ENTROPY-BASED INDOOR CHANGE DETECTION USING LIDAR DATA AND A 3D MODEL

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ABSTRACT:

Indoor change detection is important for building monitoring, building management and model-based localization and navigation systems because the real building environment may not always be the same as the design model. This paper presents a novel indoor building change detection method based on entropy. A sequence of real LiDAR scans is acquired with a static LiDAR scanner and the pose of the LiDAR scanner for each scan is then estimated. Synthetic LiDAR scans are generated with the pose of the LiDAR scanner using the 3D model. The real LiDAR scans and synthetic LiDAR scans are sliced horizontally with a certain angular interval and the entropy of all slices of LiDAR scans is then calculated. Differenced entropy between two corresponding slices of real LiDAR scans and synthetic LiDAR scans is calculated for the classification of the changes. Each slice of real LiDAR scans will be classified into one of the four categories of changes: unchanged, moving objects, structural change and non-structural change. Experimental results show that unchanged slices and slices containing moving objects can be accurately detected, achieving 100% accuracy while non-structural and structural changes are detected with an accuracy of 98.5% and 86.3% respectively.

1. INTRODUCTION

Indoor building change detection plays an important role in building monitoring and building management, and it enables improvement of robustness and accuracy of model-based indoor localization and navigation systems (Zhao et al., 2020, Meyer et al., 2022, Iandola et al., 2016, Zhao et al., 2023). The differences between the real environment and the 3D model are inevitable because the real environment of buildings cannot be the same as the design model and indoor environments can change drastically due to building renovation and remodelling. Such differences between the 3D model and the real environment will introduce errors to model-based localization and navigation systems (Khoshelham, 2016, Caron et al., 2014).

LiDAR scanner can provide accurate distance measurements in horizontal field of view, from which structural features can be easily extracted (Tavasoli et al., 2023, Santos et al., 2022). Detecting changes between the real environment and the 3D model is the process of detecting differences between LiDAR scans and the 3D model. Learning-based change detection approaches have been studied and developed recently (Czerniawski et al., 2021, Voelsen et al., 2021, Chen et al., 2022, Ma et al., 2020). Such learning based methods rely on sufficient annotated real LiDAR data or generated synthetic LiDAR data, which require a prolonged labelling procedure and training stage. The trained change detection networks can only perform well in the environments which are sufficiently similar to the training environments and will fail for change detection in unseen environments.

Geometry-based change detection methods have also been developed to perform change detection between LiDAR data and 3D models (Tamke et al., 2016, Marani et al., 2016, Tran and Khoshelham, 2019, Koeva et al., 2019). The proposed approaches detect changes by calculating differences between LiDAR data and the 3D model, but they fail to detect moving objects or small items.

Entropy is first proposed to measure the value of received information (Shannon, 1948) and then approximate entropy developed to measure regularity and complexity in scientific fields (Pincus, 1991, Richman and Moorman, 2000, Ocak, 2009, Altieri et al., 2018). The ability to describe randomness and disorder enables detecting changes in spatial data (Sun et al., 2010, Particke et al., 2018, Dolenc et al., 2015). The observed spatial data show a different entropy level where changes exist and drastic changes can result in a larger entropy difference than that of minor changes. We pose the research question: how to identify sections of the view captured in a LiDAR scan with changes, and how to classify the change?

Inspired by the ability of entropy to detect changes, this paper presents a change detection method using entropy and generated synthetic LiDAR data. The pose of each acquired real LiDAR scan is estimated and then used to generate a synthetic LiDAR scan. The pair of the real LiDAR scan and the synthetic LiDAR scan are sliced with a certain angular interval horizontally and then the entropy of each slice of both scans is calculated. The differenced entropy between each slice of the real LiDAR scan and the corresponding slice of the synthetic LiDAR scan is then calculated and used to detect changes. To detect moving objects, entropy changes of consecutive scans acquired statically by a LiDAR scanner are used. The contributions of this paper are as follows:

(1) The problem of detecting changes of the real environment with respect to the 3D model is formulated as detecting differences between real LiDAR scans and synthetic LiDAR scans;

(2) We show that the entropy of lidar slices enables detecting moving objects and small items.

