APPLICATION OF SELF-ORGANIZING MAP ON FLIGHT DATA ANALYSIS FOR QUADCOPTER HEALTH DIAGNOSIS SYSTEM

De-Li Cheng,*, Wei-Hsiang Lai

[1] Dept. of Aeronautics & Astronautics, National Cheng Kung University, No.1 Univ. Rd., Tainan, Taiwan - (P46061225, whlai)@mail.ncku.edu.tw

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ABSTRACT

The UAS fault problem has led to many potential risk factors behind its rapid development in recent years. Therefore, the diagnosis of UAS health status is still an important issue. This study adopted the SOM machine learning method which is an unsupervised clustering method to establish a model for diagnosing the health status of quadcopter. Take the vibration features of three flight states (undamaged, motor mount loose, unbalanced broken propeller). Through those training data the model can cluster different vibration pattern of fault situation. It not only can classify the failure status with 99% accuracy but also can provide pre-failure indicators.

1. INTRODUCTION

In recent years, the development of UAS has been changing with each passing day, and has been applied to military exploration, freight transportation, meteorological observations, and civil aerial photography. As UAS get closer to human life, UAS are bound to be a potential risk factor for human security. Therefore, how to diagnose the health status of the UAS is an important issue. The diagnostic system of UAS has gradually developed in recent years and many applications have been completed like (Olson et al. 2013). There are a lot of characteristics in the UAS that can provide pre-failure symptoms of multi-rotors, such as EKF, current and voltage changes, etc. As (Kandaswamy et al. 2017) done. However, to complete the health of the overall components of the UAS Diagnosis systems are not easy because of the many different factors that must be considered. Despite that, vibration has always been an important issue for rotating machinery, as well as UAS. There are many UAS vibration analysis and diagnostic studies, like analysis of UAS vibration elimination (Radkowski et al. 2014); Fourier transform for analyzing the frequency domain characteristics (Ghalamchi et al. 2018) and time domain vibration characteristics and sound characteristics and with mechanical learning for failure classification (Misra et al. 2018).

That's why embarked on the development of quadcopter health diagnosis system. In particular, the diagnosis of the state of the vibration of the quadcopter. The main power source of the quadcopter is propeller and the brushless motor which cause quadcopter continuously vibrate itself. When the two are slightly damaged, the common user is difficult to detect, but as time goes by, these injuries will gradually enlarge and even affect flight safety. This study hopes to use a variety of common failure states (Misra et al. 2018, Yong Keong Yap. 2014) with SOM algorithms to classify the vibration changes between multiple states to achieve quadcopter health diagnosis

2. EXPERIMENT DESIGN

2.1 Conditions of Flight

The data obtained in this study was collected by using a common type of quadcopter (see Figure 1). There are several essential well-controlled conditions that applied in this experiment. First, quadcopter flied indoor that means it won't be affected by the wind. Second, we applied Althold mode which was created by Ardupilot to the flight experiment. Third, battery used in every experiments would remain 3.7V per cell, to avoid powerless problem.

Because of motors revolution speed changes, there are several pattern of vibration will generate. Especially, when quadcopter maneuvers, motors revolution speed will change separately, and it would make vibration data too complex to analyze. To avoid the uncertainty of flight data, the flights in this study are hovering and operating just by passive manipulations.

Fig. 1. The quadcopter used in experiment

2.2 Fault Characterization

The main topic of this paper is fault diagnosis of power system. In order to avoid the classification model is too strict or lax, there are two essential concepts about fault experiments. First, when the fault is applied on quadcopter, it still can fly and maneuver. Second, fault situations need to make the quadcopter unstable to some extent. These two concepts may not clear defined, but the machine learning model could still classify the relative fault. Besides, the model would have enough classification ability and it also won't be too lax. There are two fault situations data were applied in this research. First one is unbalance broken propeller (Yong Keong Yap. 2014) (see Figure 2.), one blade was fault free and another blade was cut. it would mount in one of motor of quadcopter. When unbalance broken propeller is used to fly, it will directly lead to insufficient lift and the eccentric rotating mechanism will inevitably generate a lot of vibration.

