PROGRESSIVE MESH BASED ITERATIVE CLOSEST POINTS FOR ROBOTIC BIN PICKING

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Abstract: This paper describes a hierarchical registration process using the iterative closest point algorithm combined with a Progressive Mesh. To find the exact pose of objects in a robotic bin picking process we simulate the appearance of object poses and compare them with the real range data provided by laser range sensors. The coarse pose is estimated in a first step and then refined with the well known iterative Closest Point (ICP) algorithm combined with Progressive Meshes for hierarchical object localization. We evaluate our approach with different test scenarios and show the comprehensive potential of this idea for other registration problems.

1 INTRODUCTION

Today robots get more and more involved in industrial processes, because they are superior to man regarding requirements on strength, speed and endurance. Robotic automation processes became very successful in the last years, and offers a wide range for research. The task of robotic bin picking is easy to explain: Pick a known or unknown object out of a bin with an unsupervised industrial robot. This is called the “bin picking problem”(Hashimoto & Sumi,1999), (Katsoulas, 2005). It is also known as the de-palletizing problem, which occurs in nearly every industrial sector. The approach in this paper focuses on the object localization step, which is the most challenging step in the whole process. We introduce a simulation of a full laser scanning process. Industrial laser range sensors are modelled to transfer a cad-aided-design (CAD) model to a 2.5D range data representation. This virtual range data is aligned to the real range data of the scene with the help of combination of the Iterative Closest Point algorithm (Besl & McKay, 1992) and Progressive Meshes (Hoppe, 1996). Beside the significant improvement in speed our approach leads to better accuracy and robustness of the whole system. After the overview in section 2 the coarse pose estimation for a pose pre-selection is introduced in section 3. In the refinement step of our system we use the Progressive Mesh based Iterative Closest Point (PMICP) algorithm to derive optimal solution with high accuracy. We evaluate our approach with test range data in section 4 and conclude with upcoming extensions of our approach.

2 SYSTEM OVERVIEW

An overview of the proposed object localization system is shown in the figure 1.

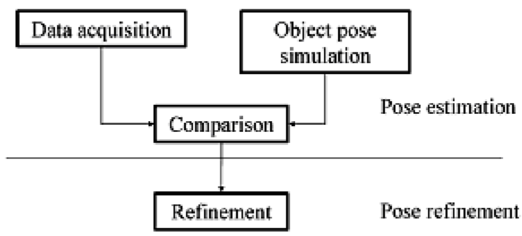

Figure 1: System overview.

The object localization is separated into pose estimation and refinement. To reduce the number of possible poses in the computational expensive refinement step, we make a pre-selection in the pose estimation step. The refinement step uses a modified registration algorithm to increase the accuracy. The components of our system are introduced in detail in the following sections.

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3 POSE ESTIMATION

The purpose of the object pose estimation is to find adequate coarse positions of an object in the scene.

The object pose simulation creates a virtual range image (VRI) with help of a simulated sensor and a virtual scene points. The triangulated CAD-based object model is used to generate virtual range images with the help of the simulated range sensor. The sensor model virtually scans the object and produces a range image in the same way like the real scene. For every possible position and orientation a VRI is produced. This VRI is indexed with a known position and orientation of the model in a database. The range data representation of the VRI and the real range image (RRI) are datasets of three dimensional points with the position x, y and z. Every VRI is compared to the RRI determining the difference between the distance values z for acquired data from the range sensor and the simulated data with the following error function:

$$Error = \frac{1}{N}\sum_{i=0}^{x}\sum_{j=0}^{y}\left|z_{VRI}(i,j) - z_{RRI}(i,j)\right| \qquad (1)$$

The error is defined as the mean of the difference between every distance value Z_1 of the simulated object and the distance value Z_2 of the scene. We use this efficient calculation considering the fact, that both coordinate systems of RRI and VRI are equal due to knowledge of the real scene setup. Different VRI's for different kind of objects are compared to the RRI in the same way. So the object classification is integrated in the step of object localization. One advantage of this pre-selection of matching positions is the fact, that all VRI can be calculated offline and stored in a database. So the process for our coarse pose estimation can be summarized in that way:

- the RRI is delivered by the sensor
- all VRI in the database (one for each possible pose) are compared to the RRI
- these VRI with the best error value are selected for pose refinement

We take the VRI candidates within the best 10-20% of all error values in the coarse pose estimation. These VRI candidates are delivered to the pose refinement process, starting with the best matching candidate.

