Automated progress monitoring of masonry activity using photogrammetric point cloud

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Abstract

Information retrieval and automated progress estimation of on-going construction projects have been an area of interest for researchers in the field of civil engineering. It is done using 3D point cloud as-built and as-planned model. Advancements in the field of photogrammetry and computer vision have made 3D reconstruction of buildings easy and affordable. But the high variability of construction sites, in terms of lighting conditions, material appearance, etc. and error-prone data collection techniques tend to make the reconstructed 3D model erroneous and incorrect representation of the actual site. This eventually affects the result of progress estimation step. To overcome these limitations, this paper presents a novel approach for improving the results of 3D reconstruction of a construction site by employing two-step process for the reconstruction as compared to the traditional approach. In the proposed method, the first step is to obtain an as-built 3D model of the construction site using 3D scanning techniques or photogrammetry in the form of point cloud data. In the second step, the model is passed through pre-trained machine learning binary classification model for identifying and removing erroneous data points in the captured point cloud. Erroneous points are removed by identifying the correct building points. This processed as-built model is compared with an as-planned model for progress estimation. Based on the proposed method, experiments are carried out using commercially available stereo vision camera for 3D reconstruction.

Keywords –

3D reconstruction, point cloud, as-built, as-planned, progress estimate

1 Introduction

Traditional monitoring of construction projects has always been manually driven process involving visual inspection and human judgment. This makes these methods slow and inaccurate, reducing the ability of infrastructure managers to monitor project performance indicators, including schedule and cost. These poor monitoring techniques are comprehended as one of the reasons for cost and time overruns in construction projects [1]. Importance of accurate and efficient progress monitoring have been reiterated by several researchers. Research establishes project monitoring as a critical success factor for in-budget completion of a construction project [2]. The time taken for identification of inconsistency between the as-built and as-planned model is proportional to the cost overrun and increased difficulty in implementation of the corrective measures in a project [3].

In the past, several automated methods of progress monitoring have been developed and tested by researchers and practitioners to enable better monitoring. Automated progress monitoring can be divided into four steps: (1) Data acquisition, which is capturing digital representation of as-built scenes, (2) information retrieval, this refers to extraction of useful information from the data collected without loss of any information required for accurate progress estimation, (3) progress estimation, this is a comparison between as-built model and as-planned model in order to determine the state of progress, (4) visualization of the results obtained via previous steps [4].

Recent advancements in the field of reality capture technologies, like, 3D imaging, laser scanning, in-situ sensing equipment, onboard instrumentation and electronic tagging, has made data acquisition possible for automated progress estimation. Moreover, developments in the field of machine learning and computer vision have made analysis of the acquired data efficient. While the impacts of these advancements are compelling, numerous challenges continue to persist. [5][6] These challenges prevent them from maturing into technologies that could be deployed to an on-going construction site for monitoring without human intervention. It can be alleged that there are no practices which offer automated analysis of construction data to estimate progress [4].

Thus, the goal of the study is to improve the result of progress estimate of a construction by generating a correct 3D reconstruction of construction. Considering the high variability in site conditions and data collection techniques, the method should be robust to these variations for any given site.

It should be noted that 3D reconstructed point cloud model is obtained using commercially available stereo vision camera. The process of 3D registration of images to produce point cloud is known to be error-prone, producing erroneous points with no correspondence in actual site [7][8]. Thus, data pre-processing becomes of paramount importance, involving outlier removal and noise filtering. But these methods are preliminary in nature and erroneous points continue to exist in the point cloud data. Therefore, there is need to identify these error points.

In this study, we work to improve the results of progress estimate of construction calculated by comparing as-built model, obtained using a commercially available stereo vision camera, and as-planned model. The research employs machine learning techniques for processing and refining 3D point cloud model before progress estimation is made. The processing involves detection of the masonry followed by its distinction from erroneous points. This is done to obtain a more accurate representation of the captured scene as compared to the output of 3D reconstruction. Subsequently, this processed as-built model is used for progress estimation by comparing it with the as-planned model.

