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UAV-BASED WIRELESS TELEMETRY SYSTEM FOR THE ESTIMATION OF SHIP AIR WAKE PATTERNS

Anil Kumar
George Washington University
Washington, DC, USA

Pinhas Ben-Tzvi
George Washington University
Washington, DC, USA

Murray Snyder
US Naval Academy, Annapolis, MD, USA
George Washington University
Washington, DC, USA

ABSTRACT

This paper presents the development of a wireless instrumentation system for estimation of air turbulence patterns in real-time. The proposed system uses off-the-shelf RC helicopter flying in wind turbulent regions and uses the oscillations caused by wind gusts to measure turbulence. This paper presents the proposed system as a tool to measure off-board ship air wake patterns generated by a cruising naval patrol craft. Two aviation grade Inertial Navigation Systems (INS) with onboard filters are used in this system. These filters precisely measure the dynamics and the location of the helicopter with respect to the vessel. The data is then wirelessly transmitted to a base station on the vessel where Back Propagation neural networks are used to remove the effects of pilot inputs from vibrational data in real time to extract the oscillations caused by the turbulence alone. The system was tested in Chesapeake Bay in a wide range of wind conditions and the results are shown as air wake intensity patterns plotted on helicopter trajectory around the cruising vessel. The proposed system will be used for experimental validation of CFD models to predict ship air wakes.

NOMENCLATURE

INS	=	Inertial Navigation System
IMU	=	Inertial Measurement Unit
$\boldsymbol{\omega}$	=	Angular rate vector (rad/s)
PWM	=	Pulse Width Modulation (μs)
RC	=	Radio Controlled
$\boldsymbol{\theta}$	=	Attitude vector (deg)
$\mathbf{V}$	=	Velocity Vector (m/s)
M	=	Mass of helicopter (kg)
g	=	Acceleration due to Gravity (m/s^2)
BPNN	=	Back Propagation Neural Network
CFD	=	Computational Fluid Dynamics
VTOL	=	Vertical Take-Off and Landing

I INTRODUCTION

Launch and recovery of VTOL aircrafts like helicopters from cruising naval vessels is a challenging and potentially hazardous task [1]. It is mainly because of three main reasons:

(1) Interaction of ship air wakes with the aircraft leads to undesirable motion in the helicopter;
(2) As the helicopter approaches the landing deck the downwash of the helicopter leads to an effect called ground effect which significantly changes the helicopter control dynamics;
(3) There is limited area on the flight deck to operate the helicopter.

Thus, to minimize these risks, it is important to have a system capable of experimentally estimating ship air wakes and its impact on the aircraft in real-time. The existing CFD models are not mature enough [2-8], and there is a need of actual air wake measurements for validation [9,11].

In this paper, we present a wireless telemetry system capable of predicting air wake patterns by measuring the impact of air wake on the helicopter. The presented system is a technological successor to a system which has been published before [11-13]. Most of the existing systems use anemometer arrays to measure air wake patterns. But these systems have several limitations: (1) they cannot be deployed off of the flight deck; (2) they are very expensive and bulky to handle. To overcome these limitations, the proposed system indirectly estimates the ship air wake patterns by wirelessly measuring the air wake's impact on an inexpensive off the shelf RC helicopter [10].

The predecessor of the proposed system [11-13] had a limitation. It was dependent on the history of pilot inputs to estimate the components of pilot input in the helicopter's dynamics as the attitude information was not in the system. In this paper, the system presented tackles the above issue by employing INS, which delivers attitude and accurate position.

II PROPOSED SYSTEM

The central idea behind the proposed system is that a flying helicopter experiences undesired oscillations in wind turbulence. These oscillations are captured to generate turbulence patterns [10,12,13]. Air wake is turbulence, which originates from pressure gradients created by moving objects and further results in violent wind gusts. During flight in an air wake zone, the helicopter experiences differential airflow velocities that cause tilting of the aircraft. Thus it can be inferred that monitoring angular velocity patterns of a helicopter provides a good description of air wake patterns. Fig. 1 shows tilting of an RC helicopter with angular velocity ω as a result of differential wind velocity (V1>V2).

