XXI IMEKO World Congress “Measurement in Research and Industry”
August 30 – September 4, 2015, Prague, Czech Republic

3D LASER MAPPING FOR ADVANCED ROBOTICS APPLICATIONS

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Abstract – This paper presents the gathering, processing and presenting 3D data for use in Advanced Robotics Applications like Search and Rescue operations. The data are gathered by unmanned ground platforms, in the form of 3D point clouds via laser scanning systems. The clouds are matched and transformed into a consistent, highly accurate 3D model. The paper describes the pipeline for such matching based on Iterative Closest Point algorithm supported by loop closing done with LUM method. The pipeline was implemented for parallel computation with NVIDIA CUDA, which leads to higher matching accuracy and lower computation time.

Keywords: laser data, 3D mapping, robotics applications

1. INTRODUCTION

Use of unmanned platforms in Advanced Robotics Applications like Search and Rescue (SAR) is an important and interesting research topic. Broad overview of the work done in the area can be found in literature [11], [12], [9]. There were also numerous attempts to use unmanned platform during real emergencies: the 2001 World Trade Center attack [14], the 2004 earthquake in Mid Niigata, the 2005 USA hurricanes [13], or the 2011 Japan tsunami. Despite the effort put into the subject, there still exists a number of limitation that prevent unmanned SAR tools from being accepted and widely used by End Users [7].

The goal of many projects [5] is to combine robotic components into a common technology platform, capable of increasing the situational awareness of the action in a SAR mission. One of the module developed in the project is the support system for data processing and visualization [3]. During our work we have discovered that interpreting raw data gathered by unmanned platforms is a major problem for the End Users. This is especially true for data gathered by 3D laser scanning systems. In this paper we describe a pipeline for combining raw data into a consistent 3D model and discuss on the subject of best visualization strategy for such information.

The visualization of gathered data is a problem that can be approached in various ways. The 2D representations of unstructured environments tend to be occupancy maps [10], because of their usefulness for planning and low memory consumption. In paper [17] the authors use Rich Information Maps for environment representation. This approach fusses a Kinect 3D map with object and human recognition and tracking to present a fuller representation of the environment. In [16] a polygon mesh representation, created using iso-surfaces of a coarse 3D occupancy grid is presented. Another approach is using voxels for environment representation [4]. Finally, work is being carried in the area of using augmented reality for visualization to better integrate the operator into the robot’s decision making [8]. In this paper we concentrate on the colouring and the light in the point cloud as the factor that increases the readability.

2. 3D LASER MAPPING

The 3D mapping system is shown on Figure 1 and 2 [1].

Fig. 1. Mobile robot equipped with 3D geodetic laser measurement system Z+F IMAGER 5010.

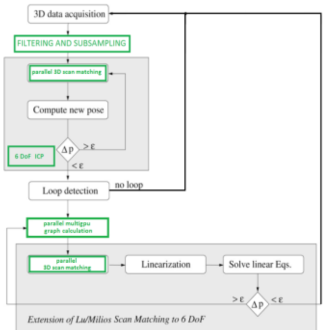


Fig 2. Improved 6DSLAM algorithm by parallel implementation with NVIDIA CUDA.

The system is composed of mobile robot Husky equipped with geodetic terrestrial 3D measurement system Z+F IMAGER 5010 and improved 6DSLAM algorithm by parallel implementation with NVIDIA CUDA. The range is 170m and it can acquire 3D cloud of points in adjustable density. The map is build based on 18 raw 3D point clouds. In this section we would like to present an improvement of our 3D mapping system. Previously we reached 2.5 cm average error in comparison to geodetic measurements with accuracy of 2.9 mm. In this paper we show increased accuracy, thus we reached 15 mm of average error. Figure 2 shows improved 6DSLAM algorithm by components marked by green color. It is composed of two main parts:

- Iterative Closest Point with metascan,
- loop closing with extension of LUM (Lu/Milios Scan Matching) method [15].

We proposed parallel implementation for improving data filtering and subsampling, NNS (Nearest Neighbourhood Search) and graph creation.

The subsampling algorithm reduces number of points in a point cloud to accelerate the further calculations

and to provide uniform density. The main idea is to partition the space using 3D regular grid. Size of the grid determines the mean distance between the points in resulting point cloud. For each cube, named bucket, centroid is computed. In the next step the point with minimal distance to centroid is found for each bucket. Resulting point cloud will have size equal to the number of non-empty buckets and consists of found points.

Figure 3 shows a sample point cloud before and after subsampling process.

Fig. 3. Subsampling example using 7.3 million points (left image). Resulting point cloud has about 400,000 points (right image).

Increased density around the 3D laser scanner location is eliminated. It is clear that the uniform density of points can be reached only in areas, where the density before was higher than expected after subsampling. Computation time increases for small and large values of grid size. For small values of grid size, the space is partitioned.

