User-Guided Dimensional Analysis of Indoor Scenes Using Depth Sensors

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ABSTRACT

In many civil engineering tasks, dimensional analysis of environmental objects is significant for spatial analysis and decision-making. Tasks such as as-built geometry generation need to efficiently interpret the critical dimensions of specific objects (e.g., diameter of a pipe, width of an opening) in a potentially cluttered environment based on data gathered from different positions. This paper presents a user-guided dimensional analysis approach to automatically acquire geometric information from a single frame of a depth sensor. Firstly a depth sensor is used to capture three-dimensional (3D) point clouds of indoor scenes. Then by extracting planes and performing geometric analysis, the dimensional information of objects of interest is obtained from a single frame. Our user guidance system evaluates the quality of the current data and measurement and provides interactive guidance for moving the sensor to acquire higher quality data, from which more accurate geometric measurements can be obtained. The proposed method has been tested on seven hallways and six door frames. The experimental results demonstrate that the method offers significant promise in enabling accurate dimensional analysis in a wide variety of civil engineering measurement contexts.

Keywords

User guidance; Dimension; Depth sensor; Indoor scene; Geometric measurement

1 Introduction

Dimensional information of the built environment and other civil infrastructure can be useful for a wide range of applications. During the construction phase, dimensional information should be monitored so that it can meet the requirements of the specifications and the drawings. During the maintenance phase, dimensional information is necessary to check whether it remains consistent with existing building codes and to quantify any developed flaws (e.g., cracks). In addition, in the context of construction automation, dimensional information is useful for any robot performing tasks in the construction or built environment. For example, for a window installing robot, the robot needs to know the real size of the window frame on the construction site instead of the designed size due to tolerance discrepancies. With this dimensional information, the robot can then install the window correctly and ensure that it can fit the panel in the frame accurately. Additionally, the dimensions of any openings are of high significance for an autonomous robot to move in indoor environments. For example, when passing through a door, the robot has to detect the dimension of the opening space so that it can automatically decide whether to directly go through this door or to find another way.

In this paper, we propose a user-guided dimensional analysis approach that is able to get the dimensions of indoor scenes from a depth sensor. We perform dimensional analysis on a single frame obtained from a depth sensor to achieve high computation efficiency and to avoid error accumulations in multi-frame registration. Due to the limited field of view of the sensor, a single frame cannot guarantee that all the interesting dimensional information can be computed. In addition, the quality of the computed dimension is limited by the sensor's intrinsic accuracy. To overcome the drawbacks of a single frame, a knowledge-based user guidance system is developed to guide a user (or a robot) to move the sensor to a better position so that sufficient and high quality data suitable for dimensional analysis is collected. After a high quality single frame data is collected, the geometric analysis is performed to obtain the necessary dimensional information.

The remainder of the paper is organized as follows: Section 2 reviews related work. Section 3 illustrates the designed methods in detail. Section 4 describes the experiments and the results. Finally Section 5 draws conclusions and discusses ongoing and future work.

2 Previous Work

In the context of getting dimensional information from built environments, many research studies have focused on creating 3D models by using high-end 3D laser scanners (2D rotational laser scanner or terrestrial LiDAR), which can provide accurate and rich 3D point clouds of a large environment. Budroni and Boehm [1] used a plane sweep algorithm and a priori knowledge to find floors, ceilings, and walls, and created a 3D model by intersecting these elements. Díaz-Vilariño et al. [2] combined laser scan data and high-resolution images to detect interior doors and walls and automatically obtained optimized 3D models. Nüchter and Hertzberg [3] used semantic labelling to find coarse scene features (e.g., walls, floors) from point clouds obtained by a 3D laser scanner. In addition, researchers in construction have also used accurate laser scanners to obtain 3D models of dynamic construction environment and equipment. Wang and Cho [4] designed a smart scanning system to rapidly identify target objects and update merely the target's point clouds. Then they used concave hull surface modeling algorithms to get a 3D surface model. Cho and Gai [5] used laser scanning to obtain 3D point clouds of the environment and identified 3D target models by comparing them to a model database. The field results of these two papers demonstrated that the method can greatly improve productivity and safety in heavy construction equipment operations. A drawback of these approaches using high-end 3D laser scanners is that they need professional setups and operations (e.g., attaching markers in the environment for registering point clouds). Moreover, the post-processing methods used to extract 3D models from point clouds usually take time since these sensors obtain more than millions or even billions of points.