Figure 2. Unbalance broken propeller

Second one is motor mount loose in asymmetrically pattern (see Figure 3.), the screws loosen the same side will make thrust distribute on the bottom of motor unevenly. It will cause extra moment on the arm of quadcopter and it also cause extra vibration.

Figure 3. Motor mount asymmetrically loose

3. FEATURE EXTRACTION

3.1 Vibration Characterization

This paper only applied time domain feature to do extraction. Because Not only we can't measure motors RPM precisely, but also we don't have even sample rate of flight data. After many test, we find that the SD card on-board can't maintain writing speed because of computational amount, specification of onboard computer and SD card specification etc. Because of that, there are approximate 5-10 percent of data have a big gap between default sample rate. The rest of data approximately reach default sample rate but its still have some concussion. For the above reasons, we can't use features which very depend on the accuracy of sample rate. That is why we use time domain feature (see Table. 1.) which won't affect easily by little change of sample rate.
Vibration signals are all collected by the on-board computer which mounts at the center of quadcopter. Although sensors are far from the motors and propellers, and the vibration signals are more complex than the sensors below motors, diagnosis system must be approachable.

3.2 Vibration Feature Extraction

This paper use gyro and accelerometer to obtain vibration signal and then do pretreatment to the flight data (e.g. remove low sample rate data). Then we applied three methods which are Standard deviation, Root mean square, sample entropy (Richman et al. 2000) (see table 1) to extract the feature from the data.

Table. 1. Features of vibration

	feature	description
1	Root mean square	$RMS = \sqrt{\frac{\sum_{i=1}^{n} x_i}{n}}$
2	Sample entropy	$SE = -\log \frac{\phi_{n+1}(r)}{\phi_n(r)}$
3	Standard deviation	$\mathrm{SD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)}$

Feature extraction remove useless data and preserve important data. In the beginning of process, the data before quadcopter take off and land be removed. Second the data with low sample rate (5-10% of data set) also be removed. Additionally, sample rate which below 900Hz is belong to low sample rate (default sample rate is 1000Hz). Third, for the purpose of eliminating the effect of moving acceleration, high-pass filter was applied to filter the signal which below 5Hz. Next, statistical methods (see Table 1) are used to extract relevant feature from data. After above process, signal data transfer to representative characteristic data.
The feature extraction of three flight data is shown at Figure 4 Among them, the orange line is unbalance broken propeller, the yellow line is the motor mount loose, and the blue line is undamaged (see Figure 4(g)). It can be clearly seen from Figure 4 that the root mean square and standard deviation characteristics of the unbalanced broken propeller are greater than the other two conditions. In fact, the flight with unbalance broken propeller is indeed the most unstable of the three conditions. The gap between motor mount loose and undamaged RMS and STD is not obvious, but relying on sample entropy can still distinguish between two different states such as Figure 4, (a) (b) (d).

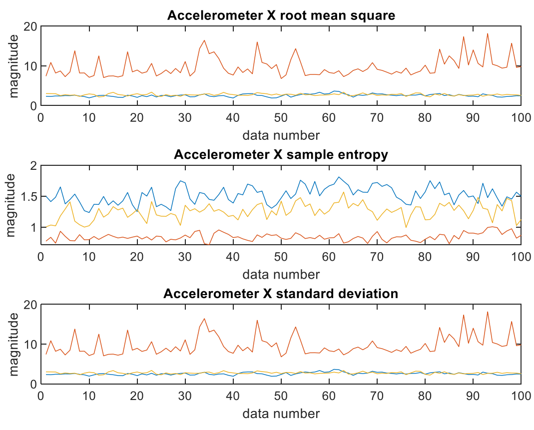

Figure 4. (a)