(3) We show that entropy is effective for detecting unchanged slices and moving objects and that structural changes have a larger entropy than non-structural changes.

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The remainder of the this paper is organised as follows: Section 2 provides a review of related works. The methodology is introduced in Section 3. Section 4 presents the dataset, experiments and results. Section 5 discusses limitations of the presented method. Conclusion of this paper is presented in Section 6.

2. RELATED WORK

Indoor change detection approaches can be classified into two categories: learning-based approach and geometry-based approach.

2.1 Learning-based change detection

Learning-based change detection methods are inspired by LiDAR segmentation networks (Czerniawski et al., 2021, Voelsen et al., 2021, Chen et al., 2022, Ma et al., 2020) and satellite image-based change detection methods (Xu et al., 2021, Meshkini et al., 2022, Bai et al., 2022). LiDAR segmentation techniques can be modified to have two inputs for two LiDAR point clouds taken from different epoches respectively to perform change detection between these two LiDAR point clouds. In Czerniawsk et al.'s work, synthetic LiDAR scans were generated in a complete BIM and an incomplete Building Information Modeling (BIM) and the generated pairs of LiDAR scans were used to train a LiDAR segmentation network to perform change detection (Czerniawski et al., 2021). The changes can be accurately detected but moving objects were not taken into consideration. Compared with real LiDAR scans, synthetic LiDAR scans generated from a BIM are neat and clean due to the lack of details. To apply advantage of matured 2D convolutional neural networks (CNN) (Szegedy et al., 2017, Zhu and Newsam, 2017, Chollet, 2017), LiDAR scans are converted into range images, where the intensity of each pixel represents a distance measurement (Milioto et al., 2019, Yadav et al., 2022). A UNet-based change detection was presented to perform change detection using LiDAR data collected from different epoches. The buildings were classified into one of four categories: new, demolished, tall and short (Yadav et al., 2022). To improve classification accuracy, self-attention mechanisms are introduced to the change detection network (Chen et al., 2022), which enables change detection from subtle features. The Learning-based approaches can perform change detection accurately but they require sufficient training data with exact labels. Labeling data is a slow and laborious process and the trained change detection network will fail in detecting changes on unseen objects.

2.2 Geometry-based change detection

Geometry-based change detection methods have been widely studied in recent years (Gu et al., 2019, Radanovic et al., 2021, Huang et al., 2022). A change detection method by calculating the difference between the LiDAR data and the BIM but the system ignored small items such as furniture has been proposed (Tamke et al., 2016). Calculating differences between two registered 3D LiDAR point clouds to detect changes were presented by Nikoohemat et al. (2018). The changes were classified into permanent change and dynamic changes (Nikoohemat et al., 2018). Three ways are defined to detect changes by comparing two 3D models, comparing a 3D model and a LiDAR dataset, and comparing two LiDAR dataset, and changes are classified into structural change and insignificant change (Koeva et al., 2019). A change detection method has been proposed, where LiDAR point cloud was compared with the BIM model to detect the redundant and new building structures (Tran and Khoshelham, 2019). The coverage ratio of points on the surfaces of the 3D model indicate the redundant or missing structures of the 3D model.

Entropy stems from information theory to measure the informational value (Shannon, 1948) and following his work, entropy is also used to measure randomness and disorder in many field (Pincus, 1991, Richman and Moorman, 2000). Entropy are widely used for image change detection (Sun et al., 2010, Sun et al., 2010). Entropy of two images were calculated and compared to find the different parts. Entropy-based LiDAR complexity detection appraoch has been recently developed (Chen et al., 2017, Botteghi et al., 2020, Liu et al., 2022). An entropy-based LiDAR scanner initialization approach has been proposed, which initialized the LiDAR pose coarsely by calculating coherence between two scans and finding optimal transformation parameters (Chen et al., 2017). The minimum entropy between two scans is used to determine the final output. The forest canopy entropy can be used to detect forest changes in terms of canopy density and vertical canopy layering (Liu et al., 2022).

