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Evaluation of the Multi-scale Feature of Point Cloud for Underwater Object Recognition

Yi-Horng Lai, Chia-Ming Tsai, Jau-Woei Perng and Yung-Da Sun

***Abstract*— In this paper, we evaluate the multi-scale PCA feature characteristics of point cloud and apply the feature in the underwater object recognition task. We analyses the raw point cloud from ModelNet database and compare the multi-scale feature among interested category. We also device the underwater experiment to evaluate the proposed algorithm. The result of experiment demonstrate the potential of multi-scale PCA feature in underwater object recognition task.**

***Keywords*—PCA, multi-scale, underwater, object recognition**

I. Introduction

Underwater sensing is an important issue in oceanic research field. The optical and acoustic instrument are the most popular sensors used for underwater sensing. The 3D passive optical sensors include underwater RGBD camera and stereo photographical camera. Due to the limited visibility in the water environment, the passive visual based sensor has only effective in the close range. Active range sensors, based on time-of-flight (ToF) principle, can detect object and measure the time delay between radiation and reflection. The point cloud can directly generated from the active scan [1-3].

Although the point cloud can reflect the geometrical appearance of object, the quality of point cloud dataset will suffer from undesirable scattering signal, such as missing data, heterogeneous density, overlapping points and noise. For these reasons, a lot of point cloud operation approaches were proposed to salve the aforementioned problem [4].

The high resolution 3D fusion model for underwater scene recognition and reconstruction was studied in [5]. First the 3D acoustic scanner provided a large scan of the interested scene. Then the high resolution depth map was merged from a set of underwater photograph through using the Scale Invariant Feature Transform (SIFT).

Yi-Horng Lai, Chia-Ming Tsai, Jau-Woei Perng
Dept. of Mechanical and Electro-Mechanical Engineering, National Sun Yat-sen University
Taiwan, R.O.C.
lai81.tom@gmail.com

Yung-Da Sun
Naval Meteorological and Oceanographic Office R.O.C.
Taiwan, R.O.C.

Scale invariant is an important criteria in feature extraction. The multi-scale algorithm of point cloud was used in [6]. The multi-scale characterizes is defined as the radius of sphere centered on each local point cloud. When the radius of the sphere vary, the geometry feature of local cloud across scales can be measured. The high accuracy rate of classification was shown in author's experiment results.

The traditional feature extraction approaches required the hand-crafted features cooperating with a machine learning classifier. The performance of hand-crafted feature usually limited in specific task. Recently deep learning approach have been intensively used in feature extraction researches. For example, Convolutional Neural Network (CNN), a kind of deep learning network, has been successfully utilized for image recognition. Following the success of image application on CNNs, the concept of 3D Convolutional Neural Network (CNN) have be extend from CNNs. The basic architecture of 3D CNNs include input layer, convolutional layer, pooling layer and fully connected layer. Training 3D CNN model does not require the feature knowledge of interested object. The benefit of 3D CNN include reducing the tedious labor for labeling or segmentation task [7, 8].

Similar 3D CNN approach include voxel CNN. First, by using the definition of orientation and resolution, the LiDAR data are converted into the volumetric representation. The binary state of voxel is decided by the occupancy model [9]. In [10], 3D ShapeNet used the probability distribution model to describe the binary variables of voxel grid. The public ModelNet dataset was used to train the Convolutional Deep Belief Network (CDBM) in training stage. The experiment result demonstrated the 3D geometric shape can be recognized.

While using volumetric representation, the data sparsity may constrained the resolution of the point cloud [9, 11]. In addition, due to lacking the appropriate and enough training dataset, the deep learning approach seldom be applied in underwater object recognition.

BlueView BV5000, a kind of 3D acoustical sonar, is an effective tool for underwater exploration. The 3D point cloud can directly generated from this sensor. The comparison of quantitative measurement between BV5000 and Terrestrial Laser Scanner (TLS) was evaluated in [12]. Through the tilt angle calibration and error correction, the detailed defect on underwater infrastructure can be found. For this kind of 3D sonar scanner, the more quantitative and qualitative assessment of underwater measurement can be expected.

