Deep Learning Aided Sensor Fusion for Drift Reduced IMU Orientation Estimation

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Abstract

Inertial Measurement Units (IMUs) are widely used in a variety of applications such as Body Sensor Networks (BSNs) for orientation estimation, however the gyroscope suffers from drift due to sensor bias and noise that when integrated accumulate over time. This **FIXME:** project investigates a deep learning-based approach which aims to mitigate gyroscopic errors which can be integrated with sensor fusion techniques to achieve more accurate orientation estimates. The proposed deep-learning architecture leverages both neural networks and a temporal history to learn complex and nonlinear error patterns in IMU data, exploring if it outperforms a standard Kalman Filter without learned corrections. The network outputs a correction for the incoming gyroscope sample and ad the measurement noise covariance dependent on the incoming acceleration and magnetometer updates. The data used in training, testing and validating the model come from simulations through MATLAB's Navigation Toolbox and from public datasets such as Berlin Robust Orientation Estimation Assessment Dataset (BROAD).

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Contents

List of Figures

Lorem

List of Tables

Lorem

1 Introduction

1.1 Inertial Measurement Units (IMUs) and their applications

TODO: IMU exists → IMU is attractive → but IMU-only drifts → so we need fusion → but fusion has failure modes → so we propose learning-aided fusion.

IMUs are composed of multiple sensors which include a gyroscope, accelerometer, and occasionally a magnetometer. These three sensors measure the angular rate, linear acceleration, and the local magnetic field vector respectively. These measurements can be used to estimate the orientation of an object through integration of the angular rate. This data acquisition is essential for several applications such as BSNs, robotics, and autonomous vehicles where these systems rely on high-rate orientation updates.

IMUs have emerged as a key technology due to the ability to work in a self- contained environment. In environments where external references of orientation are unavailable or unreliable, technologies such as IMUs are attractive however, they suffer from drift due to sensor bias and noise accumulating over time. This can be partially mitigated through the use of sensor fusion algorithms like Kalman filters. Filters allow the use of accelerometers and magnetometers to guide and correct state estimation, but these also suffer from failures like magnetic disturbances and high linear accelerations corrupting a gravitational reference. This project investigates a deep-learning model which aides sensor fusion, by providing angular rate corrections to the filter.