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Vision-based Navigation for Space Exploration

Anne Bettens[1*], Peter Gibbens[1], Gregory Chamitoff[2] and Xiaofeng Wu[1]

Introduction

The pursuit of autonomous navigation capability within space exploration is integral to enhancing the efficiency and versatility of various mission scenarios. This research explores vision-based navigation techniques, in the context of robotic spacecraft, with the aim of achieving autonomy in space exploration endeavours. Specifically, with a focus toward improving pose estimation of non-cooperative spacecraft, where the primary sensory input for this estimation is images captured by onboard cameras. The key facet to achieving this is harnessing the synergies between machine learning and Kalman filter (KF) techniques to enhance dynamic pose estimate within spacecraft navigation.

Aims

This research aims to provide a general solution for pose estimation, with the ability to learn in orbit. The overarching goal is to enable seamless collaboration between Convolutional Neural Networks (CNN) and KFs thereby enhancing the performance of both in dynamic pose estimation.

Methods

The integration of the CNN and KF in a closed loop for spacecraft pose estimation presents a solution that combines the advantages of both techniques. CNN excels in handling complex, data-driven patterns and can adapt to diverse scenarios. KF, on the other hand, provides a robust framework for tracking and filtering, particularly in dynamic environments. The KF informs the loss function withing the NN, hence closing the loop while also providing realistic dynamic information to the system.

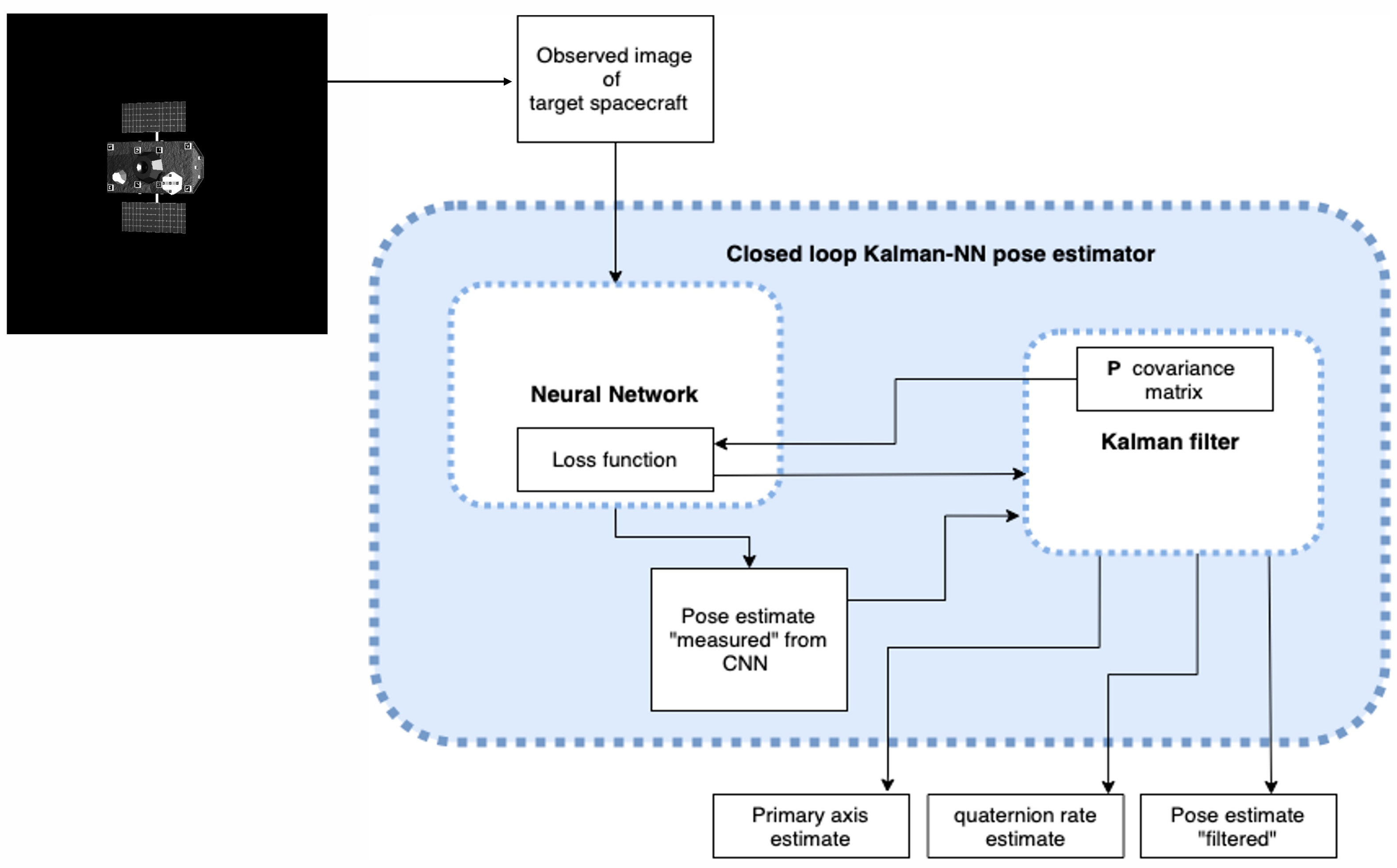

Figure 1: Overview of closed-loop Kalman NN pose estimator (simulated spacecraft image courtesy of Thales Alenia Space)