4 POSE REFINEMENT

In the previous section the coarse pose estimation creates an error value for every pose. The best VRI candidates were chosen and used as input for the pose refinement to find the best matching candidate.

The task of the pose refinement is to find a nearly exact match between the object in the scene and the simulated image. The classical and most commonly used algorithm for determining rigid transformations is the Iterative Closest Point algorithm (Besl & McKay, 1992), (Chen & Medioni, 1992). Because of the slow convergence speed, the ICP was improved by many researchers (Rusinkiewicz & Levoy, 2001).

We use the ICP algorithm in combination with Progressive Meshes (Hoppe, 1996) to find the exact matching pose for every VRI candidate in the real scene captured by the laser range sensor. We call this combination Progressive Mesh Iterative Closest Point Algorithm (PMICP). The major problems of the ICP algorithm are the low performance calculating a huge amount of points in scene and model and its sensitivity to outliers (Rusinkiewicz and Levoy, 2001). In every iteration step all points of the two datasets must be compared to each other with a complexity of $O(N_{RRI}*N_{VRI})$ where N_{RRI} and N_{VRI} are the numbers points in the datasets. Our hierarchical approach now reduces this complexity by comparing only a reduced number of points N_i of each dataset. The representation of Progressive Meshes provides a highly efficient implementation for adjusting the level of detail in a point dataset and includes an inbuilt noise reduction. This representation is given by a set of meshes M_0 to M_n. M_0 is the mesh with the lowest accuracy and M_n is the mesh with the highest accuracy. The process of generating Progressive Meshes from point datasets is described in detail in the work of Hoppe et. al.(1993). In our experiments we choose the simplest way to connect the hierarchy of the Progressive Mesh representation to the ICP: The Progressive Mesh representation M_i is increased by a fixed increment and starts with a defined level of detail in each iteration step. The obvious advantage is the increased performance. But the profoundly effect is the increased robustness against outliers. By reducing the mesh up to M_0 outliers can no longer affect the result of the distance calculation. The shape of the model in representation of M_0 is similar to the M_0 representation of the scene representation. This leads to a very good initial position in the iterative process of the closest point algorithm. We have evaluated our PMICP with several experiments which are described in the next section.

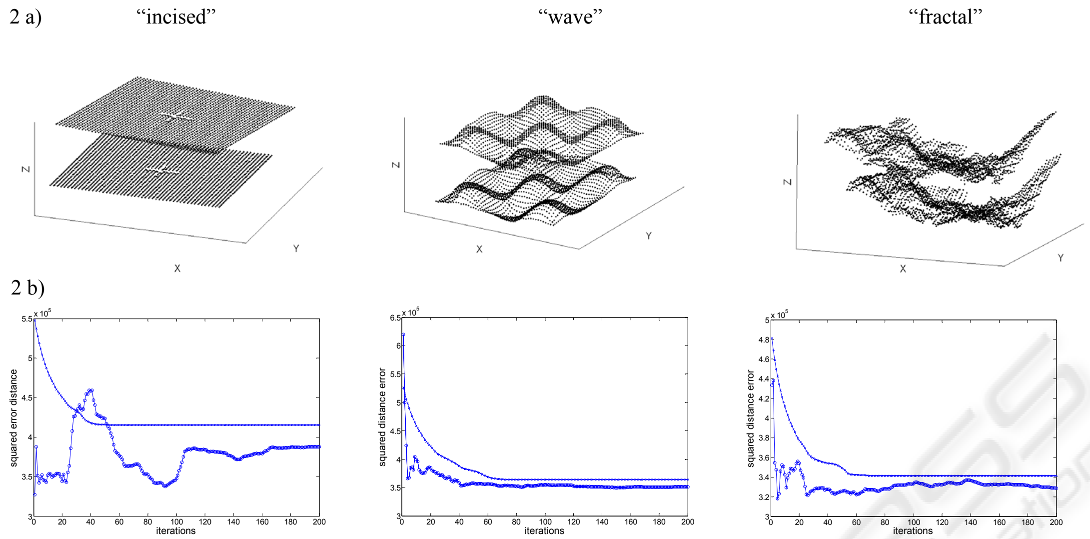

Figure 2: Test scenarios (2a) with convergence performance (2b).

