

Recurrent Neural Network Based Temperature Drift Compensation in TFG

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Abstract—Tuning fork gyroscope (TFG) is a gyroscope that works on the principle of Coriolis effect. These are typically used in inertial measurement units along with the accelerometers to enable inertial navigation, and find wide use in commercial, aerospace, military and space applications. They are reliable, simple and cheap with low mass and power consumption. However, the drift in gyro bias with ambient temperature is a major problem for this class of gyroscope and can lead to degradation in navigation accuracy. Classical piecewise and polynomial regression models have limited ability to predict and compensate this drift as they are not suited to handle gradients or hysteresis effects in the input data. This paper explores the use of memory based neural networks (NN) namely, simple recurrent NN, long short-term memory (LSTM) NN and gated recurrent (GRU) NN for the same. Results indicate that the temperature compensation models generated using memory based neural network give an improvement of the order of 50% in the sensor drift bias performance.

Keywords—recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), tuning fork gyroscope (TFG), temperature drift compensation

I. INTRODUCTION

Owing to the recent development in machine learning algorithms and technology, neural networks have a wide range of applications in diverse domains. The prediction and compensation of temperature induced drift in gyroscopes using neural networks is of great interest owing to its ability to handle non-linear problems [1].

Tuning fork gyroscope (TFG) is a Coriolis vibrating gyroscope (CVG) which works on the principle of Coriolis force and uses metallic forks as vibrating elements to measure the angular rate. Since the velocity of vibration and the resonator characteristics of forks are very much sensitive to ambient temperature, these parameters need to be controlled precisely for accurate scale factor and bias stabilities [2, 3].

There has been an explosion of applications of neural networks in the past decade, and the field of inertial sensors has also started to explore the same. Ref. [4] gives an extensive study on ordinary neural networks for gyro bias thermal drift in MEMS gyros. Ref. [5] discusses temperature

drift calibration of MEMS gyros using neural networks, while also considering the implementation feasibility of large neural networks on actual application environments. This is very relevant to inertial sensors like the TFG, which typically work in an embedded environment with limited computational resources.

This paper presents a novel methodology based on linear search approach to identify and implement an optimal memory based neural network model for the temperature induced drift compensation in TFG.

The paper is organized as follows: Section II defines the problem statement. Section III describes the sensor configuration along with the neural network models. Section IV gives the methodology and Section V provides the data sets used for training, validation and testing. Section VI presents the results and discussions followed by the conclusions in Section VII.

II. PROBLEM STATEMENT

In general, the outputs of TFGs are found to be rather sensitive to temperature and usually require some form of temperature control or compensation. It is observed that the ADC, DAC, passives, piezos, etc. which form the actuation and displacement sensing elements have delayed responses to temperature. The gain response of each element changes with the ambient temperature but each has its own speed at which it reaches a settled value. Due to difficulties in singling out each of these elements and calibrating and compensating for each, it is more time and cost effective to compensate for the overall rate output of the gyro to the temperature. However, delayed response of the elements causes effects like hysteresis during a temperature cycle and is not straightforward to compensate using methods like linear or polynomial fits. At minimum, a gradient based fit is called for.

The study, hence, focuses on the identification and implementation of memory based neural network models namely, simple recurrent NN, long short-term memory (LSTM) NN and gated recurrent (GRU) NN to compensate for the bias drift in TFG with temperature.

There are multiple parameters like resonance frequency, force voltage requirement, card temperature and sensing element temperature that represent the state of the sensor. These inputs can be used to train memory based neural

networks. An exploratory work is done to try and arrive at the size and configuration of a neural network that would do a fair job on bias compensation of TFG.

III. SENSOR CONFIGURATION

A. TFG Configuration

The tuning fork gyro consists of a vibrating element that can vibrate along two directions. One of the directions (primary) is initially set into motion, and controlled to a predetermined velocity. In the event this structure (gyro) comes under an external angular rate, Coriolis force works to the effect as to induce a force, and thus a displacement in the secondary direction. This displacement is a function of the primary direction's velocity and the magnitude of the external angular rate. The displacement, or the force required to suppress any displacement in the secondary direction is read out as the angular rate.