Instead of using high-end laser scanners, simultaneous localization and mapping (SLAM) techniques have been widely used for registering multiple 3D frames and obtaining 3D models of large-scale environments with affordable sensors (e.g. low-cost depth sensors, cameras). Newcombe et al. [6] presented KinectFusion, which employed an iterative closest point (ICP) algorithm to register a current depth map to a global model reconstructed by fusing all previous depth maps. Taguchi et al. [7] proposed the point-plane SLAM system that uses both points and planes as primitives. Cabral and Furukawa [8] proposed a method for reconstructing a piecewise planar and compact floor plan from multiple 2D images, which provides better visualization experience but probably less geometric details. Although the 3D models generated by those methods enable dimensional analysis in large-scale environments, the accuracy is limited due to drift error accumulations in multi-frame registration.

Compared to the previous work, this paper aims to obtain accurate dimensional information from a single frame of an affordable depth sensor. Our single-frame approach avoids the error accumulations in multi-frame registration. In order to overcome the limitation of a single frame, such as the limited field of view and measurement distance, this paper designs a user guidance system for dimensional analysis to provide guidance for the user to obtain better and more accurate results.

The most relevant work to our paper is [9], which presented a hand-held system for real-time interactive acquisition of residential floor plans. The system in that paper integrates a depth sensor, a micro-projector, and a button interface to help the user capture important architectural element in indoor environments. Instead of obtaining the floor plan of a building using a SLAM technique as in [9], this paper focuses on obtaining dimensional information of specific objects in indoor environments from a single frame. Moreover, our user guidance system not only assists the user to observe essential components, but also gives evaluation of current data quality.

Our user guidance system was inspired by [10] and [11]. Richardson et al. [10] presented a user-assisted camera calibration method that suggests the position of calibration targets in the captured images to obtain reliable, stable, and accurate camera calibration results. Bae et al. [11] proposed the computational rephotography system that, given a reference image, guides the user to capture an image from the same viewpoint. In order to obtain accurate dimensional information from a single frame of a depth sensor, our user guidance system evaluates the data quality of the current frame and then suggests the user to move the sensor to get better results for the application. By simple guidance, our system can lead the user who does not have to be an expert to get high quality data and thus high quality dimensional measurements.

3 Dimensional Analysis System

In this paper, we focus on the dimensional analysis of civil infrastructure with planar surfaces in indoor environments from a depth sensor. The system framework is shown in Figure 1. Firstly, a frame of 3D point clouds is acquired by a depth sensor. Then the preprocessing is conducted on the point clouds, including extracting planar surfaces and computing topological relationships of these planes. Based on the planes and their relationships, geometric analysis is performed to compute the initial dimensions of the scene. Combining the scene type and the initial dimensional measurements, the user guidance system evaluates the quality of the current frame and dimensional measurements. If the data quality is low, then the user guidance system provides guidance for moving the senor so as to get higher quality data and thus better dimension measurements.

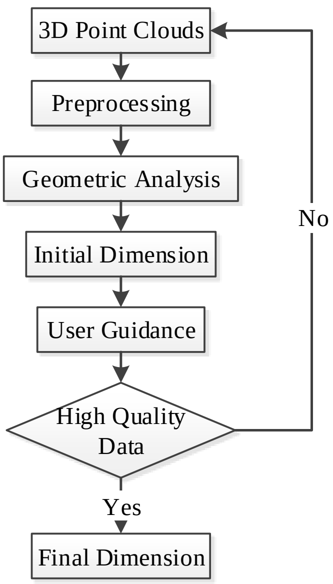


Figure 1. System framework

3.1 Preprocessing

In this paper, we assume that the object of interest is composed of, supported by, or surrounded by planar surfaces. Since the proposed method works on dimensional analysis of indoor scenes, this assumption is reasonable as the common objects in indoor scenes have planar surfaces. Based on this assumption, geometric analysis is performed to get dimensional information of specific infrastructures.