In this paper, a novel method is proposed to classify between normal and erroneous points using machine learning techniques. "Normal" class representing points which correspond to constructed parts in the 3D point cloud model whereas "erroneous" class represents points which have no correspondence or correspond to parts other than constructed elements. In this method, a supervised binary classifier is built by training it over data collected. This trained classifier is used for identifying masonry points and thereby removing erroneous points from a point cloud, eventually producing better progress estimate. The study has been done for masonry construction, but can be extended to other types of construction.

2 Problem Statement

The aim of the paper is to develop an approach to reduce erroneous points generated in 3D reconstruction. Thus, it trains a classifier to reduce false positive in the 3D point cloud model reconstructed. The study also deals with the impact of the different site conditions like lighting, and different data collection parameters, like the speed of capture, yaw of the camera, the pitch of camera, etc. on the 3D reconstruction and progress estimate. The methodology developed needs to be independent of these parameters.

3 Review of the literature

Laser scanning and photogrammetry are two popular techniques for obtaining as-built point cloud of a construction site. Although laser scanning produces dense point clouds capturing tiniest details of the site, it is very costly. On the other hand, though the camera has the drawback of lower geometric accuracy; flexibility to use and cost-effectiveness makes them a favorable choice. Bohn & Teizer have explored advantages and challenges of camera-based progress monitoring [9]. The efficacy of stereo vision cameras to obtain as-built point cloud model using 2D images and depth map has been studied and proved by various researchers. [10]–[12]. Thus, imaging (stereo vision camera) system is used to obtain input for the as-built modeling stage.

The accuracy of reconstruction has a crucial impact on the progress estimate. The reconstructed models are highly corrupted with outliers and missing values because of imperfect conditions in which scanning is done, for instance, the motion of the object, multiple reflections, object occlusion, etc. Therefore, the output of the data acquisition step, that is reconstructed point cloud model, needs to be processed and analyzed before feeding to the next step of information retrieval and progress estimation. The standard tasks involved in pre-processing of point cloud data are (1) Outlier removal, (2) Handling missing value and (3) Reducing noise (or smoothening) of data [13]. For large point clouds, downsampling through voxelization is done, in order to reduce the computational time and cost.

Outlier removal for point cloud is a non-trivial task because of following reasons: geometrical discontinuities, no apriori knowledge of outlier distribution, and varying local point density [14]. Outlier removal methods in literature are mostly based on local properties of points, popularly calculated using density-based approach [15] and distance based approach [16]. Some of the local statistics are local point density, nearest neighbor distance, eigenvalues of the local covariance matrix, etc. [17]. Wang et.al, proposed connectivity-based and clustering approach for detection of outliers [14]. Similarly, the point cloud is processed for noise smoothening, involving noise filtering and point update.

The processed as-built point cloud is to be compared to as-planned BIM model for progress estimate. There are two ways to do the comparison: (1) convert the point cloud model in BIM model (involving semantic segmentation and object recognition) and compare, (2) convert the as-planned model to point cloud format and compare. In this paper, latter is adopted progress estimation.

It is worthy to note that in almost every data pre-processing techniques, no apriori knowledge of error (i.e. outliers) distribution is used. Thus, though these techniques help in cleaning data to an extent, they cannot

