FEATURE SELECTION FOR QUALITY ASSESSMENT OF INDOOR MOBILE MAPPING POINT CLOUDS

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ABSTRACT

Owing to complexity of indoor environment, such as close range, multi-angle, occlusion, uneven lighting conditions and lack of absolute positioning information, quality assessment of indoor mobile mapping point clouds is a tough and challenging task. It is meaningful to evaluate the features extracted from indoor point clouds prior to further quality assessment. In this paper, we mainly focus on feature extraction depend upon indoor RGB-D camera for the quality assessment of point cloud data, which is proposed for selecting and screening local features, using random forest algorithm to find the optimum feature for the next step's quality assessment. First, we collect indoor point clouds data and classify them into classes of complete or incomplete. Then, we extract high dimensional features from the input point clouds data. Afterwards, we select discriminative features through random forest. Experimental results on different classes demonstrate the effective and promising performance of the presented method for point clouds quality assessment.

Keywords: quality assessment; point clouds; feature extraction; random forest

1. INTRODUCTION

Images usually are only considered a degraded reason because the quality of the image is usually consistently distributed. Comparing with two dimensional images, degradation reasons of point clouds data have great difference in different locality, which lead to the extremely uneven of quality distribution of point clouds. Besides, degradation has diversity, i.e. different degradation reasons lead to significantly different degradation phenomenon. As point clouds data is obtained in indoor mobile environment, there exists degradation diversity and locality. Thus, the evaluation of point clouds quality can potentially improve point clouds quality. Data-oriented recovery of point clouds data quality assessment cannot be obtained before the degradation, which is a kind of quality assessment in the absence of reference conditions. Another difficulty of point cloud data quality assessment is the limitation of labelled samples for available quality assessment modeling. At present, oriented data processing is seldom mentioned in literatures.

Regarding the problem of indoor point clouds feature selection, evaluating the quality through the overall feature descriptions makes local information overlaid or averaged by statistical methods, which leads to the loss of some information about the global scene (e.g. spatial positions). Therefore, it is inappropriate to evaluate the quality of point clouds in a global scheme. We must evaluate the point clouds quality in a local way. For example, we can split an indoor point clouds scene into dozens or hundreds of voxels, from which we extract features.

The significant features of the scene and structure features of the point clouds are meaningful in quality assessment. Generally, the significant features include HOG, SIFT, color Histogram and DAISY. The structure and geometric features of the point clouds include spin image, FPFH and shape context, etc. When utilizing the above-mentioned methods to extract tremendous features of point clouds, the evaluation of the quality of indoor point clouds based on effective features becomes important. In this paper, we present a method that can effectively select local features with random forest algorithm to find an optimum analysis, serving for the quality assessment of indoor point clouds depending on RGBD camera. Consequently, we obtain the best features that can be applied to next stage of point clouds quality assessment.

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The remainder of this paper is organized as follows. In section II, relative work is reviewed. In section III, the indoor point clouds feature selection method is presented, which mainly introduces the data acquisition, feature extraction, and feature selection using random forest. In section IV, experimental results are demonstrated and discussed. Conclusions and future works are given in section V.

2. RELATED WORK

Currently, researches related to indoor mobile mapping mainly focus on how to carry out effective systems integration and build 3D indoor mapping based on the original point cloud data. However, few papers consider the enhancement of point cloud data quality by post processing methods. In some literatures, it has been believe that the quality of the automotive and airborne point clouds data in the long-distance are equal to accuracy. For the analysis of the spatial structure, Feng et al. analyzed the spatial structure of objects in 3D coordinate axis projection to determine the quality level of point clouds data for the position accuracy. In their research, they compared control point coordinates which collected by laser radar system and total station to determine position accuracy [1]. Luethy et al. put forward a comprehensive way to evaluate point cloud data from precision, application requirements, defects of point cloud data, and integrity [2]. Sander et al. analyzed the impact of the quality between the input point cloud data and the quality of 3D model corresponding, and evaluated the quality of point cloud data based on 3D model [3]. Habib et al. used the inconsistencies between conjugate surface elements of two parallel point cloud belts to evaluate the quality of airborne laser scanning point cloud data. The causes of inconsistency by diagnosis provide the basis for optimizing mapping system to improve the quality of the point clouds data [4]. Most literatures related to quality assessment of laser scanning point clouds data are focusing on global quality assessment. The purpose of the evaluation is to verification and calibration for the system, but there are few works about local quality evaluation of 3D indoor mobile mapping.