To extract planar surfaces efficiently, the fast plane extraction algorithm for organized point clouds proposed by Feng et al. [12] is employed. This algorithm first segments the point clouds into groups and uses them as nodes to create a graph. Then an agglomerative hierarchical clustering is performed on this graph to merge nodes on the same plane. Finally the planes are refined by pixel-wise region growing.

Once all the planes are extracted from the point clouds, based on the plane parameters, the topological relationships among these planes are estimated. Four types of plane relationship are defined as follows:

- Parallel: if the normal vectors of two planes are parallel to each other, the two planes are parallel planes.
- Coplanar: if two planes have the same parameters, they are coplanar planes. Coplanar planes are also parallel planes.
- Intersecting: if two planes are not parallel to each other, they are intersecting planes.
- Perpendicular: if the normal vectors of two planes are perpendicular (orthogonal to each other), the two planes are perpendicular to each other.

It should be noted that due to the uncertainty in sensor measurements, these relationships are determined approximately. For example, in this paper, if the angle of normal vectors of two planes is less than 5 degrees, they are considered as parallel planes.

3.2 Geometric Analysis

If all the measurements from the sensor are perfectly accurate, the dimensional information can be directly computed based on the geometric representations of the infrastructure. However, the sensor is not perfect and the measurements have uncertainty. To get robust and accurate dimensional information, least squares methods are utilized. In this paper, the distance between two parallel planes and the distance between boundary points of coplanar planes are of interest. Methods for these two distance computations are proposed to obtain robust estimation.

3.2.1 Distance between Parallel Planes

After extracting the planes, the plane parameters are estimated from the points by least squares. Given the set of points $p_i^k = [x_i^k, y_i^k, z_i^k], k = 1, \dots, K$ assigned to Plane i, whose parameters are represented by $P = [a_i, b_i, c_i, d_i]^T$, the plane equation $a_i x_i^k + b_i y_i^k + c_i z_i^k + d_i = 0$ needs to be satisfied for all the K points. Thus a linear system can be constructed as

$$AP = 0 \tag{1}$$

where the matrix A can be constructed by stacking the row vectors $[x_i^k, y_i^k, z_i^k, 1]$. To get the least squares estimation, one solution is performing singular value decomposition (SVD) on the matrix A and then the plane parameters P are extracted from the results of SVD.

Since we know that there exist parallel plane sets, the plane parameter estimation results can be more robust and accurate by using this prior information. Suppose Plane i and Plane j are parallel to each other and the sets of points assigned to these planes are given as $p_i^k, k = 1, \dots, K$ and $p_j^l, l = 1, \dots, L$. To enforce the parallel constrains, Plane i and Plane j share the same normal vector and the equations are defined as

$$\begin{aligned} a_i x_i^k + b_i y_i^k + c_i z_i^k + d_i = 0 \\ a_i x_j^l + b_i y_j^l + c_i z_j^l + d_j = 0 \end{aligned} \tag{2}$$

Then a linear system similar to Equation (1) can be constructed with $P = [a_i, b_i, c_i, d_i, d_j]^T$ and the matrix A constructed by stacking $[x_i^k, y_i^k, z_i^k, 1,0]$ and $[x_j^l, y_j^l, z_j^l, 0,1]$. Therefore by using SVD, the plane parameters of parallel planes are computed using all the points on the planes.

Once the plane parameters are obtained, the distance between the parallel planes is calculated directly based on the plane parameters as

$$dist_{ij} = |d_i - d_j| \tag{3}$$

3.2.2 Distance between Boundary Points of Coplanar Planes

Due to the limited field of view of the sensor, the height of a door might not be deduced because the supporting plane points are not measured. This paper thus discusses the estimation of the width of a door. In this context, the width is the distance between boundary points of two coplanar planes. To compute this width, the boundary points of the door frame are extracted and then two lines are fitted based on the boundary points. The distance between these two parallel lines is the width of the door frame.