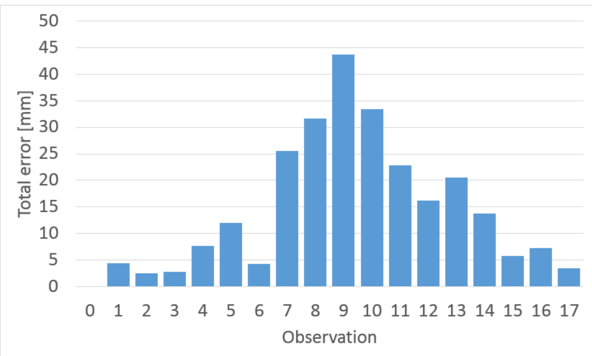


Fig. 4. Total error for each observation. Average error is 15mm.

In Figure 4 the total error after loop closing procedure for each observation is shown. The position error increases with the distance from the reference observation 0. The average error is 15 mm.

In the figures below is shown how usage of multiple GPUs can speed up data alignment. We compared a performance of 4GPUs (NVIDIA GRID K2) with single GPU (NVIDIA TESLA K40). The computational problem is related with the GPU RAM capacity. Large 3D data sets require more RAM space, therefore GPU with limited capacity can process only smaller data sets assuming parallel computation in a single step.

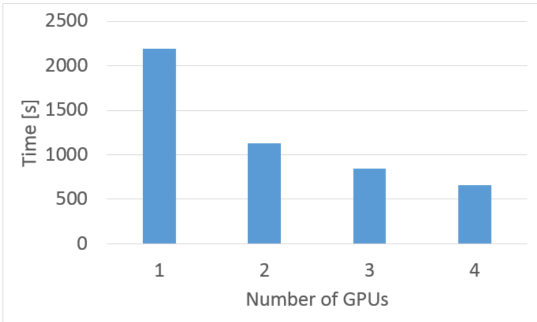


Fig. 5. First loop closing step using different number of GRID K2 GPUs.

Figure 5 shows computation time using from 1 to 4 GRID K2 GPUs. Single GRID K2 board has two GPUs so using 2 boards (4 GPUs) we can speed up the computation about 3.4 times. Each GRID K2 GPU has 1536 CUDA cores, therefore the system of 4 GPUs results 6144 cores. It is more than Tesla K40 GPU (2880 cores), which is dedicated for complex scientific computation. However, Tesla K40 has 12 GB of memory in comparison 2 × 4 GB available in GRID K2. Increased memory allows processing larger data sets (lower value of the grid size for subsampling) and as a result achieve higher accuracy of the model (Figure 6). The last loop closing step cannot be processed on GRID K2 GPU because of limited memory size. Another observation is that the total time of computation with 4 GRID K2 GPUs is about 2 times shorter than K40 and it is related with higher total number of available CUDA cores in the system (more threads can be run in parallel).

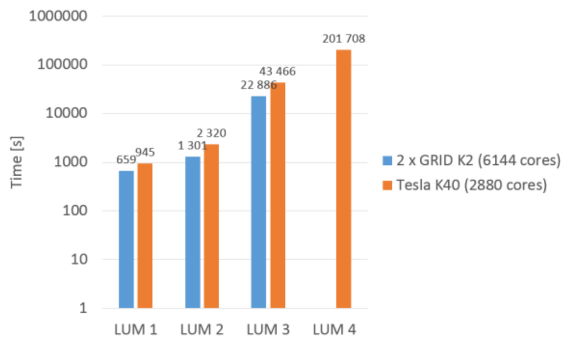


Fig. 6. Comparison of two computational strategies - use of 4 GRID K2 GPUs, and one Tesla K40.

3. DESIGN OF LIGHT SYSTEM IN INDOOR SCENE

We have implemented a light simulating environment to test if it could help in interpreting the 3D model. Such functionalities are already available in state of the art software such as 3Ds MAX. The realistic simulation of light propagation is however very expensive computational operation. Because of that existing solutions often do not produce results of good quality. For our test we have chosen to use NVIDIA OptiX application acceleration engine. A great advantage of this library is the use of parallel computation for faster and more accurate lighting simulation. The difference in quality is shown in Figure 7, where the same view is generated through 3DsMAX and out tools using OptiX.

Fig. 7. Difference between quality of light simulation between 3DsMAX software on the left and OptiX library on right.

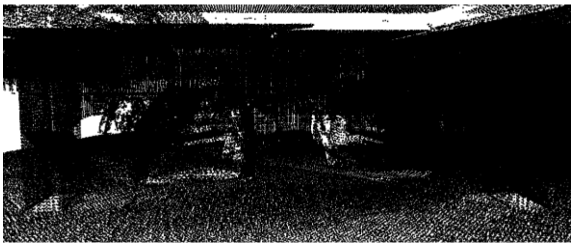
For testing purpose we have prepared a model of partially full underground garage. The model has a form of a 3D point cloud, subsampled using grid size 0.04 m. Resulting point cloud has approximately 35 million points. For each point a normal vector was estimated based on PCA (Principle Component Analysis) using SVD (Singular Value Decomposition) method.