In summary, learning-based change detection methods require sufficient training data, the generation of which is a challenge, and hardly attain generalizability for unseen objects and in unseen environments. Geometry-based change detection methods aim to detect changes by deterministic rules but such rules are specific to the shape and pose of a limited set of objects. Entropy is a suitable indicator to detect changes without needs of deterministic rules and training data. Therefore, this paper presents an entropy-based indoor change detection method using synthetic LiDAR data generated in a 3D model to detect changes between the real environment and the 3D model.

3. METHODOLOGY

3.1 Framework

Figure 1 shows the framework of the change detection method. As show in Figure 1, the pose of acquired continuous LiDAR scans is estimated using a plane-based LiDAR registration method (Zhao et al., 2022) and the estimated poses are then used to generate synthetic LiDAR scans in a 3D model of the environment. The real LiDAR scan and the synthetic LiDAR scan are sliced by a LiDAR scan slicer at a regular horizontal angular interval. Figure 2 shows an example of a sliced LiDAR scan with 30 degree horizontal angular interval. The entire LiDAR scan is sliced into 12 slices horizontally. The entropy of each slice of the real LiDAR scan and the synthetic LiDAR scan is calculated and the differenced entropy of slices of the real LiDAR scan and the corresponding slices of synthetic LiDAR scans is calculated and then used to perform change detection. Each slice of the real LiDAR scan is classified into one of the four categories of changes: unchanged, structural change, non-structural change and moving object. In this paper, the structural change refers to the changes of main structures such as walls and stairs. Temporary changes are the objects that are easily movable or have frequently changeable states such as tables, chairs, bins and doors.

3.2 Entropy calculation

The LiDAR scan is sliced horizontally using an angle θ and the entire LiDAR scan is then sliced into k parts, where $k = 360/\theta$. The total number of points of the $m-th$ slice is N_m. For each slice of the LiDAR scan, entropy is calculated using the distribution of LiDAR points p_m^i in a certain distance range

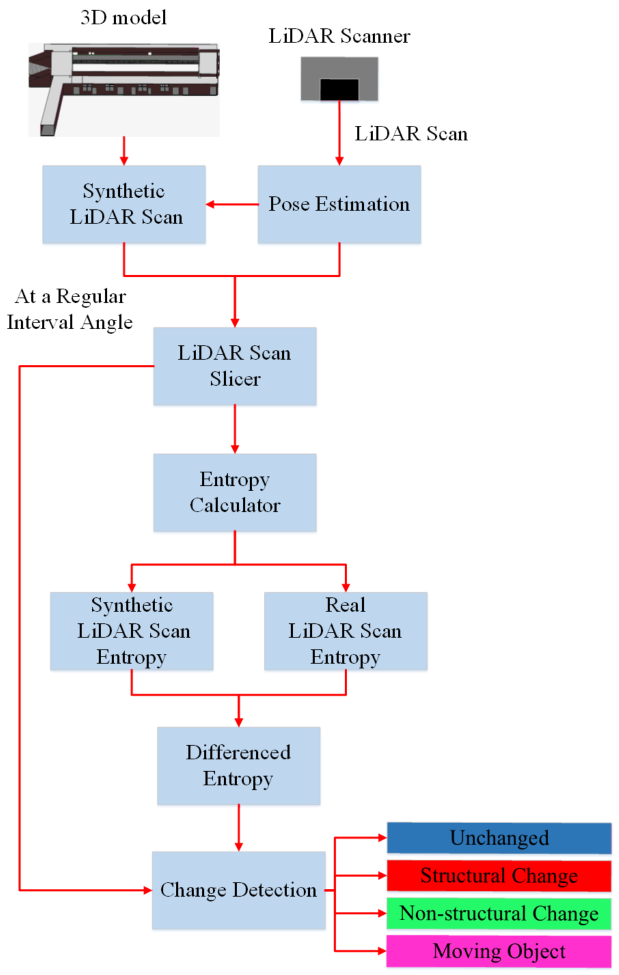


Figure 1. The framework of the proposed change detection method.