Algorithm 1 Extract Door Frame Boundary Points

function EXTRACTBOUNDARY($CP1, CP2$)
    $BP2$ = EXTRACTEACHBOUNDARY ($CP1, CP2$)
    $BP1$ = EXTRACTEACHBOUNDARY ($CP2, CP1$)
    return $BP1, BP2$;

function EXTRACTEACHBOUNDARY($CP1$, $CP2$)
    is_searched[1:size($CP2$)] = **false**;
    for each $pt \in CP1$ **do**
        // Search the nearest point to pt in $CP2$
        k = search_nearest_point($CP2$, pt);
        is_searched[k] = true;
    end for
    for each i=1:size($CP2$) **do**
        if is_searched[i] = true **then**
            BP.add($CP2$ [i]);
        end if
    end for
    return BP

In order to automatically find door frames, firstly the topological relationships between extracted plane surfaces are estimated based on the plane fitting results. After detecting the coplanar planes, all the coplanar planes are rotated to a 2D space. To obtain the door frame boundary points, a method (Algorithm 1) by searching nearest points between two planes is proposed. Firstly the boundary points of the two planes, $CP1$ and $CP2$, are separately extracted by using the 2D alpha shape algorithm [13]. Then for the first plane, for each point in $CP1$, the nearest point in the other plane boundary points $CP2$ is searched. After iterating all the points on the first plane, the points in $CP2$ that have been searched as the nearest points, $BP2$, are the door frame boundary points on the second plane. By repeating the process for the second plane, the door frame boundary points on the first plane, $BP1$, are found. Once the door frame boundary points $BP1$ and $BP2$ are detected, the two lines are estimated from the two sets of boundary points respectively. The distance is estimated from the two lines.

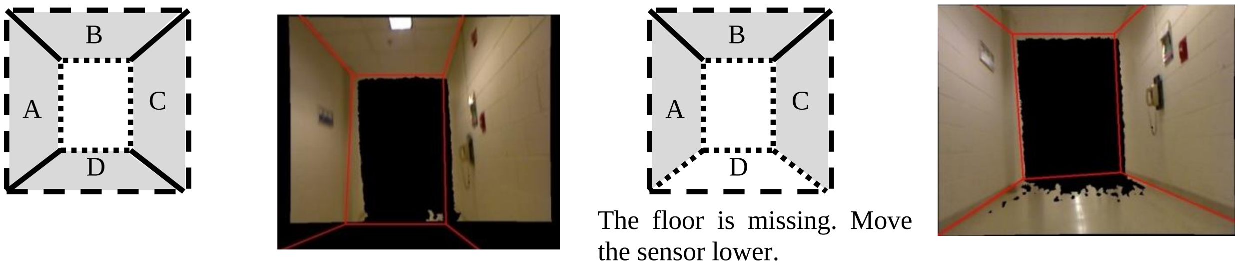
3.3 User Guidance

Our user guidance system is based on the prior knowledge of the scene of interest. The goal of the user guidance system is to indicate the quality of the current frame data in terms of obtaining the dimensional information from the scene. In this paper, we define high quality data as a single frame including sufficient data from the supporting planar surfaces of the infrastructure features of interest. The user guidance system evaluates the quality of obtained data based on the characteristics of the sensor and the scene. To fully utilize the prior information, the user guidance system visualizes the topological relationships of planar surfaces. In this paper, two general cases, box shape and opening, are described in detail.