There are several elements in the vibration sensing and actuation chain responsible for maintaining the primary direction's velocity, whose properties change with temperature e.g., piezos that are the actuation and sensing elements. In addition, the resonator itself could produce spurious forces by virtue of change in its damping and stiffness due to temperature change that can be misinterpreted as external rate. The problem is that the typical control loops employed in CVGs can tackle only a specific subset of the problematic parameters that change with temperature [3]. Out of the parameters that cannot, it is seen that many of them have a delayed response to temperature, and the delays are different from parameter to parameter. This makes polynomial based fits less effective, when rapid temperature changes are encountered, and is the major motivation behind exploration of memory based neural networks.

B. Neural Network Models

NN are extensively used to model and predict many complex system dynamics [6, 7]. The accuracy of the prediction relies on how well the configured model fits into the problem. Here, the study emphasizes on memory based NN viz., RNN, LSTM and GRU to predict the non-linear time variant system output based on the experimental time series data.

Recurrent NN is powerful with its built-in memory capability while handling time series data [7]. However, since it uses gradients to update the weights, if the gradient values are too small, it deteriorates the learning and hence it forgets the past inputs in longer sequences resulting in vanishing gradient or short-term memory problem. LSTM and GRU address this issue by using its internal gated mechanism [8, 9]. The gating mechanism enables the network to identify and keep only the relevant data in the long sequence data chain. Further, GRU with reduced number of gates offers faster computation and lesser implementation complexity in comparison to LSTM.

IV. METHODOLOGY

First, the methodology for acquiring data for training, validation and test purposes is identified. Bounds for the input space were arrived at taking into account prospective applications of the sensor, and are given in more detail under section V.

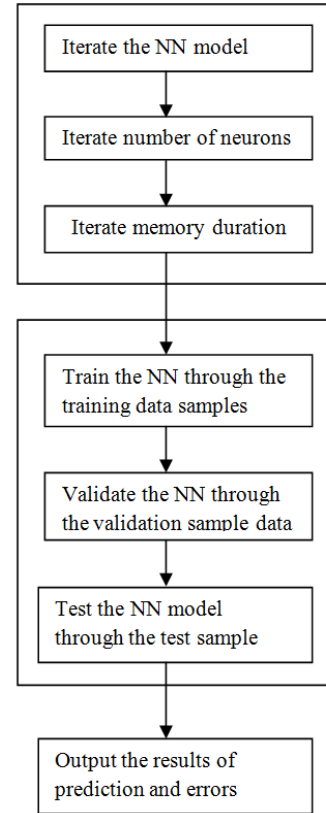


Fig. 1. Flow chart illustrating the process flow for compensation

NN model (RNN, LSTM or GRU) is selected and the number of neurons and the memory duration are to search for the best performing model as given in Fig. 1. The basic methodology thus is to correct the output data using the measurable parameters. Further, the input features to be used for training needs to be decided.

The general idea behind input feature selection is to provide the neural network as much information as possible about the current state of the sensor. There are several candidates, viz. resonance frequency, forcing amplitude and quadrature suppression voltage. Resonance frequency of the vibrating element is continuously tracked using a control loop and its value is available digitally for online compensation. It is the primary parameter used for many compensation schemes as it is an accurate representation of the temperature of the resonating element. Forcing amplitude is the value of the sinusoidal voltage required at the resonance frequency to maintain the velocity of vibration. This value is also readily available in digital format for online compensation. Quadrature suppression voltage is a measure of the frequency split of the resonator. The resonator has two degrees of freedom and has two distinct frequencies associated with it. The difference in these frequencies is termed as frequency split and is available from one of the control loops as quadrature suppression voltage. Although, this quantity is crucial in representing the state of the resonator, it cannot be used for compensation as it has a term influenced by external angular rate. But it is still explored anyway, as in future, we may have a quantity that represents split but is independent of external rate. Also, as temperature drift calibration is done in static conditions, quadrature can be used to see if a measure of frequency split is effective in compensation.

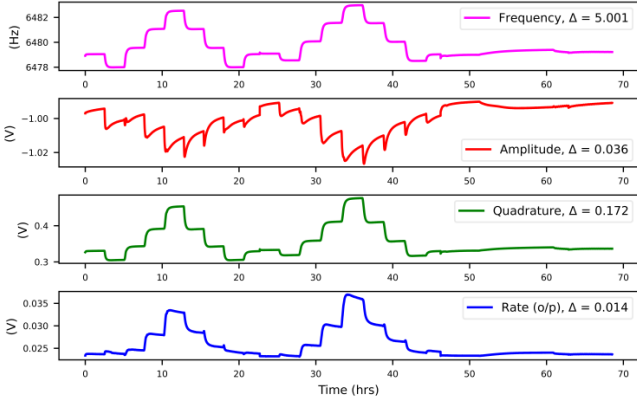


Fig. 2. Input features used for training and the rate output

Tensor flow libraries have been used with Anaconda python environments for development of these models on a desktop PC with Intel i5 processor and 8 GB RAM.

