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Navigation for Satellite Formation Flying

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Abstract. This paper deals with the case of a target satellite in an unknown orientation and location with respect to the master satellite. Feature based monocular pose estimation vision system was presented. The results of analysis, implementation and testing of simulation intended for vision-based navigation applications such as rendezvous of satellites and formation flying are shown. The mobile robot was used as the platform for the vision system. Pose estimation algorithms were implemented in Matlab environment. It was obtained that the proposed method is robust on varying and low light conditions.
Keywords: satellite, vision navigation, autonomous docking

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1. INTRODUCTION

This paper deals with the problem of a target satellite in an unidentified orientation and location with respect to the chaser.

A method for calculating the position and orientation of uncooperative space objects is presented. The results of analysis, implementation and testing of simulation intended for satellites formation flying are described. It was done under the project conducted by Warsaw University of Technology. A servicing satellite is sent to capture a target object and to execute servicing tasks [1]. The described method focuses on final phases of rendezvous. It was assumed that an image of an object, taken by a calibrated camera in each step of time is known, and it was assumed a 3D representation of an object is known. It was proposed a solution for tracking rigid objects that promises good computational performance. The proposed method is stable and robust on the tracking failures. Point-to-point correspondences are used to calculate the pose of the target, assuming a calibrated camera. The target is passively non co-operating, although the inspection craft has prior knowledge of the target structure. The target object cannot aid in a process such as rendezvous or docking. It does not have actuators, its actuators are disabled and it does not have visual aids such as markers.

2. STATE OF THE ART

This task of visual object tracking is encountered in different application fields, of which the most prominent ones of which will now be briefly summarized. Autonomous Rendezvous and Docking is receiving attention fromthe research community. With TriDAR [2], a solution of the pose estimation problem is available, combining the LiDAR approach with triangulation. The idea is to combine the advantages of both methods: the long range capabilities of a LiDAR sensor and the accuracy of a triangulation approach in the near range [3]. The resulting sensor system is expensive, when compared to purely camera-based systems [4]. A more inexpensive method is to rely on monocular vision [5]. Common is the use of a scanning LiDAR sensor for estimating the pose of the target [2]. The target is detected in a first step and a range is estimated. Then, a 3D model is fitted, after which the full pose is available [6]. The successor of the sensor used in the Orbital Express mission –the Automated Video Guidance Sensor is primarily intended for the crew exploration vehicle [7]. A lot of projects related to autonomous Rendezvous and Docking use laser-based sensors [2]. Often, fiducial markers must be present on the target. Monocular vision is rarely used for full 6-DoF pose estimation, apparently due to accuracy concerns [8]. Stereo vision is more common, but still seldom proposed in this context [9]. LiDAR-based sensors are dominating in this area.

The possibility of directly and reliably measuring the distance is important, therefore the method proposed in this work looks promising after a review of the relevant literature and may especially present an alternative to close-range laser-based sensors. Rendezvous phases are defined [23] as phasing, far range (10-100 km), close range, and final approach (100-500 m to contact).

Different types of sensor types are currently chosen according to the operation range and performance. Radar type or ground based navigation would suit phasing and far range rendezvous phases. On the other hand, only an optical sensor type will be suitable for relative navigation during close range rendezvous phases with non-cooperating spacecraft [3]. In fact either a camera type sensor or laser range-finder sensors dot not require a cooperating target. However, relative navigation using scanning laser range-finder would be challenging since: relative distance should be small between the satellites, the laser beam is narrowed which limits the area of scope to detect the target, and its accuracy relies on optical corner-cube reflectors as an interface mounted on the target satellite.