3.3.1 Box Shape

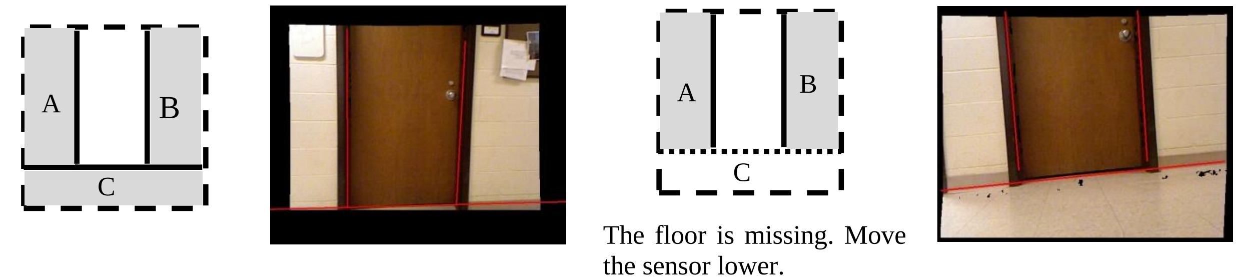
A box shape is defined as the shape that contains two sets of two parallel planes while the two sets are perpendicular to each other. As shown in Figure 2 (a), Plane A and C are parallel to each other, so are Plane B and D. Moreover, Plane A is perpendicular to Plane D. The solid lines denote the intersection lines between planar surfaces. To help the illustration, we use a hallway as an example. To get the dimension of this structure (the width and height of the hallway), all the four plane points should be acquired by the sensor. The user guidance is designed to make sure that the sensor captures sufficient points from all the four planar surfaces with high accuracy.

The user guidance assumes that at least three planes are detected from the scene. This assumption is reasonable because if the sensor only observes two planar surfaces, then the sensor may not be able to obtain all the four planes. This happens when the hallway is too high and it is impossible for the sensor to capture all the four planes. If one planar surface is not obtained in the data, the geometric analysis is also performed based on the partial data. Based on the prior information of the scene



(a) The box shape template.
(b) One frame data and the measurement.
(c) The shape and the user guidance.
(d) A better frame data and the measurement.

Figure 2. Box shape user guidance. (a) The template of a box shape, where gray shapes denote planar surfaces. (b) One frame from a depth sensor is processed. The red lines are inferred from the data. (c) Based on the template and the data, the shape of the current data is constructed. The solid lines are created by intersecting planes and the dotted lines are hypothesized from the solid lines and the point clouds. By comparing (a) and (c), the user guidance is provided. (d) Guided by the system, another frame is obtained and an accurate and complete shape is built.



(a) The opening shape template.
(b) One frame data and the measurement.
(c) The shape and the user guidance.
(d) A better frame data and the measurement.

Figure 3. Opening shape user guidance. (a) The template of an opening shape, where gray shapes denote planar surfaces. (b) One frame from a depth sensor is processed. The red lines are inferred from the data. (c) Based on the template and the data, the shape of the current data is constructed. The solid lines are created by fitting lines to the door frame boundary points and the dotted line is hypothesized from the solid lines and the point clouds. By comparing (a) and (c), the user guidance is provided. (d) Guided by the system, another frame is obtained and an accurate and complete shape is built.

and the captured data, the hypothesized shape is reconstructed so as to guide the user. For example as shown in Figure 2 (b), let us assume Plane D (i.e., the floor) is not detected from the data.

Since the ceiling and the two walls are detected, the intersection lines between them can be derived, as denoted by the two solid lines in Figure 2 (c). By vertically extending the end points of the two solid lines, the two vertical dotted lines are hypothesized and the other end points are found based on their equations and the point clouds. The two horizontal dotted lines are created by connecting the end points. Hence the box shape (the red lines in Figure 2 (b)) is constructed for this frame and an abstract template (Figure 2 (c)) is also created. However, the height is not accurate since it is computed by hypothesizing the vertical dotted lines and their end points. To obtain the accurate height the user guidance system will provide the corresponding guidance for this context based on Figure 2 (c).

Since the system detects that there are no points from Plane D, the system suggests the user to move the sensor lower so as to get points from Plane D, the floor. By following the guidance, the sensor is moved lower and then a new and better frame is obtained Figure 2 (d). In this frame, all the four planes can be extracted from the point clouds and a box shape similar to the template can be constructed without using any hypothesis. Thus both the height and the width of the hallway can be computed by geometric analysis.