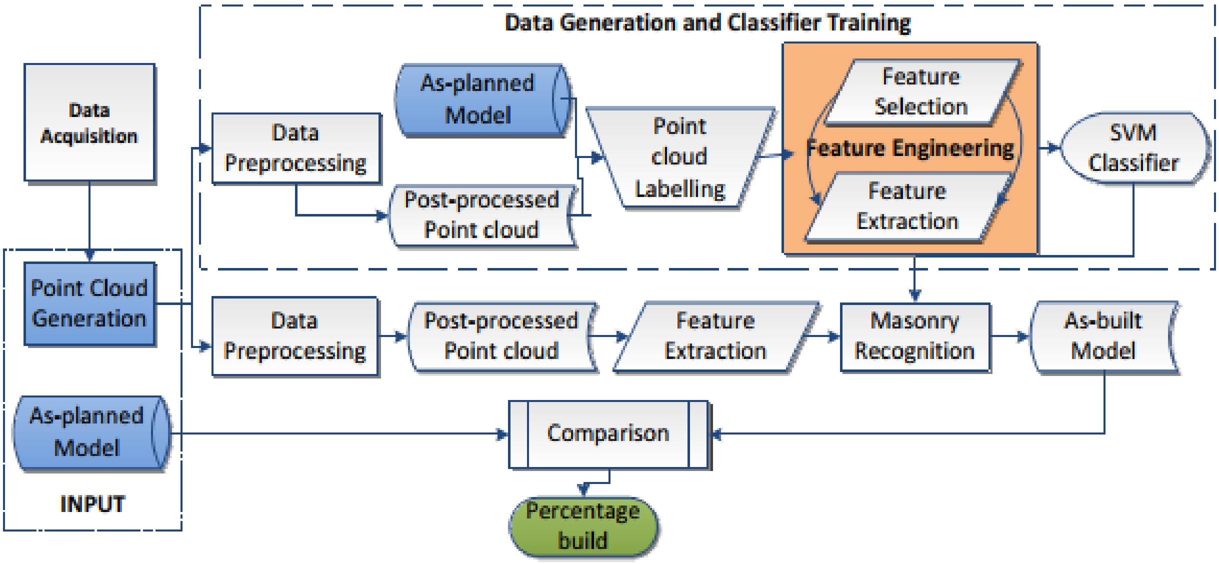


Figure 1. Proposed Methodology

remove incorrectly reconstructed points which are dependent on the methodology followed for reconstruction, data collection technique, and site conditions. In this paper, we propose a method to learn the characteristics of the construction materials and elements and use this knowledge to detect the same, and thereby removing the erroneous points. The erroneous points are detected using machine learning technique. This detection is posed as standard binary classification problem to classify between normal and erroneous points, which is solved by training a classifier based on local and contextual features (which are discussed in detail in later sections).

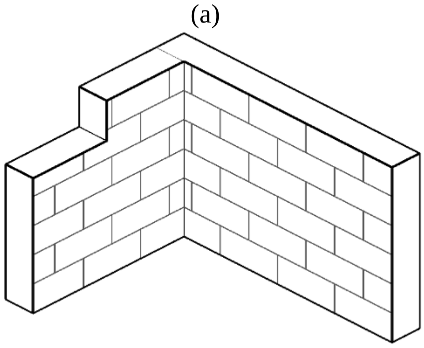
4 Methodology of Research

In this research, we focus to improve the as-built model reconstruction accuracy. In addition to, data pre-processing, the point cloud is subjected to supervised binary classification for construction material detection. This detection method has two-fold advantages – First, it eliminates the need to manually assign threshold values, which requires expertise. Second, it enhances the ability to scale the method, as this can be easily re-implemented after re-training. The proposed methodology excluding data acquisition and pre-processing (outlier removal and noise smoothing), can be divided into four components: (1) Data generation, (2) Feature Engineering, (3) masonry recognition using machine learning based supervised classification, (4) progress estimation and evaluation. Each of the above components are discussed in detail in the following sub-sections:

4.1 Data generation

This is the first step in the proposed framework. The input to this method is point cloud data and corresponding BIM model. The point cloud is annotated

(a)



(b)

Figure 2. A sample of 3D models used for data generation (a) as-built model showing erroneous points marked in yellow (b) as-planned model corresponding to the model in figure 2(a).

using BIM model as ground truth. Instead of following the common strategy for point cloud labeling, which involves over-segmenting the data and then assigning labels to segments. The data is annotated pointwise, considering two-fold advantages – (1) to avoid inheritance of error from segmentation step (2) to prevent classifier from learning hand-crafted rules of segmentation algorithm, when used for training [18].

3D annotation is done by manually comparing the point cloud model with the BIM model. The two models are overlapped and annotation is done view-by-view. A view is fixed and in this view, all the points lying within the boundary of BIM model, with a small tolerance value, are marked as normal while the rest of the points are marked as erroneous. This process is iteratively repeated for different views until all the possible views are covered. The problem with this way of annotation is that, same points appear in different views, appearing erroneous in one view and normal in another. To tackle this problem, a point is marked normal if it appears normal from all possible views and erroneous if it appears as erroneous from any possible view. Eventually, the point cloud is separated and labeled into two classes – “normal” and “erroneous”.

