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Detecting Problematic Vibration on Unmanned Aerial Vehicles via Genetic-Algorithm Methods

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***Abstract*— Unmanned Aerial Vehicles (UAV) problematic vibration detection as a flaw detection and identification (FDI) method has emerged as a feasible tool for assessing a UAV's health and condition. This paper shows the potential of optimization-based UAV problematic vibration detection. A proposed fitness function based on the frequency domain has been detailed. The fitness function with the Genetic Algorithm (GA) optimization method is tested and evaluated based on Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and detection time. 51 sets of data have been collected using software in the loop (SITL) methods and are used to determine the effectiveness of the proposed fitness function and GA. The test results show promising results with obtained mean RMSE = 1407.2303, mean MAPE = 0.7135, and mean detection time = 2.6129s for a data range of between 3955 to 9057.**

Keywords—Problematic Vibration, Genetic Algorithm, Frequency-Domain, Root Mean Square Error, Mean Absolute Percentage Error.

I. INTRODUCTION

UAVs (Unmanned Aerial Vehicles) are becoming increasingly important in a variety of applications, including but not limited to structural health monitoring and fault identification. UAV vibration detection as a means of fault detection and identification (FDI) has emerged as a viable tool for analyzing the health and condition of a UAV.

Previous research has demonstrated the importance of sensor placement and optimization in UAV applications. A study on "Optimisation and control application of sensor placement in aeroservoelastic of UAV" for example, emphasized the incorporation of vibration energy-based observability measurement for sensor location [1]. Furthermore, a study on "A Path Planning Method with Perception Optimization Based on Sky Scanning for UAVs" shows the ability to maximize sensor node lifetime, emphasizing the need for optimization in UAV operations [2].

Furthermore, the employment of optimization approaches for state estimation and problem detection in UAVs has piqued the interest of researchers. For example, a study titled "Optimal control and state estimation for unmanned aerial vehicle under random vibration and uncertainty" highlighted the importance of optimal estimation in inferring information about the UAV state [3]. "Vibration-Based Fault Detection in Drones Using Artificial Intelligence" developed a fault detection method based on multirotor arm vibration, demonstrating the use of a Neural Network in vibration-based fault detection [4].

Furthermore, the integration of computer vision and optimization algorithms for structural vibration assessment utilizing unmanned aerial vehicles (UAVs) has been investigated. A succinct assessment emphasized the advancements and applications of unmanned aerial vehicle-based computer vision in structural dynamics, emphasizing the potential for new measuring methods [5]. A study titled "A Bridge Vibration Measurement Method by UAVs Based on CNNs and Bayesian Optimisation" demonstrated the use of convolutional neural networks and Bayesian optimization for vibration measurement, demonstrating the potential for advanced techniques in UAV-based vibration detection [6].

Other fault diagnostics in UAV are Neural-Network Extended Kalman Filters (NN-EKF) [7], Particle Filter (PF) with k-means cluster, and Multilayer Perceptron (MLP) [8] and EIKF with Bhattacharyya distance [9]. None of the aforementioned articles dealt with optimization-based fault detection and identification.

The suggested method in this work intends to find out the feasibility of using the optimization method as problematic vibration detection for fault detection and identification. This paper will provide the formulated fitness function and the evaluation matrix used to evaluate the formulated fitness function in genetic algorithms (GA) optimization methods.

II. METHODOLOGY

The methodology of this research starts by acquiring data sets for the problematic vibration during flights. As of the date this paper is written, there are no available data sets online. The data sets can be obtained from the author with proper application.

With the data sets acquired, the frequency domain fitness function is established and with the use of Genetic Algorithm (GA), the performance of the fitness function is accessed.

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A. Data Sets

Data were collected using the software-in-the-loop (SITL) method with four software. The software is Mission Planner, MAV Proxy, ArduCopter, and physics simulation sim_multicopter [10]. The Mission Planner was utilized as a data logging tool. MAVProxy is a user-interactive software to input commands to ArduCopter. The use of MAVProxy will enable ArduCopter to run with physics simulator sim_multicopter in the background without specific hardware. The SITL setup can be seen in Fig 1. This setup has been used by other researchers and published in a paper [10].

Fig. 1. SITL setup.

The quadrotor is flown autonomously with the use of waypoint navigation. While cruising, a vibration is injected into the quadrotor sensors to depict problematic vibration due to component failure on the quadrotor. The placement and duration of the vibration are varied for each data set. Besides that, surrounding wind velocity and direction are also varied. By using Mission Planner Software, the attitude (roll, pitch, and yaw angular velocity) and altitude (z-axis) data are logged. A sample of data obtained in the roll angular velocity channel can be seen in Fig 2. A total of 51 sets of data were collected.

