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Underwater 3D Reconstruction Based on Geometric Transformation of Sonar and Depth Information

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Abstract. 3D reconstruction is of vital importance to detect and monitor the underwater environment. A method based on geometric transformation of mechanical scanning sonar and depth information is proposed, in which the point cloud data from sonar and depth gauge are acquired to reconstruct the underwater 3D environment. However, noise and interference can affect the measurement of sonar, and movement of sonar during measurement can lead to distortion of the received data. Meanwhile, translation and rotation movement of sonar head may happen when ROV dives which can lead to different body reference coordinates of different scanning. To solve this, pre-processing and motion compensation are implemented at first, and underwater matching correction algorithm is used to calculate the translation and rotation of the sonar head. Then the inverse operation is implemented to convert the scan data of every depth into the same coordinate reference system. Finally, surface reconstruction of point clouds from sonar the depth information are used to reconstruct underwater environment based on MLS (Moving Least Square Method) using PCL (Point Cloud Library). Water tank experiments verify the effectiveness of the proposed method.

1. Introduction

There is increasing interest in underwater imaging and inspection in recent years. The most common technique adopted to complete underwater 3D reconstruction is based on optical cameras and sonar devices. However, the measurement ranges of the optical devices are rather limited without external sources of light and almost non-existent with high turbidity, and these make acoustic imaging the most reliable means to obtain information from underwater environment [1].

There has been many 3D reconstruction techniques using all kinds of sonar. In [2], a novel model-based approach for 3D underwater scene reconstruction is proposed using Side Scan Sonar (SSS) arrays in complex and highly reverberating environments, while in [3], shape-from shading technique is adopted to process reconstruction using side scan sonar arrays. Beyond that, Synthetic Aperture Sonar (SAS) techniques also have interesting results in [4]. Nevertheless, SSS and SAS are all too expensive to be widely used. However, the underwater environment we need to reconstruct is simple, so, we use a mechanical scanning sonar and reduce the influence of vertical aperture through choosing the maximum value of the returned echo intensity as the obstacle in horizontal plane as vertical aperture zero.

As for 3D reconstruction, there has already been many studies. In [5], the surface is reconstructed through the use of computational geometry techniques. Paper [6] presents a practical mesh method to achieve an accurate reconstruction of seabed surface from raw sonar records. The method we use to reconstruct the underwater environment is MLS based on PCL, which is a comprehensive free, BSD licensed, library for n-D Point Clouds and 3D geometry processing [7].

2. Processing of point cloud data from depth gauge and sonar

2.1. Acquirement of point cloud data

A depth gauge is a pressure gauge that displays the equivalent depth in water, which is well known and will not be described in detail here. And the sonar we use to reconstruct the underwater environment is a Tritech Micro DST sonar, which can be programmed to cover variable length sectors from a few degrees to full 360 °scans with an operating range of up to 75 meters.

The sonar performs scans in a horizontal 2D plane by rotating a mechanically actuated transducer head at pre-set angular increments [8]. For each emitted beam, an echo intensity profile is returned from the environment and discretized into a set of bins [9]. However, in a practical application, every ping received will contain noise and interference except for useful information, especially within the limited space like a water tank. Meanwhile, the ROV's motion can induce a distortion in the acoustic image when ROV moves, which is very common in water. So, it is necessary to compensate the distortion induced by motion and pre-process the sonar data before reconstructing the underwater environment. The method we use to compensate the motion induced distortion and pre-process the sonar data are shown in our previous paper [10]. The result of the acquirement with one sonar scan after underwater matching correction algorithm is as in figure.1.