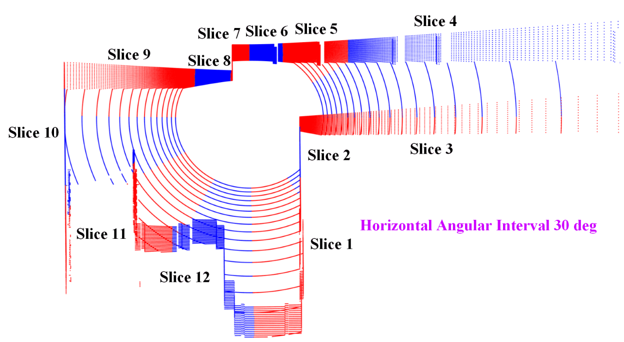


Figure 2. An example of a sliced LiDAR point cloud. The point cloud is sliced horizontally with the 30-degree interval. The red and blue colors are used to show adjacent slices.

$r_i = [dist^i_{min}, dist^i_{max}]$ with a distance interval l, where $l = dist^i_{max} - dist^i_{min}$. For each distance range r_i, the number of points within the specified distance range is counted as N^i_m and then the probability of points locating in r_i for the $m-th$ slice can be calculated by $p^i_m = N^i_m / N_m$. The entropy can then be calculated by the following formula:

$$H_m = -\sum_i (p^i_m) * log(p^i_m) \quad (1)$$

Where H^i_m denotes the entropy value of the $m-th$ slice. After the entropy of all slices of the real LiDAR scan and the corresponding synthetic LiDAR scan is calculated, the differenced entropy of each corresponding slice can be calculated by $d^m_N = H^{real}_m - H^{synt}_m$.

3.3 Change simulation

The proposed change detection method classifies each slice of the real LiDAR scan into one of the four categories of changes: unchanged, structural change, non-structural change and moving object. The structural change refers to the changes of main structural changes such as walls and stairs. Non-structural changes refer to minor changes and easily movable items such as furniture boxes and bins. Moving objects are humans moving through the environment. Structural and non-structural changes consist of new objects and redundant objects. New objects refer to the objects present in the real environment but not present in the 3D model while redundant objects refer to the objects present in the 3D model but not present in the real environment. In this paper, moving objects can only be present in real environments and not present in the 3D model.

To simulate such changes, items such as tables, bins, extinguishers and rubbish bins were added to the 3D model as non-structural changes. Walls were also added and removed in the 3D model to simulate structural changes because in the real environment, structural changes can hardly be simulated. New structural objects refer to a wall removed from the 3D model but present in the real environment. In real environment, small items such as chairs, tables and boxes were placed into the environment to simulate non-structural changes. People were walking and running in the environment while LiDAR scanner was working to simulate moving objects.

3.4 Classification of changes

The movement of objects will cause entropy increase and decrease in different slices because the differences caused by the moving object between the synthetic LiDAR scans and the real LiDAR scan are different. For static objects, the differenced entropy remains unchanged among the consecutive scans acquired by a static LiDAR scanner.

The classification process therefore is divided into two stages: classification of moving objects and classification of static objects. Moving objects result in entropy changes across consecutive scans whereas the other changes result in the same entropy difference across consecutive scans. The first step is to detect moving objects by the differenced entropy between real LiDAR scan and synthetic LiDAR scan. Consecutive LiDAR scans are acquired when the LiDAR scanner is working statically.