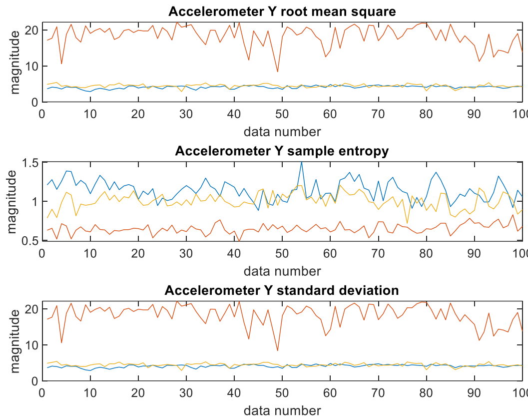

Figure 4. (b)

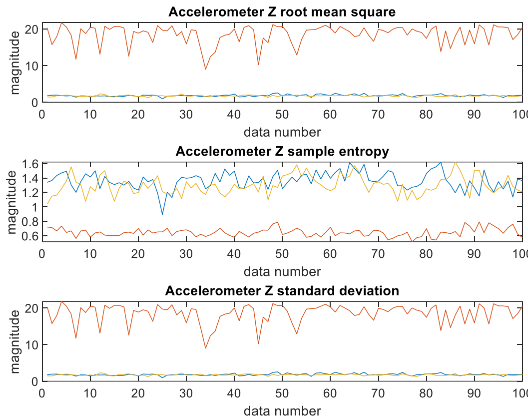

Figure 4. (c)

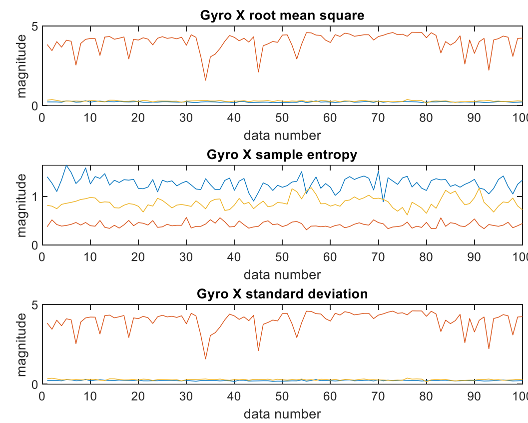

Figure 4. (d)

Figure 4. (e)

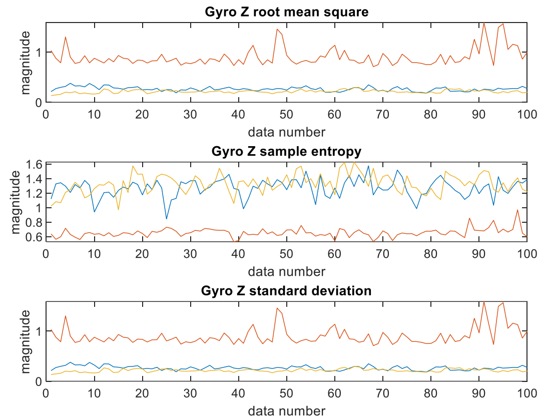

Figure 4. (f)

Figure 4. (g)

4. BUILDING MACHINE LEARNING MODEL

4.1 Self-Organizing Map

Self-organizing map (Kohonen et al. 1995) is an unsupervised clustering machine learning method and is a type of artificial neural network that is trained to produce a low-dimensional and discretized representation of the input space of the training samples, called a map, and is therefore a method to do dimensionality reduction. SOM applies unsupervised and competitive learning, it means in every iteration will come out with a winning neuron which has the shortest Euclidean distance, and then winning neuron will update weight vector and neighbourhood also. Usually, neurons are interconnected by $N \times N$ hexagonal grids. Summarily, the purpose of SOM methodology is clustering data and find the pattern of the data set, and the neurons which have the similar weight will cluster together at the training process. After SOM trained, SOM preserve the topological properties of the input space and create low-dimensional map (output space), and it make the clusters of neurons represent different situations.