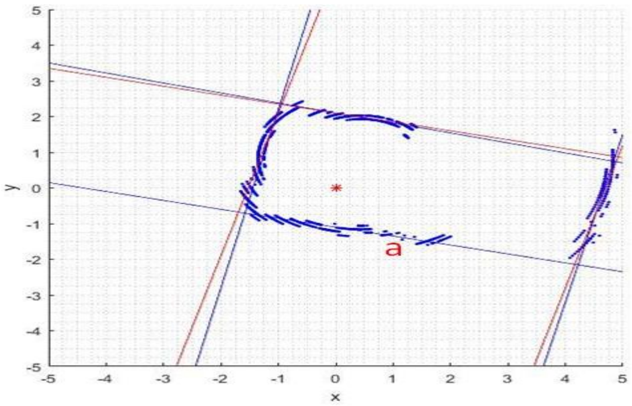

Figure 1. Point cloud data of one sonar scan after correction.

2.2. Transformation of Point Cloud Data

Let's define each scan as $S_i(i = 1, 2, \cdots n)$, where n means the nth scan at the nth depth. At the same time, we set the first scan as the reference with other scans transformed to the same coordinate system of the first scan $S_1 = S_{ref} = \{q_1, q_2, \cdots q_n\}$, where q_i represents the ith measurement in a scan. For each scan, the position of the sonar head is calculated using the geometric matching correction algorithm to measure the relative translation displacement of two adjacent measurements based on the position the sonar head relative to the base reference coordinate system, meanwhile, the slope of the base line in two adjacent scans at different depth is used to calculate the rotation angle. The reason for choosing the base line in two adjacent scans is that the change between two adjacent scans is very small and easily recognized. When we calculate the translation displacement and rotation angle of two adjacent scans at two adjacent depth, we can deduce the relative translation displacement and rotation angle using recursive computation.

For two adjacent depth as shown in figure.2, the position of the sonar head relative to origin of the base reference system is calculated using geometric matching correction algorithm, as in figure.3.

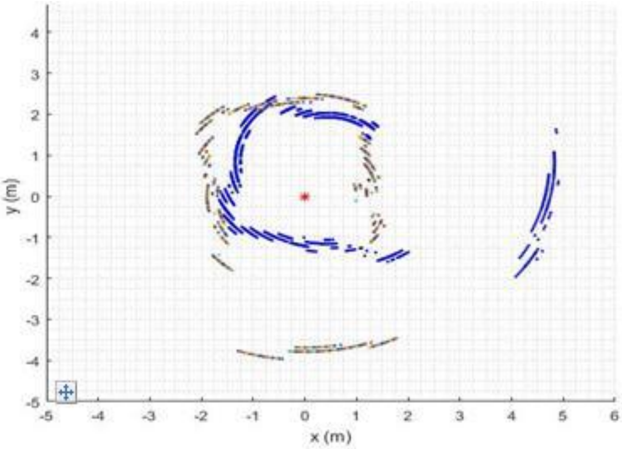

Figure 2. Example of two adjacent scans.

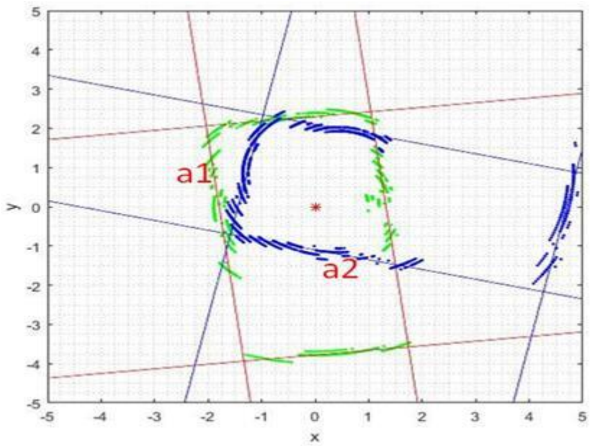

Figure 3. Geometric matching correction of the two adjacent scans

Let's assume that the scan with a1 inside is the S_{ref} , the scan with a2 inside is the second scan, then, the translation the second scan relative to the last scan can be calculated using the algorithm above, which can be defined as $\left[T_x,T_y\right]$. The relative rotation angle, which is also the angle of a1 and a2, can be calculated using equation (1) with k_1 and k_2 the slopes of the straight line a1 and a2 with counter clockwise direction positive.