The second step is to classify static objects into one of three categories: unchanged, structural change and non-structural change. A set of LiDAR scans were used to determine the confidence interval for classification. The interquartile range of differenced entropy is calculated to find the boundary of the confidence interval for each category and the mahalanobis distance between the entropy value and the distribution of each category is used for classification purpose. If the calculated entropy value of a slice locates in a confidence interval for a certain class, the slice will be classified into the corresponding category. If the calculated entropy value fails to locate in a certain interquartile range, mahalanobis distance is then calculated to find the closest category. The mahalanobis distance in this paper is calculated as follows:

$$D(x, Q) = \sqrt{(x-u)^T S^{-1}(x-u)} \quad (2)$$

Where D denotes the distance between the calculated entropy x and the distribution of a category Q, and u represents the mean of the entropy values in Q. S is the positive-definite covariance matrix.

For unchanged slices, the differenced entropy value is expected to be close to zeros because the synthetic LiDAR scan and real LiDAR scan have the same level of entropy. Structural changes are expected to result in a larger entropy difference because they cause differences in more points than non-structural changes.

4. EXPERIMENTAL RESULTS

4.1 Experiment dataset

The experiment was conducted in a university corridor environment where a 32-channel Velodyne LiDAR scanner was used to acquire real LiDAR scans. The velodyne lidar scanner acquires distance measurements in 32 certain vertical angles from -30.67 degree to 10.67 degree at a 1.33-degree angular resolution. Each real LiDAR scan contains approximately 69000 points and synthetic LiDAR scans were generated using Blensor software (Blender, 2018), which can simulate Velodyne LiDAR scanner in a 3D model.

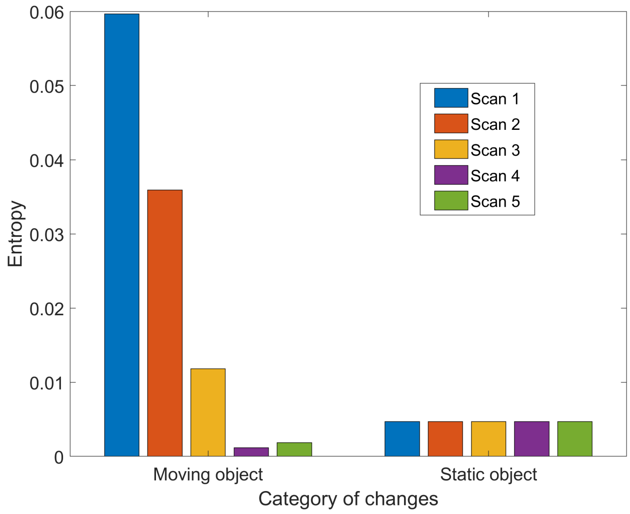
A total of 150 real LiDAR scans were collected in the real environment and the poses of these scans are estimated (Zhao et al., 2022) to generate 150 synthetic LiDAR scans using Blensor (Blender, 2018). The 150 pairs of LiDAR scans are used to determine the confidence interval for classification purpose. The horizontal angle interval to slice LiDAR scans is set to 30 degree in this experiment, resulting in 12 slices for each LiDAR scan and the distance interval to calculate distribution and entropy is set to 0.2 meter. The 150 real LiDAR scan were collected at 30 locations, with 5 consecutive scans at each location. At each location, the LiDAR was scanning statically to avoid introducing changes to entropy of static objects. The differenced entropy values of 30 pairs of LiDAR scans were calculated and analyzed to determine the confidence interval to differentiate unchanged, structural change and non-structural change.

A total of 100 real LiDAR scans were collected at 20 locations in real environment to evaluate the accuracy of the change detection method. With respect to the 100 real LiDAR scans, 100 synthetic LiDAR scans are generated using the 3D model. The determined confidence interval is used to classify the slices of real LiDAR scans into four categories: unchanged, structural change, non-structural change and moving object according to the differenced entropy.

