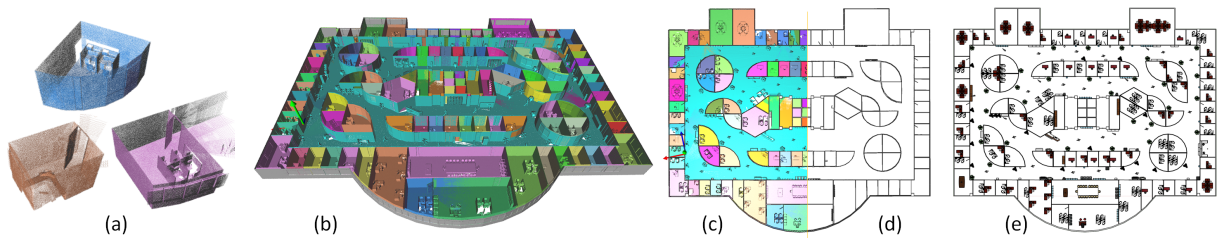
**Figure 13:** The effect of portals in registering the scans of the building shown in Figure 1. We first introduce new scans by positioning the scanner at the doors. Then we gradually drop 5 scans each time and run the two methods. The loss rate is computed as the portion of scans that cannot be registered.

chosen to connect overlapping blocks, we can also conclude that geometric features take control of the registration when strong overlaps exist, and the portals only influence the result if common features are too weak or absent from the scans. All our tests suggest that portals are valid and important features, and they play a critical role for registering building scans.

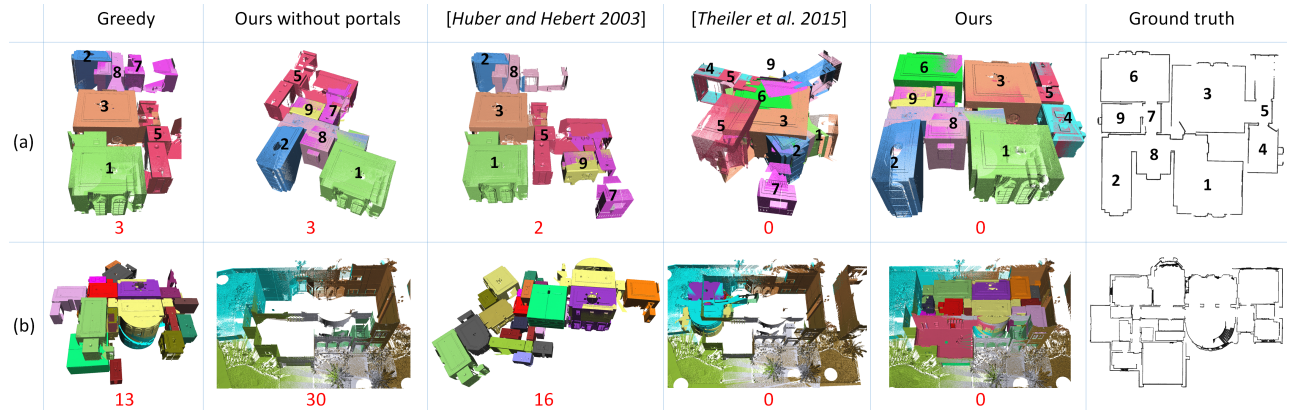
To further examine the effect of portals, we randomly drop scans of a scene and compare the registration results with and without the portal information. Before dropping scans, we first introduce more scans obtained by positioning the scanner at the doors and we leave the doors open during the scanning. Then, we gradually drop scans and run our method both with and without portal information. We record the number of the scans that cannot be registered and plot the ratio of unregistered scans. Figure 13 shows the comparison result on the scene shown in Figure 1. We can see that although more overlapping regions are introduced, one still cannot obtain a satisfactory registration without portal information. In contrast, the use of portals ensures a more stable registration as scans are gradually dropped.

**Iterative constraint adding.** By using the strategy of iteratively adding local constraints instead of exhaustively enumerating them at the beginning of the optimization, we can efficiently solve our optimization problem defined in Equation 6. Experiments reveal that only a few iterations are sufficient to achieve a globally consistent registration of the scans. See Table 1 for the runtime of the block assembly step and the number of iterations taken for all the examples in the paper. We also compare our strategy of iteratively adding constraints with the exhaustive constraint enumeration on the scene shown in Figure 1. We record the timings for both methods by incrementally adding blocks into the

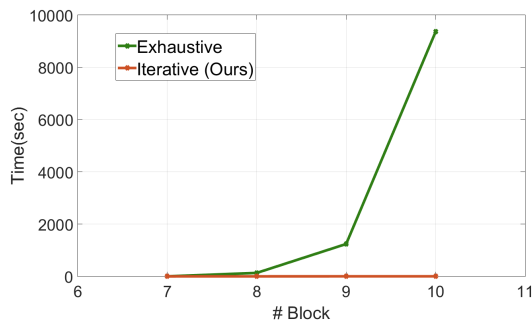




**Figure 15:** Registration result of a large virtual scene consisting of 102 isolated rooms. (a) 3 out of the 156 input scans. (b) The registered scans of the entire scene. (c) A top view of the assembled blocks. (d) A cross section of the entire floor. (e) The ground truth floor plan.



**Figure 16:** Comparisons of our global registration method with four competing methods on two sets of scans. (a) The scans of the second floor of the building shown in Figure 6. (b) The scans of the entire building shown in Figure 1. The value at the bottom of each sub-figure indicates the number of scans that cannot be registered by the corresponding method.