$$\theta = \arctan\left(\frac{k_2-k_1}{1+k_1k_2}\right) \tag{1}$$

After knowing the translation displacement and rotation angle, we can get equation (2),

$$\begin{bmatrix} x_2 & y_2 & 1 \end{bmatrix} = \begin{bmatrix} x_1 & y_1 & 1 \end{bmatrix} \bullet \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \bullet \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ T_x & -T_y & 1 \end{bmatrix} \tag{2}$$

The equation (2) can also be simplified as follows,

$$S_2 = S_1 \bullet T_1 \bullet R_1 \tag{3}$$

Where, T and R represents the corresponding translation matrix and rotation matrix, respectively. Then all the second scan points $S_2 = \{q_1, q_2, \cdots q_n\}$ can be transformed to the same coordinate system as the first scan. Similarly, we can calculate each scan's translation displacement and rotation angle relative to the last scan, and transform all the other scans to the same coordinate system as the first scan, just as equation (4).

$$S_i = S_1 \bullet T_1 \bullet R_1 \bullet T_2 \bullet R_2 \bullet \cdots T_{i-1} \bullet R_{i-1} (i = 2,3 \cdots n) \tag{4}$$

With all the measurements scanned at different depths transformed to the coordinate system of the first scan, we can process the surface reconstruction of underwater environment with the point cloud data from sonar and depth information.

3. Surface reconstruction of point clouds data

For the point cloud data we collect is discrete and irregular, we should preprocess the point cloud at first before surface reconstruction.

3.1. Outlier removal

Radius outlier removal filter is implemented to remove the outliers. The principle is as shown in figure.4. At first, we set each point as the centre of a circle with radius R, respectively. Then, we set the minimum neighbours represented using N within R. If the numbers of the neighbours within R is less than N, then the point is considered as the outlier and will be removed. The values of the R and N depend on the circumstances.

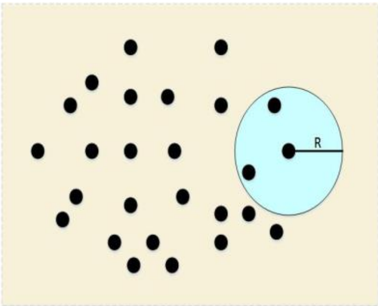

Figure 4. Radius outlier removal filter.

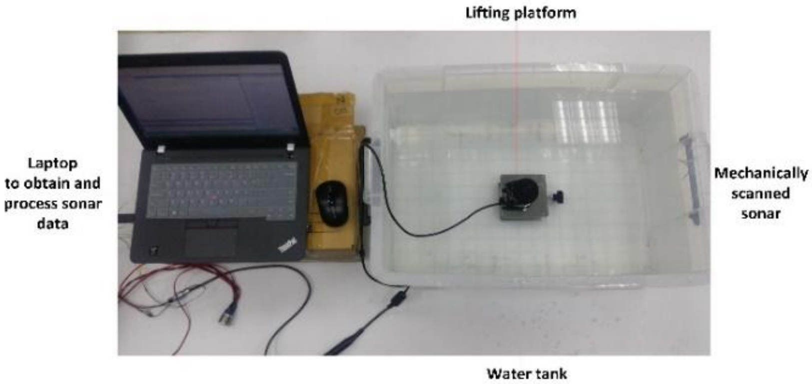

Figure 5. Water tank experimental platform.

