Visual Navigation for Rendezvous and Docking using PMD Camera

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1 RESEARCH PROBLEM

There is one common problem of the satellite which is quite widely discussed: the lifespan. Depending on the mission the lifespan of large and expensive geostationary satellites can last about 10-15 years, whereas the satellites in Low Earth Orbit have significant shorter life cycles. Therefore an idea to extend the operational lifetime or improve the performance of a satellite on the orbit instead of replacing it by a new one is concluded in On Orbit Servicing (OOS) projects (Ellery et al., 2008; Stoll et al., 2009).

The typical scenario of OOS is Rendezvous and Docking (RvD) of the approaching chaser to the target and taking over attitude control. There have been several studies focused on providing OOS (Figure 1): DEOS (DEutsche Orbital Servicing mission) for Low Earth Orbit and Smart-OLEV (Orbital Life Extension Vehicle) for geostationary orbit. In DEOS like scenarios, a service satellite approaches a tumbling client in Low Earth Orbit and uses a robotic manipulator in order to capture the uncooperative target satellite (Wolf et al., 2012; Boge et al., 2013). In the OLEV scenario the servicer satellite will dock with a specific docking tool to the apogee thruster of client satellite in the geostationary orbit (Kaiser et al., 2008).

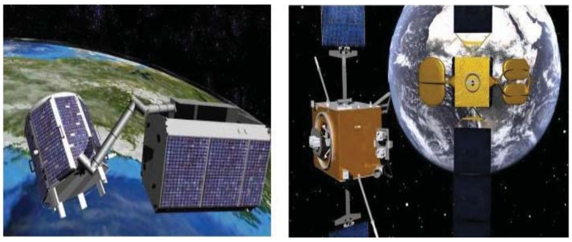

Figure 1: DEOS Servicer capturing a tumbling client satellite in Low-Earth Orbit (left) and OLEV approaching a geostationary client satellite (right).

The rendezvous phase starts at the distance where the navigation process switches from absolute navigation to the relative navigation. For this purpose, a variety of 3D-vision rendezvous and docking approaches based on laser scanners, stereo vision, structured light and LIDAR (LIght Detection And Ranging) has been developed. In 2000, the new product Photonic Mixer Device (PMD) camera appeared at the market as a new sort of the 3D Time-of-Flight (ToF) sensor which, moreover, has never been used in space environment (Schilling and Regoli, 2011). The main feature distinguishing PMD cameras from the above described systems is the following. A PMD camera emits modulated light to derive by phase shift a distance measurement for every pixel. The PMD technologies are rather new and have some drawbacks. A general problem of the PMD sensors is a limited distance range due to the measurement principle. Also an output data provided by PMD sensor is affected by many factors and quite noisy with different side effects. These side effects cannot be neglected, as they influence the system performance. Therefore, further research in this direction with a prerequisite for the future to use PMD camera in space environment is of great interest to date.

2 OUTLINE OF OBJECTIVES

The main focus of this work is to investigate the use of a PMD camera for motion detection and pose estimation with regard to space applications. During the research phase the following points are considered:

- Initial pose estimation with a subsequent real-time object tracking.
- Extension of the measurement range of the PMD sensor. In a work of Tzschichholz (Tzschichholz, 2014), the measurement range was extended with an appropriate algorithm up to 75 m.
- Data preprocessing. Camera calibration.
- Performance measurements with a RvD simulation facility like EPOS 2.0 (European Proximity Operations Simulator)

This paper mainly focuses on the first objective, pose estimation with a PMD sensor.

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3 STATE OF THE ART

As it was already mentioned, the use of a PMD camera for space applications for visual navigation is of interest up to date. Therefore, there is no variety of prototypes of ToF cameras. However, some have been applied and tested under quite realistic space environment. Tzschichholz (Tzschichholz, 2011) and Schilling (Schilling and Regoli, 2011) used PMDTec 19 k for pose estimation and motion prediction of the spacecraft. Later, Tzschichholz (Tzschichholz, 2014) applied a newer model of a ToF camera, the PMDTec CameCube 3.0, used in conjunction with a CCD camera for rendezvous and docking.