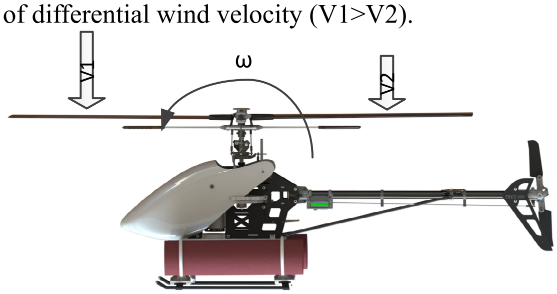

Figure 1. Interaction of air wake with helicopter

The proposed telemetry system works as a two unit system. The first unit is called as *rover module* and is retrofitted on an RC helicopter. The second unit is called as *base module* and is fitted on the ship under study. Both battery powered telemetry modules are equipped with aviation grade VN200 INS and wirelessly communicate with each other over a Wi-Fi network. Fig 2 shows the telemetry system setup.

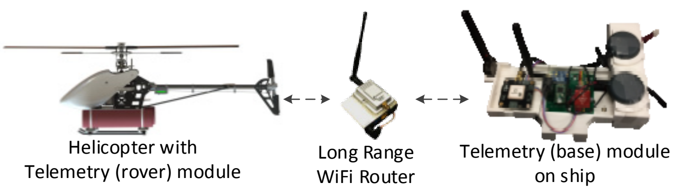

Figure 2. Telemetry System Setup

A small light weight RC helicopter with rotor diameter of 4.5ft is used to mount the rover module as it responses well to external wind disturbances. The RC instrumented helicopter is flown in the aft of a modified YP676 patrol craft in serpentine-like trajectory to estimate air wake patterns.

A. Rover Module

The Rover module uses an ARM Cortex M4 microcontroller as its central control unit. It acquires raw IMU data packet at 40Hz, INS solution at 40Hz and Raw GPS at 8 Hz from VN200 development overboard over SPI (Serial Peripheral Interface) link and sends the data at 40Hz to the base module. The previous versions [11-13] of telemetry system used GPS for position estimates which provide position estimates at 5Hz. The INS board used in the current system not only provides better helicopter position, but also gives accurate attitude and heading estimates. The use of attitude information in pilot input compensation is explained in later sections. With high speed Wi-Fi router and high gain antenna, the rover module is capable of transmitting data from one mile line of sight at a data rate of 72 Mbps. The XBee RF data link used in previous versions was limited to 250 Kbps. Replacement of RF link to Wi-Fi has made the proposed telemetry system useful in applications like rotor dynamics analysis where high speed data acquisition is needed. Fig. 3 shows rover module mounted on RC helicopter approaching YP676 during an underway flight.

Figure 3. Rover module mounted on helicopter approaching flight deck of Modified YP676 vessel

B. Base Module

The base module receives pilot inputs and data from the rover module. Similar to the rover module, the base module has been upgraded with Wi-Fi and INS. Unlike the rover module, the ARM cortex M4 microcontroller in base module is used to read pilot input signals whereas, a USB to quad UART hub acts as central unit of the module. The hub connects up to 4 serial devices to a computer via USB port. The microcontroller reads PWM inputs from a RC receiver connected to the base module and sends the pilot inputs to the PC via serial port of the hub. The other serial ports are used to interface XBee Wi-Fi and VN200 INS module to the system. The fourth serial port is left unused for future upgrades to interface other sensors with the system.

C. Air wake pattern extraction

In addition to air wakes, major components of tilting and oscillations are caused by pilot inputs in the process of controlling the helicopter. The proposed system uses back propagation neural network to estimate and compensate for dynamics arising from pilot inputs in order to extract the impact of air wakes on the helicopter. The relative position of the helicopter was obtained from position and attitude estimates from the VN200 INS mounted on the rover and base modules. The YP676 patrol craft is equipped with anemometer array to help the craft master maintain constant relative wind conditions. Fig. 4 shows the schematics of the proposed system and the steps involved in air wake pattern estimation. The dotted lines represent the wireless communication whereas the solid lines represent wired communication.