4. COMPARISON OF DIFFERENT 3D DATA VISUALIZATION STRATEGIES

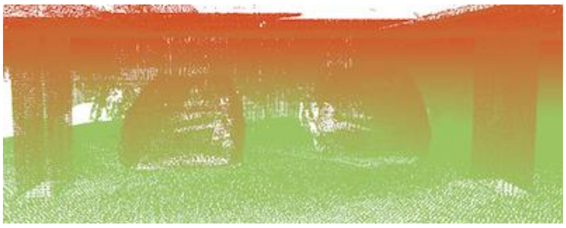
To evaluate the effect of light simulation on the readability of a 3D point cloud we have compared it with other approaches. The cloud described in previous chapter was visualized using 4 different strategies. In each of them the points were assigned colours based on different features:

(a) No colours, only black points
(b) Points with assigned colours based on height,
(c) Points with assigned colours based on normal vectors,
(d) Points with assigned colours based on neighbourhood type.

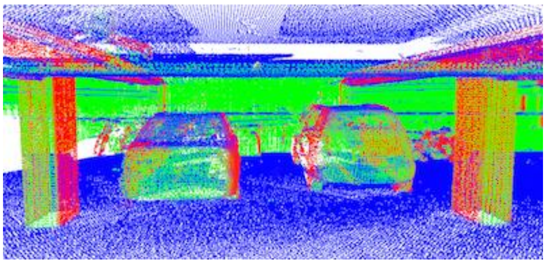
The first strategy shows the raw point cloud data. Colours in second strategy were assigned with linear functions for each colour channel: Red is growing from the lowest to highest point, while Blue is decreasing. Green channel reach its peak in the middle and then fades. Normal vectors were computed using PCA/SVD, with a neighbourhood size of 0.1m. Colours are assigned based on the value of the vector (Red for X, Green for Y and Blue for Z). Finally the fourth strategy is based on 3 descriptors computed from eigenvalues: linear, planar and volume [6]. Additionally the ground and planar surfaces parallel to it are shown separately. Colour scheme is as follows: red - planar neighbourhood, blue - linear neighbourhood, black - ground, pink - parallel to ground, yellow - volume. Example views of each strategy are shown in next figures.



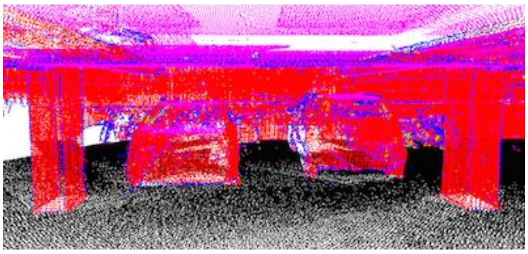
(a) No colours, only black points



(b) height-based colouring



(c) normal vector based colouring



(d) descriptors based colouring

Fig. 8. Visualization of 4 strategies for data visualization.

From the results of the survey we have concluded that dual strategy for data visualization is the best approach. In situations when data can be used offline (mission planning, documentation) light simulation is the preferred approach. However for the online operation and control of unmanned platforms it may be more beneficial to use much faster approach with normal vectors, especially when the computation power is limited.

5. CONCLUSIONS

In this paper a pipeline for gathering, processing and visualizing 3D data was shown. A parallel approach to 3D point clouds matching has been discussed. Strategies for data visualization has been compared and evaluated, including a new approach based on light simulation. It was concluded that light simulations give the best basis for human data analysis, however for time critical tasks normal vectors approach is and acceptable alternative.

The data were shown to a group of 6 experienced unmanned platforms operators. The operators have used the platforms for operations similar to SAR, such as demining and military operations. Moreover the environments where the machines were used were similar to those normally most affected in emergencies (urban areas). Each participant was asked to answer 3 questions:

Q1 - Which visualization strategies allow to recognize objects in the scene?

Q2 - How many details can you read form the visualization? (score for 0 - no details to 10 - high number of details)

Q3 - If you were to chose one visualization for planning and executing a task with unmanned platform, which would it be?

It is important to clarify that in this survey only the readability and quality of the data presentation were taken into account. The answers are as follows:

Question	**Str1**	**Str2**	**Str3**	**Str4**	**Str5**
Q1 - YES	0	3	6	6	6
Q1 - NO	6	3	0	0	0
Q2- avg	0.5	2.66	6.33	4.83	8.83
Q3	5	5	5	5	5

The results are presented for each strategy in the form of number of YES and NO answers for question 1, the average score for question 2 and the number of votes for given strategy in question 3.

The results confirm the assumption that raw point clouds are hard to read and interpret by humans, even if they are experienced in using other types of robot sensors. Adding explicit height information does not make a significant difference.

Using basic descriptor for recognizing basic shapes provides the user with basic understanding of the scene. The most significant advantage of this approach was the visibility of the ground. Artificial light simulation helps immensely in the tasks and would be the strategy of choice for all participants. It is worth noting that normal vector based visualization was also highly valued by the participants.

ACKNOWLEDGMENTS

The research leading to these results has received funding from the European Community0s Seventh Framework Programme (FP7/2007-2013) under grant agreement n285417 - project ICARUS (Integrated Components for Assisted Rescue and Unmanned Search Operations).

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