RVS3000-3D: LIDAR meets Neural Networks

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ABSTRACT

For future robotic space applications, like on-orbit servicing or space debris removal a powerful 3D imaging LIDAR system suitable for non-cooperative targets is required. Based on the experience in the field of LIDARs for space applications and previous technology development projects, the RVS3000 product family is being engineered and qualified by Jena-Optronik. In this paper, the previous LIDAR activities at Jena will be briefly reviewed and an overview over the RVS3000 and RVS3000-3D and their possible respective applications will be provided. The technical features of the RVS3000 and RVS3000-3D sensors and the differences between the two models are presented. The main part of this paper is dedicated to the RVS3000-3D and current efforts at Jena-Optronik to develop a real-time LIDAR-based Pose Estimation solution. The sensor is currently able to track an object in space in 6 Degrees of Freedom, given an initial attitude estimate by higher GNC. However on the path to full autonomy the system requires the implementation of quick pose initialization techniques. This paper will provide an overview and assessment of existing ideas and strategies and finally present a new pose initialization algorithm developed by Jena-Optronik based on neural networks. Simulation results for the application of neural networks as initialization option in high dynamic rendezvous and docking scenarios are provided outlining the algorithms characteristics and advantages compared to existing strategies.

1 SPACE LIDAR HERITAGE AT JENA-OPTRONIK

LIDAR activities at Jena-Optronik started in the 1990es with the project ARP (ATV Rendezvous Pre-Development) which successfully delivered the prototype rendezvous sensor ARP-RVS for two flights to the Russian space station MIR on board the NASA Space Shuttle missions STS-84 and STS-86.

The next step was to design, build and qualify the final flight hardware rendezvous- and docking sensor RVS for use within both the European ATV and the Japanese HTV programs as well Cygnus from OrbitalATK. Up to now, a total of 43 RVS have been delivered with flawless operative flight heritage.

Figure 1. RVS Optical Head (left) and Electronics Box (right)

Both the RVS LIDAR heritage at Jena-Optronik and new building blocks of a 3D Imaging LIDAR developed in the frame of ESA and DLR German Space Agency programs represented the basis for the next step – the LIRIS-2 3D Imaging LIDAR on ATV-5. The goal for the mission was to demonstrate the 3D Imaging LIDAR technology functional principle by gathering 3D point cloud data of the ISS during rendezvous and docking of ATV-5 while providing both internal housekeeping and telemetry data of the sensor to verify design assumptions as a basis for future development steps.

Figure 2. LIRIS-2 sensor components optical head, electronics box, and data recorder.

The resulting data showed the successful operation of the LIRIS-2 sensor during ATV rendezvous and docking as well as a nominal transition between the different scan modes implemented in relation to the distance between ATV and ISS. The first return signals from ISS were detected at a distance of about 2.5 km. In addition to the retroreflectors, target returns from ISS surfaces started to become visible at a distance of about 260 m.

2 THE RVS3000 AND RVS3000-3D PRODUCT FAMILY

2.1 Overview

A comprehensive design effort for a 3D Imaging LIDAR was performed with support of DLR German Space Agency. The design developed in this context draws from the experience of previous projects and integrates all sensor components in one single housing thereby eliminating the need for electrical or fiber-optic cabling between the components.

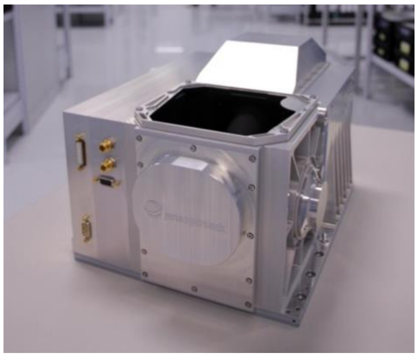

Figure 3. RVS3000 Engineering Model

Two major mission types were identified and considered in the design of the 3D Imaging LIDAR:

- Rendezvous and Docking using retroreflectors ("cooperative target"), coming from ISS supply mission heritage utilizing the RVS LIDAR
- Space robotics applications against diffusively reflecting "non-cooperative targets", e.g. on-orbit servicing, space debris removal, as defined within e.g. the DLR DEOS or ESA e.Deorbit missions.