3.2. Surface fitting based on MLS

As we all know, the cloud data can't be connected together simply to process surface fitting, especially when it is discrete. If we know the style of the surface, we can use least square method to get the fitting surface by solving linear equation sets. However, the least square method won't work if the discrete point cloud data is larger and the style of the surface is unknown and complex. In this situation, the MLS is very suitable for surface fitting. During the processing of MLS, the fitting function is defined in the local sub-domain of the fitting area, just as equation (5).

$$\mathrm{f}(x)=\sum_{i=1}^{m}\alpha_i(x)p_i(x)=P^T(x)\alpha(x) \tag{5}$$

Where, $\alpha(x)=\left[\alpha_1(x),\alpha_2(x),\cdots\alpha_m(x)\right]^T$ is function of spatial coordinate x, $P(x)=\left[p_1(x),p_2(x),\cdots p_m(x)\right]^T$ is the basis function, with m the number of the basis function. As an example, if it is linear basis function for two dimensional problems, then,

$$P(x)=[1,x,y]^T, m=3 \tag{6}$$

Or else, it is the quadratic basis function, then,

$$P(x)=\left[1,x,y,x^2,xy,y^2\right]^T, m=6 \tag{7}$$

So, in order to get the optimal fitting surface, we should get the optimal $\alpha(x)$, which can be obtained by obtaining the minimum value of the weighted discrete L2-norm as shown in equation (8).

$$J=\sum_{i=1}^{n}\omega_i\left[P^T(x_i)\alpha(x)-y_i\right]^2 \tag{8}$$

Where, n represents the number of nodes in the region, y_i represents the value of the node x_i, and ω_i is the weight function of the node x_i. The weight function in the MLS should have the characteristic of compact support, which means that the value of weight function in a sub-domain of x is nonzero while the value is zero outside of the sub-domain. Besides, the weight function should be nonnegative, and should be monotonically decreasing with the increase of x. The most commonly used weight function is a spline function. To get the optimal $\alpha(x)$, we should deduce the minimum value of equation (8), as shown in equation (9).

$$\frac{\partial J}{\partial \alpha}=0 \tag{9}$$

Then, we can get,

$$\sum_{i=1}^{n}\omega_i p(x_i)p^T(x_i)\alpha(x)-\sum_{i=1}^{n}\omega_i p^T(x_i)y_i=0 \tag{10}$$

Let's assume that,

$$A(x)=\sum_{i=1}^{n}\omega_i p(x_i)p^T(x_i) \tag{11}$$

$$B(x)=\sum_{i=1}^{n}\omega_i p^T(x_i) \tag{12}$$

$$y^T=[y_1,y_2,\cdots y_n] \tag{13}$$

Then, we can get,

$$A(x)\alpha(x)-B(x)y=0 \tag{14}$$

$$\alpha(x)=A^{-1}(x)B(x)y \tag{15}$$

Finally, we can deduce the solution of the MLS with equation (15) substituted into equation (5).

$$f(x)=p^T(x)A^{-1}(x)B(x)y \tag{16}$$

After figuring out the principles of the MLS, we can easily programme in the PCL using its function library, to get the fitting surface using the point cloud data we get.

4. Water tank experiment

In order to verify the effectiveness of the 3D underwater reconstruction algorithm, we build a test platform to get the absolute value of the depth information and the environment information for the lack of suitable underwater environment.

4.1. Experiment test platform of the underwater 3D reconstruction

The water tank we used is as in Figure.5, which is composed of mechanically scanned sonar and a lifting platform. The size of the water tank is 580mm×380mm×280mm (length×width×depth), with water depth 212mm during the experiments. The range of the lifting platform is from 46mm to 150mm, which means the height the upper surface of the lifting platform relative to the ground surface.

During the experiment, the height of the sonar to the bottom of the water tank is set up manually using micrometre to measure, which substitutes for the depth gauge of the ROV equivalently. The direction of the sonar head is different each time of the scanning, which needs to be transformed using geometric transformation. A total of 33 set of data the sonar relative to the bottom of the water tank is collected, which is shown as in figure.6.

