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 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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I would also like to acknowledge the authors and maintainers of the publicy available datasets of BROAD and RepoIMU. Their efforts in collecting and labelling high quality IMU data and optical motion capture ground truth enabled the training, testing, and validation of the neural network. I am grateful for their contributions and cite them accordingly in this report.

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1 Introduction

1.1 Inertial Measurement Units (IMUs) and their applications

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 **FIXME:** cite, 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. Filters, such as the Kalman filter, 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. Due to these limitations, there is significant motivation to explore data-driven methods that compensate for these conditions and errors.

WORDS: 170

1.2 Problem Statement: IMU Drift and Its Impact

IMUs have shown promise in determining the orientation of an object in motion. However, IMUs suffer from a limitation called drift. IMU drift is characterised by the accumulation of errors through the integration of the angular rate. The sources of these errors include constant bias, scale factor errors and others expanded in **FIXME:** section. Errors are not exclusive to the gyroscope but also affect the accelerometer and magnetometer. Drift is also dependent on the type of IMU that is used. Lower cost/grade IMUs suffer from drift at a higher magnitude which results orientation inaccuracies much quicker compared to higher cost/grade IMUs. Errors then lead to inaccuracies in the orientation estimation of an object determined by the IMU.

Kianifar et al. explored using IMUs for automated orientation estimation in a clinical setting. They found that for rotation angles parallel to gravity, drift due to gyroscope bias cannot be compensated by the accelerometer.**FIXME:** cite. Even with multiple sensors, it is still challenging to find an accurate orientation estimation. Thus it is important to try and address the orientation problem by addressing gyroscopic drift.

Therefore, this project aims to address gyroscopic drift by using deep-learning methods to learn complex and non-linear nature of biases and errors.

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1.3 Research Question and Hypotheses

The question this project aims to answer is: **Can Deep Learning be used to learn the drift pattern to get drift free orientation estimation?** While this is the overarching question, it can be broken down to the following:

- How effectively can deep learning learn the drift experienced?
- Can this model be generalised or will the model only apply to a single IMU?
- What are the advantages or disadvantages of using Deep Learning compared to traditional approaches?

TODO: Write out the Hypotheses

2 Deep Learning Drift Mitigation: Literature Review

3 IMU Basics and Operational Principles

As mentioned before, IMUs consists of tri-axial gyroscope, accelerometer, and magnetometer. They measure angular rate, specific force, and the local magnetic field vector. The sensors are mounted so that it measures their components in the three orthorgonal axes x^b, y^b, z^b.

3.1 Gyroscope: Operations and Errors

The gyroscope is the main component that is used to determine the orientation of the object. It measures the angular rate in its orthorgonal axes $\omega^x, \omega^y, \omega^z$ which is used to determined the object's orientation at a discrete time. The orientation is determined through the integration of angular rate.

3.1.1 Angular Rate Integration

Starting in continuous-time kinematics, we can define a quaternion that is represented by the angular rate, where $\omega_q(t)$ is the real angular rate.

$$\omega_{\mathbf{q}}(\mathbf{t}) = [0,\ \omega_x(t),\ \omega_y(t),\ \omega_z(t)] \tag{1}$$

The orientation evolves according to

$$\dot{q}(t) = \frac{1}{2} q(t) \otimes \omega_q(t) \tag{2}$$

where $\otimes$ denotes quaternion multiplication. The solution over $[t_0, t]$ can be written using the quaternion exponential

$$q(t) = q(t_0) \otimes \exp(\frac{1}{2} \int_{t_0}^{t} \omega_q(\tau)\, d\tau) \tag{3}$$

These equations show that the orientation update is determined by integrating the angular rate over time and mapping the resulting rotation into a quaternion via the exponential.

3.1.2 Gyroscope Error Sources

Constant Bias

The bias of a gyroscope is the average output from the gyroscope when it is not undergoing any rotation **FIXME:** cite. This is measured in $^\circ/h$ and can be estimated by taking an average of the output. However, as discussed further in this section other error sources can make this difficult to determine.

White Noise / Angle Random Walk (ARW)

The gyroscope is also affected by some white noise that fluctuates at a higher rate than the sampling rate of the sensor **FIXME:** cite. This white noise sequence is zero-mean uncorrelated random variables between samples and across axes. When the gyroscope signal is integrated to obtain an angle, this white noise produces an ARW. The units of ARW is denoted by $^\circ/\sqrt{h}$, where if this value is $0.2^\circ/\sqrt{h}$, the ARW in one hour is $0.2^\circ/\sqrt{h}$ and in two hours is 0.28° This shows that the deviation of angle error grows proportionally to $\sqrt{t}$.

Flicker Noise / Bias Stability

Temperature

Scale Factor

4 Deep Learning Architecture

5 Data: Training, Testing, and Validation

6 Conclusion and Next Steps