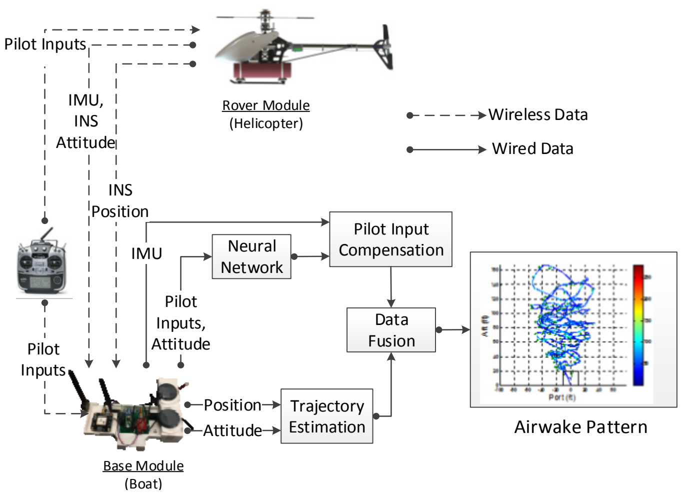

Figure 4. Schematics of proposed Telemetry System

III PILOT INTPUT COMPENSATION

As mentioned before, the vibration data collected on the helicopter contains a pilot induced component which needs to be removed. In a simplified rigid body model of the helicopter [14], its motion is governed by tilting of the main rotor's plane. For example, the longitudinal cyclic pitch control applies differential thrust on the rotor plane to tilt for forward movement (Fig. 5).The helicopter experiences a pendulum like counter torque when tilted forward as the point of rotation (which is the center of the rotor plane) is higher than the center of mass. Also, high velocity of the air around the fuselage makes the helicopter to maneuver in terminal velocity region for most of the time. This makes angular velocity of helicopter a nonlinear function of cyclic pitch input (pilot input) and attitude of helicopter. In an ideal case, the angular rate measurements can be considered as a vector sum of two components, one arising from external air turbulence and the other from the helicopter's own motion. Since, helicopter consists of discrete moving parts, it generates a lot of high frequency vibrational noise, which needs to be removed from the final results.

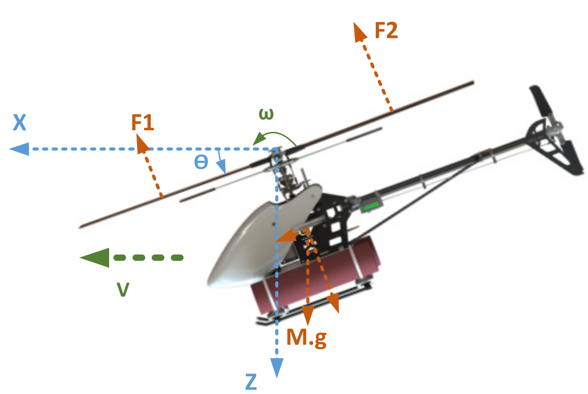

Figure 5. Effect of pilot inputs and attitude on angular rates data

Although any nonlinear machine learning technique will suffice, we choose back propagation neural networks (BPNN) to compensate for pilot inputs because it is easy to implement and at the same time very reliable tool for nonlinear regression. Briefly stated, Neural Network is an inter-connected network composed of neurons, where each neuron is regarded as a multi-input and single output system [15-18]. Each neuron calculates weighted sum of all the inputs, subtracts a characteristic value (bias) from the sum and then applies a characteristic function to obtain the output of the neuron. The capacity of a neural network to modal complex data largely depends on the network topology and the characteristic functions associated with each neuron. Thus training of neural network consists of finding the optimal set of weights and biases.

