



# Motion estimation of uncooperative space objects: A case of multi-platform fusion

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## Abstract

This work describes an efficient technique to sequentially combine estimates resulting from individual sets of measurements provided by a network of satellites. The prescribed method is especially effective to estimate motion states of an uncooperative space object using range image data. The technique, which is fast and suitable for on-line applications, could also be effective to capture stray objects or those satellites that require periodic servicing. Such missions call for high degree of precision and reliable estimation methods. In fact, the proposed estimation architecture consists of a network of synchronized platforms, i.e., Observer Satellites (OS), each with processing power and transmission capability, that are observing a common Target Space Object (TSO). All OSs are expected to have suitable measuring devices, such as active vision sensor, that provide sensory range image data. Each platform could also independently estimate its objective based on its own observations. The estimates are then transmitted to a fusion center to assimilate the fused estimate that is more accurate than any individual estimates. As a specific example, we show exploiting efficient algorithms in processing of range image data, filtering, and fusion of estimates enables the proposed method to be especially effective for active debris removal. Different case studies confirm that the method is capable of processing measured data fairly quickly and producing fused estimates with a tangible decrease in estimation error.

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## 1. Introduction

During the past fifty years, space applications were basically limited to Earth observations and telecommunication, as space trips were extremely costly and required governmental and in some cases international support. Nonetheless, the current effort to decrease the cost of such missions, through for example reusable rockets, have brought many new applications into light. Applications such as space hotels, space tourism, and space-based manufacturing. Obviously, these interesting ideas demand the

space environment to be safe and free of hazardous or uncooperative objects. All such efforts come down to a critical juncture to be able to precisely identify any moving object in the space. The current work is an efficient effort toward that goal. When it comes to safety, handling Uncooperative Space Objects (USO) is important. Among all existing USOs and missions that deal with them, some are of particular interest, such as capture of stray objects, capture and servicing of satellites, asteroid exploration as well as active debris removal, or in some cases space-assembly missions (Hiroshi et al., 2002; Flores-Abad et al., 2014; Yoshida et al., 2006; Kubota et al., 2005; Bonnal et al., 2013; Chashmi and Malaek, 2016). Successful and safe accomplishment of such missions relies heavily on the accurate knowledge of Target Space Objects (TSO)

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motion and its associated inertial parameters. However, any estimation technique relies on the nature of the data and how it is collected (i.e., proper sensor). Different works suggest on-orbit vision sensors either active (Opromolla et al., 2017; Liu et al., 2016; Shang et al., 2007) or passive (Kanani et al., 2012; DAmico et al., 2014; Liu and Hu, 2014) are much more effective, especially where uncertainties govern. Uncertainties, on the other hand, are due to the aging effect, collision with other space objects, gravitational field, and irregular fuel consumption. In this work, we have assumed that the data is available through an active sensor, as active sensors' data is not affected by typical extreme sensing condition of space environment (Aghili, 2012). It is further noticed that active vision sensors are quite diverse. The preferable ones are laser range finder, scanning LiDAR, and flash LiDAR for their proven robustness in the space environment (Bonnal et al., 2013; Opromolla et al., 2017).

In the following, we provide a brief overview of available and well-established methods with Aerospace applications that involve USO motion estimation using range image data filtering. For example, Lichter in Lichter et al. (2004) presents a method that implements a sensor-level fusion of raw image data acquired by a cooperative team of uniformly distributed on-board vision sensors. With some extensive manipulations, the work finally reaches dynamic states and shape of the target as the outputs. However, the results rely on hardly acceptable assumptions. For instance, the sensors are assumed to be synchronized (i.e., no latency and failures are considered in transmitting data to the fusion center) with known relative navigation states. On the contrary to Lichter et al. (2004), in the current work, we use track-level fusion that does not need such simplistic assumptions. In the same line of work, Hillenbrand et al. (2005) describes long-term motion prediction and model identification for a free-floating space object using a least-squares estimation technique that filters range image data. The proposed method helps identify six inertia parameters of an USO. In Aghili et al. (2011), however, a closed loop configuration of Iterative Closest Point (ICP), initially proposed by Besl and McKay (1992), together with an Extended Kalman Filter (EKF) is employed for both motion and parameter estimation of a free-floating object. The ICP algorithm itself uses the EKF's pose prediction whenever new range image data is acquired by the vision sensor. As the last reference, we examine (Opromolla et al., 2017) that discusses the problem of pose estimation of a spacecraft in close proximity. It is interesting to note that (Opromolla et al., 2017) combines different techniques such as principal component analysis and template matching together to reduce the computational cost. In the current work, we have also employed similar approaches in the pose estimation phase. There are quite a few other references that address a wide variety of other Aerospace applications involving motion estimation of space objects using 3-D range image data

(Liu et al., 2016; Shang et al., 2007; Aghili, 2012; Opromolla et al., 2015; Rhodes et al., 2016; Kelsey et al., 2006).

In this work, the main concentration is to develop a method which is fast and accurate enough to help expand space missions involving motion estimation. Here, we propose a new architecture that estimates the dynamic states and inertial parameters of an USO using sensory range image data. With Fig. 1, the method employs efficient algorithms to process noisy range image data, together with appropriate filters to estimate uncertain dynamics, and further provides reliable strategies to reduce the estimation error. Fig. 1 particularly illustrates the overall block diagram of the proposed estimation architecture in which a network of  $N$  synchronized agents are working as a team of Observer Satellites (OS). In fact, the  $i^{\text{th}}$  OS in the network maintains a local estimate of the USO's dynamic states. The network is expected to perform three major tasks, the first one involves a 3-D image registration algorithm, which is a customized version of the ICP that converts sensory range image data into a rough estimate of the USO pose. The second task computes the full dynamic states and inertial parameters of the USO using two separate filters, a Kalman Filter (KF) and a modified version of Unscented Kalman Filter (UKF). The local filters exploit the rough estimates of the first task as the measurements for the second task. The third task entails transmitting the local estimates to a fusion center where the improved global estimates are assimilated. Here, we assume that the position and orientation of all observer satellites are accurately known. Further, images provided by each OS are dense enough to guarantee that all TSO external edges have been captured.

Here, the number of observer satellites  $N$  plays an important role in the performance of the estimation architecture. As a starting point, a track-level fusion can be conducted with at least two estimates (i.e., two observer satellites). The accuracy of the fused estimates is, however, guaranteed to be higher than that of each local estimate of either OS. With more agents involved in the network, a sequential method could be utilized to fuse all local estimates and the accuracy of the resulting fused estimate, again, is expected to increase. However, in space applications operational cost, safety issues, computational time and resources are decisive factors in determining the number of observer satellites leading to the size of the network. The problem associated with computational time and resources can be tackled using efficient algorithms. Thus, the operational cost of a network of satellites and safety issues determine the size of network. In the current work, we first consider a network of two satellites and then show how to extend the network.

The superiority of this work as opposed to the previous ones stems from the fact that it employs more efficient algorithms to expedite the computational time and enhance the estimation accuracy. The efficiency of image registration

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