3.1 Available ToF Cameras

The previous prototypes of the PMD cameras have a low resolution of the sensor chip and camera measurements are subjected to external influences. Especially the pixels of a sensor are oversaturated under strong illumination of background light.

Table 1: Available ToF cameras and their relevant properties.

Camera	Resolution [pixel]	Max. range [m]	Field of view
Argos 3D, Bluetechnix Group GmbH	160 x 120 352 x 288	up to 10 Indoor, up to 3 Outdoor	30°,60°,90° 110°
iZ™ OIVS-1000, United Kingdom	1280×1024	0.5-10	15°, 30°,60°
Fotonic, Sweden	160 x 120	0.15 - 10	70º x 53º 45º x 34º
Ifm, O3D303, Germany	176 X 132 64x50 64x16	up to 30 Indoor	60°x45° 40° x 30°

Since the science in different fields moves forward and new technologies are developed, it was rationally to start exploring new hardware devices with more ameliorated characteristics. Products with their characteristics, which could be presently purchased from companies, are depicted in Table 1. For future tests and experiments, we intend to use the Argos 3D sensor with a resolution of 352 x 288 pixels and with a field of view of 30°.

3.2 PMD Principal

PMD camera is a ranging imaging system, based on the time-of-flight principle (Boge et al., 2013). The camera measures the distance to the object for every pixel of its sensor chip. Figure 2 depicts the distance measurements, where color indicates distance in meters.

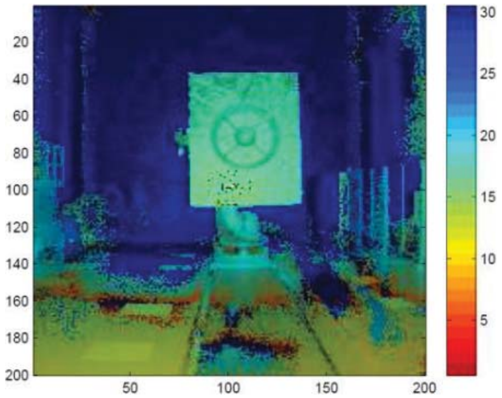

Figure 2: 3D image obtained with PMD camera showing a satellite mockup in EPOS laboratory.

The target area is illuminated by incoherent modulated light (LED or laser diodes), where the wavelength of the light source has to be synchronized with the spectral sensitivity of the detector. ToF cameras usually employ NIR light in range of 780nm to 850nm (Fuchs, 2012). In order to reduce the impact of the background illumination, it would be also practically to use a narrow band-pass filter. The light is reflected by the scene, collected by the lens system of the camera and projected onto the sensor matrix. The distance from the target is calculated by correlation of the received modulation light with the modulation signal of the illumination unit, where the phase shift corresponds to the distance. Noise from the background light can be suppressed by the Suppression of Background Light (SBI) circuitry but SBI cannot be controlled by software. In the Figure 3, the functionality of the PMD principal is depicted.

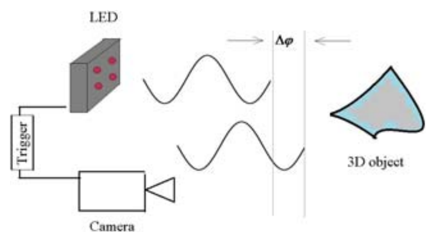

Figure 3: Measurement principal of the PMD camera.