In this paper, we evaluate the multi-scale feature characteristics of point cloud and apply the feature in underwater object recognition task. First we analyses the raw point cloud from ModelNet database. Then we compare the multi-scale feature among different categories. We also device the underwater experiment to evaluate the proposed algorithm.

The methodology of proposed approach are explained in Section II. The feature extraction procedure and experimental are described in Section III. In Section IV, we conclude and proposal the pointers to future work.

II. Method

Local dimensionality can describe whether the 3D point cloud looks like a line (1D), a plane surface (2D), or a voxel whose volume around the specific location (3D). The PCA feature extraction is a kind of pointwise approach. The points are from a sphere with a specific scale radius. Any point with nearby neighboring points represent a feature subset. Let the scale as the radius of a sphere centered on an interested point. The 3D point cloud dataset is defined as $\{PC_i = (x_i, y_i, z_i)\}_{i=1\cdots N}$. Through rearranging the Cartesian coordinates of dataset, the PCA feature of dataset can be extracted by using Principal Component Analysis (PCA) [6].

Let λ_i be the eigenvalues output by PCA analysis and sorted the magnitude λ_i in descend order as $\lambda_1 \geq \lambda_2 \geq \lambda_3$. Each eigenvalue λ_i represents the explainable variance corresponding to each reference axial. For 2D point cloud dataset, the first two eigenvalues are enough to represent the variance of the dataset. Moreover, the 3D dataset exist three eigenvalues to contribute the total variance. Therefore the proportions of eigenvalues $P_i = \frac{\lambda_i}{\lambda_1+\lambda_2+\lambda_3}$ can be defined as the local dimensionality at a given scale. The PCA feature space is dominated by the first two proportions of eigenvalues and shown in Fig. 1.

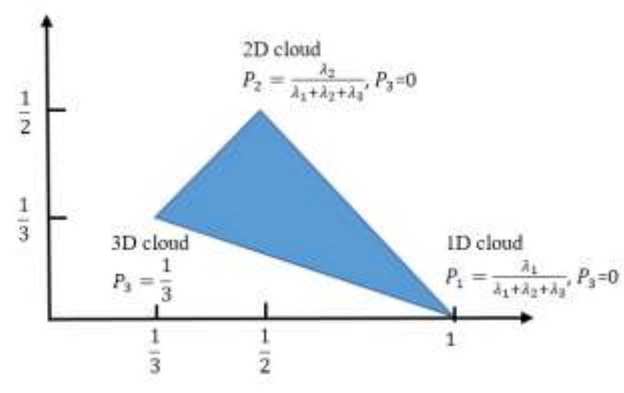

Figure 1. The PCA feature space

Sometimes, the user may not know the appropriate scale in the practical tasks. On the other hand, the point cloud dataset may be missing scales, especially in low point density. To overcome the problem mentioned above, the multiscale criterion, an adaptive radius variance process, had been performed in [6,13]. The main idea is to combine different PCA scale features and find the best separable feature for recognition task.

About the multi-scale criterion, we consider a target point with multiple spherical radius $R = \{r_1, \cdots, r_{Nr}\}$, Nr being the number of scale. Three PCA features are computed for each scale. For single scale criterion, the PCA feature vecter $P = [p_1, p_2, p_3]$ with dimension 3; For multi-scale criteria, $P_{ms} = [P_1^T, \cdots, P_{Nr}^T]$ with dimension $3 * Nr$. The latter case of P_i corresponds the PCA feature values with the radius r_i.

III. Experiment

The existing multi-scale feature approaches has been successfully applied in recognition of outdoor environment. For the terrestrial recognition task, the multi-scale PCA feature can exactly represent the object category (e.g. ground, building, vegetation, rock, etc.) [6, 13]. Following the application on the ground, we want to evaluate the multi-scale criterion in the underwater object recognition task.