Apart from steering the sensor to find the missing plane, the user guidance system can also provide comments on the quality of the measurements based on the data quality. For example the uncertainty of the depth sensor usually grows as the distance between the object and the sensor increases. Thus if an object is far from the sensor, the points of this object have high uncertainty, which affects the accuracy of dimensional measurements. Therefore when all the four planes are detected from the data, for each plane, the distance between its centroid and the sensor is calculated. If the distance to the sensor is larger than a threshold (3.0m in this paper), the user guidance system suggests the user to move the sensor closer to that plane so as to minimize the measuring uncertainty.

3.3.2 Openings

An opening structure is defined as an opening in a planar surface while there is another supporting planar surface (i.e., the floor) for the first planar surface. In this paper, a door frame that is indent in a wall is used as an example of an opening structure. As shown in Figure 3 (a), Plane A and Plane B are vertical walls and they are on the same plane (their relationship is coplanar) while Plane C is the floor which is perpendicular to Plane A and Plane B. To get accurate width of the opening, the floor is necessary to provide constraints in reconstructing the walls. Thus the user guidance is implemented to guarantee that the floor is observed by the sensor.

If Plane C, the floor is not measured in the data, the system can still reconstruct an estimated shape as shown in Figure 3 (b). Here the two vertical lines are estimated by using the method described in Section 3.2.2, while the boundary line between the walls and the floor is hypothesized by using the end points of the two vertical lines. Even though the width can be estimated based on these two vertical lines, since the sensor measurements around depth boundaries may be inaccurate, the line estimation as well as the computed width is not always accurate. By comparing Figure 3 (c) and (a), the user guidance system asks the user to move the sensor lower so that the data of the floor can be obtained. In this way, a new frame with better quality data is captured (Figure 3(d)). The estimation of door width is improved by adding the constraint that the lines are vertical to the floor.

In addition, since the door usually indents in the walls, the wall might block the view of the sensor if the sensor view direction is not perpendicular to the door. Therefore the user guidance system also takes this into consideration. The normal vector of the door surface is used for this evaluation. If the sensor view direction is not perpendicular to the door surface, the user guidance system offers feedback about adjusting the view direction of the sensor.

4 Experiments and Results

4.1 Experimental Setup

In the experiments, a Kinect for Xbox 360 sensor is used as the depth sensor to obtain 3D point clouds of indoor scenes. Equipped with an infrared (IR) camera and a color (RGB) camera, Kinect is able to get a depth map and a color image of the environment. The depth map can be registered to the color image by using sensor calibration to obtain 3D colored point clouds.

To fully utilize the knowledge of the measured environment, during the experiments the sensor must be held almost horizontally by the user. Within this context, the floor is almost horizontal while the wall is almost vertical in the point clouds. This assumption is reasonable in terms of the potential applications. For a robotic platform, it is easy to mount the sensor in this position. For a user holding the device, the sensor can be easily adjusted to meet this assumption.

4.2 Geometric Measurement Accuracy

To evaluate the geometric measurement accuracy, multiple frames are acquired by moving the sensor to different positions in order to obtain data at different viewpoints. The average values over all the measurements from those frames are used to evaluate the accuracy and performance of the system. The ground truth of the dimensional information is obtained by tape measurement. The error of this system is calculated by subtracting the average value from the ground truth.

In terms of a hallway structure, the method is tested on seven hallways in four different buildings. The overall accuracy of the widths and the heights of the hallways is shown in Table **1**. The average error of the width measurement is -0.09m while that of the height is -0.13m. Thus generally the width measurement has a lower error compared to the height. The reason is that the width of a hallway is usually less than its height and Kinect tends to obtain low quality data from the ceiling or the floor because the uncertainty of the sensor goes up as the distance increases. This is also demonstrated by the relative errors. From Table **1**, the height generally has larger relative error compared to that of the width.