The visual system task is used to identify the relative position and orientation of the customer satellite. The required hardware is simple and shall be readily available even for small space crafts with a small mass and power budget [10]. Some advantages of a camera sensor are listed below [4]:

- cost benefits compared to an active sensor,
- no need of a cooperating target and antennas attached to a target,
- the measurement accuracy increases with decreasing range, because of increasing resolution,
- the measurement of pose parameters can be obtained in single step procedure,
- camera sensor has no moving parts and is then less sensitive to orbital environment,
- low range can be covered by a sufficient field of view,

Autonomous mission as ETS-VII and Orbital Express have used camera sensors for relative navigation during close range rendezvous operations [11]. The visual marker was attached to Orihime target satellite to make possible the capture process. The Orbital Express mission has used a visual marker for the last phase [7]. A three-dimensional gold dots against a flat black background was mounted on the NextSat [12]. Visual markers are useful features on client vehicles, particularly those which are designed to be serviced or for which the ability to be repaired is considered important. Many missions cannot rely on special vision markers. Considering that most satellites have a V-flange structure that shall be a suitable mechanical interface for capturing and a natural marker for the relative visual navigation system [10]. SUMO is also designed to service many types of customer spacecraft without requiring servicing aids, the visual system identifies fiducial points in order to establish the pose estimation.

The representation of the object pose plays an important role in the estimation process. The correspondence problem deals with the question, which object feature belongs to which image feature.

Basically, either an iterative softassign algorithm [13] can be used. Pose estimation tasks appear in a vast range of applications in many different areas: cartography, tracking, indoor/outdoor robot navigation, autonomous landing, visual recognition, docking, and avoidance maneuvers. In many cases, a description of the 3D geometry of the scene is available a priori, in this case the pose estimation uses model-based techniques. An introduction of model-based techniques and some of their applications can be found in [14]. A review on point-based and higher order entities pose estimation methods are presented in [10].

Model-based techniques shall be considered as a suitable alternative for the relative navigation system during visual inspection of a non-cooperating satellite. The knowledge of the customer satellite geometric is provided by the spacecraft plan design, for example CAD models. Cropp uses such techniques for pose estimation applied to a generic microsatellite [10]. The microsatellite in this case is modelled by line-based models [3]. The simple box-shaped satellite with antennas allows to detect easily the lines in the image. The approach requires a high number of iterations and has poor convergence results for unmatched lines. Howard describes a video-based sensor intended for automatic docking systems [11]. This system was developed for NASA with intended use for satellite servicing.

Algebraic methods are used, based on three circles of retroreflective tape mounted on the satellite. In this case, the pose solution is not unique since as many as four solutions are possible with three point correspondences. An autonomous navigation system based upon point-based models and softposit is developed in [7], in which the vision system is tested in a testbed which uses a scaled satellite model and a robotic manipulator capable of simulating 6 degrees of freedom motion of a satellite in an orbit. A visual system for replacement of an orbital replace unit is developed in [15], in which the vision system uses a grasping interface mock up, and a stereo vision system is employed to compute the pose. Natural features, like corners, of the spacecraft can be extracted from the image, and afterwards, they can be matched with the correspondent spacecraft model [16]. To date, based Hough transform algorithms are widely used for feature extraction [4].

Several visual navigation systems employing landmarks attached to target satellite are addressed in [7]. A real-time visual system is described in [14], in which the optical system identifies infrared light-emitting diodes attached to the target and estimates its pose. The pose calculation is based on four-point coplanar algorithm which is provided in [17].

Originally, this problem is usually referred to as PnP [16] problem to designate the problem of determining the pose of the object w.r.t. the camera, given a set of *n* correspondences between points in the image and points in the 3D model of the object of interest.

Based-model pose problem falls into two categories of solution, closed-form and numerical solutions [18]. Methods of computing the pose by line-based schemes can be found in [19].

3. MATERIALS AND METHODS

A task of calculating the pose of an object using camera sensor is dating to 1841 [20]. Orientation of a camera given a set of n 2D-to-3D point correspondences, is a difficult problem [10].