4.2. Results of the transformation of point cloud data from sonar

After collecting the 33 set of sonar data during different depth, the underwater matching correction algorithm is used to calculate the translation and rotation of the sonar. Then the inverse operation is implemented to obtain the scan data of every depth in the same coordinate reference system. The results of the transformation of point cloud data from the mechanically scanned sonar is as in figure.7

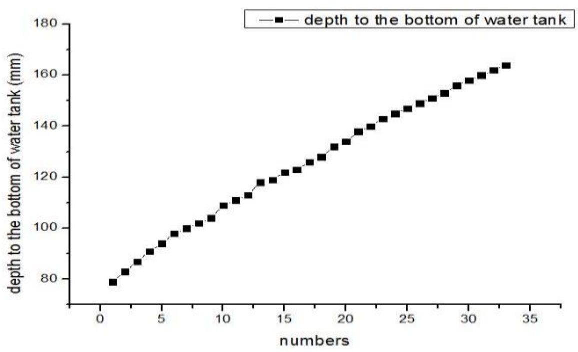

Figure 6. Height of the sonar head relative to the bottom of water tank.

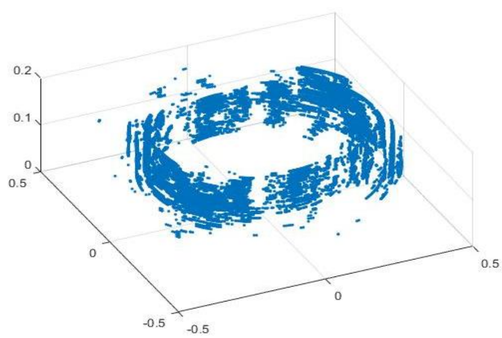

Figure 7. Results of point cloud data transformation from sonar.

Then we remove the outliers using radius outlier removal filter, with $R=0.02, N=50$. After the preliminary processing of the sonar data using PCL, the underwater environment after reconstructing is as in figure.8.

Finally, we process the MLS to fit the surface of the point cloud data, finishing the underwater environment reconstruction, the result is as shown in figure.9.

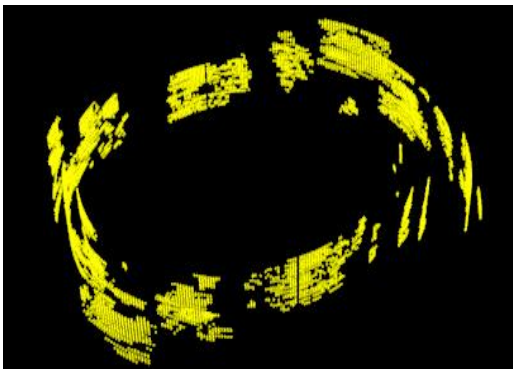

Figure 8. Preliminary processing using PCL

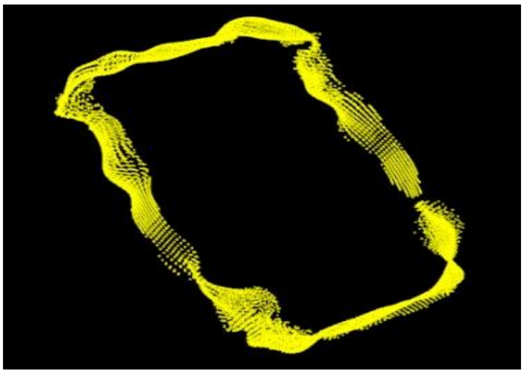

Figure 9. Result of the surface reconstruction.

5. Conclusions

The paper proposes a method to complete underwater environment 3D reconstruction based on point cloud data from mechanical scanning sonar and depth information using PCL. At first, pre-processing and motion compensation are implemented to remove noise and other interference. After that, underwater matching correction algorithm is used to calculate the translation and rotation of the sonar head. Inverse operation is implemented to convert the scan data of every depth into the same coordinate reference system in the next moment. Finally, surface reconstruction of point clouds from sonar the depth information are used to reconstruct underwater environment based on MLS using PCL. Water tank experiments verify the effectiveness of 3D reconstruction method, paving the way for future more precise 3D underwater reconstruction applications.

Acknowledgments

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