In order to cater to the needs of these two mission types, two flavors of the 3D Imaging LIDAR family "RVS3000" were defined:

- The standard RVS3000 for measuring against retroreflectors (cooperative targets), usually in the frame of short-duration LEO missions, and
- the RVS3000-3D for measuring against satellite materials (non-cooperative targets), in the frame of multi-year LEO or even GEO missions.

2.2 RVS3000 Design Concept

The RVS3000 is designed as a Time-of-Flight scanning LIDAR – the same concept as successfully used in the previous projects RVS and LIRIS-2. The concept of a scanning LIDAR provides several advantages compared to a Flash LIDAR that are integral to the operating concept of both RVS and RVS3000:

- Flexible Field-of-View: within the total Field-of-View of the sensor, any size of rectangular scan window can be set as region of interest. Such a rectangular region of interest does not have to be centered within the total field of view and can be changed on a per-scan basis
- Variable scan speed: the scan speeds for both the azimuth and elevation direction of the scan can be defined on a per-scan basis. This allows switching modes between slow high-resolution scans with "megapixel" images and fast scans for proximity operations with moving/rotating objects.
- High dynamic range and range resolution/accuracy: as the sensor only uses one send/receive channel (as compared to e.g. per-pixel readout electronics for a Flash LIDAR), this channel can be designed to allow for a high dynamic range, a high range resolution, and a high accuracy. As there is only one read-out channel per design, different pixel characteristics that need to be considered in a matrix detector are of no relevance to the data processing.

2.3 Differences Between RVS3000 And RVS3000-3D

For the design of RVS3000 and RVS3000-3D, a modular approach is followed with both sensor flavors sharing the same mechanical design. Design approaches specific to each sensor flavor are implemented only where necessary. For non-cooperative targets, a higher laser power is needed. Therefore, the fiber laser module is equipped with a capability for a higher maximum output power while keeping mechanical and electrical interfaces identical. Depending on radiation requirements and mission duration, the selection of hi-rel electronics components, optical, and mechanical elements for additional shielding is performed accordingly while keeping the same design. To cover the high data rates associated with non-cooperative target applications, the microprocessor board is equipped with additional processing capabilities on a~~n~~ FPGA coprocessor board and a more powerful data/command interface to the spacecraft (SpaceWire instead of MIL-1553B).

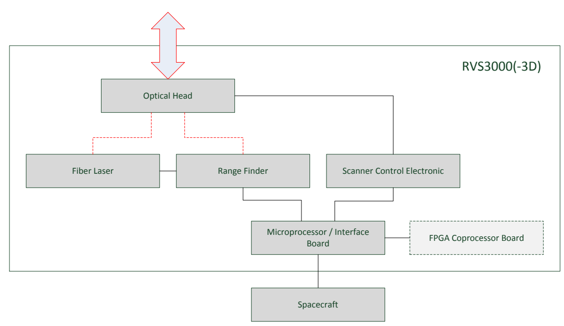

Figure 4. RVS3000 and RVS3000-3D simplified block diagram

3 RVS3000-3D Pose Estimation

3.1 Motivation

The RVS3000-3D is designed to cover the full range of future robotic space applications. The baseline for such scenarios are the sensors high resolution imaging capabilities. 3D Point Clouds of the target object can be acquired by the LIDAR system, which contain valuable information for the chasers GNC about the targets relative position and attitude. However the deduction of this information requires the application of computational demanding image processing techniques.

3.2 Pose Estimation

In general state of the art LIDAR-based pose estimation solutions comprise the following two functionalities:

- Pose Initialization
- Pose Tracking

The *Pose Tracking* routine calculates 6DOF information based on a version of the Iterative Closest Point (ICP) Algorithm via model matching with an apriori given reference model of the target object. For tracking of the targets state from scan to scan the ICP is always initialized with the previous pose result. However if no initial information about the objects position and attitude is available a rough but quick initialization is necessary. Such *Pose Initialization* routines are usually based on finding rough correspondences between a sparse LIDAR scan and a data base containing geometrical information about the target object. Such information can e.g. be the targets contour, which might be the basis for a template matching technique.