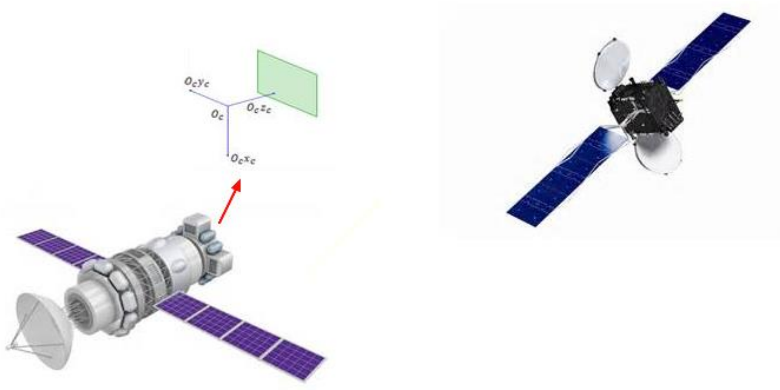

Fig. 1. Pose estimation problem

The ability of the navigation system to deal with different light condition is another relevant factor over the close-range operation. Lighting conditions in space is a major factor to be considered during visual inspection and can change rapidly and dynamically. The following sources have to be considered according to the importance of their effects (Fig. 2): the Sun, reflections of sunlight on target surface, reflections of sensor illuminator light on target surface, direct light or reflections of other light sources [21].

The problem of determining the position and orientation (Fig. 1) of a camera from a set of 2D-to-3D point correspondences is known as the Perspective-n-Point (PnP) problem [20]. The PnP problem is to get the position and orientation of a camera given a set of n correspondences between 3D points and their 2D projections [1]. The minimal number of correspondences to solve PnP problem is three.

The Grunert's formulation appears in each P3P problem [22]. Fischler found that P4P problem with non-coplanar points had many solutions and with coplanar points had only one solution.

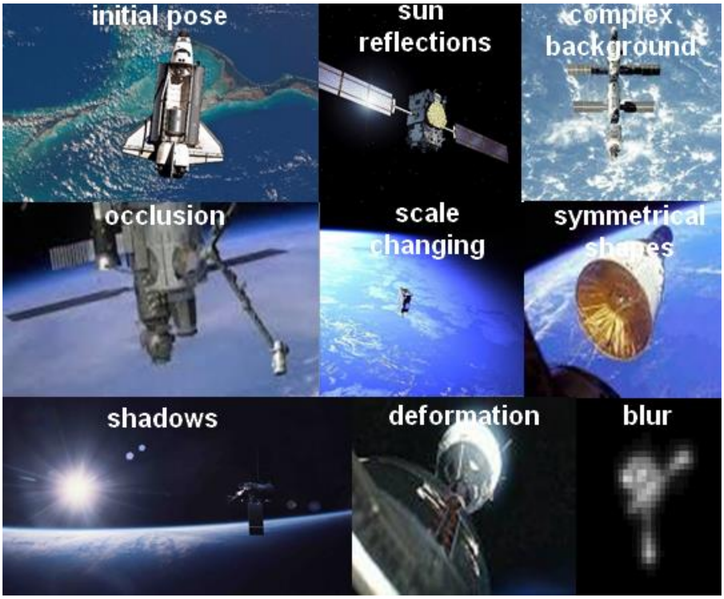

Fig. 2. Some of problems commonly found in image processing

For P5P problem there were as many as two solutions [22]. For more than 6 correspondences, it is Direct Linear Transformation [1]. First approaches were based on tracking of the contour of a target. The 3D positions of the fiducials in the world coordinate system are assumed to be known and are observable at all times. This approach in case of satellites is impractical because many existing ones have not these fiducial markers (Fig. 3).

The other popular approach is based on three-dimensional models. In this case pose computation is achieved by minimization the distance between 3D model edges and the corresponding edge features in the image. The weakest point of approach, based on 3D model, is reliance on geometric model. When the object is complex there are achieved low frame per second rates. To reject outliers algorithms such as Random Sample Consensus (RANSAC) are implemented to achieve robustness to illumination conditions in space [22]. Camera sensors can provide capabilities to obtain relative pose. The use of the interface circle used to attach the satellite to additional vehicle has been proposed for capturing the satellite. This has a disadvantage because it is limited for proximity operations.

Feature matching computer vision approaches have been developed but they are computational intensive and cannot be used during entire mission [23].

Critical sensitivity to illumination and occlusions of a target had been observed. Learned database is also used on Orbital Express and the algorithms are based on edges in this case. Lepetit suggested using corner features with a single camera for tracking objects in 3D [12]. This approach was robust to partial occlusion.

Drawback of this method was a camera should be close enough to one of key frames and tracking must be initialized after tracking failure. It is better to rely on naturally present features, such as edges, corners, or texture (Fig. 3).