V. DATA SETS

Three sets of thermal cycling data and five sets of standard room conditions (SRC) data are generated to train, validate and test the proposed neural network models. Temperature profile for first, second and third thermal cycling data sets and the corresponding rate of change of temperature are as follows:

- 25-15-30-45-60-45-30-15-25 °C at 3°C/minute,
- 25-20-35-50-65-50-35-20-25 °C at 1°C/minute and
- 25-10-25-40-55-4-25-10-25 °C at 2°C/minute

Each Temperature is held for 2.5 hours. This is to give the sensor output enough time to settle at a steady value. In our test location SRC is seen to vary 27 ± 3 °C. Fig. 2. represents the input features used for training and the rate output.

VI. RESULTS AND DISCUSSIONS

Brute force search approach is used to arrive at the best performing neural network configuration required to compensate the drift in TFG bias due to ambient temperature. Best among the seventy-two neural network models generated are discussed here.

First and third sets of thermal cycling data and two sets of SRC data are used for training, second set of thermal cycling data is used for validation and the remaining three sets of SRC data are used for testing.

A. Configuration 1: 2F_10min_LSTM10

Frequency and amplitude are taken as input features with 10 minutes memory and the configuration is based on LSTM model of order 10. The graphical representation of the compensation on the validation data and test data 1 are shown in Figs. 3 and 4, respectively. After compensation in the validation data, the peak-to-peak bias variations (Δ in deg/s) reduced by 80%.

B. Configuration 2: 3F_5min_GRU1

Frequency, amplitude and quadrature are taken as input features with 5 minutes memory and the configuration is based on GRU model of order 1. The graphical representation of the compensation on the validation data and test data 1 are shown in Figs. 5 and 6, respectively. After

compensation in the validation data, the peak-to-peak bias variations (Δ in deg/s) reduced by 87%.