Mathematically the output of a neuron is calculated as follows:

$$y = f\left(\sum_{i=1}^{N} x_i w_i + b\right) \tag{1}$$

Here f is the characteristic function, w_i is weight corresponding to i$^{\text{th}}$ input (x_i), b is characteristic bias and N is number of inputs to a neuron.

Complex networks with large number of neuron layers can model fine variation in training data but increases the risk of overtraining and loss of generalization. Unfortunately, no analytical method exists to determine optimal network topology and one needs to rely on 'trial and error' methods based on the nature of training data for determining the optimum topology of a neural network.

BPNN is a multilayer feed-forward network and uses error back propagation algorithm for training [15-20]. The neural network was trained to predict the 3axis angular rates of helicopter components resulting from pilot inputs obtained from the receiver module. The helicopter was flown in closed aircraft hangar (Davison Air Field), free of external air disturbances to collect the data for training of the Neural Network. Thus the recorded angular rate data contains only pilot input components and noise caused by helicopter's motion. Four indoor flights were conducted with T-REX 600E Pro helicopter to collect training data. During these training flights, a variety of helicopter maneuvers were performed. A versatile dataset of pilot inputs along with helicopter attitude with angular rates was created. During flight the helicopter was flown significantly higher than the floor to prevent disturbances due to ground effect [21]. Approximately, 75000 data samples were collected during these indoor training flights and 10% of the total data was used for training the networks. The remaining 90% was used for testing the performance of the networks.

A. BPNN Training

In previous version of the telemetry system [11-13], due to absence of attitude information, pilot input history was used to model pilot inputs. This not only increased the dimensionality of the input vector (which was 15 in the previous system) but also made network response dependent on the length of the pilot input history considered. Addition of attitude information (acquired from INS) to input vectors fixes these problems as it directly includes the helicopter's state estimates in the model. The proposed system uses two (hidden) layered BPNN to estimate the pilot input component in each of the three Cartesian components of angular rates. The number of nodes in input and output layer of BPNN are determined by the dimensionality of the input vector and the output vector respectively. We used six dimensional input vector comprising of 3 PWM inputs for swash plate, 1 PWM input for tail rotor, pitch angle and roll angle. Each BPNN has 1 dimensional output vector which is a Cartesian component of helicopter's angular rate.

Both input and output vectors are normalized to zero mean and unit standard deviation. It helps in assigning uniform weights to input vectors which leads to better prediction accuracy. These normalization parameters are stored to normalize the input vectors and to rescale the output to the original scale during the testing phase.

The number of neurons in the hidden layers were assigned by trial and error method. The number of neurons in the hidden layers were varied from 3 to 15 and all combinations were tried. During the training of a BPNN, local minima of error in parameter space was estimated and all the weight and parameter were initialized with random value. Thus, it is possible that the trained network may not be the best network. Therefore, each network topology was trained 15 times with random initial weights to overcome the above issue. MATLAB implementation of efficient Levenberg–Marquardt algorithm [19-20] was used for error back propagation training. The "tansig" and "purelin" were used as activation functions for the hidden layers and the output layer respectively. Ten-fold cross validation method [22-23] was used to prevent overtraining of the networks.

The topology delivering the best prediction accuracy on test data was finally selected for air wake patter estimation. The final topologies of the three trained neural networks are given in Table 1.

Table 1. Topologies of the three trained neural networks

Neural Network	Input Layer	Hidden Layer 1	Hidden layer 2	Output layer
Net1 (X axis)	6	5	3	1
Net2 (Y axis)	6	6	3	1
Net3 (Z axis)	6	4	4	1

B. BPNN Performance and Analysis

As mentioned earlier, in addition to pilot input's component, the measured data also includes noise generated by the helicopter itself. Random sensor noise emanating from the gyroscope can be neglected for being very small in comparison to the measured values. The source of helicopter's noise is its rotor motion which rotates at a constant speed. The noise is highly periodic in nature and can be removed by frequency domain filtering. During each training flight the helicopter was kept hovering for some time with minimum pilot inputs for the above purpose. This provided a dataset with helicopter noise only. The data was then treated with different types of Gaussian low pass filters until the noise was removed. It was experimentally determined that a Gaussian low pass filter with a cutoff frequency of 11Hz gave acceptable results. The low pass filter was not applied before training as it would have affected the performance of the BPNNs. Fig. 6 shows prediction results of BPNNs for angular rates along X, Y and Z axis respectively, overlaid on corresponding actual measurement and low pass filtered data.