3.3 Mission Scenarios

The near-term application scenarios for a LIDAR equipped with pose estimation algorithms are expected to be following two mission types:

a. GEO satellite servicing (e.g. life-time extension or refueling)
b. Active Debris Removal (ADR) of possibly tumbling space debris

The two scenarios share similar concepts for trajectory and approach corridor design but can tremendously differ in the targets dynamic state. As operating GEO satellites are 3-axis-stabilzed the relative dynamics are rather low. Typically the chaser approaches with velocities between mm/s and a few cm/s. In addition the relative rotation of the target object is mainly driven by the chasers approach trajectory as the target objects rotational movement can be neglected. An appropriate pose estimation solution therefore needs to follow motions in the order of approximately < 5-10 cm/s and < 0.1-0.5 deg/s.

On the contrary the ADR of space debris is much more challenging. The debris object, which can e.g. be a~~n~~ defunct satellite or a burned-out upper stage, might be wild tumbling with up to several deg/s including precession and nutation of its rotational axis. However approach velocities of the chaser are usually similar to the mentioned GEO RnD. Therefore for this application scenario a pose estimation solution is required, which is capable to track the targets state in relative dynamics of approximately < 5-10 cm/s and < 1-5 deg/s.

3.2 LIDAR-based Pose Estimation by JOP

Jena-Optronik developed a real-time LIDAR-based pose estimation solution consisting of the RVS3000-3D as the sensor component and high performance image processing algorithms. The algorithms run on the dedicated FPGA Coprocessor Board within the RVS3000-3D and enable a unique symbioses between imaging laser scanner and pose estimation algorithms. The FPGA Coprocessor Board is based on the Microsemi RTG4 as main processing unit supported with a set of different memories of various size and type.

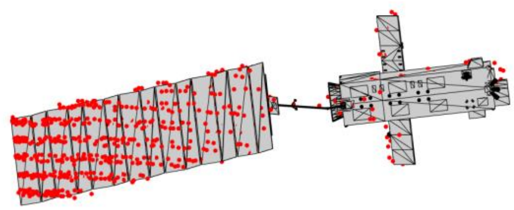

Figure 5. Matching result of JOP pose estimation algorithms between LIDAR scan and ENVISAT CAD model (bottom)

In the current status the system is designed for the discussed mission type a) of low-dynamics GEO servicing. For this application the image processing solution consists solely of a *Pose Tracking* algorithm as higher GNC can provide a rough initial pose estimate to the LIDAR based on the well know state of the chaser relative to the target object. Once the target objects pose is acquired RVS3000-3D is capable to provide relative pose estimates with attitude better than 0.5-1deg and position better 1-3cm depending on the targets geometry and the visible feature to the LIDAR at an update rate of 2Hz and a latency of 1s.

An RVS3000-3D EM including the presented LIDAR-based Pose Estimation algorithms for *Pose Tracking* is currently under test at Jena and will be fully qualified and validated within 2018 in environmental and functional tests in e.g. robotic facilities.

Although the RVS3000-3D system (including the currently available pose algorithms by JOP) is already capable to meet common customer requirements for GEO satellite servicing, the goal of JOP is to develop a purely autonomous solution, which will also enable the application of the RVS3000-3D in future ADR scenarios like e.g.

ENVISAT robotic rendezvous and capture. The goal of current developments at Jena is therefore to design a *Pose Initialization* routine, which on the one hand supplements the current *Pose Tracking* algorithm and on the other hand will allow an implementation within the given coprocessor architecture based on the Microsemi RTG4.

4 Pose Initialization Algorithms

4.1 Introduction

Pose Initialization is defined as a routine, which calculates a rough but quick estimate of a target objects pose based on a sparse 3D LIDAR scan. The result can consecutively be used to initialize a *Pose Tracking* routine based on an ICP algorithm. In order to enable the application of the RVS3000-3D even in the most challenging scenario of tumbling space debris ADR, the initialization algorithm needs to be able to provide a pose estimate better than 2-5 deg in attitude and 0.1-0.5m in position at an update rate of >= 2Hz. In addition an FPGA implementation is envisaged, which supplements the available *Pose Tracking* algorithms at JOP.