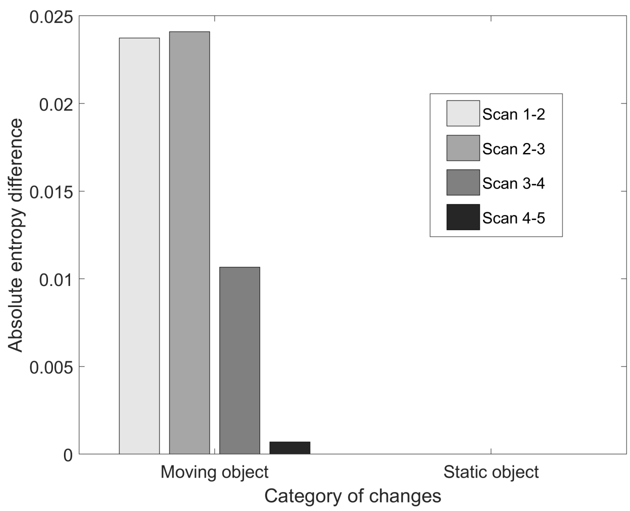
4.2 Classification of moving objects

The proposed change detection method calculated the entropy of the 5 consecutive scans at each location, with 1 second time interval and observe if entropy increase or decrease was shown in the calculated entropy. If the entropy increases or decreases among the 5 observations, the change indicates moving objects presenting in the slice. Figure 3 shows a comparison between a slice containing moving objects and a slice without moving objects, demonstrating differenced entropy values and entropy changes among the 5 consecutive scans. As shown in Figure 3, The moving object causes entropy increase and decrease in 5 consecutive scans while for slices only containing static objects, the entropy change is close to zero, with very tiny level entropy change caused by noises. Figure 4 shows the comparison of multiple slices, across which an object moved, and a slice without moving objects. The moving object causes entropy increase and decrease in multiple slices while the entropy change for the slice with moving objects is close to zero.

The experimental results show that the change of differenced entropy of consecutive LiDAR scans with a static LiDAR can accurately detect moving objects because the movement will cause changes in in the differenced entropy while without moving objects, the differenced entropy of each slice remains the same.