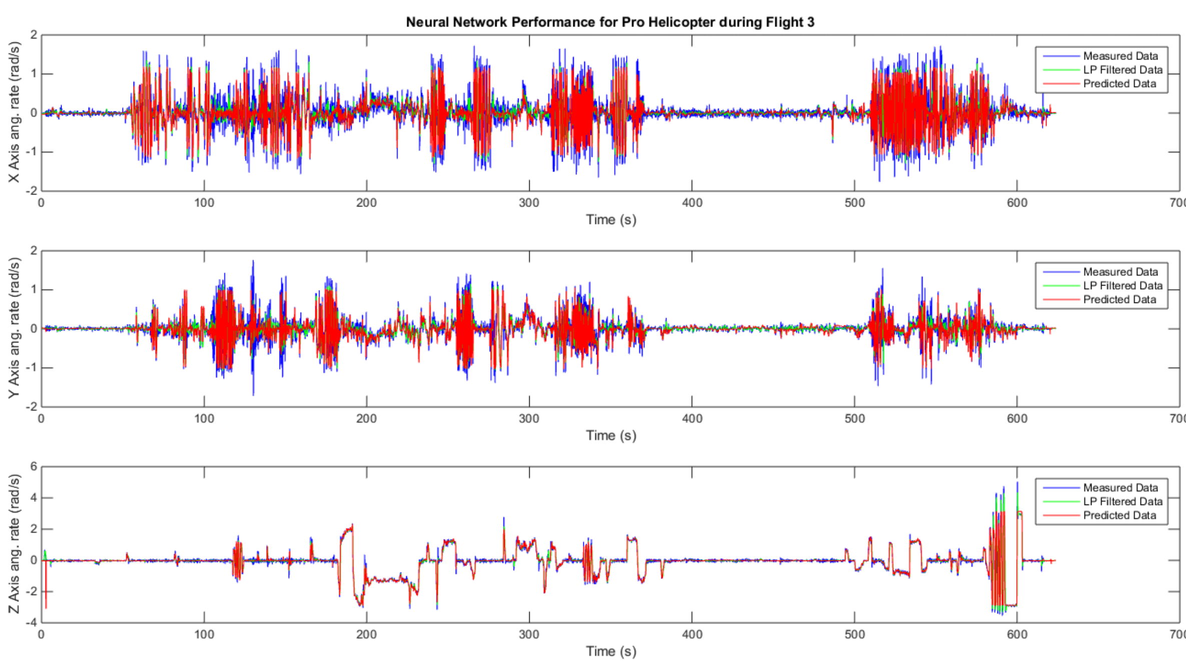

Figure 6. Neural network test results on one of the test data of one of the indoor test flight

The plot between 370s and 500s shows hovering phase of the test flight. The 90% of the total data recorded was used for testing the performance of the trained networks. The normalized output of each of the BPNNs was scaled up to match with original training data scale. Fig. 7 shows prediction results (enlarged) for X axis angular rates. The close overlap of predicted data and low pas filtered data confirms the effectiveness of the system in extracting pilot input components.