4.2 Feature Engineering

Performance of any machine algorithm is only as good as the ability of the features (or parameters) used to distinctly define the underlying distribution. In this regard, we attempt to learn a list of features which can be used to identify point corresponding to masonry in a point cloud. Rashidi et.al., realized three categories of construction materials depending upon appearance and color features[19]. Thus, discriminating features are learned for masonry data through an iterative process of, feature extraction and feature selection. The types of features learned are spatial and color, which are discussed below:

4.2.1 Spatial Features

These features are used to model the geometrical properties, like angles, distances, and angular variations, of masonry data. In a 3D point cloud, these features for a point in space is calculated by considering the spatial arrangements of data points in the neighborhood. The neighborhood can be assumed to spherical [20] or cylindrical [21] with a fixed radius. The neighborhood can also be selected based on k-nearest neighbor, depending on 3D-distance from the query point, where $k \in \mathbb{N}$ [22]. For classification, spatial features were calculated for fixed radius spherical neighborhood. In order to obtain appropriate and uniform features across different data models, features are calculated at a fixed scale.

Neighboring points in a 3D model are known to be correlated and interdependent [23]. And therefore in order to capture this correlation, apart from individual features, some of the features are obtained which take this interdependency into consideration. Some of the features which are used are:

- **Individual**: Normal, local point density
- **Contextual**: Fast point feature histogram (FPFH) descriptor

FPFH descriptor is calculated in two steps: (1) for every point p, relationships are calculated between the neighbor and the query point, this histogram is named as simplified point feature histogram, SPFH. (2) In this step, for each of the query point, its nearest k neighbors are found, and FPFH is calculated using equation (1)

$$\mathrm{FPFH}(p)=\mathrm{SPFH}(p)+\frac{1}{k}\sum_{i=1}^{k}\frac{\mathrm{SPFH}(p_k)}{w_k} \quad (1)$$

where, k represents the number of nearest neighbors to a query point, w_k represents the distance between the query and the neighboring point.

Figure 3 illustrates the influence diagram of a point and highlights the neighborhood of a point which contributes the feature at that point [24]. These features are computed using Point cloud library [25].

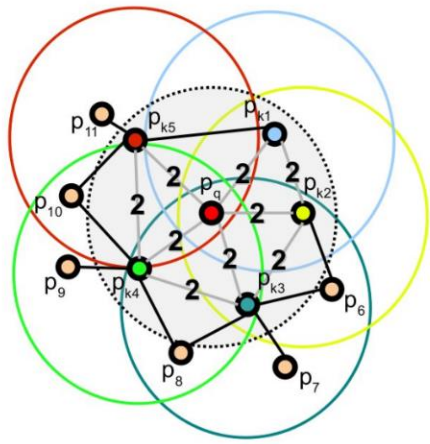


Figure 3. Influence diagram of FPFH to capture the interdependence of the neighboring points in the 3D point cloud [24]

4.2.2 Color Features

For the recognition of masonry, color values are very effective feature given its distinctive bright red color. It serves as an effective indicator for differentiating masonry from rest of the objects found on a construction site. However, it is worthy to note here that though the color value for a given does not vary drastically in a given point cloud, it might vary significantly when the same material is compared from two different point clouds, captured for different site conditions. This is illustrated in figure 4.

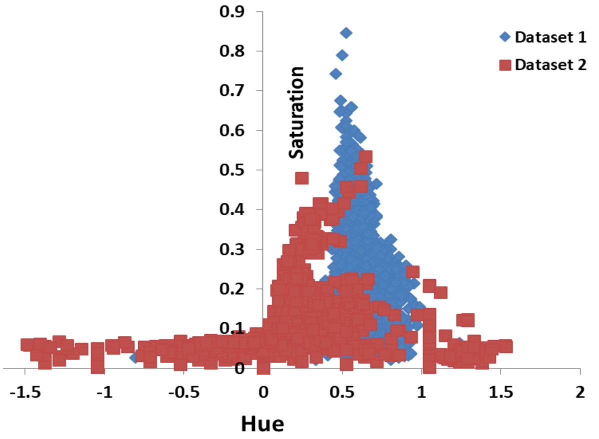


Figure 4. Hue and Saturation plot for two different datasets, collected under different conditions