(Vesanto et al. 2000) use SOM to complete the problem of high-dimensional data clustering and classification to simplify high-dimensional data.

(Lin. 2016, Chiang. 2017) use SOM method and data feature extraction to analyze the vibration signal of rotating machinery and complete its health diagnosis. It means that SOM is suitable for high-dimensional features of UAV status classification. This study used the SOM function built in Matlab.

4.1.1 Normalization

Original feature data in different dimensions are with various scale range. That's why before SOM start training, features will be normalized by z-score method, ensure that every feature can compete at the same standard. By using Z-score, features in the same dimension are with scale range of standard deviation.

$$D_i = \sum_{i=1}^{m} \frac{x_{ij}}{m} \quad , j = 1, 2, \dots, n \tag{1}$$

$$S_j = \sqrt{\frac{1}{m-1} \sum_{i=1}^{m} \left(x_{ij} - D_j\right)^2} \, , \; j = 1, 2, \dots, n \tag{2}$$

The variable minus mean then divided by standard deviation, so come, the distance between mean and variable can be measure by scale range of standard deviation.

$$\bar{x}_{ij} = \frac{x_{ij} - D_j}{S_j} \quad , i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{3}$$

4.2 Important Parameter

In this study, a total of three flight states (undamaged, motor mount loose and unbalance broken propeller) were added for SOM training. One set of feature vectors has a total of 18 dimensions, including accelerometers and gyroscopes x, y, z. Standard deviation, root mean square and sample entropy. Each states are trained in about 110 row data to ensure that the final model of the neurons can be evenly distributed.

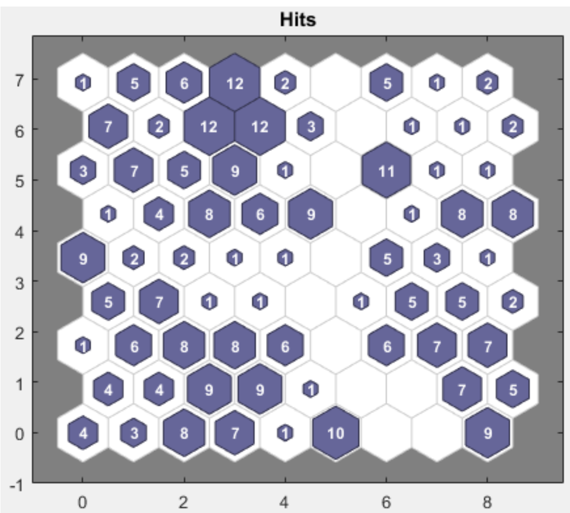

Figure 5. Cluster of neurons

4.3 Clustered Result

The results of the model training show that three clusters of neurons representing different states can be separated by SOM due to the difference in feature patterns (as shown at Figure 5) In the case of clustering, the upper left corner is an undamaged cluster, the lower left corner is a motor mount loose failure condition cluster, and the right side is an unbalanced broken propeller failure status cluster. The number represented in hexagonal is the number of recent training data around the neuron referred to as hits.

5. FAULT DIAGNOSIS

5.1 Diagnosis

It can be seen from Figure 5 that even if each cluster of neurons is well clustered, different hits in each cluster represent that the neurons correspond to several training data (a training data only corresponds to one neuron). So different hits mean different representation. In order to be able to make a better classification and also low the error, this study only took neurons with more than 5 hits in each cluster for subsequent diagnosis of quadcopter health to ensure the representation of neurons.

5.1.1 Cluster Test Data

After selecting the neurons whose hits number is greater than 5, we sorted out three representative neuron clusters (representing undamaged, motor mount loose and unbalanced broken propeller respectively). Classification: First, the test data need to normalize by z-score used standard deviation of training data and mean of training data. Next, clustered the test data in 1-NN method, it will find the nearest neuron called best match unit (BMU) and the distance between BMU and test data is called Minimum quantization error (MQE). After finding the BMU, the cluster of test data is the cluster of BMU. This completes the clustering and completes classification at the same time.

$$C_n^{1nn}(x) = Y_{(1)} \tag{4}$$

x is test data, Y is neurons.

