Error Compensation of Dynamically Tuned Gyroscope Under Vibration Environment

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Abstract— Inertial Navigation System (INS) performs measurement of vehicle accelerations and angular rates by means of inertial sensors instrumented in sensor unit. Dynamically Tuned Gyroscope (DTG) along with the Servo Accelerometer is mounted in the INS sensor unit. An important concern is the errors induced in the gyro outputs in the vibration environment. It is very difficult to model and compensate this vibration induced errors for a gyroscope. In this paper vibration induced error of the DTG is modeled using Radial Basis Function (RBF) neural network. The Navigation accelerometer output, which is part of the cluster of sensors, is used as the vibration measurement for this compensation. The effectiveness of this compensation is demonstrated by the substantial reduction of the residual errors after the compensation.

I. Introduction

THE implementation of Strap down inertial navigation system requires a precise knowledge of vehicle angular rates as well as linear accelerations. These are provided respectively by high accuracy Dynamically tuned gyroscopes and servo accelerometers [1] mounted on the inertial sensor unit cluster.

Performance of gyro is established by the accuracy with which it is capable of measuring angular rates under various environmental conditions. Hence, a thorough understanding of the errors and their sources is very important to correct the errors and improve the accuracy of the gyro [2,3]. Sensor error measurements obtained from the calibration testing are used to compensate the sensors, in which the sensor error model equations are applied to compensate the sensor errors.

In critical applications, sensor unit can be configured in different ways to have redundant information about the attitude of the body. One such realization commonly in use is the skewed geometry of the sensors. With this configuration for each principal axis, apart from the measurement of that particular axis gyro, two more measurements are derived from the outputs of other two gyros. Fault detection and isolation logic is used to detect failure of sensor in any axis by parity equation residual checks and reconfigure the measurement scheme by processing the sensor output after error compensation.

DTG is sensitive to angular rate of the body and also sensitive to the local vibration induced rates during the motion of the body. The vibration induced sensor errors results in undesirable performance of the gyro. This vibration input is sensed by the accelerometers mounted along with the DTG in the sensor unit cluster. Using the navigation accelerometer outputs as the vibration measurement for gyro error compensation is better than using an independent vibration sensor mounted outside the sensing unit. The advantages are the servo accelerometers which is part of sensor cluster is very accurate and the physical proximity of these accelerations to the gyro gives more realistic vibration input actually experienced by gyro sensors. For better measurement accuracy the vibration induces errors of the gyro has to be compensated partially for critical applications like missiles and launch vehicles.

This paper deals with an approach to develop a model to compensate for this vibration induced gyro errors. An initial attempt was made to identify a linear model using optimization technique, which proved to be inefficient. Nonlinear model was developed using Radial Basis Function Network of neural network [4] and was found to be adequate for this compensation.

The paper is structured as follows: Section 2 describes about Inertial Navigation System, Section 3 describes the application of Radial Basis Function in the current work. Some simulation results are provided in Section 4. The conclusion of this study is drawn in Section 5.

II. INERTIAL NAVIGATION SYSTEM

Inertial navigation system performs measurement of vehicle accelerations and angular rates in the instrumented reference frame. Dynamically Tuned Gyroscope along with the Servo Accelerometer is used in inertial navigation system sensor unit. The navigation processor compensates the measured inertial data for sensor errors, uses failure detection and isolation logic to isolate failed sensor, updates the co-ordinate transformation of vehicle to navigation frame by means of measured vehicle rates, transforms the measured acceleration to the reference frame and finally computes the vehicle position and attitude information.

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A. *Dynamically Tuned Gyroscope*

A gyroscope is an inertial sensor that measures angular rate with respect to inertial space about the input axis. The two-degree of freedom dynamically tuned gyros are usually used. It consists of housing, torquer assembly, pick offs and rotor with its fixed suspension system [1]. The rotor with tuned suspension has a motor hysteresis ring assembly, which is driven to tuned speed by the hysteresis synchronous motor. The torquers coils and pick offs suspensions are attached to the case. The two end covers are fixed to the gyro case.