From Table 1, it is also shown that both the error and the relative error have a small standard deviation, which indicates that the developed method is able to provide stable results in the dimension analysis of hallway structures.

Table 1. Errors for the hallway width and height measurements. Avg. and Std. denote average value and standard deviation of each column respectively.

ID	Error (m)		Relative Error	
	Width	Height	Width	Height
Hallway 1	-0.02	-0.07	0.010	0.027
Hallway 2	-0.08	-0.12	0.043	0.047
Hallway 3	-0.11	-0.15	0.045	0.051
Hallway 4	-0.1	-0.11	0.040	0.044
Hallway 5	-0.09	-0.13	0.036	0.053
Hallway 6	-0.11	-0.15	0.044	0.056
Hallway 7	-0.15	-0.15	0.076	0.056
Avg.	-0.09	-0.13	0.043	0.048
Std.	0.04	0.03	0.02	0.01

For door frames, the method is tested on six door frames in the same four different buildings. The overall accuracy of the width of doors is shown in Figure 4. The average error is -0.05m, which shows that the method measures door width with high accuracy. The standard deviation is 0.05, which reflects the stability of this method in measuring door width. The maximum absolute error is 0.14m while the minimum absolute error is 0.01m. The maximum absolute error value occurs at Door 3, whose frame is indented in the walls. In this paper, the door width is measured as the distance between the left and right frame on the door frame. However, the door frame of Door 3 is not involved in computation since it contains a small number of points and all its points are discarded in the plane extraction process. Thus the door is "expanded" by the dimension of the door frame which is 0.10m (0.05m each on the left and right). If this value is subtracted from the measurement, the error is -0.04m which is close to the errors of the other doors.

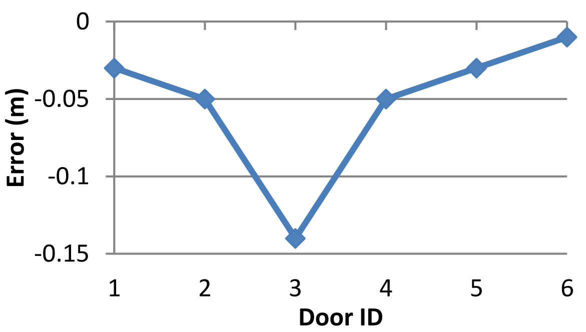


Figure 4. Errors for the door width measurements

As shown in Table 1 and Figure 4, the width and height measurements of hallway, and the door width measurements are generally greater than the ground truth. This indicates that there is a system error in the data collected by the sensor. The possible reason is that in these experiments the default calibration parameters for Kinect are used for computing 3D point clouds. The actual calibration parameters of the Kinect used in this paper might be different. With calibrated parameters of the Kinect, this system error is expected to be removed.

This system is developed in C++. The Point Cloud Library (PCL) [14] is utilized for grabbing 3D point clouds from Kinect. The Computation Geometry Algorithms Library (CGAL) [15] is used for geometry computation. The system on average spends 1.3 seconds per frame for the hallway while it takes 5 seconds for the door frame. The experiments were conducted on a laptop with Intel Core i7-3520M CPU of 2.90GHz and RAM of 8GB. The implementation does not employ any multi-threading or GPU techniques.

5 Conclusions and Future Work

In this paper, a user-guided dimensional analysis system for indoor scenes is introduced. The system uses a single frame from a depth sensor to obtain the dimensions of an indoor scene by extracting planes and performing geometric analysis. To overcome the disadvantage of the single frame data, a user guidance strategy is employed to provide guidance for a better sensor position so as to acquire high quality data. Experimental results show that this system can compute the width of doors within 10cm and the size of hallways within 15cm. The user guidance system is able to provide correct and useful guidance.

As mentioned in Section 4, there exist system errors in the data and the dimensional measurements are greater than the ground truth. Future work will calibrate the sensor so as to obtain accurate parameters. In addition, this system is only tested on doors indented in the walls and does not measure the height of the door. In the future, the system will be improved to account for these conditions. Moreover, the system will be explored on more complicated indoor scenes.

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