A. *ModelNet Database*

ModelNet is a public dataset especially for researchers in computer vision, computer graphics, robotics and cognitive science. The database collect 48,000 3D CAD models. We select two kinds of interested categories (human and car) from ModelNet database. The reason for choosing human category is we want to evaluate the potential about using underwater 3D sonar to detect the drowning human. As for the second category, the car CAD model can provide enough 2D facets for comparison.

In the practical scanning process, the 3D point cloud generated from LiDAR is different with 3D CAD model. All the LiDAR sensor exist the shielding effect. Due to only half of appearance of object can reflect radiation, the 2.5D point cloud dataset is the normal consequence for the specific object in a single scan. Furthermore, the position orientation of interested object is usually unknown. We segment the original 3D CAD model into 3 parts: Original CAD model (3D), left side profile (2.5D) and up side profile (2.5D), respectively.

Fig. 2 illustrate the first human CAD model. The human CAD model is composed with basic body component. Two scales (r=0.2m and r=0.35m) are used to compare the difference in feature space. The multi-scale PCA feature space between two 2.5D dataset are shown in Fig. 3. Observing Fig. 3(b) scale r=0.35m, the feature space of left side profile model were dominated by two proportions of eigenvalue p_1, p_2. The PCA feature can reflect exactly the slim shape of object.

Fig. 4 illustrate the second human CAD model wearing uniform and carrying a gun. The multi-scale PCA feature space between two 2.5D dataset are shown in Fig. 5. Again, the multi-scale PCA feature can reflect the slim shape of object.

Fig. 6 illustrate the car CAD model. The multi-scale PCA feature space between two 2.5D dataset are shown in Fig. 7. For the symmetry geometrical object, the feature space is similar in two scales.

Fig. 8 demonstrate the comparison between the human model and car model. The human model has more the third proportion of eigenvalues p_3 in feature space. The multi-scale feature can discriminate the human model and car model.