Principle of operation is described as follows: Consider a rotor supported and driven by a hook joint suspension at a high speed. When an offset angle is introduced between the rotor and the supporting case, because of high angular momentum, the rotor tends to maintain its spin axis orientation fixed in inertial space. Due to kinematic constraint imposed by the suspension systems, the rotating gimbal oscillates in space producing acceleration effects on the rotor. The dynamic torque transmitted to the rotor because of the acceleration effects of the gimbal is of a negative type. By replacing the bearings in a conventional hook joint by flexural pivots, a positive torque is created whenever an offset angle is introduced. The dynamic torque is a function of the gimbal inertias and increases with the square of the spin frequency. On properly choosing the gimbal inertia, the flexural stiffness and spin speed such that the dynamic torque equals the flexural torque (positive) the net torque transmitted to the rotor is made zero. Then the rotor behaves as a free gyro devoid of any restraints.

Various error parameters of DTG are bias, Scale factor, Input axis misalignments, Anisoinertia, Anisoelastic (g^2 sensitive) and Mass unbalance (g-sensitive). Error coefficients of these parameters are obtained from ground calibration tests and gyro outputs are compensated for these errors.

B. Servo Accelerometer

Inertial navigation and guidance depend upon the measurement and integration of linear acceleration to successfully compute velocity and position and the generation of proper steering signals. The choice of the type of accelerometer needed for the mission is generally a function of overall accuracy required of the inertial system. Size, weight, power, cost and reliability are important considerations, which also influence the choice. Servo accelerometer is a type of pendulous accelerometer [1] used in various applications. The servo accelerometer consists of a proof mass hung from a hinge, pick off, forcer and servo loop. Principle of operation is that, if acceleration is applied to this assembly, a force is exerted on that mass and it will attempt to move from the null position. Pick off which is a differential transformer detects this motion. The pick off output is demodulated and through a compensator passes to a servo amplifier, which generates a current to drive the forcer system and this current is proportional to the acceleration of the body.

Operating the sensor near its null condition improves the linearity over a wide range. The bandwidth of the servo loop has to be appropriately selected depending on the application.

C. Typical Skewed Orientation in a Navigation System

DTG along with the servo accelerometer is used in inertial navigation system. There are many sensor redundancy schemes available in literature. One popular scheme is described below. The DTG's in INS inertial sensor unit are mounted in a skewed configuration to permit analytical redundancy of measured angular rate about vehicle principal axis. The transformation matrix from the ISU frame to each DTG frame and resolving of the applied acceleration and body rates are derived below in order to obtain the error model in gyro reference frame.

Typical sensor mounting configuration in ISU is as shown in Fig 1. INS uses three DTG's, which provides six axes of rate measurements and five pendulous accelerometers and necessary associated electronics.

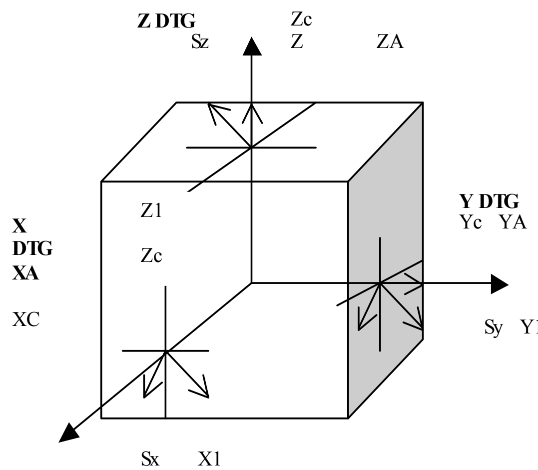

Fig. 1. Typical Sensor Mounting Configuration

Three accelerometers are mounted along the thrust axis direction to have redundancy. DTG's are skewed such that the second axis of each gyro is skewed 45^0 from the orthogonal set of axes.

1). DTG Reference Frame

Typical yaw (X) DTG gyro frame is described as follows. The yaw (X) DTG frame is obtained by the rotation of the ISU cluster frame about Xc axis in the YcZc plane such that the spin axis Sx is –45 deg from –Zc axis. The transformation from cluster frame to X-DTG frame (X1, X, Sx) is

$$\begin{bmatrix} X1 \\ X \\ SX \end{bmatrix} = \begin{bmatrix} 0 & 1/\sqrt{2} & -1/\sqrt{2} \\ 1 & 0 & 0 \\ 0 & -1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix} \begin{bmatrix} Xc \\ Yc \\ Zc \end{bmatrix} \tag{1}$$

The acceleration components applied to the cluster frame when resolved to X-DTG frame are given by Equation (2).

