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Local quality assessment of point clouds for indoor mobile mapping

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ABSTRACT

The quality of point clouds obtained by RGB-D camera-based indoor mobile mapping can be limited by local degradation because of complex scenarios such as sensor characteristics, partial occlusions, cluttered backgrounds, and complex illumination conditions. This paper presents a machine learning framework to assess the local quality of indoor mobile mapping point cloud data. In our proposed framework, a point cloud dataset with multiple kinds of quality problems is first created by manual annotation and degradation simulation. Then, feature extraction methods based on 3D patches are treated as operating units to conduct quality assessment in local regions. Also, a feature selection algorithm is deployed to obtain the essential components of feature sets that are used to effectively represent local degradation. Finally, a semi-supervised method is introduced to classify quality types of point clouds. Comparative experiments demonstrate that the proposed framework obtained promising quality assessment results with limited labeled data and a large amount of unlabeled data.

1. Introduction

Indoor 3D models are essential sources in acquiring information for many applications such as earthquake rescue tasks, cultural heritage protection, and intelligent building design. The quality and accuracy of creating an indoor 3D model are influenced by the quality of data collected from the real world. Point cloud data, a way to describe the 3D indoor environment, are widely exploited in building indoor 3D models [1–5]. With the rapid development of indoor mobile mapping systems (IMMSs), many IMMSs have been used to collect indoor point cloud data [6–10]. Typical IMMSs include wheeled mobile systems, backpacked mobile systems, and hand-held devices, etc. The wheeled mobile system smoothly integrates multi-sensors, including cameras, laser scanners, and inertial measurement units on a mobile platform, e.g., pushcart or robot. In the backpacked mobile system, the user backpacks a multi-sensor integrated system to collect data in motion. In the hand-held system, a data acquiring device, e.g., Kinect, is held by users when acquiring data. This way, it is convenient for these hand-held devices to collect data under certain conditions, especially in areas that are difficult for other IMMSs to access. In our proposed framework, the dataset is collected by a Kinect camera mounted on a mobile robot [7].

Some quality problems, or data degradation, such as missing data, occluded data, sparse data, blurred data, and very dark or very bright data, are inevitable for IMMS point clouds. Causes of data degradation include the characteristics of the sensing device, large rotation angle of the mobile platform in motion, and uneven illumination distribution in an indoor environment. Compared with image degradation, the reasons for the degradation of point clouds differ in different local areas, leading to an uneven distribution of point cloud quality. Moreover, different reasons of degradation lead to a diverse degradation of point clouds. Therefore, the qualities of point clouds have the characteristics of diversity and locality for indoor mobile mapping.

The local quality assessment of point clouds are to handle the data quality assessment by considering the diverse and local degradation of the IMMS point clouds. In general, good indoor point cloud data should not only have complete structure information but also maintain consistency between the appearance and structural information. Poor quality data need to be discriminated because they will not provide effective and sufficient information. However, in our dataset, there is an imbalanced problem, i.e., the amount of low-quality data is much greater than high-quality data. The local quality assessment of point clouds can classify these data into different degradation types and prepare for the further repair of these data based on different strategies. One main challenge for automated quality assessment of IMMS point clouds is the

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establishment of a training dataset in terms of time and cost. On one hand, it is difficult to classify different quality types in one point cloud by manually labeling because of the diverse and local degradation of point clouds. On the other hand, it is difficult, or impossible, to obtain the ground-truth (or reference data) without degradation, which indicates that our quality assessment problem needs to be considered in the absence of reference situations. Thus, it is essential to know how to use limited labeled data to predict the labels of a large number of unlabeled data. A semi-supervised learning method, i.e., a method requiring only a small amount of labeled training data, provides an efficient way to address this challenge.

In this paper, we propose a new framework to assess the local quality of indoor mobile mapping point clouds. First, we describe the IMMS point cloud degradation by geometric feature descriptors. To effectively analyze the essential components of these geometric feature descriptors, a feature selection method is integrated into the proposed framework to reduce the redundancy of these used features. To avoid the intensive labor costs of manual labels, a semi-supervised method, named Safe Semi-supervised Support Vector Machines (S4VMs) [11], is integrated into our proposed framework to conduct quality assessment tasks by manually labeling a small portion of the training dataset. Additionally, we establish a point cloud dataset (benchmark) with multiple kinds of quality problems to evaluate the proposed framework.