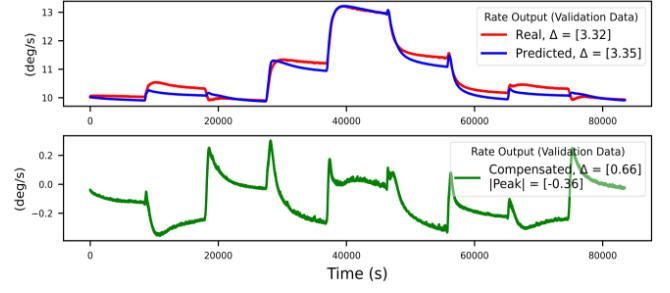


Fig. 3. Validation data compensation results for configuration 1

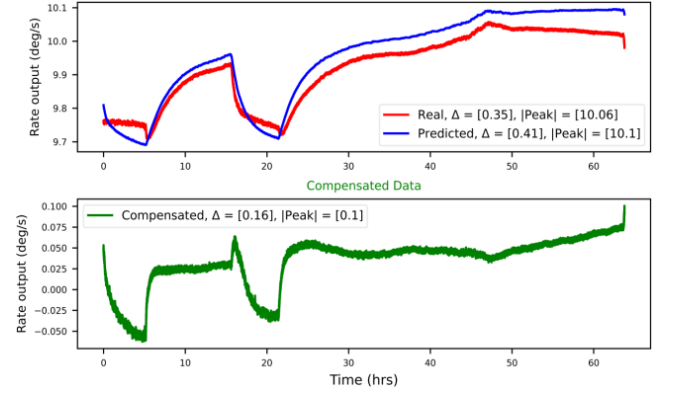


Fig. 4. Test data 1 compensation results for configuration 1

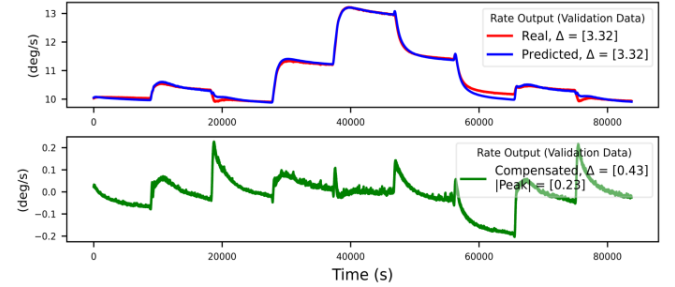


Fig. 5. Validation data compensation results for configuration 2

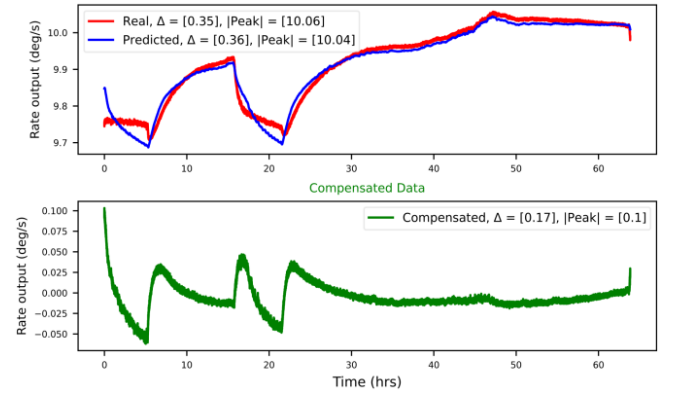


Fig. 6. Test data 1 compensation results for configuration 2

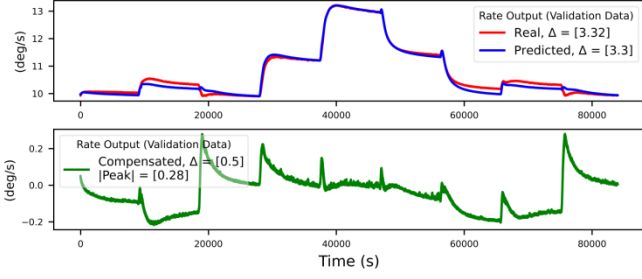


Fig. 7. Validation data compensation results for configuration 3

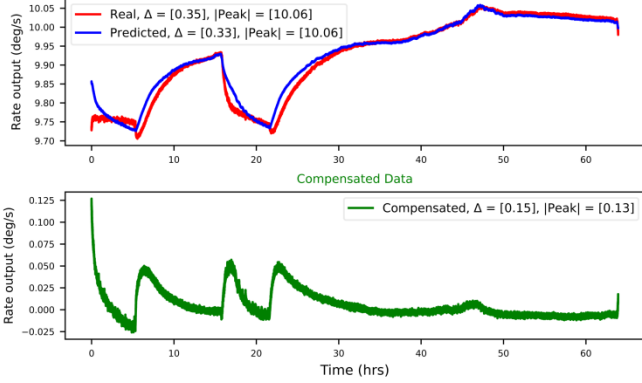


Fig. 8. Test data compensation results for configuration 3

C. Configuration 3:3F_1min_GRU5

Frequency, amplitude and quadrature are taken as input features with 1 minute memory and the configuration is based on GRU model of order 5. The compensation results for validation data and test data 1 are shown in Figs. 7 and 8, respectively. After compensation in the validation data, the peak-to-peak bias variations (Δ in deg/s) reduced by 85%.

The performance of these neural network configurations in terms of reduction in peak-to-peak bias variations, Δ (deg/s) are summarized and tabulated in TABLE I.

VII. CONCLUSIONS

The paper explores the use of memory based neural network models for predicting and compensating temperature

induced bias drift in TFG. The improvement in performance is quantified in terms of reduction in the peak-to-peak bias variations with and without compensation. Out of the models generated three configurations using LSTM and GRU models yielded of the order of 50% performance improvement. Results conclude that LSTM and GRU neural network models can be implemented for temperature bias drift compensation in tuning fork gyroscopes.

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TABLE I. COMPENSATION RESULTS FOR DIFFERENT NEURAL NETWORK CONFIGURATIONS

Input data	Without compensation	With compensation					
	Peak-to-peak bias change, Δ (deg/s)	2F_10m_LSTM10		3F_5m_GRU1		3F_1m_GRU5	
		Δ (deg/s)	% Reduction	Δ (deg/s)	% Reduction	Δ (deg/s)	% Reduction
Validation data (Thermal cycling data)	3.32	0.50	80	0.43	87	0.50	85
Test data 1 (SRC data)	0.35	0.15	54	0.17	51	0.15	57
Test data 2 (SRC data)	0.17	0.07	76	0.08	53	0.07	59
Test data 3 (SRC data)	0.08	0.05	50	0.05	38	0.05	38