$$\begin{bmatrix} fx1 \\ fx \\ fsx \end{bmatrix} = \begin{bmatrix} (fy - fz)/\sqrt{2} \\ fx \\ -(fy + fz)/\sqrt{2} \end{bmatrix} \tag{2}$$

Similarly the applied angular rates resolved to the X-DTG frame and are given by Equation (3).

$$\begin{bmatrix} \omega x1 \\ \omega x \\ \omega sx \end{bmatrix} = \begin{bmatrix} (\omega y - \omega z)/\sqrt{2} \\ \omega x \\ -(\omega y + \omega z)/\sqrt{2} \end{bmatrix} \qquad (3)$$

where ωx, ωy, ωz represents input angular rates and fx, fy, fz represents the acceleration along X, Y, Z axis.

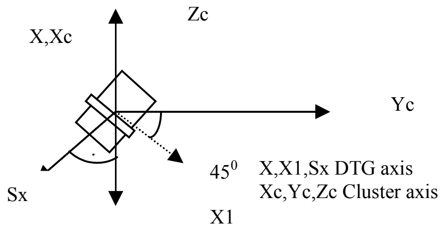

Fig .2. Reference Frame of Yaw (X) DTG

2). Measurement Equation

Measurement equation of DTG's in skewed orientation is given by Equation (4).

$$\begin{bmatrix} X \\ X1 \\ Y \\ Y1 \\ Z \\ Z1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ 0 & 1 & 0 \\ -\frac{1}{\sqrt{2}} & 0 & -\frac{1}{\sqrt{2}} \\ 0 & 0 & 1 \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \end{bmatrix} \begin{bmatrix} \omega x \\ \omega y \\ \omega z \end{bmatrix} + \begin{bmatrix} ex1 \\ ex \\ ey \\ ey1 \\ ez1 \\ ez2 \end{bmatrix} \qquad (4)$$

Measurements are compensated for sensor errors and since the DTG's are in the skewed configuration, it is possible to derive three measurements for each of the principle axis rate of the vehicle. For each principle axis, apart from that particular axis gyro two more measurements for each axis can be resolved and given by Equation (5).

$$\begin{aligned} &X\text{-axis } x0=X,\ x1=-Z-\sqrt{2}Y1,\ x2=Y+\sqrt{2}Z1 \\ &Y\text{-axis } y0=Y,\ y1=Z+\sqrt{2}X1,\ y2=X-\sqrt{2}Z1 \qquad (5) \\ &Z \text{ axis } z0=Z,\ z1=Y-\sqrt{2}X1,\ z2=-X-\sqrt{2}Y1 \end{aligned}$$

These are pair wise compared and six parity equation residues are formed and given by equation (6):

$$\begin{aligned} &K0=x0-x1; K1=x0-x2; K2=y0-y1; \qquad (6) \\ &K3=x1-x2;\ K4=y1-y2;\ K5=z1-z2; \end{aligned}$$

Residues are linear combinations of measurement errors only. Ideally these residues have to be zero.

C. Vibration Sensitive Errors

DTG is sensitive to angular rate of the body but also to the local vibration induced rates during the motion of the body. The angular input and vibration induced sensor errors results in the undesirable performance of the gyro. For better measurement accuracy the vibration induced errors of the gyro has to be compensated. To account for this error the cluster is subjected to vibration test. This paper deals with an approach to develop a model to compensate for this vibration induced gyro errors.

For this, typical test data of a sensor unit was used. In the vibration test the sensor cluster is mounted on the vibrator, taking care that the vibrator axis moves precisely along the desired direction. Sensor unit is subjected to sine and random vibration. For this work random vibration data was used since frequency spectrum ranges up to 2000 Hz. Sampling rate of test data is 20ms and the vibration duration is about 100s. With the available data, residual plot is made, the thrust acceleration and one of the residue plot is shown in Fig.3. From the residue plot, it is clear that the gyro is sensitive to vibration induced errors

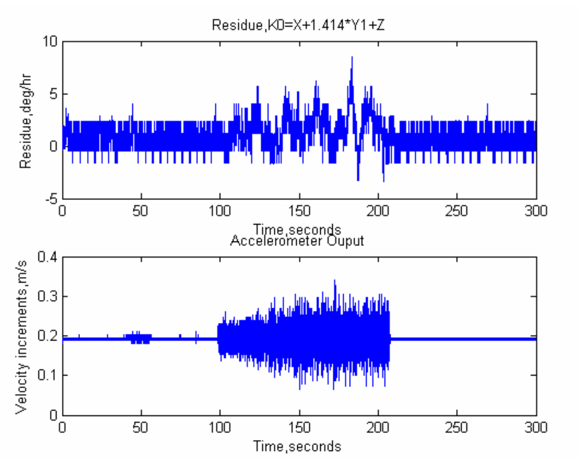

Fig.3. Residue plot and Thrust Accelerometer Data

III. Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems [4]. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, and vision and control systems.