4.2 State-of-the-Art

Several algorithmic approaches have been studied in the past, but they all share the common basic idea to find a correspondence between a sparse LIDAR scan and an apriori calculated data base representing geometrical information about the target object. In the following the main existing ideas will be summarized:

The Polygonal Aspect Hashing (PAH) algorithm, developed by Neptec [1], samples a 5-8 vertices polygon from the LIDAR scan and searches for a corresponding match polygon within a reference hash table. The quality of the found match-scan polygon pair can e.g. be assessed via a model-based ICP.

Template Matching (TM) algorithms are inspired by camera-based image processing and have been applied in different versions:

Airbus Defense & Space developed a Template Matching which first creates an grey-scale range image based on the LIDAR scan [2]. Afterwards the image is compared to a data base of templates representing the target object in different rotational states. The target attitude which provides the best correspondence will serve as attitude initialization of a consecutive ICP. The necessary relative position is estimated via centroiding over the LIDAR PointCloud.

In contrary to image templates also 3D point-based templates could be used. The University of Naples presents in [3] a~~n~~ routine, which compares the sparse LIDAR scan with a database of 3D Point Clouds representing the target in possible rotational states. Position is again estimated via simple centroiding over the LIDAR scan. But the correspondence is now assessed via a nearest-neighbor based matching between scan and reference point clouds.

Most recently in [4] an approach was presented, which is based on the main ideas of the PAH technique. The authors propose an algorithm called Congruent Tetrahedron Align (CTA). The procedure first calculates the convex hull of the LIDAR scan and then compares sampled tetrahedrons from the convex hull with an available database in form of a hash table.

4.3 Analysis Of Existing Strategies

All available techniques are validated within their respective literature and show to be capable of initializing an ICP even in the high dynamic ADR scenario. However they share the commonality of a computational demanding search within a given model database.

For the PAH and CTA algorithm such techniques are expected to require a processor architecture as the logic behind pruning and searching through the hash table might imply some issues for a pure FPGA implementation.

On the other hand template matching (TM) might be a more suited candidate. However TM can require a high amount of memory for storage of the templates. The accuracy of the technique is directly linked to the number of available templates, which represent discrete state candidates of the targets attitude within the 360 deg search space. In addition a TM algorithm is expected to require a high percentage of the resources available within the RTG4 FPGA. A combined implementation of JOP's *Pose Tracking* algorithm and a TM initialization might therefore be very challenging.

The solution for a pure FPGA implementation of a *Pose Initialization* algorithm within the given architecture of the RVS3000-3D's coprocessor board might therefore be a customized algorithm, which reuses a lot of the already available ICP functionality of JOP's *Pose Tracking* routine. Inspired by the PAH and CTA algorithms, JOP therefore designed an algorithmic solution based on the recognition of the target object within the LIDAR PointCloud via a neural network.

4.4 Neural Network Pose Initialization

Neural Networks have been successfully applied to a variety of image processing tasks and recently also found their way to robotic space applications (see e.g. Mars Rover 2020 and NASA Europa Clipper). They basically represent a multidimensional function approximator, which acts like a "black box". Some inputs are provided to the network and consecutively some outputs are calculated. The transfer function between input and output can be tuned to a required tolerable error between expected and calculated result via training of the network. With this procedure a network can e.g. be trained to perform convolutional operations on image data or to approximate a given mathematical function.

The basic idea of the mentioned PAH and CTA algorithms is to perform a search within a given hash table in order to find a corresponding match polygon/tetrahedron for a sampled scan polygon/tetrahedron from the sparse LIDAR scan. JOP has successfully trained a Neural Network to perform this task.