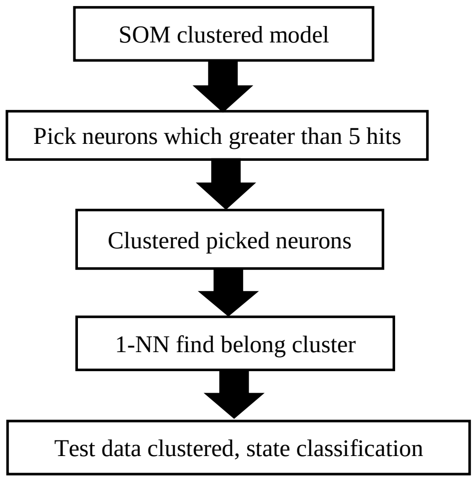

Figure 6. Process of classification

5.1.2 Fault Classification

The confusion matrix was applied to test classification ability of model and also put another fault to test how SOM model can do. The results are shown below (see table 2 and table 3).

According to the results of the confusion matrix, we can confirm that the SOM model has a good classification ability, and the total accuracy can be as high as 99%, and the Recall of failure situation can reach 100%. This paper added data similar to the training status for the classification of the balance of the slightly broken propeller, the unbalanced complete propeller, the motor symmetry loose, and it represent by the second confusion matrix. ◦

The unbalanced complete propeller and motor symmetry mount loose still have a good Recall after classification by the model, so that similar failure conditions can be classified because the vibration modes are similar. Besides, the condition of Balance slightly broken propeller are not ideal. 71% are classified as non-failure but 28.9% are classified as invalid.

Table 2 Confusion matrix of model

Actual / Predict	undamaged	Unbalance broken Propeller	Motor Mount Same side Loose	Precision
undamaged	283	0	0	100%
Unbalance Broken Propeller	0	210	0	100%
Motor Mount Loose	5	0	161	96.98%
Recall	98.26%	100%	100%	99.24%

Table 3 Confusion matrix of model

Actual / Predict	Balance Broken propeller	Unbalance Propeller	Motor Mount diagnal Loose
undamaged	201	0	5
Unbalance slight Broken Propeller	0	210	0
Motor Mount Loose	82	0	113
Recall	28.9%	100%	95.7%

5.2 Flag of Fault

The establishment and diagnosis of the SOM model are basically based on the comparison of Euclidean distance. Therefore, in addition to diagnosing the health status of the quadcopter, this model can also provide the Euclidean distance ratio of no damage neuron to other failure status neuron as a kind of judging quadcopter health. It can provide us an indicator for diagnosing slightly failure situation (e.g. Table 3 balance broken propeller fault).

After the test data (whether undamaged, or not) is clustered, the Euclidean distance of the nearest neuron between the test data and each clusters of neurons are calculated, and the Euclidean distance between the neurons in the failure state (i.e. MQE to the failure clusters neuron) is the denominator, naturally distance to the undamaged neuron (i.e. MQE to the undamaged clusters neuron) is the molecule. When the magnitude of ratio is lower than 1, it means quadcopter is undamaged, and if the ratio is close to one or beyond 1, the state of the quadcopter is gradually approaching the failure cluster, and the user needs to check the motor and the propeller.

Figure 7 shows the undamaged flight test data ratio curve. The horizontal axis is the number of test data and the vertical axis is the Euclidean distance ratio. Comparing with Figure 8, we realize that the ratio of the upper half of Figure 8 exceeds 1 multiple times. Even though 78% of the data in Figure 8 flight diagnosis is non-failure, it still needs to be done immediately with its motor and propeller an examination.