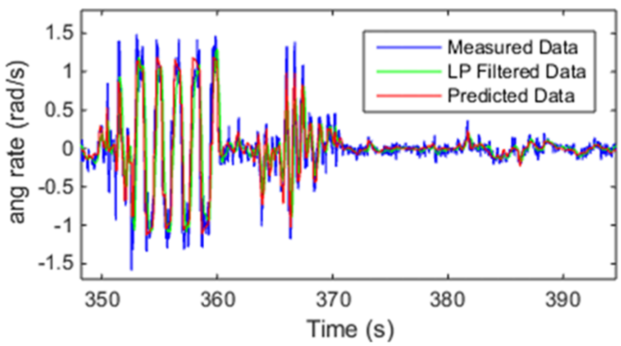

Figure 7: Prediction results for angular rates along x axis

Fig. 8 shows the overall error distribution of data in the form of histogram plot when the system was tested on a complete test data of all the four flights combined. The blue histogram shows the distribution of prediction error with respect to actual measurement of angular rates whereas the overlaid red curve I the plot shows the distribution of error with respect to filtered data. The skewness of the red curve towards zero error shows the effectiveness of the system in predicting the helicopter's response to pilot inputs. Statistical analysis shows that 79.47% of the total samples were predicted with error less than 5% of full scale reading (5 rad/s) and 99.94% of the total samples were predicted with error10% of the full scale reading.

IV SHIP AIRWAKE PATTERNS

Relative position of the helicopter with respect to the ship is necessary for generating ship air wake patterns, in addition to the air disturbances (in the form of angular rates). The relative position of the helicopter is obtained from INS sensors deployed on both the helicopter and YP676. The orientation of the vessel (base module) was obtained from the VN200 INS on the ship. If $\{\lambda_b, \varphi_b, h_b\}$ and $\{\lambda_h, \varphi_h, h_h\}$ are the geographical coordinates of the ship and the helicopter respectively, then the relative position of the helicopter with respect to ship is given by equation (2).

$$\begin{bmatrix} x_h \\ y_h \\ z_h \end{bmatrix}_b = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} [S] \begin{bmatrix} \lambda_h - \lambda_b \\ \varphi_h - \varphi_b \\ h_h - h_b \end{bmatrix} \tag{2}$$

where $[S] = \begin{bmatrix} 36.4 & 0 & 0 \\ 0 & 28.2 & 0 \\ 0 & 0 & 0.00033 \end{bmatrix} \times 10^4 (ft/\circ)$, and Θ is the heading angle of the ship. Fig. 9 shows the ship's coordinate system used for relative position of the helicopter.