Results

The proposed fusion approach, which combines CNN and KF techniques for spacecraft pose estimation, was subjected to rigorous evaluation through comprehensive simulations and analyses. The results demonstrated convergence of the integrated CNN and KF estimates, demonstrating the successful merging of these estimation techniques and the effectiveness of the fusion strategy. A significant improvement in pose estimation was achieved after observing approximately 2.7 rotations of an unknown geometry, as seen in Figure 2. An accuracy of less than ± 1 degree orientation error and ± 0.2m position error was observed in close proximity.

Importantly, these observations support the fusion approach's capability to generalise its performance across diverse objects, emphasising its adaptability in scenarios with non-cooperative robotic targets.

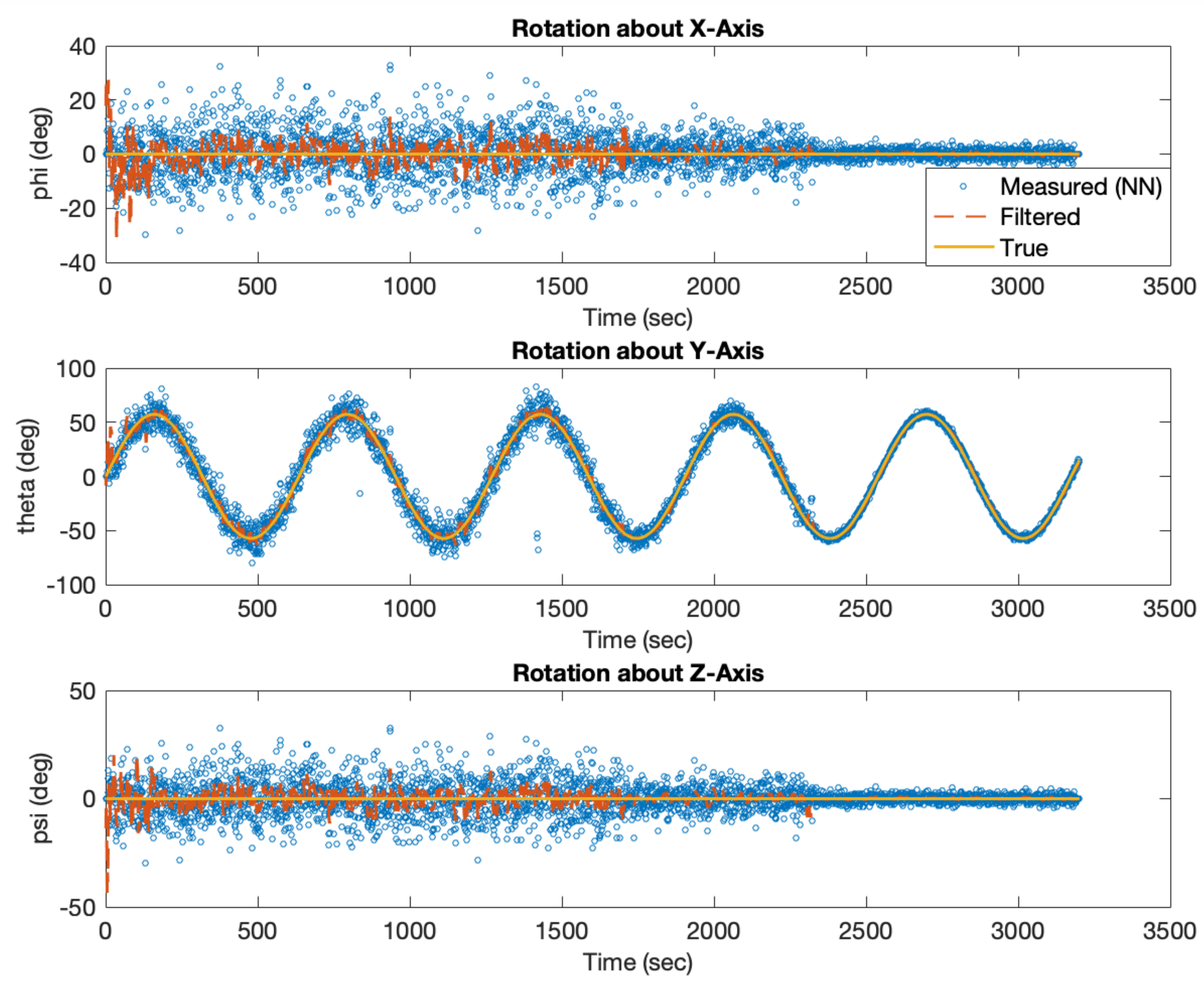

Figure 2: Euler angles of measurement from CNN and filtered values compared to truth for rotation about y-axis

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[1]The University of Sydney, [2]Texas A&M *anne.bettens@sydney.edu.au

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