4 METHODOLOGY

Before calculating the pose estimate, the problem of actually finding target must be solved. The initialization need not be accurate. The coarse capture of the model is sufficient for the further tracking process. In work of Tzschichholz (Tzschichholz, 2014), the author uses the amplitude channel of the PMD camera to locate the target object in image-space and then expands a point cloud in 3D space from a bootstrap point. The resulting point cloud provides a centroid, which is used to determine the translational components of the relative pose. A sequential probing of all the model surfaces to the point cloud provides the planar orientation of the matching model surface, and finally, the determination of the principal components of the measured point cloud provides the rotation about the normal vector, what completes the initial relative pose estimate. The algorithm suggested by Tzschichholz has one drawback, namely it does not reliably determine all six degrees of freedom of a symmetric object without additional hints to the initializer. The hints are some pieces of information which allow the initializer to narrow down the set of possible poses until only one pose remains.

The key idea of the matching method is quite simple: features found in the image are matched against the set of features in the model. The algorithm proposed in this paper is addressed to the free-form 3D objects and discussed in section 5.

4.1 Related Work

To this date, many techniques have been developed for the purpose of object recognition and pose estimation using 3D data with the focus to find a robust and efficient manner to identify objects in a scene. This can be done in various ways, depending on the format of the scene: camera image, range image, or a combination of both. One standard approach for object pose estimation is the Iterative Closest Point (ICP) method. The ICP algorithm needs a good initial estimate and is thus not suitable for initial object detection, but often used as a subsequent pose refinement step after the object is detected (Haarbach, 2015).

The techniques for detecting free-form models could be divided in two groups: global methods and local methods (Drost et al., 2010).

4.1.1 Global Methods

The idea of global methods is to not divide a model into parts or any geometrical objects. Instead, the complete model is used. To initialize objects the so-called Generalized Hough Transform is suggested in (Rabbani and van den Heuvel, 2005) but it is limited to primitive objects as the recognition of 6 degrees of freedom (DoF) is computationally too expensive.

Another automatic routine based on random sample consensus (RANSAC) to find basic shapes with point cloud input was designed in (Schnabel et al., 2007). The input data is a set of observed values, sampled and deconstructed in a model which can be fitted to the observation. The inliers are generated from random subset of the original data and tested against entire set of data in order to determine correlation between inliers and data set. The algorithm is proved to be simple and easy to implement for the primitive shapes but for complete objects it would not be the best solution.

4.1.2 Local Methods

A second class of methods, local methods, uses so-called point descriptors. The scheme of this type of algorithms identifies point to point correspondence between model and the scene. Point correspondence is built by comparing descriptors of the scene and of the model. Therefore, the descriptors must accurately and robustly distinguish between cluster and noise.

Mian (Mian et al., 2006) built a three-dimensional tensor from multiple unordered range images. The tensors are stored in a hash table and used like a lookup table during the matching phase. In (Johnson, A. and Hebert, M., 1999) Johnson and Hebert introduce a recognition algorithm based on surfaces' correspondence by matching points using the spin image representation. Spin images from points on one surface (model) are constructed and stored, the same procedure is done with the spin image of scene surface. Best point correspondence is then established and grouped for the further surface matches.

5 CONTRIBUTION

Object recognition, pose estimation and navigation for the RvD demand factors such as accuracy, robustness and also computing speed. The approach outlined below addresses the problem of estimation of the 6 DoF object pose (3D position and 3D orientation) using PMD camera measurements in cluttered point clouds. Prior knowledge of the geometry of the object (e.g. a given CAD model or any other 3D model) is needed to be known.

The method developed in the thesis is the following: A global model description is created using an oriented point feature. It is matched with the measurement data by using a fast voting scheme, similar to the Generalized Hough Transform (Drost et al., 2010). An oriented point is a three-dimensional vertex with a directional vector (normal vector). Consequently, point pair feature describes the relative position and orientation of two oriented points. Global model description consists of all model point pair features (single four-dimensional vector F_m). Vector F_m is determined as follow:

$$F_m(m_i,m_j)= (\|d\|,\angle(n_i,d),\angle(n_j,d),\angle(n_i,n_j)) \quad (1)$$

where d is difference between two points, $\|d\|$ represents Euclidean distance, the second and third components are angles between the vector d and the point normal vector n_i and n_j, respectively.