Neural networks are employed in most of the applications is that it realize some complex nonlinear decision function or to approximate certain complicated data generating mechanisms. The theoretical justification for such applications is that, provided that the network structure is sufficiently large, any continuous function can be approximated to within an arbitrary accuracy by carefully choosing parameters in the network. An obvious disadvantage of neural networks is that they are highly nonlinear in the parameters. Learning must be based on nonlinear optimization techniques, and the parameter estimate may become trapped at a local minimum of the chosen optimization criterion during the learning procedure when a gradient descent algorithm is used. Other optimization techniques although capable of achieving a global minimum, require extensive computation. A viable alternative to highly nonlinear-in-the parameter neural networks is the Radial Basis Function network, which is used in the present study.

RBF's are embedded in a two-layered neural network where each hidden unit implements a radial activated function. The output unit's implement a weighted sum of hidden unit outputs. The input layer of RBF network is nonlinear where as the output layer is linear. Their excellent approximation capabilities have been studied in [5]. Due to their nonlinear approximation properties, RBF networks are able to model complex mappings, which multilayer neural network can only model by means of multiple intermediary layers [4].

A. Radial Basis Function Network

A schematic of the RBF network [6] with n inputs and a scalar output is depicted in Fig.4.Such a network implements a mapping f_r:$\boldsymbol{R}^n \rightarrow \boldsymbol{R}$ according to

$$f_r(x) = \lambda_0 + \sum_{i=1}^{n_r} \lambda_i \phi(\|x - c_i\|) \tag{7}$$

where $x \in R^n$ is the input vector, $\phi(.)$ is a given function from R^+ to R, $\|\cdot\|$ denotes the Euclidean norm, λ_i, $0 \le I \le n_r$ are the weights or parameters are known as the RBF centers, and n_r is the number of centers. In the RBF network the functional form $\phi(.)$ and the centers c_i are assumed to have been fixed. By providing a set of the input *x(t)* an the corresponding desired output *d(t)*for *t=1 to N*, the values of the weights can be determined using the least square method [6]. Various functions can be used as activation functions. One such is the Gaussian function is given by:

$$\Phi(v) = \exp(-v^2 / \beta^2) \tag{8}$$

where β is a real constant.

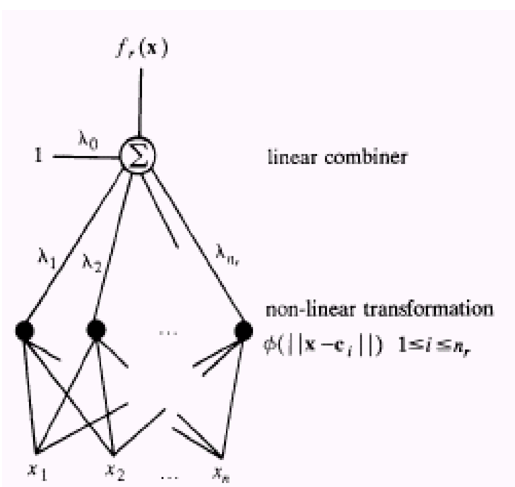

Fig.4. Schematic of Radial Basis function Network

For good generalization the set of available input/output measurements can be divided into two parts- one part for training and one part for validation. This is the basic form of cross validation. The use of cross validation is appealing particularly when we have to design a large neural network with good generalization as the goal.

B. Data Used for Simulation

The present work is based on the measurements during the Z-axis vibration test. In applications like missiles and launch vehicle the acceleration is along the thrust direction. Due to this, thrust axis accelerometer data is used. Measurements consist of six rate outputs and accelerometer outputs. The data is sampled at a rate of 20ms.

Initially the DTG and accelerometer measurement are compensated for their known error parameters using ground calibrated error coefficients. Errors that were initially compensated for were Bias, Scale factor Input axis misalignments, Anisoinertia and Anisoelastic drifts. After that, preprocessing is done with a low pass filter and is shown in Fig .5.