Dalal and Triggs [5] first described HOG descriptor significantly outperform existing feature set for human detection. Lin et al developed a Hadoop scheme that performs feature extraction, which combine dense HOG and LBP, in parallel using hundreds of mapper [6]. Kobayashi used bag-of-features and HOG to extract features for image classification. Chiu et al. proposed a layer parallel SIFT with integral image, and its parallel hardware design with an on-the-fly feature extraction flow for real-time application need [7]. Sun et al contributed an efficient feature extraction and matching implementation for large images in large-scale aerial photogrammetry experiments [8]. Mansor proposed a PCA-based feature extraction and k-NN algorithm for early jaundice detection, employing PCA method to study the behavior of the infant [9]. Naikal proposed a new solution to select informative object features using sparse PCA, and the experimental result showed that it can successfully identify important visual features that explain the maximum variance in the visual histograms [10]. Random forest is an ensemble learning method for classification and regression, which was introduced to select features in [11], [12] and [13]. Random forest used bootstrap, which is the random resampling technique, and node random splitting technique to build multi decision trees, to get the final classification result by voting [12].

3. METHODOLOGY

The feature selection algorithm proposed here includes two steps. First, we collect indoor point clouds data and classify them into different classes of complete one and incomplete one. Then we extract high dimensional features from input point clouds data, including FPFH feature, spin image feature, and spectral shape feature, etc. After that, we select discriminative features using random forest algorithm.

3.1 Data acquisition

We adopt a hand-held RGBD camera for indoor point clouds data acquisition. The operator holds RGBD camera to collect point clouds data when walking in an indoor area. RGBD depth camera has the advantages of light weight and low cost, and it is widely used in the 3D indoor mobile mapping [14]. For example, 2D laser radar has been merged with RGBD camera to design 3D indoor mobile mapping system that is based on wheeled mobile platform [15]. Fallon et al. designed a portable mobile mapping system using a 2D laser radar, IMU, barometer and RGBD cameras, which can provide real-time mapping for emergency response, and the system can obtain multi-floors building map by detecting transition of floors [16]. Barchrach et al. put a RGBD camera on a small helicopter to build 3D indoor point cloud model [17]. However, due to the limitation of work ranging and poor imaging performance of RGBD camera, it is difficult to capture fine details of 3D environment by using RGBD camera.

3.2 Feature Extraction

Firstly, indoor point clouds data have been segmented into dozens or hundreds of patches. Afterwards, we classify these patches into different categories by manually labelling. The patches are separated into two classes to construct training set: one set with high-quality patches and one set with inferior ones. Finally, feature descriptors are drawn from every single patch.

In this paper, we extract five kinds of features including FPFH, spin image, spectral shape, orientation, and bounding box. The total feature dimension is 232.

FPFH descriptor represents the geometry around a specific point by computing its surface normal and curvature estimation [18]. P_s is a source point, P_t is the query point, n_s and n_t are the surface normal of point P_s and P_t, respectively. Using the formula (1), a coordinate frame denoted as u-v-w was fixed at the source point (P_s). And we can compute a set of tuples $< \alpha, \varphi, \theta, d >$ from the formula (2) to describe the relation difference between two points P_s and P_t. Firstly, we compute only the relationships (see formula (1)) between P_q and its neighbors (P_k), and this process was called Simplified Point Feature Histogram (SPFH). Next, we compute the neighboring SPFH values of P_k to weight the final histogram of P_q as the formula (3). In this paper, we use quadruplets $< \alpha, \varphi, \theta, d >$ and divide the trigonometric circle into 2 bins, so the FPFH descriptor has 16 dimensions.