Equal point pair features grouped together in order to reduce dimension of the hash tables for voting process. An object, in general, is represented as a set of feature vectors spaced in a hush table for the further simple retrieval. Random points should be sampled from the PMD data and each pair votes for a particular pose. The pose which collects the most votes belongs to the required pose. In order to increase the accuracy of the estimated pose, we suggest to apply at the previous step the hierarchical clustering algorithm, for example, Agglomerative Clustering, and to group together similar poses.

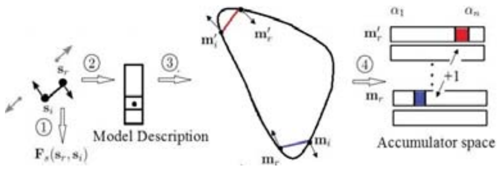

Figure 4: Visualization of the steps in proposed algorithm.

The similarity of the poses is determined by comparison with a predefined threshold for rotation and translation components. The method consists of the following steps (cf. Figure 4):

1. Let $s_i \in S$ denote points of the scene and $m_i \in M$ points of the model. The reference point s_r is paired with all other points of the scene S and their feature $F_s(s_r, s_i)$ is calculated using the same principal as for vector F_m.
2. The global model description consisted of all model point pair features $F_m(m_r, m_i)$ is calculated and generated in an offline phase. Feature F_s is matched to the global model description, which output is a set of point pairs on the model M that have similar distances and orientations.
3. For every point pair of the model matched to the point pair of the scene, the local coordinate α is calculated. The rigid motion from the model space into the scene space can thus be described by a point on the model and a rotation angle α.
4. After α is calculated, the vote is casted in a so-called accumulator space, which is similar to a hash table.

5.1 Expected Outcome of Algorithm

As the algorithm for pose initialization and estimation of the 6 DoFs is still in investigation phase, it is expected that the novel algorithm achieves significant improvement compared to the method of Tzschichholz (Tzschichholz, 2014) in terms of efficiency, stability and accuracy. Once a pose estimate is available, the next step is planned to develop an approach for tracking the target for static and dynamic cases.

6 EXPECTED OUTCOME

In this chapter some description of the additional research objectives is given.

6.1 Data Preprocessing

Before the delivered data from PMD sensor can be used for navigation tasks, the camera should be calibrated. For this, the following effects and issues must be taken in account when calibrating a PMD camera (Tzschichholz et al., 2011):

- fixed pattern noise,
- amplitude dependent distance offset,
- Wiggling effect,
- integration time dependent distance error,
- motion artifacts.

6.2 Extension of Measurement Range of PMD Sensor

Usually, in PMD cameras the modulation frequency can be tuned accordingly with regard to the needs of the user or the application. Lower modulation frequencies allow larger measurement ranges. There are also methods which can extend the measurement range of the PMD camera, for example, by using two or more modulation frequencies (Tzschichholz, 2014). Therefore, an appropriate approach in accordance with a new PMD camera's characteristics is a part of the study.

6.3 Performance Measurements with EPOS Facility

In order to ensure safe and reliable rendezvous and docking on the orbit by OOS, the processes must be analyzed and simulated under utmost realistic conditions with respect to space environment. For this purpose, simulations and tests of the PMD camera and the navigation algorithms will be performed using the European Proximity operations simulator (EPOS 2.0), a new simulation facility located at DLR, Oberpfaffenhofen, for this purpose. It is a hardware-in-the-loop simulator which comprises two industrial robots for physical real-time simulations of rendezvous and docking maneuvers (Boge et al., 2013). For such hardware-in-the loop RvD simulation, a client satellite mockup is mounted on one robot of the EPOS facility and the PMD camera is mounted on the second robot. The PMD camera measures the relative position and attitude of the client satellite and the onboard attitude and orbit controller calculates on this basis the necessary thrusters or reaction wheel commands.