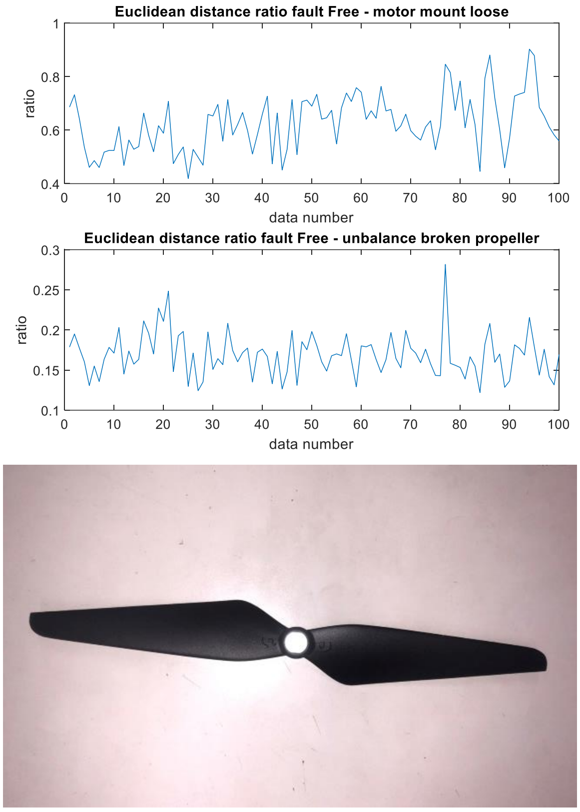

Figure 7. Undamaged

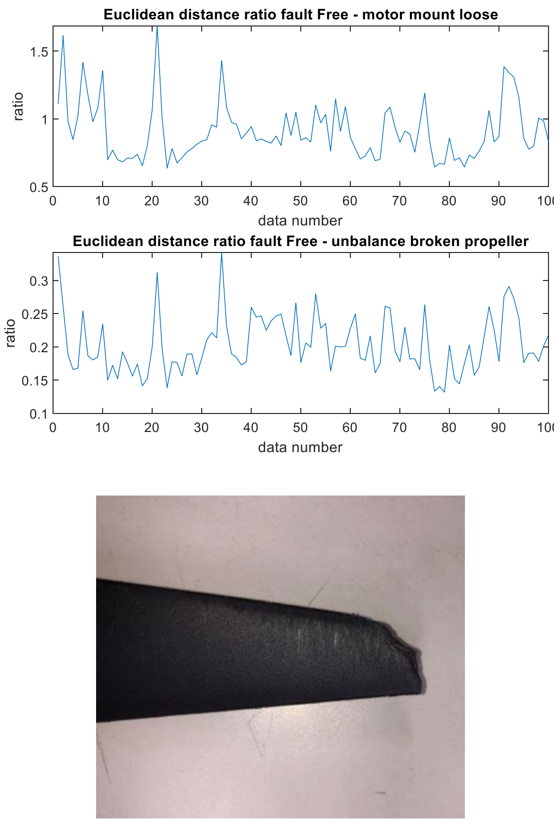

Figure 8. Little damage on the edge of propeller

The slight failure is hard to classify (see Figure8), but with the help of distance ratio and failure recall, slight failure can still be detected by the model, both of them could provide an indicator for pre-failure.

6. CONCLUSIONS

In this study, the flight data of the power system failure and the undamaged flight data were combined with the characteristics of the time domain to establish the machine learning model. The clustering model is completed by SOM and the failure detection and classification can be completed simultaneously with an accuracy of 99%, and the recall of failure situation can reach 100%. For other slightly failure it could still detect and classify through the distance ratio and failure recall.
Although the regulations of this paper are not broad enough, the state of failure that can be identified is limited, but it is a little progress to be able to diagnose in real flight data. In the future we will continue to work on other failure features including frequency domain features, and enhance model classification to enable accurate health diagnosis of quadcopter that are generally flying outdoors.

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