$$\mu = n_s, \nu = \mu \times \frac{(P_t - P_s)}{d}, d = \|P_t - P_s\|_2 \tag{1}$$

$$\alpha = \nu \cdot n_t, \varphi = \mu \cdot \frac{(P_t - P_s)}{d}, \theta = \arctan(w \cdot n_t, u \cdot n_t) \tag{2}$$

$$\mathrm{FPFH}(\mathrm{P_q}) = \mathrm{SPFH}(\mathrm{P_q}) + \frac{1}{k}\sum_{i=1}^{k} \frac{1}{w_k} \cdot SPFH(\mathrm{P_k}) \tag{3}$$

Spin image descriptor is mainly used for surface matching and object recognition of 3D scenes [19]. The spin image of the query point P_q can be computed by projection $<\alpha_i, \beta_i>$ of its neighbors (P_k) on its tangent plane. In this paper, we use 13 rows and 16 columns, so the spin image descriptor has 208 dimensions.

Spectral shape descriptor is implemented in spectral analysis of point clouds for three geometric features [20]. For the query point P_q, we select k neighbor points of radius r, and then calculate the covariance matrix using formula(4). Where $\bar{P}$ represents centroid position of the k neighbor points of P_q. And τ_j and $\vec{v}_j$ represent the j^{th} feature value and feature vector in the covariance matrix, respectively. The smallest component of $\vec{v}_j$ refers to the normal vector of P_q. The curvature of P_q is represented as formula (5). The feature vector is (S, L, F), where S, L and F represent the scatter-ness, the linear-ness and the flatness of a local neighborhood around interest points. In addition, this spectral shape descriptor is used to compute in orientation descriptors which contain 2 dimensions: one represents the normal orientation and the other represents tangent orientation.

$$\mathrm{Cov} = \frac{1}{k}\sum_{i=1}^{k}(P_q - \bar{P})(P_q - \bar{P})^T,$$

$$\mathrm{Cov} \cdot \vec{v}_j = \tau_j \cdot \vec{v}_j, \mathrm{j} \in \{0,1,2\}\,. \tag{4}$$

$$\mathrm{C}_{P_q} = \frac{\tau_0}{\tau_1 + \tau_2 + \tau_3} \tag{5}$$

Bounding box descriptor denoted as (a, b, c) is computed in principle component space, where a, b and c represent the length along the principle eigenvector, the middle eigenvector and the smallest eigenvector, respectively.

3.3 Feature Selection

Classification accuracy of Out-of-bag (OOB) data are usually used to measure variable importance in random forest [21, 22]. The variable importance of features can be computed as formula (6). Assumed that we have samples $\mathrm{b} = 1, 2, \cdots, B$, and $\bar{D}_j$ represents the variable importance of j^{th} feature. Besides, R_b^{oob} represents the number of correct classification using decision tree T_b, and $R_{b_j}^{oob}$ represents the number of correct classification after permuting j^{th} feature. We can get the ranking of features by formula (6). Every time, we deleted the last five features of the raking to build a new feature subset. And then the feature subset was used to train the random forest classifier. The advantage of feature subset can be judged by classification accuracy of random forest.

$$\overline{D}_j = \frac{1}{B}\sum_{b=1}^{B}(R_b^{oob} - R_{b_j}^{oob}) \quad (6)$$

4. EXPERIMENTAL RESULTS

The proposed algorithm is tested on point clouds data of different office scenes. The data used in the experiments was collected by Kinect for Windows, which is a RGBD camera. Program was implemented in Visual studio 2012 and Weka (Waikato environment for knowledge analysis, Version3.7.11, [23]) on a Window 7 64 bit platform. The hardware system is a computer with a CPU clock rate of dual-core 3.20 GHz and 4GB main memory.