The rest of this paper is organized as follows: first, Section 2 reviews the related work; next, Section 3 details our proposed framework in three parts, including the establishment of a dataset with multiple kinds of quality problems, the feature description of the degraded data, and the local quality assessment of indoor point clouds; then, Section 4 reports the experimental results and presents the comparative experiments; finally, Section 5 concludes the entire paper.

2. Related works

Most recent works on data quality assessment focused on 2D images [12–16]. Xue et al. [12] established a codebook to assess the quality of images by computing quality-aware centroids of each patch in the training images. Ref. [13] presented a sparse feature representation method to learn a dictionary on the spatial correlations between training images. Two deep neural network methods in Refs. [15] and [16] were introduced to address non-referenced image quality assessment by incorporating a semi-supervised method and multi-scale directional transform, respectively. Compared with the great achievements of image quality assessment, the quality assessments of point clouds have been mainly focused on positioning accuracy [17–20]. Sander et al. [17] analyzed the relationships between the geometric quality of input point cloud data and the corresponding generated 3D models. In [18], a deviation analysis between the building information models and point cloud data was proposed to assess the quality of the models. In [19], the quality assessment of point clouds was considered as a spatial structure projection in coordinate planes and positioning accuracy, which represented the deviation between sign coordinates collected by a laser scanner and precise coordinates collected by the total station. Many researchers have conducted investigations on the quality assessment of Kinect depth data in recent years [21–22]. However, few research results have presented a systematic quality assessment of IMMS point clouds, thus raising the demand to establish a suitable benchmark for IMMS point cloud quality assessment metrics.

In the past decades, semi-supervised learning has attracted increasing attention [23–31] because only a part of the sample is required to be manually labeled for learning a statistical model. In [23], semi-supervised discriminant analysis (SDA) was exploited for both labeled and unlabeled data to reduce the dimensionality. Yu et al. [24] presented an adaptive hypergraph method for image classification by simultaneously learning the labels of unlabeled data and optimizing the weights of hyperedges. In [25], a stochastic learning method was proposed to address the image classification problem by acquiring a high-order distance from hypergraph and integrating labeling information from different views. Liu et al. [28] proposed a hypergraph model with adaptive probability to find related media content for media event enrichment task. In [27,30], and [31], hypergraph combined with sparse representation was introduced to address prediction or classification problems. In [11], S4VMs were presented to generate a multiple low-density separator pool and to maximize the performance of each candidate separator. S4VMs mainly focused on producing a safe model by a training dataset containing both labeled and unlabeled data. Compared with other methods, S4VMs have the advantage of a safe generalization performance. The safe of S4VMs is that its generalization performance is never statistically significantly worse than these fully supervised methods. In our proposed framework, we only use a small portion of labeled data to reduce labor costs and exploit S4VMs for considering both labeled and unlabeled data to learn a statistical classifier for quality assessment tasks.

3. Proposed method

3.1. Point clouds acquisition

An IMMS integrating a 2D laser scanner and a RGB-D camera is adopted for collecting 3D indoor point clouds in this paper [7]. The 2D laser scanner and RGB-D camera are used to build 2D map and to obtain point clouds, respectively. Moreover, this IMMS can achieve a 2D trajectory of the mobile platform while building the maps. However, the acquired data have some quality problems, such as missing data, occluded data, too sparse data, blurriness, and too much darkness or brightness. To deeply delve into these problems, the main reasons that lead to data degradation are detailed as follows.

The characteristics of the Kinect sensor include the limited measurement range of the sensor and the low image resolution of the camera (Fig. 1(a)). Unlike a hand-held camera system, our mobile robot-based IMMS acquires data while exploring the environment. In this case, when the moving speed of the mobile robot is too fast, data quality may be decreased because it is difficult to ensure that the RGB and depth images are synchronous. This RGB information drift may result in blurred data (Fig. 1(b)). Moreover, when the mobile robot is too close to (or too far away from) perceived objects in the measuring range, the acquired data density will be too dense (or too sparse) (Fig. 1(c)). Uneven illumination in an indoor environment is shown in Fig. 1(d). For example, some place may separate into different areas with different illumination conditions by object occlusions or by being close to (or far away form) the light source when acquiring data in motion. Certain perceived objects, such as transparent and refractive objects (e.g., glass, monitors, etc.), possess obvious degraded quality problems, while the smooth surfaces and non-refractive objects are almost invisible (Fig. 1(e)). The structure and feature details of the perceived objects are incomplete (Fig. 1(f)). For example, the bent arm of a chair will not be detected because of its irregular structure. Furthermore, detailed structural information of a small table pot will be missing because of the complicated structure of the pot.