



شبكة المعلومات الجامعية
التوثيق الإلكتروني والميكرو فيلم

بسم الله الرحمن الرحيم



HANAA ALY



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التوثيق الإلكتروني والميكروفيلم



شبكة المعلومات الجامعية التوثيق الإلكتروني والميكروفيلم



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جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم

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GPS DENIED NAVIGATION USING LOW-COST INERTIAL SENSORS AND RECURRENT NEURAL NETWORKS

By

AHMED ALI AHMED ABDULMAJUID

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the Requirements for the Degree of
MASTER OF SCIENCE
in
AEROSPACE ENGINEERING

**FACULTY OF ENGINEERING, CAIRO UNIVERSITY
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GPS DENIED NAVIGATION USING LOW-COST INERTIAL SENSORS AND RECURRENT NEURAL NETWORKS

Key Words:

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Summary:

Autonomous missions of drones require continuous and reliable estimates for their velocity and position. Traditionally, Extended Kalman Filtering (EKF) is applied to measurements from Gyroscope, Accelerometer, Magnetometer, Barometer and GPS to produce these estimates. When the GPS signal is lost, estimates deteriorate and become unusable in a few seconds, especially when using low-cost inertial sensors. This thesis proposes an estimation method that uses a Recurrent Neural Network (RNN) to allow reliable state estimates in the absence of GPS signal. On average, EKF positioning error grows to around 40 kilometers in five minutes of GPS-less typical drone flight. The proposed method reduces that error by 98% in the same GPS outage period.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

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