(a) Entropy of different change categories

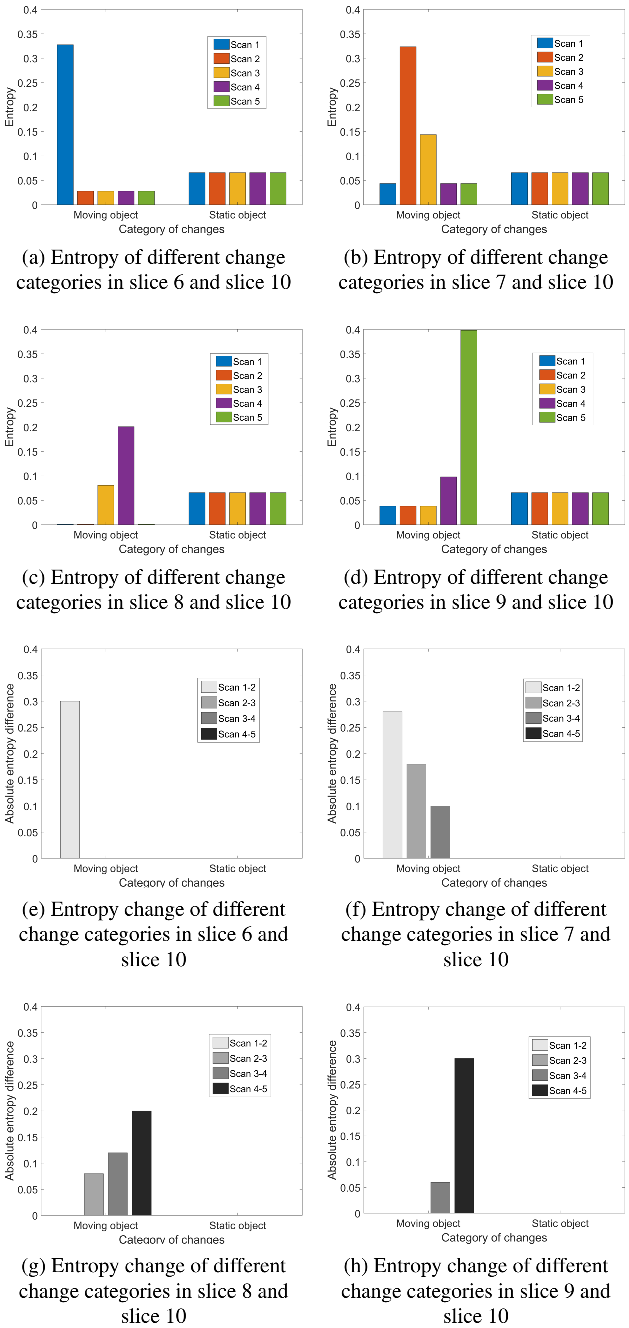


(b) Entropy change of different change categories

Figure 3. An example of entropy change caused by human movement in the first slice.

4.3 Classification of structural and non-structural changes

The proposed change detection method determines the confidence interval for the classification of unchanged, structural change and non-structural change by the interquartile range of the entropy distribution of 30 pairs of LiDAR scans at 30 locations. Figure 5 shows the box plot of differenced entropy of unchanged, structural change and non-structural change categories for the



(a) Entropy of different change categories in slice 6 and slice 10

(b) Entropy of different change categories in slice 7 and slice 10

(c) Entropy of different change categories in slice 8 and slice 10

(d) Entropy of different change categories in slice 9 and slice 10

(e) Entropy change of different change categories in slice 6 and slice 10

(f) Entropy change of different change categories in slice 7 and slice 10

(g) Entropy change of different change categories in slice 8 and slice 10

(h) Entropy change of different change categories in slice 9 and slice 10

Figure 4. An example of differenced entropy change caused by human movement in multiple slices.

30 pairs of LiDAR scans. As shown in Figure 5, the entropy of different categories is able to be separated using the interquartile range and the distribution of three categories of most changes can be clearly separated apart from some extreme situations, which will be discussed in the discussion section.

We conducted experiments with 20 pairs of LiDAR scans to perform change detection using the confidence interval. Table 1 shows the classification accuracy for the three categories. The accuracy is defined as the percentage of correct classification. If the predict label equals to the ground truth label, the classification is considered as correct. As shown in Table 1, the proposed method can accurately detect moving objects and the unchanged slice, achieving 100% classification accuracy. The accuracy of detecting non-structural changes is slightly lower than that of unchanged and moving objects, achieving 98.5% classification accuracy. The accuracy drops to 86.3% accuracy for detecting structural changes because of the wide range of the distribution of structural changes.

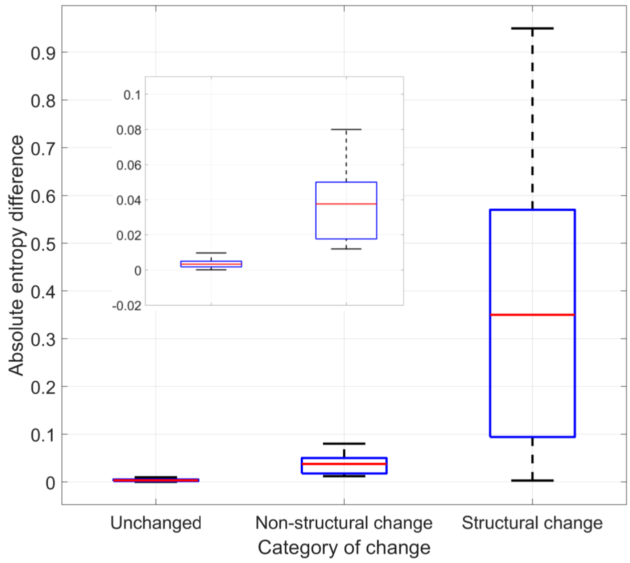


Figure 5. Box plot of the entropy for unchanged, non-structural change and structural change categories of the 30 pairs of LiDAR scans.