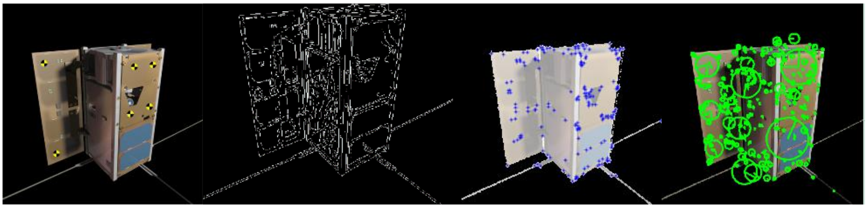

Fig. 3. Example of the markers, line features, corners and local features on the PWsat2 satellite

The proposed system is planned to deal with finally stages of satellite rendezvous from far proximity operations, when the satellite is about 2 km from satellite to the contact of satellites. Someone can divide PnP algorithms according to the method used to solve them to non-iterative and iterative. Non-iterative methods formulate the problem as a system of linear or non-linear equations, which is solved in a sequence of operations using algebra. Iterative approaches usually minimize an error function but may fall into local minimum and result in pose ambiguity. Among iterative approaches, Dementhon presented Pos with Iteration (POSIT) algorithm to solve PnP problem for more than four non-coplanar correspondences [19]. In order to get accurate pose estimation results, iterative approaches are good choices. Depending on the number of point correspondences between 2D and 3D space, someone can split pose estimation algorithms into minimal ones which use the smallest possible set of point correspondences between 2D and 3D space to calculate camera pose, and non-minimal, which use more point correspondences to linearize the task or to return the more precise result. Minimal algorithms are usually used to filter out incorrect correspondences, which are called outliers, for example using RANSAC [24]. Once correct correspondences are known one can use non-minimal algorithms to get better final result.

To find correct correspondences, it is significant to have a fast algorithm which uses the smallest number of measurements to calculate the camera pose. It is because such an algorithm is executed a lot of times inside the RANSAC loop. When more than a minimal number of measurements is made, it could be possible to improve the estimate of its pose.

Technically it is possible to extend this solution to more than 5 points, but this solution is not practical since the number of possible triplets grows exponentially with the number of input points. It is known that three point correspondences are sufficient to recover the camera rotation and translation in the case of a calibrated camera – that is why the name of the problem is P3P – and there are up to four real solutions to the problem.

The most convenient the Direct Linear Method, evaluating the rotation and the translation, is not suitable for space applications since it produces a rigid transformation only in the cases when the image is free of noise. Several methods solve the problem analytically when a few measurements are given and when the model points are in a specific configuration.

Fischler gives a closed form solution for three or four coplanar model points [4]. One of the methods suggested to solve the matching problem is to evaluate the pose and the matching, simultaneously during the iterative process the pose of the object is estimated from a partial interpretation and this pose estimate is used to eliminate irrelevant interpretations at the next interpretation stage. When the correspondences are known, pose can be computed in an iterative loop by minimizing the object function. A camera pose can be calculated from various kinds of image measurements, for example from a set of 2D projections of 3D points or 3D lines, from a combination of points and lines, projections of the known planar objects like chessboards, coplanar circles, intersections of parallel lines, edges and more.

The estimation from rich objects, like lines or circles, might appear more precise, but it is needed to solve computer vision tasks such as detection, and to compensate the fact that image is affected by distortion. Moreover, the unknown correspondences between the image and model features result in a large search space for ambiguity resolution, and thus in a significant computational load. A pose estimator should rely on a minimum number of image features, be robust to ambiguous pose solutions, compensate for image noise and offer solutions of increasing accuracy. The definition of a proper spacecraft model is a fundamental step of the pose estimation strategy. On one hand, the spacecraft model has to be as minimalist as possible to reduce the system complexity and the search space for matching. The estimate of the initial pose is certainly the most challenging task of the pose estimation procedure. Many authors assume a-priori knowledge of the relative position and orientation to aid the vision navigation system. Using a single monocular image, and utilizing knowledge of the target spacecraft, estimation of the target's relative rotation and translation parameters with respect to the camera is found. In this part, the projected method was described.

The presented method of the solution is applicable to monocular camera systems. There are given photos of the known object which is seen from different camera locations at every step of time.