**Figure 14:** A comparison of our iterative constraint adding strategy with the exhaustive constraint enumeration on the scene shown in Figure 1. Since exhaustive constraint enumeration is too slow, we stopped when the number of blocks increased to 10.

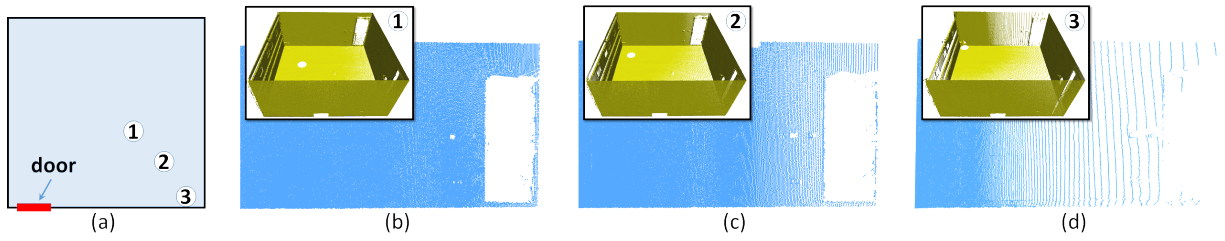
scene. The runtimes of the two strategies are compared in the plot in Figure 14. We can see that our strategy of iteratively adding constraints can significantly speedup the optimization process and that the exhaustive constraint enumeration will be too costly for the larger examples presented in this paper.

**Scalability.** In addition to the examples of real scenes discussed above, we also tested our optimization-based block assembly algorithm with a large synthetic scene. Figure 15 shows this virtual scene consisting of 102 isolated rooms, captured by 134 virtual scans. Our strategy of iteratively adding constraints enables us to efficiently register such a large number of blocks (see Table 1 for the timings).

**Timings.** The running times of initial constraint detection and block assembly for each set of scans are shown in Table 1. For the initial constraints, we compute local conflicts for every triplet of blocks, which is the most time consuming step. Assuming a scene consisting of  $M$  scans, the total number of conflict computations is  $C_M^3 = M(M-1)(M-2)/6$ . These are not large numbers of tests and can be efficiently performed for most of the scenes shown in our paper. However, for the virtual scene consisting of 156 scans (see Figure 15), the total number of conflict tests is large (i.e., 620620) and it takes more than four hours.

**Comparison.** We also conducted comparisons of our global registration method with four other approaches: 1) a greedy approach. In this approach, we first sort the matching scores of all the edges in the connection graph. Then, starting from the edge with highest matching score, we incrementally search and add scans that have the highest matching score with the registered ones. To ensure consistent registration, only blocks that do not cause a conflict can be added; 2) a global registration method using our framework but all portal matchings are omitted; 3) a global registration method proposed in [Huber and Hebert 2003]; 4) another global registration method proposed by Theiler et al. [2015]. As can be seen from Figure 16, the results of the other four registration methods have completely wrong layout of the rooms due to the ambiguities in the pairwise matchings. Moreover, methods 1), 2), and 3) only managed to register part of the scans that contain common regions. In contrast, our method successfully registers all the scans in their correct positions.

**Acquisition guideline.** Since portals reside in walls, their shapes are usually clearly captured. This can be seen in Figure 17 where the same room was scanned at different positions. However, a portal may not be properly captured in some extreme cases. For example



**Figure 17:** A room with a door scanned at three different positions with an increasing scanner angle. (a) An illustration of the door portal and scanner positions. (b), (c), and (d) show the extracted wall where the door resides for the three scanner positions respectively. The inset in each subfigure shows the original scan of the room.

in Figure 17 (d), the scanner was positioned at the corner of the room with a very large oblique scanning angle. This results in a point cloud with a severe density decrease and the door portal can only be partially captured. In such a case, our method cannot detect this door portal. In general, to ensure that portals can be properly captured, we advise to avoid scanning at room corners.

**Limitation.** When scans do not have overlap, our method relies purely on the geometry of the portals and the non-penetrating constraints for registration. In this case, our method may not position rooms of identical geometry in their correct positions. For example, the virtual scene shown in Figure 15 consists of many duplicated rooms. In our result, 36 rooms (i.e. 35%) are in wrong positions due to the rooms and portals having the exact same geometry. In this example, we regard such assembly as a valid interpretation of the input scene.

## 6 Conclusions and Future Work

We presented a global registration framework for aligning building scans. Our local registration strategy relies on portals to establish the potential connections between non-overlapping scans or scans with only limited overlap, as well as traditional local registration using feature matching. We formulate the global registration as a combinatorial optimization problem. We also proposed an acceleration strategy by iteratively adding constraints, which significantly improves the overall efficiency. In our results, we demonstrated the capability of our method in registering scans of indoor scenes both with and without exterior scans. Unlike existing methods that are very sensitive to the positioning of the scanner to ensure reasonable overlap between neighboring scans, we do not make any particular assumptions on data acquisition, allowing more freedom for the users to scan the scenes.

In future work, we plan to exploit a crowdsourcing strategy for scanning even larger buildings so that isolated rooms can be simultaneously scanned by many scanners and users. Scanning in such a fashion can lead to very large overlaps and missing parts in the acquisition. We believe that this will pose very interesting and challenging registration problems that have not been tackled before.

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