5 EXPERIMENTAL RESULTS

It is obvious that some results depend on the used registration data and the initial pose. In our applications the ICP has to find the transformation between range images (RRI) and the simulated range images (VRI), which are more or less similar in shape to the “fractal” scenario of the following test scenarios. To evaluate our idea we used the reference datasets of Rusinkiewicz and Levoy (2001). We us the same test environment with synthetic meshs of 2000 points added with Gaussian noise and outliers. The datasets are shown in figure 2a. The “incised” dataset has two lines in shape of an “X” in the middle of a planar surface. This “wave” dataset is an easy scenario because of low frequency features and a smooth surface. In opposite to the wave scenario the “fractal” dataset represents landscape data of terrain registration and has features in all level of details.

5.1 Results

To compare our results we implemented the standard ICP algorithm according to (Besl & McKay, 1992) without approximation and any other possible improvements described by Rusinkiewicz and Levoy (2001). We changed the distance error calculation from Euclidian distance to

$$E = \sum (x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2 \qquad (2)$$

to avoid computational floating point errors and increase calculation performance. We implemented the Progressive Mesh based Iterative Closest Point Algorithm (PMICP) based on the Progressive Mesh implementation of Hoppe in DirectX (Hoppe 1998). In our tests we start with an initial meshs consisting of five triangles and increase the number of vertices in the meshs by five triangles for each iteration step.

The initial M_i does not suffer from outliers like the standard ICP does. With the increasing iteration steps and the number of points in the datasets the PMICP implementation degenerates more and more to the reference algorithm with a better robustness. The convergence performance (figure 2b) of the “wave” scenario is similar to the “fractal” scenario. The algorithm outperforms the standard algorithm in the “incised” scenario over most iteration steps. The higher error between iteration step 20 and 40 shows the rotation ambiguity of the alignment of two plane surfaces. Especially in the first few iteration steps the PMICP aligns the datasets to a good initial pose. The squared distance error is always smaller when comparing to the standard ICP.

All this experiments concentrate on convergence robustness and final distance error issues. But the experiments show, beside the improvements mentioned above, that the overall performance of the refinement process can be increased significantly. The complexity of the ICP algorithm depends mainly on the number of points in the dataset. The search of the closest points has a computational complexity of $O(N_j*N_i)$. We reduce the number of points in the dataset, starting with only a few points and increase the number in every iteration step. The computational complexity is reduced in average to $O((0.5*N_j)*(0.5*N_i))$ assuming we do not stop the iteration until we reach the end (M_n mesh).

If the iteration process is stopped, because the ICP reached the minimum, the performance of our implementation is always better than $O((0.5*N_j)*(0.5*N_i))$. Our Progressive Mesh ICP experiments need in average 25% of the time of the standard ICP implementation.

6 FURTHER EXTENSIONS

Many of known modifications of the ICP can be combined with the PMICP without loss of generalization. For example the performance in the closest points search is often increased using Kd-Trees implementations (Z. Zhang, 1994) to $O(N_j*log(N_i))$. The Kd-Tree search could be used in addition to our PMICP leading to a significant improvement in speed especially in the higher level of details. The ICP algorithm is known to be very sensitive to wrong initial poses of the two datasets because of the fact, that the ICP will always converge to the local minimum (which is of course commonly not identical to the global minimum). So the determination of the optimal initial start value for the number of points in the mesh is very important. In the current implementation the level of detail in the Progressive Mesh is connected to number of iterations in the ICP. Finding the optimal number of points for each iteration step in ICP iterations is one of possible improvements in the next steps of our research.

7 CONCLUSIONS

We described a system to align range data surfaces in a context of industrial process automation. We focused on the improvements in the refinement step of our hierarchical object localization system. The well known and proven ICP Algorithm is modified with the use of Progressive Meshes. To be sure to meet the requirements of different applications we evaluated our system with test scenarios, which cover many types of possible range data scenes.

The simulation of real scenes offers the possibility to use our approach in many scenarios. The described two-step object localization is integrated in our system robotic bin picking covering different application scenarios (Boehnke, 2007).

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