The features used to describe the target object are in 3D, while the projection of a feature found in the image is in 2D. The pinhole camera model is used to done the projection of the 3D coordinates of the object features with respect to the camera frame to the 2D coordinates found in the image [12]. This transformation from the 3D coordination to the 2D coordinate is also called a perspective projection.

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_u & 0 & u_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{1}$$

where α_u and α_v are the scale factors, u_0 and v_0 are the coordinates of the principal point, s is the scale factor. The translations t_1, t_2, t_3 and elements of the rotation matrix $r_{11} \dots r_{33}$ are unknown.

There are 2 sets of points: a 3D set representing the model denoted by $\widetilde{M} = [X \quad Y \quad Z]^T$, and a 2D set detected from the image denoted by $\widetilde{m} = [u \quad v]^T$. Assume it is known that each point in the 2D set is the image local feature which is in the 3D set. The correspondences between the 2D features and 3D is not known. This leads to the problem known as the correspondence problem. It is the process of finding out which features in a set correspond to a feature in another set. If the position of the target is approximately known, the correspondence problem becomes simpler because one can project the geometric representation onto the image plane and associate each projected model feature to the closest image feature to obtain the correspondence. A feature representation of an object is more effective to the pose determination. The below diagram of the proposed algorithm was presented (Fig. 4).

Local features of every entity are locally evaluated and represent a small part of the object. The advantage in using point features in the pose estimation solution is the relative ease of extracting these features. There are unknown six parameters that can describe relative pose of two objects: three coordinates which describe the linear translation of an object in relation to the camera and three angles of rotation (roll, pitch, yaw) which describe mutual angular orientation of two objects in space [8].

In most 3D tracking methods, the internal parameters are assumed to be fixed and known, what means that the camera cannot zoom, because it is difficult to distinguish a change in a focal length from a translation along the camera-axis. The angular orientation of the object was parametrized by using the Euler angles [21]. These three angles form three free parameters that describe any rotation transformation. There is singularity when the coordinate frames are rotated mutually by pitch angle equal [6]. The proposed method works in a such manner as described downwards. At first, a photo of an object is taken. Next, there are detected local features on this photograph.

Local features of the object are usually associated with a change of image properties simultaneously, although it is not necessarily localized exactly on this change. To handle, as wide as possible, a range of viewing conditions, feature point extraction should be insensitive to the scale, viewpoint, and illumination changes. The local features of the object are extracted by using the Scale Invariant Feature Transform (SIFT) detector and descriptor proposed by Lowe.

