Abstract:

This study proposes an on-device learning methodology for the self-calibration of Micro-Electro-Mechanical Systems (MEMS)-based sensors, including inertial units, comprising accelerometers and gyroscopes, as well as standalone pressure sensors. These sensing elements stream real-time measurements to an embedded digital signal processor (DSP), super integrated into the sensor package, which executes artificial intelligence (AI) workloads according to in-sensor processing computing paradigma. The data produced by inertial and pressure sensors are subject to several sources of degradation, such as time-varying bias, temperature-induced drift, and other nonlinear disturbances. Traditional calibration procedures, typically relying on linear error models, are insufficient for compensating nonlinear error components across different sensing modalities.

The proposed approach employs Radial Basis Function Neural Networks (RBF-NNs) to estimate and correct nonlinear sensor drifts. Unlike conventional implementations, the method does not rely on backpropagation, and its low computational complexity enables deployment under strict memory constraints (e.g. 8 KiB data and 32 KiB program RAM). This allows the calibration algorithm to run entirely on the embedded DSP, performing learning and inference directly within the sensor system and eliminating the need for external micro-controllers. Sparse on-device learning ensures continuous recalibration and long-term stability of both inertial and pressure measurements.

The solution was implemented in both 32-bit floating-point and 16-bit quantized integer formats and deployed on two hardware platforms. The first is the B-U585I-IOT02A board, which integrates an ISPU together with two pressure sensors (LPS22HH and LPS22DF). The second is the STM32F401RE platform equipped with an IMU and an ISPU. Both implementations operate within the stringent memory constraints of the in sensor integrated DSP and enable autonomous, real-time calibration of inertial and pressure sensors directly at the edge.