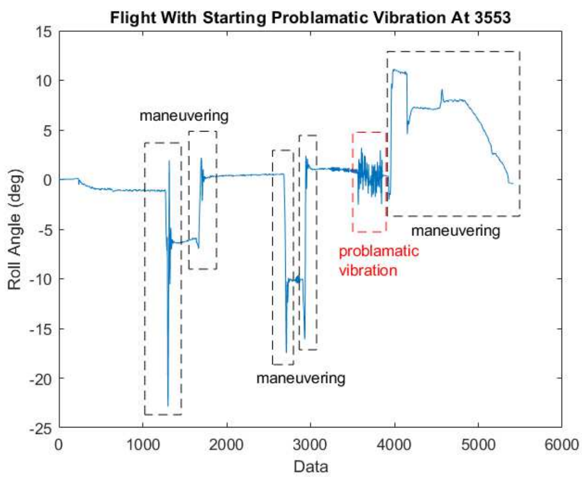

Fig. 2. Sample Roll Angle Data.

Fig 2 shows a sample of flight data whereby the vibration is induced at data 3553 (marked in red dotted line and labeled problematic vibration). The surrounding spikes are due to the quadcopter maneuvering in variable wind velocity in the x-direction. The fitness function while using GA must find the starting point of the problematic vibration.

B. Fitness Function

The fitness function developed is initially based on paper [11] by using Discrete Cosine Transform (DCT) which is altered to meet fault detection and identification (FDI) purposes. The block diagram for the fitness function can be seen in Fig 3.

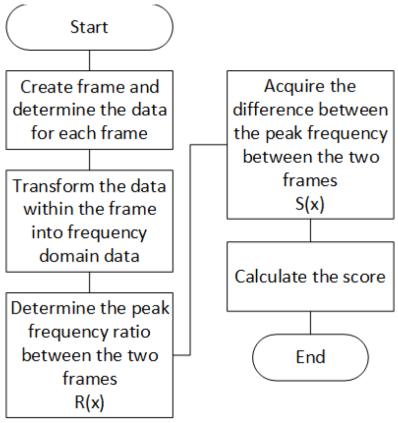

Fig. 3. Fitness function flow chart.

Two back-to-back frames made of 30 data per frame are used. The data in each frame is transformed into frequency domain data by using DCT. The peak frequency for the first frame is compared to the second frame. If the peak frequency of the second frame is twice or more larger than the first frame, then it is considered a problematic frequency. This is to ensure that the beginning of the problematic vibration is captured by considering operational vibration. Next, the peak of the second frame is subtracted from the first to determine the severity of the problematic frequency. Equation (1) will calculate the score of the fitness function. The minimum the score, the more accurate the detection.

$$f(x) = abs(10 - (R(x) + S(x))) \tag{1}$$

Where x = data position, S(x) is the severity of the problematic frequency and R(x) is depicted in (2).

$$R(x) = \begin{cases} 0, & k(x) < 2 \\ k(x), & k(x) \geq 2 \end{cases} \tag{2}$$

Where k is the ratio between the peak frequency of the second frame to the peak frequency of the first frame.

C. Genetic Algorithm

The GA for this study is based on paper [12] and is stated here for completeness of this paper. Algorithm 1 shows the GA pseudo-code.

Algorithm 1: Genetic Algorithm pseudo-code

```
FOR (k = 1 to DataSet) DO
    IF (k == 1)
        Create an initial population through random generation;
    ELSE
        Create an initial population in proximity to the previously
        optimal solution.;
    END IF;
    FOR (i =1 to Ngen individuals) DO
        FOR (j =1 to N_pop individuals) DO
            Assess the fitness of an individual j: fj(i);
        END FOR;
        Preserve the best individual in the population i+1;
        FOR (j = 2 to N_pop) DO
            Choose two individuals
            perform crossover to generate two new individuals
            mutate the newly created individuals
            integrate them into the population i +1;
        END FOR;
    END FOR;
    Preserve the optimal position;
END FOR;
Return to the final optimal position;
```

D. Evaluation Matrix

The GA with the proposed fitness function is run 500 times and the data is evaluated. Equations (3) and (4) show the two main evaluation metrics that were used to evaluate the fitness function: RMSE and MAPE. Besides that average time to detect is also evaluated.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

Where n, y_i, and $\hat{y}_i$ denote the number of samples, the actual value, and the estimated value respectively.

III. Result & Discussions

Fig 4 shows the RMSE evaluation for all 51 sets. Referring to Fig 4, the RMSE ranges from 4.5279 to 3858.4657 with the mean at 1407.2303. Since RMSE shows how dispersed the residuals are, the lower the value, the tighter the estimated location is with the real location. Based on Fig 4, the five sets of data that yield the highest RMSE are data set 18 (RMSE = 3858.47), 7 (RMSE = 3592.07), 13 (RMSE = 3378.63), 16 (RMSE = 3303.5), and 22 (RMSE = 3102.19). After reviewing the sample sets, the high RMSE on these particular sets was due to multiple vibration patterns with different intensities where the other intensity is not due to induced vibration (Refer Fig 5).