7 STAGE OF THE RESEARCH

At the moment study and investigation of the intended algorithm for pose initialization and estimation described in section 5 are conducted. Intermediate steps are implemented and tested using a Matlab toolbox. In parallel, the process of collecting data from the new purchased sensor for subsequent conduction of experiments is ongoing as well as decimation procedure for the raw data from the PMD camera.

REFERENCES

Boge, T., Benninghoff, H., Tzschichholz, T., 2013.Visual Navigation for On-Orbit Servicing Missions. *5th International Conference on Spacecraft Formation Flying Missions and Technologies.*

Choi, C.,Taguchi, Y., Tuzel, O., Liu, M-L., Ramalingam, S., 2012. *IEEE International Conference on Robotics and Automation (ICRA.).*

Drost, B., Ulrich, M., Navab, N., Ilic, S., 2010. Model Globally, Match Locally: Efficient and Robust 3D Object Recognition. *IEEE Conference Computer Vision and Pattern Recognition (CVPR.)*

Ellery, A., Kreisel, J., Sommer, B., 2008. The case for robotic on-orbit servicing of spacecraft: spacecraft reliability is a myth. *Acta Astronautica 63(5-6).*

Fuchs, S., 2012. Calibration and Multipath Mitigation for Increased Accuracy of Time-of-Flight Camera Measurements in Robotic Applications. *Dissertation, Technical University of Berlin.*

Haarbach, A.,2015. 3D Object Reconstruction using Point Pair Features. *Bachelor's thesis, Technical University of Munich.*

Johnson, A., Hebert, M., 1999. Using Spin Images for Efficient Object Recognition in Cluttered 3D Scene. *IEEE Transactions on pattern analysis and machine intelligence, vol. 21 , no. 5.*

Kaiser C., Sjöberg, F., Delcura, J. M., Eilertsen, B., 2008, SMART-OLEV – An orbital life extension vehicle for servicing commercial spacecrafts in GEO, *Acta Astronautica 63.*

Lonsberry, A., 2012. Fast recognition and pose estimation for the purpose of bin-picking robotics. *Master thesis, Case Western Reserve University, USA.*

Mian, A,S., Bennamoun, M., Owens, R., 2006. Three-Dimensional Model-Based Object Recognition and Segmentation in Cluttered Scenes. *IEEE Transactions on pattern analysis and machine intelligence, vol. 28, no. 10.*

Rabbani, T.,van den Heuvel, F., 2005. Efficient Hough Transform for Automatic Detection of Cylinders in point Clouds. *ISPRS WG III/3, III/4, V/3 Workshop "Laser scanning 2005", Enschede, the Netherlands.*

Schilling, K., Regoli, L., 2011. The PMD 3D-camera for Rendezvous and Docking with Passive Objects. *In 8th International ESA Conference on Guidence, Navigation& Control Systems.*

Schnabel, R., Wahl, R., Klein R., 2007. Efficient RANSAC for Point-Cloud Shape Detection. *The Eurographics Association and Blackwell Publishing.*

Stoll, E., Letschnik, J., Walter, U., Artigas, J., Kremer, P., Preusche C., Hirzinger, G., 2009. On-orbit servicing. *IEEE Robotics & Automation Magazine 16(4).*

Tzschichholz, T., 2014. Relative pose estimation of known ridged objects using a novel approach to high-level PMD-/CCD- sensor data fusion with regard to applications in space. *Dissertation, University of Würzburg, Germany.*

Tzschichholz, T., Ma, L., Schilling, K., 2011. Model-based spacecraft pose estimation and motion prediction using a photonic mixer device camera. *Acta Astronautica 68, (2011).*

Wolf, T., Reintsema, D., Sommer, B., Rank, P., Sommer, J., 2012. Mission DEOS – Proofing the Capabilities of German's Space Robotic Technologies. *International Symposium on Artificial Intelligence, Robotics and Automation in Space–i-SAIRAS.*