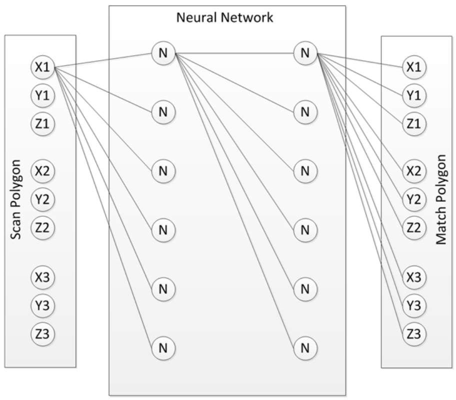

Figure 6. Calculation of a Match Polygon corresponding to a Scan Polygon sampled from a LIDAR Scan via a Feed-Forward Neural Network

The basic principle is shown in Figure 6. The scan polygon is presented as input to a neural network. The data propagates through the network and generates an respective output, which is interpreted as an match polygon of single points with X,Y and Z coordinates. The network therefore performs a projection of the scan on a model it has been trained with.

Neural Networks perform basic matrix multiplication operations and are therefore predestinated for implementation within FPGA architectures. The most complex operation might be the applied activation function per neuron.

Based on the presented matching concept via a neural network, JOP developed a *Pose Initialization* routine, which embeds the neural network into an ICP-like framework. The proposed algorithm is shown below:

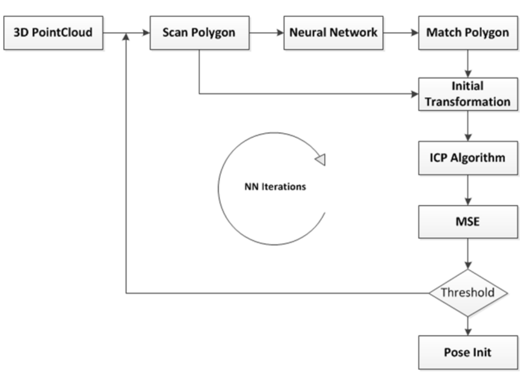

Figure 7. Pose Initialization Algorithm based on Polygon-Matching via Neural Network

The top-level algorithm flow is the following:

1. Sample a random scan polygon from the LIDAR 3D point cloud
2. Apply neural network to find a match polygon candidate
3. Calculate initial relative transformation based on scan-match polygon correspondence
4. Initialize a model-based ICP with the pose estimate and run ICP for “X” iterations
5. Evaluate the residual Mean-Squared-Error (MSE) of the ICP after “X” ICP iterations
6. Abort if MSE < Threshold; else init new Iteration of initialization routine

The challenge of this procedure lies within the design and training of the matching network. Some network architectures might work better than others. In addition the engineer needs to make sure that the network has been trained with an as representative as possible trainings data set with respect to the later application on real data in space. Therefore the coverage of the possible parameter space represented in the training data needs to be high enough such that the network performs as intended within the possible scenarios. However the capability of a network to be trained to a large amount of training samples might simultaneously require a high amount of neurons. This results in longer processing times and higher demands with respect to FPGA resources. Therefore finally a trade-off between network size and required performance is necessary.

In addition another driver of the final update rate of the proposed Neural Network Pose Initialization algorithm is the number of iterations “X” used by the ICP algorithm after every scan-match polygon initialization. Sometimes the network might find a very good pose estimate and the ICP might converge very quickly under the requested MSE threshold. In other situations the neural network initialization might be only very rough, but assuming that the ICP can be applied with a sufficient number of iterations, the criteria for successful pose initialization might be fulfilled as well.

4.5 Proof Of Principle

In order to evaluate the algorithms performance and to make design decisions, JOP conducted tests with an ENVISAT CAD model, an RVS3000-3D LIDAR simulation model and the virtual testbed VEROSIM.

Figure 8. Simulation of ENVISAT ADR in virtual testbed VEROSIM

The simulation positioned ENVISAT in 1000 randomly chosen poses and produced LIDAR scans corresponding to a scan rate of 2 Hz. Based on those point clouds and the known target pose during their respective acquisition, a training data set for neural network training was generated. The result was a training data set of 1000 scan-match polygon pairs.
As a baseline JOP choose completely meshed feed-forward networks. The networks were trained via the Levenberg-Marquardt algorithm.
First a parameter sweep was conducted in order to find network architectures capable of learning the desired matching task. The smallest network architecture, which showed an acceptable residual error after training, was a net with 3 hidden layers and 100 neurons per layer.
The network was now integrated into the presented *Pose Initialization* algorithm of Figure 7 and validated within the discussed ENVISAT ADR scenario. For the validation of the algorithm a different set of 1000 scans of random ENVISAT poses has been produced in order to challenge the network with different scenes compared to its trainings data set.
In the following the success rate of the *Pose Initialization* algorithm is shown after application of the algorithm on the total set of 1000 scenes in dependency of the applied top-level algorithm iterations (NN Iterations) vs. ICP iterations (performed per NN Iteration).