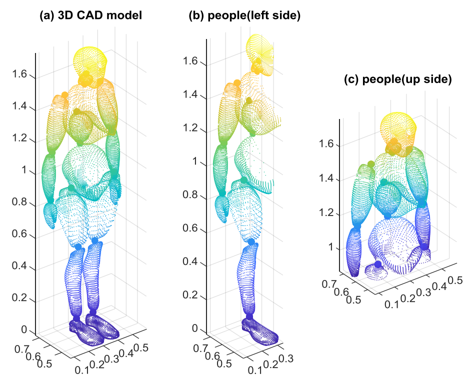

Figure 2. The first human CAD model

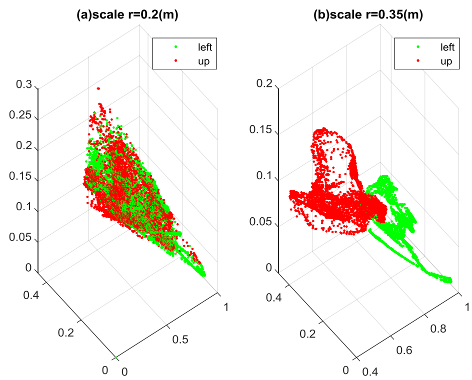

Figure 3. The multi-scale feature space

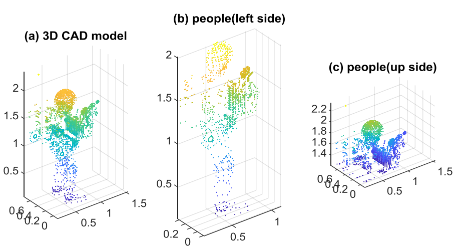

Figure 4. The second human CAD model

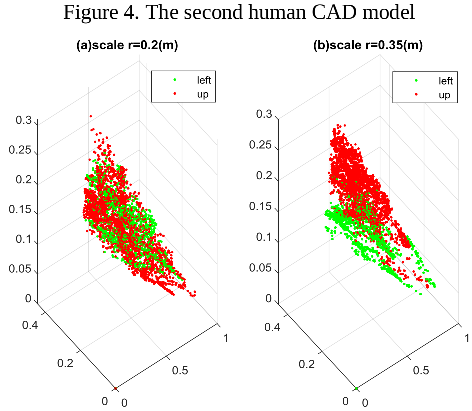

Figure. 5 The multi-scale feature space

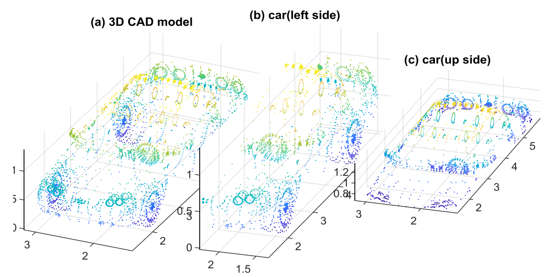

Figure 6. The car CAD model

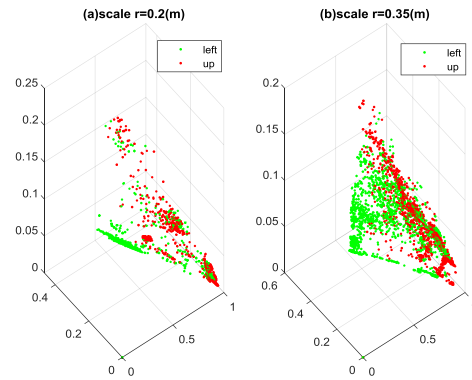

Figure 7. The multi-scale feature space

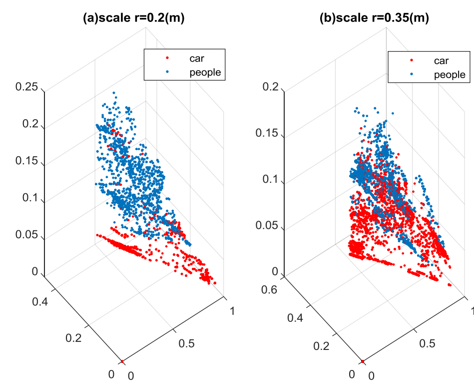

Figure 8. The multi-scale feature space

B. *Underwater Experiment*

The underwater scan has been applied to evaluate the proposed methodology. BV5000 is a kind of multi-beam 3D sonar with a vertical swath direction and a mechanical horizontal rotation system. The specifications of the device are given as follow:

- Spherical Scan Area: 360 º
- Operation Frequency: 1.35 MHz
- Maximum Scan Range: 30 m
- Number of Beams: 256
- Beam Width (º) 1 x 1
- Vertical Spatial Resolution: 16 mm at 10 m

- Horizontal Spatial Resolution: 30 mm at 10 m
- Weight: 22 kg

The experimental scene and data acquisition have been carried out in one of fishery harbor in Kaohsiung, Taiwan. The underwater environment locate along the dock structure which supported by a serial of piers. The piers is roughly 5m deep. The wasted tires, originally used for anti-collision cushion, are the main underwater object on the bottom of harbor.

The dummy person was drop into the prefixed positon in harbor where the seabed condition was known. Then BV5000 sonar was placed near close the dummy people for obtaining a necessary dense of cloud point. In this experiment, the location of dump person (i.e. ground truth) is known (Fig. 9). Besides, a lot of wasted tires distributed among on the nearby seabed surface.

For detection efficiency, we only focus on the underwater object. Therefore the seabed surface can be filtered through RANSAC surface fitting estimation. After deleting the points of seabed surface, the outlier point cloud of RANSAC just belong to the interested underwater object (Fig. 10).

The categories of object include one dummy person (3D dataset), two wasted tires (3D dataset) and seabed surface (2D dataset). Fig. 11 present the PCA feature space of 3 kinds of underwater object under 2 scales.