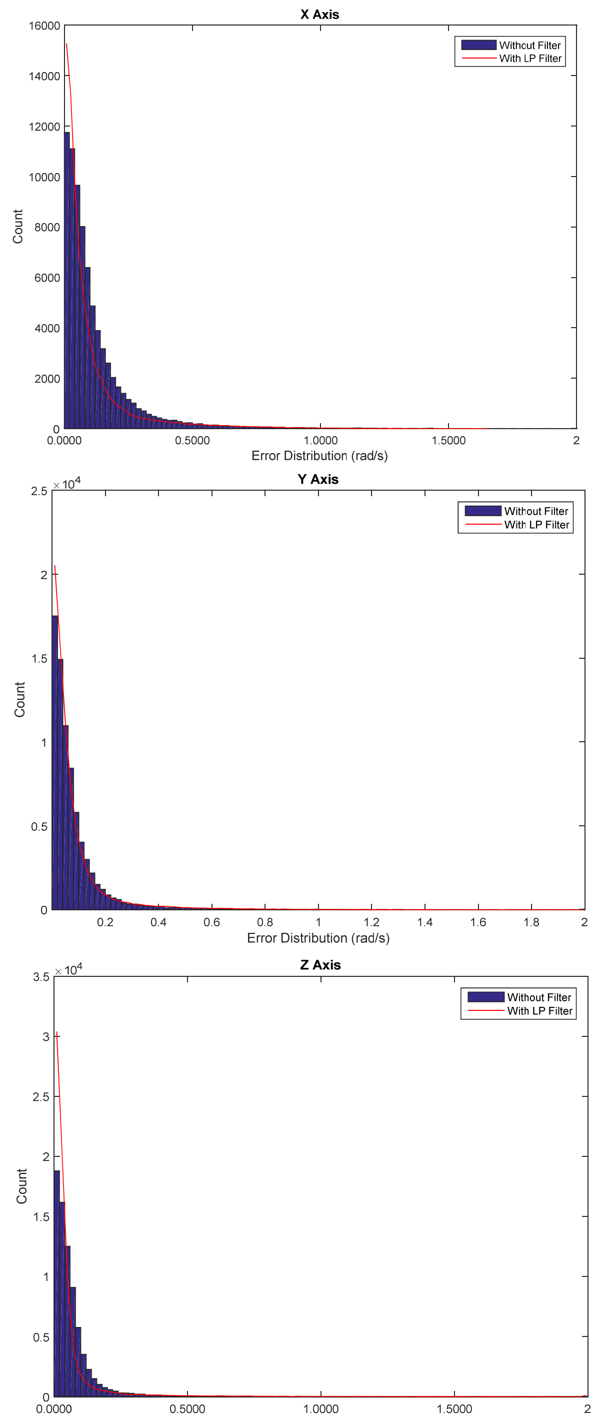

Figure 8. Histogram plots of prediction error for the three trained BPNNs with respect to filed and measured data

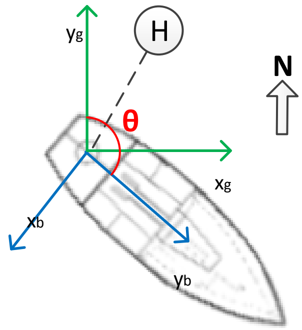

Figure 9. Coordinate system of the ship

Since air wake is the source of oscillations in the helicopter, the air wake intensity pattern is the same as the angular rates intensity after removal of pilot inputs and helicopter's vibration. If $\{\omega_x, \omega_y, \omega_z\}$ is the low pass filtered angular rate vector ($\boldsymbol{\omega_f}$) of the helicopter and $\{\omega_x', \omega_y', \omega_z'\}$ is the angular rate vector ($\boldsymbol{\omega_f}'$) predicted by the network, then the magnitude of the net angular rate (ω_r) is obtained as follows:

$$\omega_r = \left\| \boldsymbol{\omega}_f - \boldsymbol{\omega}_f' \right\|. \quad (3)$$

The magnitude of the angular rate is then plotted on the helicopter's trajectory to obtain ship air wake intensity patterns. Fig. 10 shows ship air wake intensity pattern for one of the outdoor test flights.

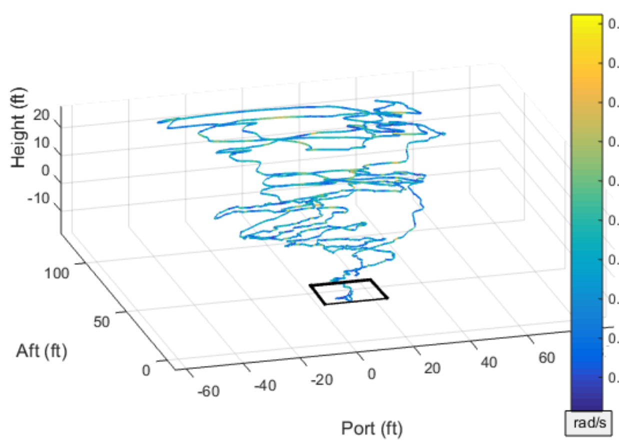

Figure 10. Isometric view of the ship air wake intensity plotted on the helicopter's trajectory.

IV CONCLUSION AND FUTURE WORK

This paper presented a new system capable of estimating external disturbances on a helicopter as a measure of ship air wakes. The proposed system provides a relatively low cost solution for problem involving mapping of wind turbulence by making use of off-the-shelf RC helicopter. Significant improvement has been made both in terms of hardware and software in the presented system as compared to previous versions, which not only improves the system's prediction accuracy but also makes the system useful for other applications. Currently, this system estimates only the rotational component of air wakes. Future work includes use of a more precise positioning system to estimate translational effect of air wakes. Bayesian regression methods will be implemented to model data and noise separately for better prediction accuracy. Furthermore, this work will be extended to develop an autonomous flight control system capable of rejecting external disturbances.

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