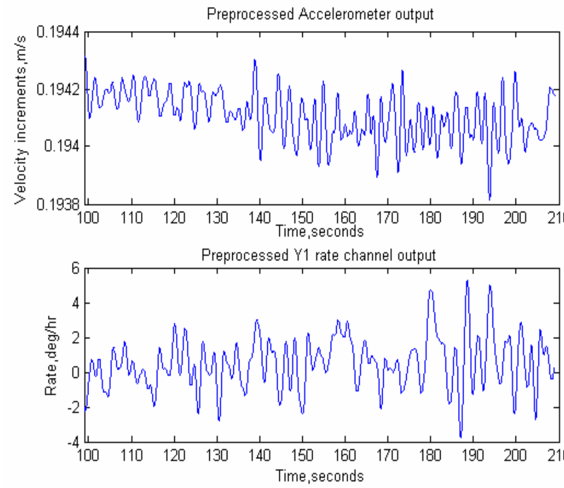

Fig .5. Processed Acceleration and Rate Output

An input of vector dimension 50 is chosen and 2500 such data were used to form the input vector and corresponding target vector constitutes the training set. Vector is chosen in an interleaved manner. Similar input vector dimension is chosen for validation set also.

IV. SIMULATION RESULTS

Simulations are done using MATLAB version 6.5. Simulation results, when applying RBF network are discussed in this section.

A. Network Simulations

A network simulation for a particular rate channel is discussed. Network is trained for training set ant is simulated for both training and validation set and the error between the actual target and simulated target vector is made. The network training performance is shown below for training and validation set is shown in Fig.6.Typical network-training values are given below:

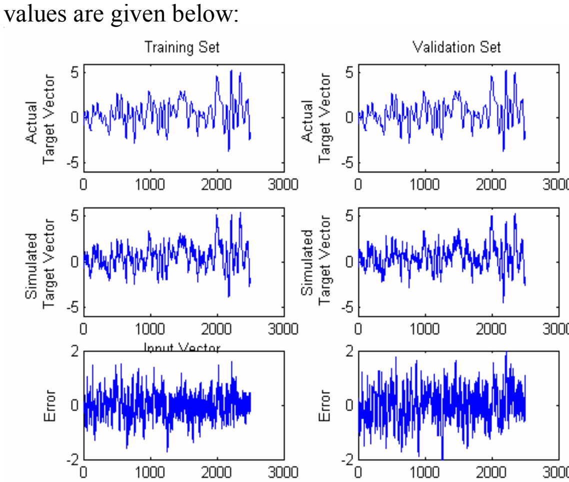

Fig.6. Simulations for Trained and Validation Set

B. Error Compensation

For all six-gyro rate channels RBF network was identified and network is simulated for the entire processed acceleration data and this is used to compensate the rate channel output. Then the rate channel output is used to compensate the rate outputs and the residues are computed using the compensated output.

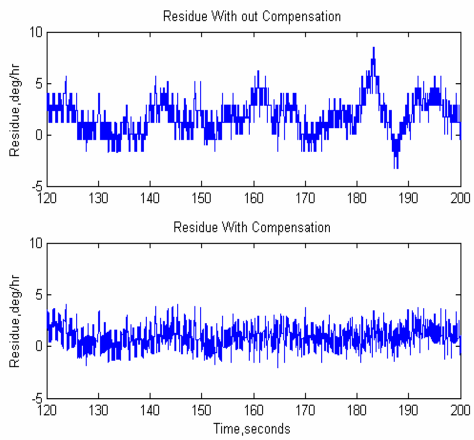

Fig.7. Comparison plots of Residue

Residues are compared with and without this compensation. Comparison plots are shown in Fig.7. Substantial reduction of residue with compensation is achieved. This validates the compensation procedure.

V. CONCLUSION

In this paper, a new approach is developed to model the vibration induced errors of a gyro using the accelerometer data and the gyro data during the vibration test using a RBF neural network. The vibration induced gyro errors are found to be nonlinear and nonlinear modeling is essential. Test data is used to identify this nonlinear model using RBF neural network. Compensating the gyro outputs with the developed model and ensuring substantial reduction in the residues establish the modeling accuracy.

Further work has to be carried out extending this modeling with flight data ensuring adequate reduction in residues before implementing algorithm for onboard applications.

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