For 2D object, i.e. seabed, the PCA features were dominated by two proportions of eigenvalue p_1, p_2. For 3D object, e.g. dummy person and wasted tire exist the third proportion of eigenvalues p_3. From the viewpoint of scale analysis, we can find the PCA feature space of dummy person and wasted tire mixed together in scale r=2m (Fig. 11a). The different kind of 3D object cannot discriminate from feature space. However, in scale r=3.5m, the PCA feature space can discriminate the difference of 3D object (Fig. 11b). Comparison with two feature spaces, the PCA multi-scale criterion provides more separable feature spaces.

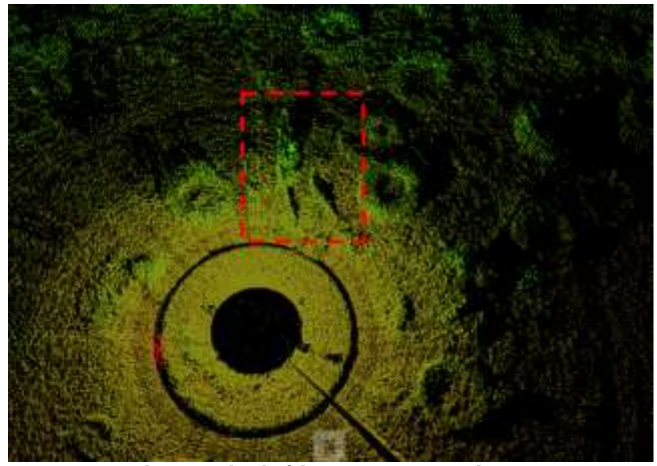

Fig. 9. The point cloud of dummy person in underwater scan

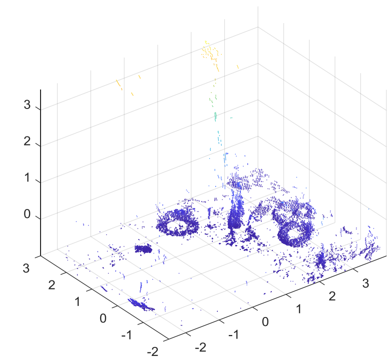

Fig. 10. Using RANSAC algorithm to delete sea floor.

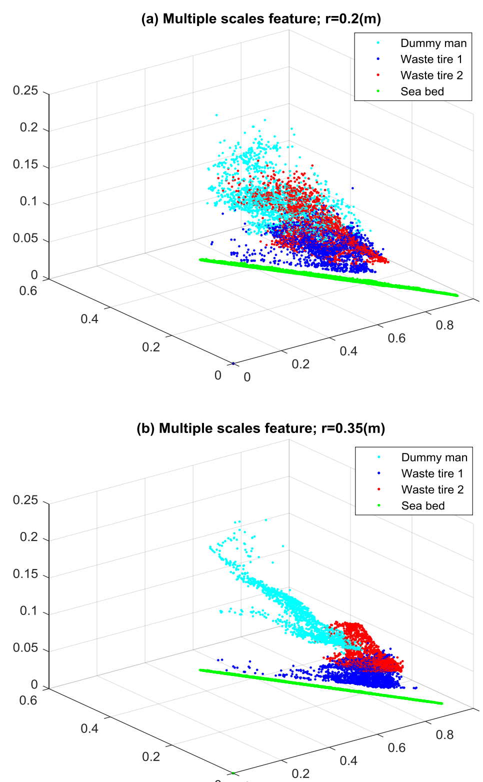

Fig. 11. The multi-scale PCA feature space. (a) scale=0.2m; (b) scale=0.35m

IV. Conclusion

The PCA multi-scale feature for underwater object recognition was studied in this paper. We evaluated the multi-scale feature from public ModelNet dataset and an underwater experiment. The PCA multi-scale feature can be extracted from point cloud and reflect the shape characteristic. Next, the multi-scale feature criterion for underwater object recognition can be a baseline reference and compared with another different recognition approach.

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