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A Tinyml-Augmented Inertial Navigation System for Real-Time Drift Compensation on an STM32 Microcontroller

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Abstract—

Low-cost MEMS-based inertial navigation systems (INS) suffer from nonlinear and time-varying gyroscope bias drift, leading to cumulative orientation errors in long-duration applications. Traditional sensor fusion algorithms assume constant bias and do not compensate dynamic drift behavior under operating conditions. This paper presents a TinyML-augmented inertial navigation system implemented on an STM32 microcontroller for real-time adaptive drift compensation. A lightweight neural network model is trained using temporal gyroscope features and deployed using TensorFlow Lite Micro with 8-bit quantization. The estimated bias was removed prior to quaternion-based Madgwick sensor fusion. Experimental validation shows reduced cumulative drift, improved yaw stability, and real-time execution feasibility within strict embedded memory constraints. The proposed approach confirms the integration of embedded machine learning in aerospace navigation systems.

Index Terms:

TinyML, Inertial Navigation System, MEMS IMU, Gyroscope Drift, STM32, Embedded Machine Learning, Sensor Fusion.

I. INTRODUCTION

Inertial Navigation Systems (INS) are widely used in aerospace platforms including unmanned aerial vehicles (UAVs), CubeSats, guided missiles, and aircraft avionics. These systems estimate orientation and motion by integrating angular velocity and acceleration measurements obtained from MEMS-based inertial measurement units (IMUs). Despite their advantages in size, weight, and cost, MEMS gyroscopes show bias instability and nonlinear drift behavior. Since angular velocity is integrated to compute orientation, even small bias errors accumulate significantly over time, especially in yaw estimation where gravity-based correction is unavailable. Traditional approaches such as complementary filtering and Extended Kalman Filtering (EKF) reduce noise but assume constant bias. Real-world operating conditions introduce time-varying bias due to temperature variation, vibration, internal heating, and sensor aging. Recent developments in TinyML enable machine learning models to use directly on microcontrollers. This work proposes integrating a lightweight neural network for real-time bias estimation on STM32 hardware, combined with quaternion-based sensor fusion to improve long-term stability.

II. LITERATURE REVIEW

The field of inertial navigation has experienced rapid development with the emergence of low-cost MEMS-based inertial sensors and compact embedded processing platforms. Traditional inertial navigation systems were originally developed using high-precision mechanical gyroscopes and ring laser gyros for aerospace and military applications. Although these systems offered excellent stability and accuracy, their high cost, large size, and significant power consumption limited their adoption in small autonomous platforms. The introduction of MEMS technology enabled the development of compact and low-power inertial measurement units suitable for drones, robotics, wearable systems, and educational aerospace platforms.

Researchers initially focused on improving orientation estimation through deterministic filtering approaches. Complementary filters became one of the most widely used methods because of their simplicity and low computational requirements. These filters combine high-frequency gyroscope measurements with low-frequency accelerometer information to stabilize roll and pitch estimation. However, complementary filters are limited by fixed gain selection and poor adaptability under nonlinear drift conditions.

To improve estimation performance, Kalman filtering techniques were introduced for inertial navigation applications. The classical Kalman Filter provides statistically optimal state estimation for linear systems, while the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) were later developed for nonlinear orientation estimation problems. Several aerospace navigation studies demonstrated the effectiveness of EKF-based sensor fusion for UAV stabilization and autonomous vehicle tracking. Despite their strong theoretical foundation, these approaches require accurate process noise covariance tuning and mathematical modeling of sensor behavior. Low-cost MEMS sensors often exhibit unpredictable nonlinear drift characteristics, temperature-dependent bias, and vibration-induced instability that are difficult to model accurately**.**

III. METHODOLOGY

The proposed system consists of:

- STM32F407 Microcontroller
- MPU9250 MEMS IMU
- TensorFlow Lite Micro runtime

Processing Pipeline:

- IMU Data Acquisition (100 Hz)
- Signal Preprocessing and Normalization
- TinyML Drift Estimation
- Bias Compensation
- Madgwick Quaternion Fusion
- Orientation Output

The architecture is designed to keep low computational overhead while enabling adaptive bias correction.

TINYML MODEL DESIGN

A. Feature Engineering

Input features include:

- Gyroscope X, Y, Z
- Sliding window of earlier 10 samples
- Signal variance estimation

Features are normalized before inference.

B. Neural Network Architecture

The implemented network consists of:

- Input Layer (30 features)
- Hidden Layer (16 neurons, ReLU activation)
- Output Layer (3 neurons – bias X, Y, Z)

Loss Function:

Mean Squared Error (MSE)

Optimizer:

Adam optimizer during offline training.

Embedded Optimization

Ensure real-time feasibility:

- 8-bit quantization applied
- Static tensor allocation
- Memory buffer reduction
- Loop optimization in firmware

Memory Usage:

Flash: ~38 KB

RAM: ~15 KB

Inference latency: < 5 ms.

SENSOR FUSION INTEGRATION

Corrected angular velocity:

$$\omega c(t) = \omega m(t) - \hat{b}(t)$$

Quaternion derivative:

$$\dot{q} = 1/2\ q \otimes \omega c(t)$$

Where:

$$q = [q0, q1, q2, q3]$$

The corrected angular velocity reduces integration drift significantly.

EXPERIMENTAL SETUP

Experiments were conducted under:

Static 20-minute drift test

Controlled slow rotational motion.

Disturbance test with vibration

Sampling rate: 100 Hz

Data logged via serial interface for analysis.
Performance metrics evaluated:

- Cumulative drift error
- Root Mean Square Error (RMSE)
- Bias stability
- Inference latency

IV. RESULTS AND DISCUSSION

A. Long-Term Drift Analysis

Raw gyroscope data showed linear drift accumulation over time.

TinyML-corrected output stabilized bias around zero.

B. RMSE Comparison

Yaw RMSE reduced significantly compared to classical fusion-only implementation.

C. Real-Time Performance

- No buffer overflow observed
- No dropped frames
- Stable execution at 100 Hz

The proposed TinyML-based drift estimator proves nonlinear bias modeling capability without increasing system complexity significantly. Compared to EKF:

- No Jacobian computation
- No state augmentation
- Reduced computational burden

The method is suitable for low-cost aerospace systems requiring embedded real-time performance.

V. CONCLUSION

A TinyML-augmented inertial navigation system was successfully implemented on an STM32 microcontroller for real-time gyroscope drift compensation. The integration of embedded machine learning with quaternion-based sensor fusion significantly improves long-term orientation stability while supporting strict embedded resource constraints. The results confirm the feasibility of deploying TinyML for intelligent aerospace navigation systems.

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