4.1 Labelled Data

In order to process point clouds data conveniently, we used CloudCompare, which is an excellent software in 3D point cloud and mesh processing, to obtain labelled data. This processing is exhibited in Fig. 2. Fig. 2(a) shows the original point clouds data. According to the human cognition, we segmented the original data into two parts as shown in Fig. 2(b), one of which contains high-quality part and the other with the inferior ones. Finally, as shown in Fig. 2(c), we used Octree class in OpenCV library to segment each part into dozens or hundreds of patches, and these patches were classified into different categories. In this process, we set the voxel cell size as 0.2. Thus, these patches have their own labels, i.e. we labelled the high-quality patches with 0 and the inferiors with 1. In this paper, we used 306 point clouds scenes, which were finally divided into 34052 patches. Both the two classes of 0 and 1 had 17026 labelled patches.

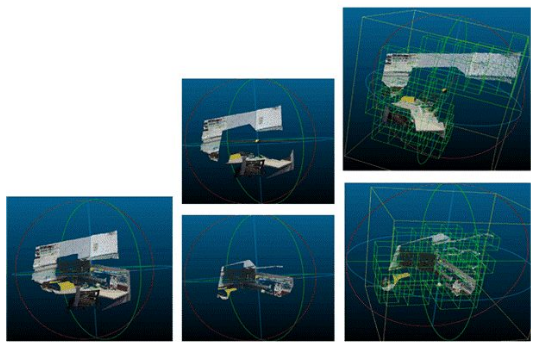

Fig. 1. Labelled data. (a)The original point clouds data. (b)After segmentation, we get two parts, one of which contains high-quality part and the other class includes inferior ones. (c)Each part segments into dozens or hundreds of patches and these patches are classified into different categories.

4.2 Feature Contribution Analysis

To ensure the stability of the experimental results, we used 10-fold cross-validation for result analysis. The data set was divided into 10 parts, 9 of which were used to build a random forest classification and the rest was used for validation. In this process, we selected feature contribution rate sequence of the highest classification accuracy of iteration as a criterion for deleting features. The average classification accuracy of 10 iterations was regarded as the final classification accuracy. Classification accuracy can be computed as formula (7), where TP, TN, FP and FN represent true positive, true negative, false positive and false negative, respectively [21].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Fig. 2 shows the contribution rate of each dimension feature in random forest. From Fig. 2, we know that FPFH descriptors have lower contribution rates, which lead them to be deleted in feature selection process. Though FPFH descriptors can be computed extremely quickly and easily, most scenes contain many points with the same or similar feature values, reducing the global informative characteristics [18]. Both the spectral shape descriptors and orientation and bounding box descriptors have relatively high contribution rates. Thus, they are important features to get better classification accuracy.

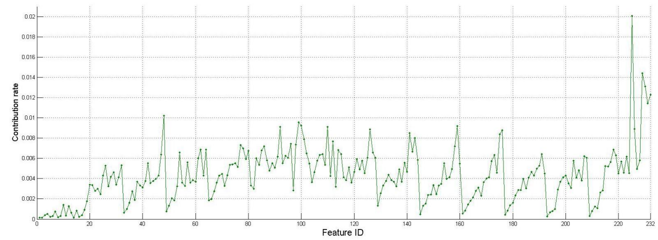

Fig. 2. The contribution rate of each dimension feature in random forest.

4.3 Performance Comparison

The performance comparison results using random forest and PCA methods are shown in Fig. 3, Fig. 4 and table. 1. Fig. 3 shows the relationship between the cumulative contribution rate and feature number of three methods. And Fig. 4 shows the relationship between classification accuracy and feature number of three methods. In these figures, the green line represents random forest while the red one represents PCA. In addition, the blue line represents InfoGainAttributeEval, which is a single-attribute evaluator based on information gain in WEKA. After sorting the contribution rate of each feature dimension, we computed the cumulative contribution rate. As illustrated in Fig. 3, PCA has higher cumulative contribution rate than the others with the same feature number. For example, when feature number is 15, cumulative contribution rate of PCA is 0.534 while random forest and InfoGainAttributeEval are 0.163 and 0.171.