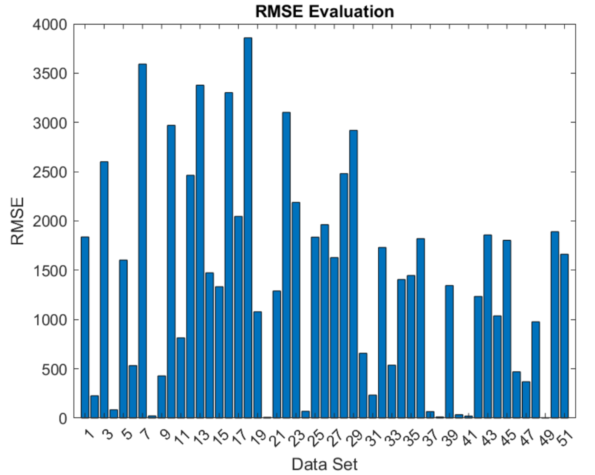

Fig. 4. RMSE of GA using a proposed fitness function.

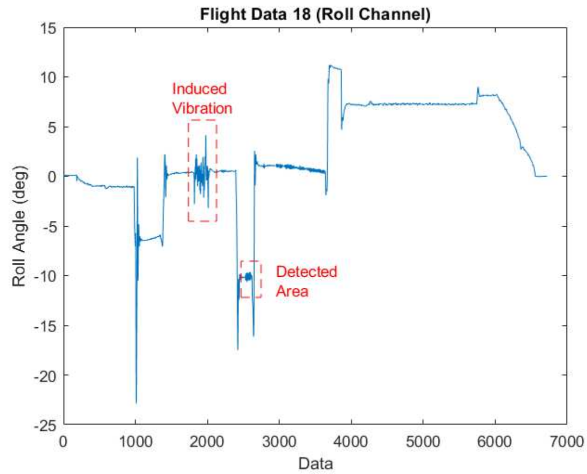

Fig. 5. Data set 18.

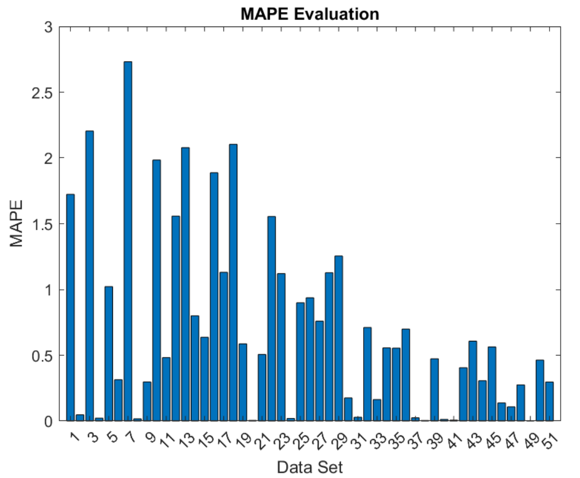

Fig. 6. MAPE of GA using the proposed fitness function.

Fig 6 shows MAPE results of the proposed fitness function with GA. Referring to Fig 6, the MAPE performance is between 0.0012 and 2.7319 with the mean at 0.7135. The lower the MAPE, the better the performance. The lowest performance was when using data set 7 which yielded MAPE = 2.7319. This is the same data set that yielded the worst

RMSE performance. But overall, the mean for vibration detection is low.

Fig 7 shows the detection time for all data sets. The detection performance is between 2.0065s to 2.9261s for the number of data points between 3955 to 9057. The mean acquired is 2.6129s.

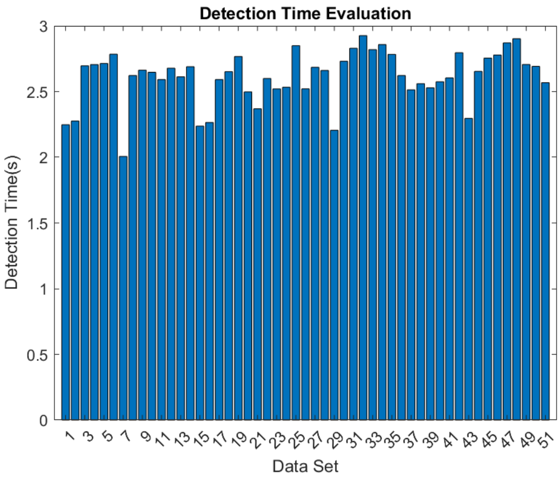

Fig. 7. Detection Time

IV. Conclusions & Future Works

This study investigated the potential of using the optimization method as a means of problematic vibration detection in UAVs. The fitness function has been formulated and is detailed in subsection B. Using GA as the optimization method, the fitness function has been evaluated. Based on the result, the fitness function using GA has resulted in mean RMSE = 1407.2303, mean MAPE = 0.7135, and mean detection time = 2.6129s. The result shows good detection time. The RMSE and MAPE for some of the tested data sets resulted in good results. This shows that the optimization method has the potential to be used for problematic vibration detection in UAVs.

To accommodate all the data sets, more work needs to be done. Future works that can be done are using other variations of optimization algorithms. Using the latest optimization algorithm might give a better result than GA. Besides that, rather than using only the frequency measurement, adding time-based data might also give better results.

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