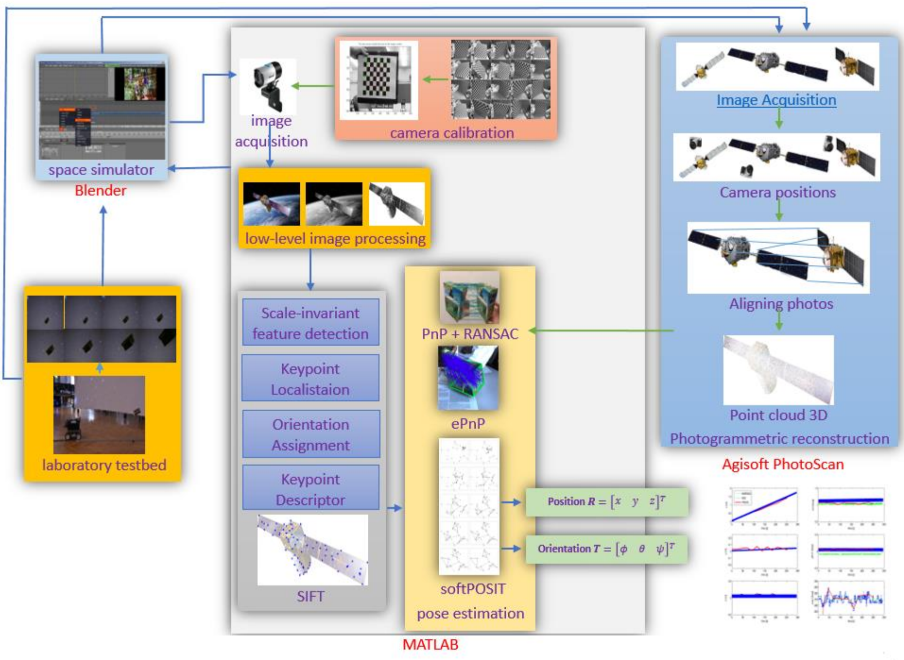

Fig. 4. Scheme of proposed algorithm

Algorithm extracts features and is for object recognition based on local 3D extrema in the scale-space pyramid build with difference-of-Gaussian filters. First the location and scale of the keypoints are determined precisely by interpolating the pyramid of Difference-of-Gaussians used for the detection. The input image is successively smoothed with a Gaussian kernel and sampled. The difference of Gaussian representation is obtained by subtracting two successive smoothed images. The Gaussian kernel and its derivatives are the only possible smoothing kernels for a scale space analysis. To achieve image rotation invariance, an orientation is also assigned to the keypoint. It is taken to be the one corresponding to a peak in the histogram of the gradient orientations within a region around the keypoint. All dig levels are constructed by combining smoothing and subsampling. The local 3D extrema in the pyramid representation determine the localization and the scale of the interesting points.

This method is stable under viewpoint changes, and it achieves an accuracy of a few degrees. An image is transformed into a group of local features. On the exit of this algorithm there is the known the two dimensional vector of coordinates of each feature and the second vector which contains the radius of each feature and the angle of orientation in radians. To further explore the methods of solving the pose estimation problem, one must be able to model the target object. It is usually described by a set of features.

During an offline training stage, a database of interest object points was build. Their positions on the object surface are known [19]. At runtime, SIFT features are extracted from the current frame, matched against the database, resulting in a set of 2D-3D correspondences. The next task is the pose estimation of the object. The object pose can then be estimated from correspondences. They have been found iteratively by using POSIT algorithm. This algorithm needs a focal length, and 4 or more non-coplanar 2D-3D correspondences.

This algorithm estimating the pose uses a scaled orthographic projection, which resembles the real perspective projection at convergence. Such approximation leads to a linear equation system. This gives the rotation and translation directly, and there is no the need of a starting pose. A scale value is introduced for each correspondence, which is iteratively updated. What is known is the distribution of the feature points on the object and the images of these points by perspective projection. If someone could build SOP images of the object feature points from a perspective image someone could apply the POS algorithm to these Scale Orthographic Projection (SOP) images and we would obtain an exact object pose. Computing exact SOP images requires knowing the exact pose of the object. Someone can apply POS to the actual image points and then can obtain an approximate depth for each feature point. Then someone can compute an SOP image. At the next step, POS to the SOP image was applied to obtain an improved SOP image. Repeating these steps, it converges toward an accurate SOP image and an accurate pose. More about POSIT algorithm can be found in [5].

4. RESULTS AND DISCUSSION

This section described the experiments which were completed. The experiments were tested in Matlab software. It was needed to perform a simulation of space environment on the Earth. The experiments were tested as follow. Satellite was modelled as a rigid box of dimensions 130 × 70 × 80 mm. The object was suspended under mounting stand. With the aim of Honeywell HMR-3500 and Microstrain GX3 inertial navigation sensors, the ground truth position of the robot was measured (Fig. 5).

Fig. 5. The sensors which were used in the experiment

The low-cost camera was mounted on a mobile robot which can be translated and rotated in relation to an object coordinate frame (Fig. 6). The space background was displayed on the 3-channel spherical screen. The source of light was fixed. There were measured six degrees of freedom. Next, the ground truth measurements were compared with the calculated results. The goal of the experiments was to check how accurate is the algorithm. It was expected that the calculated results should be similar to the ground truth measurements. The camera parameters were calculated during an offline calibration phase.

Fig. 6. The experimental testbed

The camera has a distance of approximately 1600 mm to the object (Fig. 7). At the beginning, the mobile robot is not moving. Next the robot is moving and it takes photos.

Fig. 7. Mobile robot moving along a straight line

Fig. 8. Mobile robot moving around the object

Figures 9 and 10 show image sequences from both experiments.