Change category	Classification accuracy
Moving object	100 %
Structural change	98.5 %
Non-structural change	86.3 %
Unchanged	100 %

Table 1. Classification accuracy of the proposed change detection method.

5. DISCUSSION

This paper presents a novel change detection approach using entropy, which does not require a training dataset compared with learning-based change detection method, and does not require a deterministic rules compared with existing geometry-based change detection methods. The proposed method can achieve 100% accuracy in detecting moving objects and unchanged slices of real LiDAR scans. However, there is a main limitation of the proposed change detection method. If the LiDAR is distant from changes or changes are blocked by other objects, resulting in a scanty amount of acquired LiDAR points, the entropy value cannot reflect changes correctly. Figure 6 shows an example of a simulation, where limited number of LiDAR points reflected by the structural change can be acquired due to the location of the LiDAR scanner. In such situation, the limited number of points representing structural changes can hardly cause entropy differences between two LiDAR scans. This explains the differenced entropy values representing structural changes but are smaller than 0.02 and therefore, these values introduce errors to classification accuracy.

However, the error of change detection on structural changes can be easily addressed by moving the LiDAR scanner to different places to cover the entire environments. When the LiDAR scanner is able to observe the most of the structural changes, the structural changes can be correctly detected. We will test the proposed method in different environments and outdoor environments in the future. Large non-structural changes such as book shelf and cupboard will be added to the experiments in the future test. Different angular interval and distance interval will also be tested to find a relatively good value for different environments.

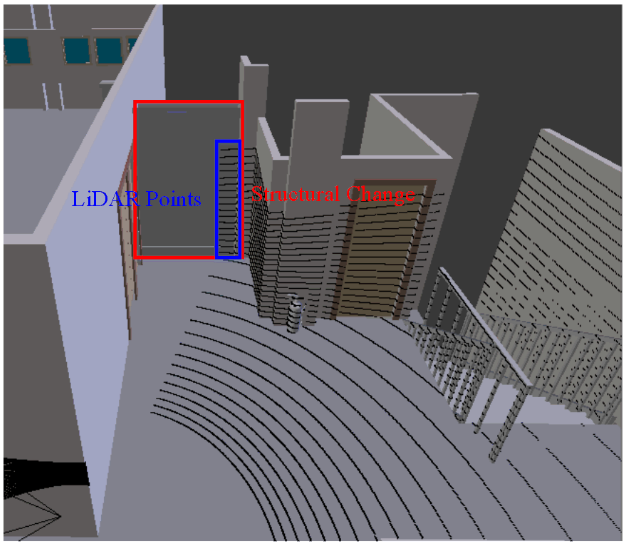


Figure 6. Limited points reflected by structural changes by the blockage due to the LiDAR position. The wall in the red rectangle added to the 3D model, not present in the real environment, is the structural change. The generated synthetic LiDAR scan captures limited number of point representing the wall due to the position of the LiDAR scanner.

6. CONCLUSION

This paper presents an entropy-based change detection method. A set of consecutive LiDAR scans are acquired and the pose of LiDAR scans are estimated to generate synthetic LiDAR scans in a modified 3D model. The pair of real LiDAR scan and synthetic LiDAR scan is sliced horizontally using a certain angle. The entropy of each slice of LiDAR is calculated and the differenced entropy is then calculated using entropy of the slices of real LiDAR scans and corresponding slices of synthetic LiDAR scans. Experimental results show that moving objects can be accurately detected by observing the change in entropy among 5 consecutive LiDAR scans. Entropy of 30 pairs of LiDAR scans calculated to determine the confidence interval for classification purposes. 20 pairs of LiDAR scans are used to test the proposed change detection with the determined confidence interval and the mahalanobis distance. Results show that the accuracy of detecting unchanged slices is 100% accuracy and the accuracy of detecting non-structural change is slightly lower at 98.5%. The classification accuracy of detecting structural changes is only 86.3% but it can be addressed by moving the LiDAR scanner to different places.

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