Table 1. Success rate of the neural network pose initialization algorithm

Success Rate [%] Parameter Sweep		ICP Iterations per NN Iteration				
		2	4	8	16	32
NN Iterations	2	0,08	0,21	0,39	0,55	0,66
	4	0,16	0,35	0,61	0,78	0,88
	8	0,24	0,51	0,81	0,92	0,97
	16	0,37	0,69	0,92	0,98	0,99

As can be seen success rates of > 90% can be achieved depending on the algorithm configuration. In addition an FPGA implementation building on JOPs heritage *Pose Tracking* is expected to meet the desired 2Hz update rate even in the shown worst case combination of 16 NN Iterations with 32 ICP Iterations per NN pose guess. Furthermore the results presented here were only a first proof-of-principle. The performance of the network is expected to be even more enhanced with optimization of the training samples/technique vs. network architecture trade-off.
Concluding the proof-of-principle showed that the technique is competitive to existing initialization strategies. The algorithm will therefore be further investigated by JOP for implementation in RVS3000-3D.

5 CONCLUSION

The RVS3000-3D represents the 3D LIDAR of Jena Optronik's new RVS3000 product family, which has been designed for current and future robotic space applications ranging from satellite servicing to debris removal. The design of the RVS3000-3D is based on the long heritage and experience of Jena Optronik in the field of LIDAR sensors for rendezvous and docking applications.
In order to provide full relative 6DOF navigation information of uncooperative targets, the RVS3000-3D is equipped with a set of image processing algorithms and appropriate high performance data processing hardware in form of the Microsemi RTG4 FPGA. In the current status the system is capable to track an object in space via a customized version of the Iterative-Closest-Point algorithm given an initial estimate of the targets attitude by higher GNC. The system is therefore already applicable to low-dynamic GEO satellite servicing.
In order to provide a fully autonomous LIDAR-based Pose Estimation solution, Jena-Optronik is currently investigating *Pose Initialization* algorithms. A review of the current research in this field showed that existing algorithmic techniques might not be suitable for the envisaged implementation in a pure FPGA environment together with Jena Optronik's *Pose Tracking* algorithms. An alternative technique was therefore developed, which on the one hand exploits the existing ICP implementation for *Pose Tracking* and on the other hand reduces the amount of additional need for FPGA resources.
Jena-Optronik developed a *Pose initialization* algorithm based on the application of a neural network for registration between LIDAR scan points and an apriori available CAD model of the target object. The networks pose results are consecutively evaluated via a model-based ICP to provide supervision of the networks operation.
The Neural Network Pose initialization algorithm has been studied within a simple proof-of-principle simulation. Once a network architecture was found, which was regarded to perform sufficiently well on the training data set, the performance of the top-level initialization algorithm was evaluated. It was shown that success rates > 90% per scan are possible depending on the algorithm configuration.
The main advantage of the presented Neural Network Pose Initialization technique is the high synergy with implementations of the Iterative Closest Point algorithm and the beneficial nature of neural networks for implementation in FPGA architectures. Furthermore the required memory for storage of the neural nets weights is expected to be lower compared to standard hash table or template based techniques.
The key towards successful application of the algorithm in future rendezvous and docking scenarios is expected to be the training of the network and its validation. The ideal case would be to train the network with a large amount of simulated data covering all possible aspects of the approach

trajectory. However bigger training data sets also require bigger network architectures, which will be limited by available FPGA resources. The main future research of Jena-Optronik on this topic will therefore be dedicated to the optimization of the tradeoff between training data size vs. network architecture.

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