The color values are obtained in the RGB space. Though these are most widely used color space, these RGB values are susceptible to a high variation on exposure to the same object under different illumination. And since illumination is an uncontrolled construction environment is ought to vary, dealing with these variations is highly important to produce effective results. Therefore, in this study, we have transformed the color space from RGB to HSI. It is compelling to make this transformation because: (1) it is very intuitive as it is similar to the way in which color is perceived by humans, (2) it separates the chrominance (color) and luminance (intensity) information, which has proved to be advantageous in image processing application. Hue (H) and Saturation (S) correspond to the color component of the RGB space, whereas Intensity (I) represents the illuminance-dependent part. Therefore, hue and saturation provide a good parameter for classifying masonry points from the rest. The color is changed from RGB to HSI using following equations:

$$H = \arctan \frac{\sqrt{3}\,(G-B)}{(R-G)+(R-B)} \tag{1}$$

$$S = 1 - 3\,\frac{\min(R,G,B)}{R+G+B} \tag{2}$$

$$I = \frac{1}{3}(R+G+B) \tag{3}$$

4.3 Masonry recognition

For the recognition of masonry in the point cloud, the pre-trained binary classifier is used. The following sub-sections explain the details of the classification.

4.3.1 Classifier training

An SVM classifier is trained over a training dataset generated using the method explained in data generation step. Instead of using voxel-based approach for training, a point-based approach is used. Despite the computationally costly and time-consuming nature of point-wise training, it is acceptable because: (1) it helps in improving recall values while detecting concrete points, (2) training is a one-time process, to be done during the setting up of the system. Hence, selection of the approach was done based on accuracy rather than computational cost.

Since the classification boundary was non-linear, Radial Basis Function (RBF) kernel was used. The parameters C and γ are to be determined for RBF kernel SVM model. C is regularization parameter and γ is kernel parameter [26]. In order to validate the results obtained using the training set, an independent validation set is used, which was obtained using a method similar to training data.

4.3.2 Masonry detection

The classifier obtained in section 4.3.1 is used for detection of points corresponding to masonry points in the post-processed point cloud. Features are extracted from the input 3D point cloud data (different from the data used for classifier training) depending on which classification is done. The point cloud is separated and classified as in two classes: “normal” and “erroneous".

4.4 Evaluation

For evaluating the performance of the system, two popular measures – Precision and recall are used.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

Where, TP represents true positives, a number of points that are correctly predicted, belonging to the normal class, FP represents false positive, points which are predicted as normal but are actually erroneous, FN represents false negative, points which are erroneous but are predicted as normal.

5 Preliminary results

Based on the study, it is observed that colour features are distinctly different for both classes and therefore contribute most to the classification results. This is attributed to rich colour properties of a masonry construction. The erroneous points are observed to have low values of hue and saturation. The performance of the system with only colour features used for the training of the classifier is 69% in precision and 72% in recall. This result of colour acting as dominating feature in masonry detection is in coherence with different studies done in the past [12] [27].

The value of the evaluation metrics obtained in the preliminary study is given in Table 1. These results were obtained using all the features discussed in Section 4.2. The precision and recall values obtained are low in comparison to other studies which were conducted using 2D images as the dataset. These low values are the result of low point density in comparison to a high pixel density of an image. Moreover, training dataset used for training of the classifier was small in number. Therefore, these values need be improved further by using a larger training dataset, which is representative of the entire population of variations causing erroneous points reconstruction.

Table 1. Precision and recall value obtained from the test dataset

Metric	Percentage (%)
Precision	73.1
Recall	77.3

6 Conclusion and Future work

This study has presented an automatic system for information retrieval and progress estimation, with a goal to improve progress estimate by introducing a step of construction elements/material recognition. Masonry brick wall is used as a construction element in the study. The work needs to be extended to other construction materials/elements. A larger dataset needs to developed which can be used produce better results by employing data-intensive machine learning techniques, like tree family algorithms and deep learning algorithms. In future work, apart from geometric and colour features, texture features and other local geometric features needs to be explored in order to obtain better results. Although stereo vision-based imaging was employed for the study, the proposed methodology is expected to perform equally well irrespective of the technique used for data collection, as long as inputs are in the form of 3D point cloud with colour features. Moreover, detection of construction material can help in case of occluded scenes, where the building is to be separated from the rest of surrounding.

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