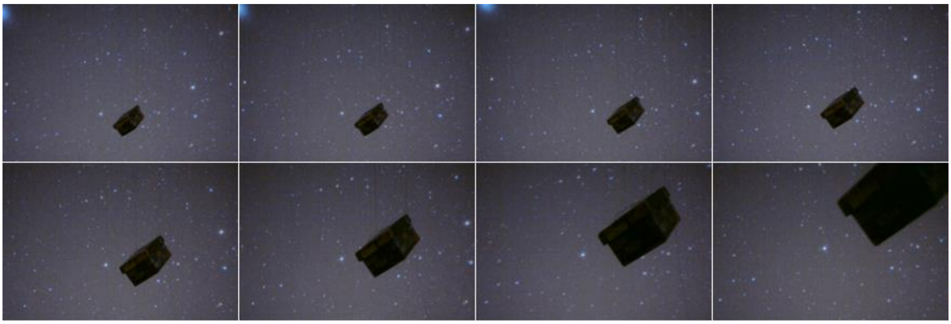

Fig. 9. Images sequence from the first experiment

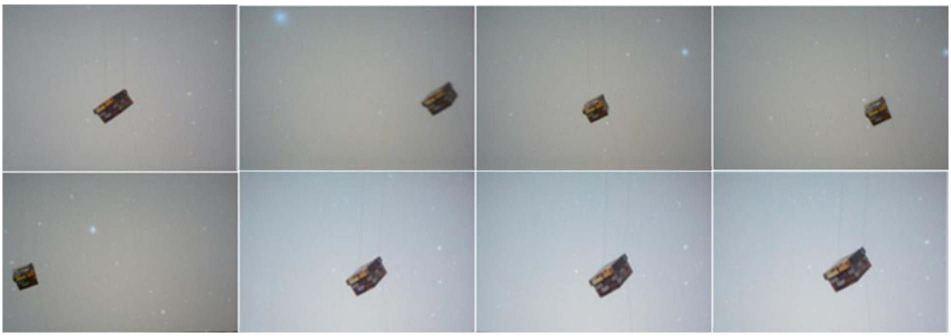

Fig. 10. Images sequence from the second experiment

The six plots present the results for the first chosen example (Fig. 11). On the horizontal axes of the first three plots there is given time in seconds and on vertical axes the measured translations in millimetres. On the next plots (right side), on horizontal axes there are given, similar as the upper figures, time and on vertical orientation in degrees.

Green line shows ground truth using HMR3500 sensor, red GX3 and blue line shows the vision system-based measurements. Ground truth (green line) should be close to the measured results. On the upper left there was presented the linear translation of the object along x axis of the camera coordinate system.

Next, there was conducted the second experiment. A mobile robot was moved in other manner as in the first experiment. Similar as in the first case, six plots are presented. The first three present linear translations along the axes of the camera coordinate system and the next three present angular orientation of the object. The first plot presents linear translation along x axis. There is small error between both measurements.

At the end of simulation, the difference is about 20 mm. On the second plot, both lines green and blue are close to each other. The measurements for angular orientation of the object are presented on the next three plots. For roll motion, an error of about 2 degrees was observed. Similar results were obtained for the pitch. Ground truth error varies around 1 mm in space.

The sixth plot presents a yaw. In this case the error is 5 mm. Of course, significant differences between the light conditions in space and at the laboratory might occur. Reconstruction of the space conditions on the laboratory stand is quite a challenging task.