In this paper, we sort feature in every dimension according to its contribution rate, then delete the last feature in the sequence. As shown in Fig. 4, the contribution rate starts to decrease from feature number 146, along with removing trivial characters successively, classification accuracy present a gradually raise as a whole. When the feature numbers of random forest, PCA and InfoGainAttributeEval are 90, 30 and 30, the classification accuracy percentages are 87.56%, 80.89%, and 83.28%, respectively. The elevation of classifier performance is generated by irrelevant features and elimination of redundant characters. Since achieving peak value, the classification accuracy appears downtrend because some important features have been erased. When the feature number is 30, PCA and InfoGainAttributeEval get the best classification accuracy 80.89% and 83.28% while random forest is 86.10%. To sum up, comparing with the above two algorithm, random forest demonstrates stronger classification capability to recognize and eliminate redundant or irrelevant features.

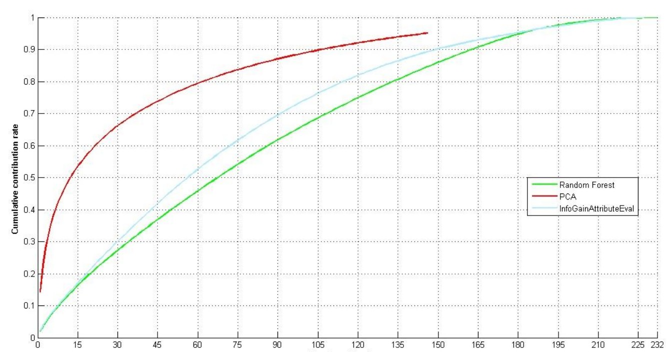

Fig. 3. Relationship between the cumulative contribution rate and feature number.

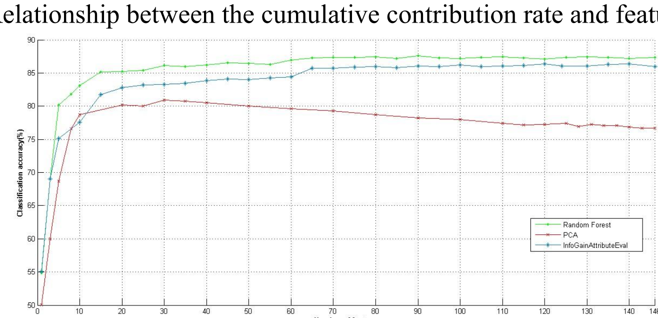

Fig. 4. Relationship between classification accuracy and feature number.

Table 1 lists the performance comparison of computational timing and accuracy among random forest, PCA, and Original features. The features column in the table shows the number of selected optimal feature subset, and the class column represents the category number of experimental data. The time column shows the time taken to build model. At last, the accuracy column represents the performance of classification accuracy.

Table 1. Performance comparison of different algorithms

Method	Feature	Classes	Time (s)	Accuracy (%)
Random Forest	90	2	27.31	87.56
	30	2	25.86	86.10
PCA	30	2	48.48	80.89
InfoGainAttributeEval	30	2	24.54	83.28
Original	232	2	29.38	86.37

From Table 1, we can see that random forest, PCA, InfoGainAttributeEval and original features have their best classification accuracies with 87.56%, 80.89%, 83.28% and 86.37%, respectively. The corresponding feature numbers used were 90, 30, 30 and 232, respectively. Compared to original features, random forest used less features and time to obtain the better classification accuracy. On the other hand, PCA reduced the feature number from 232 to 30, but got the lower accuracy and cost more time. When we used random forest and PCA method to select 30 optimal features, our method got the higher classification accuracy with a shorter time. From what have analyzed, we can easily come to the conclusion that random forest have effectiveness and promising performance on feature selection for indoor point clouds quality assessment.

5. CONCLUSION

In this paper, we focus on feature selection for the quality assessment of point cloud data based on indoor RGBD camera. We use random forest algorithm to find the best analysis to get the optimum features for the next step's quality assessment. Compared to PCA method, experimental results on different classes show that the effectiveness and promising performance of the proposed method for point clouds quality assessment. The major contribution of this paper lies on the application of local quality evaluation in the field of point clouds data. Furthermore, we introduce random forest to effectively select vital features and achieve good performance.

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