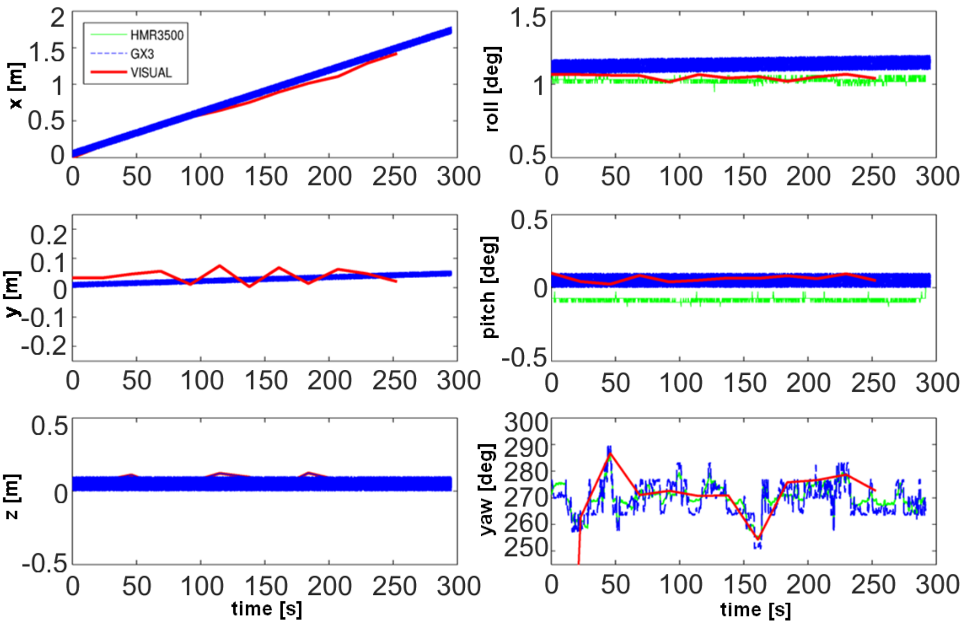

Fig. 11. Results from the first experiment

The second plot (Fig. 12) presents linear translation along *y* axis. In reality, there was no translational motion along *y* but, one can see from vision system measurements that maximum difference for *y* axis is about 10 mm.

Possible cause of this errors is a nature of the presented method. It is possible to try to reduce the errors if better correspondence generation algorithm will be obtained.

On the third plot, an error for *z* axis is about 2 mm, which is less than for *x* and *y* axis. Next, three plots present rotations around three axes of the object coordinate system. The fourth plot presents that there was rotation about 3 deg. On the fifth plot, small error between both, ground truth rotation and vision-based measurement can be observed. After 13 seconds, the error is bigger than at the beginning. Pose estimation errors of 4 degrees in orientation are obtained with the testbed experiment.

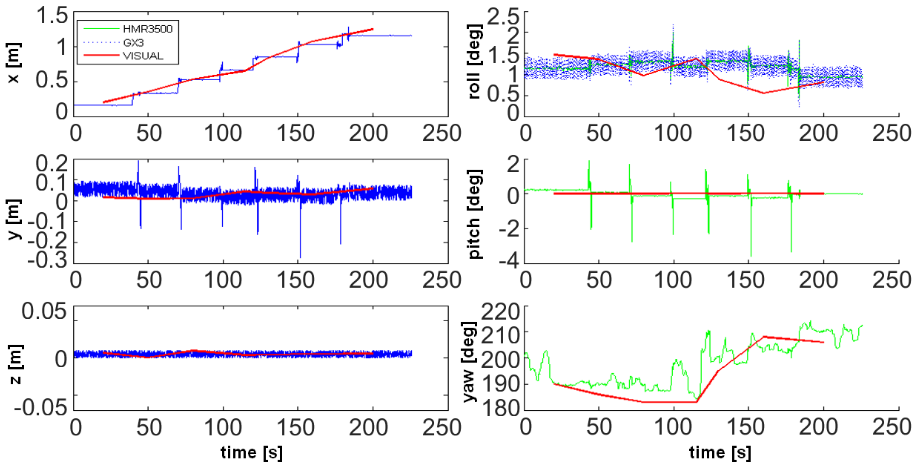

Fig. 12. Results from the second experiment

Up to 25 iterations are needed for convergence. It is mentioned that the precision can be improved, however, at the higher running time. These results were as expected. The experiments take about 133 ms per a frame on modern CPU. It was shown that the introduced method is able to run in real time.

5. CONCLUSIONS

In the last years, autonomous satellite formation flight become more and more important. This article addresses the design of a monocular vision-based navigation system for on-orbit-servicing and formation-flying applications. Feature based pose estimation vision system was presented. The results of numerical simulation were presented. Translational errors were under a few millimetres. It is a good result when compared to other methods which were described in the literature. One of the most significant advantage of the presented method is that, the tracking might be continued without initialization after tracking failure. It is planned to improve the proposed method.

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