

Diagnostic of Gravitropism-like Stabilizer of Inspection Drone Using Neural Networks

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Abstract. This paper discusses the enhancement of flight stability of using an inspection drone to scan the condition of buildings on low and high altitude. Due to aerial perturbations and wakes, the drone starts to shake and may be damaged. One of the mechanical optimization methods it so add a built-in stabilizing mechanism. However, the performance of this supporting device becomes critical on certain flying heights, thus to avoid losing the drone. The paper is divided in two parts: the description of the gravitropism-like stabilizer and the diagnostic of its status using wavelet transformation and neural network classification.

1. Introduction

Observation is a key factor in the development of science and technology. Human, analyzes the surrounding and tries to develop models that mimic the processes and mechanisms found in nature. Drones, helicopters, manipulators are results of a bionic modeling approach.

Some algorithms are developed based on physical foundation. For instance, as in the case of the potential field method, the gravity concept is used to find an optimal trajectory of the mobile robot. Similarly, the activation of some mechanisms are based on bionic approach. As an example, a gravitropism-based manipulator grasp stiffness changes with the surrounding environmental chemical concentration. So, what is gravitropism and how its notions can be used to enhance the performance of an inspection drone?

While flying, it is important to get information about the rotor condition of the drone. The jamming or failure of at least one drive will cause the drone to fall. Stabilizers are used to enhance the flight performance of the vertical takeoff and landing drones (VTOL) especially when used to scan an on altitude such as the high-rise building [1] or on a low altitude being influenced by building wakes [2].

If the stabilizer is added, the definition of the technical state and flight control becomes critical as the flight stability will be dependent on its performance. This can be achieved using methods and means of diagnosis that allow the current state of the monitored object to be assigned to one of the predetermined classes of diagnoses.

One of the drawbacks of the quadrotor drones is low load capacity, therefore, when diagnosing its rotors, heavy measuring and diagnostic tools cannot be used. It is preferable to define a way allowing one to determine the state during operation without the use of additional sensors and monitoring systems. One of these parameters is the current feeding the motor. Quadrotors are basically equipped with servo drives with low power supply, so the motor winding can be used to obtain information about its state.



2. Gravotropism-like Stabilizer

Gravitropism is the phenomena, which occurs in the plants, where cells under the influence of gravity (g) and temperature (T) alter the concentration of intracellular chemicals. Chemical concentration controls the rate of reactions initiating differential growth in the responding organ, which ultimately results in an external bending response.

By applying the gravitropism concept to a mobile robot, the differential growth is represented in movement or rotation (fig.1).

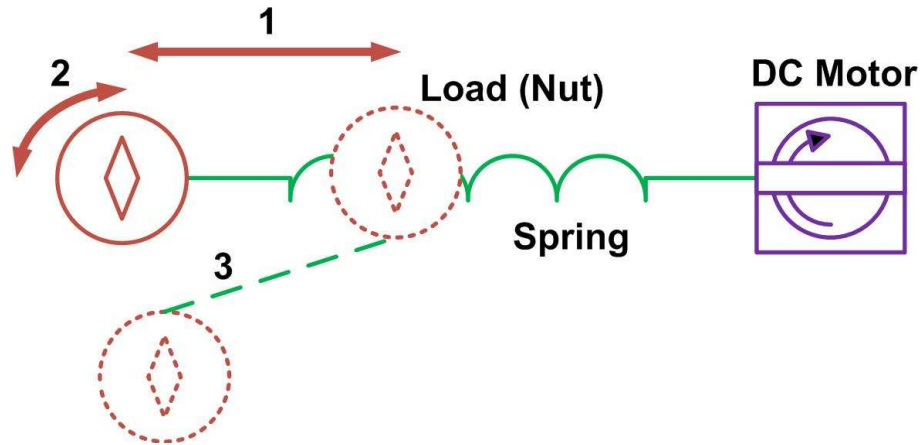


Figure 1. Single Passive Stabilizer of the quadrotor

Each complete rotation of the DC gear motor shaft achieves full rotation of the spring, which causes elongation equal to the pitch (P) of the spring. If one considers that the latter is constant for some angles of gear shaft rotation β , then one can compute elongation $\Delta\lambda$ as follows:

$$\lambda = \lambda_n + \Delta\lambda = \lambda_n + \frac{\theta}{360}P \quad (1)$$

where λ – the portion length of the spring that can be bended; $\Delta\lambda$ – elongation; θ – set of angles where the rotation is fixed; P – the pitch of the spring; λ_n – initial portion length of the spring that can be bended.

The elongation speed of the spring can be obtained from equation (1) and it is function of the rotation speed and pitch. It can be computed as follows:

$$V_\theta = \frac{M_{DC}}{60}P = \frac{N}{60}(P_0 - \frac{F_A}{NK}) \quad (2)$$

where V_θ – the elongation speed; M_{DC} – the rpm of the DC motor; P_0 – the initial pitch; F_A – the applied load, described in equation (3); N – number of active coils; K – spring constant.

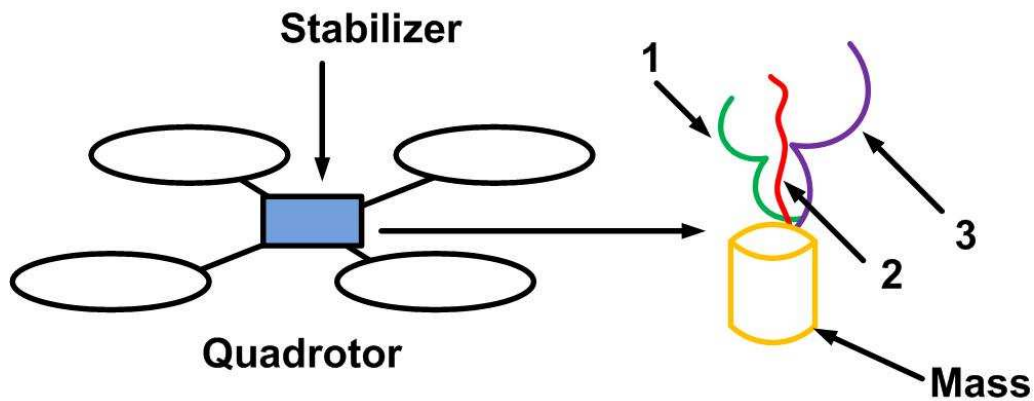
The applied force can be calculated using equation (3):

$$F_A = \frac{T}{r \frac{\sin\varphi + \gamma\cos\varphi}{\cos\varphi - \gamma\sin\varphi}} \quad (3)$$

$$\varphi = \tan^{-1} \frac{P}{2\pi r}$$

where T – the torque; r – the radius of the spring; γ – the friction coefficient; φ – angular function of the pitch of the spring.

As illustrated in Fig.2, the stabilizer mechanism consists of group of springs described above holding a load. In line of that, the whole mechanism can be described using the following criteria:

**Figure 2.** Quadrotor active stabilizer

- Total elongated length λ_T or arc length:

$$\lambda_T = \frac{\sum \lambda_n}{n} \quad (4)$$

- Plane of movement ϱ :

$$\varrho = \tan^{-1} = \left(\frac{\sqrt{n} * (\lambda_2 + \lambda_3 - 2\lambda_1)}{n(\lambda_2 - \lambda_3)} \right) \quad (5)$$

- Curvature Ξ :

$$\Xi = \frac{\sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2 - \lambda_1\lambda_2 - \lambda_1\lambda_3 - \lambda_2\lambda_3}}{d(\lambda_1 + \lambda_2 + \lambda_3)} \quad (6)$$

where d is the distance of each actuator to the body center including the deviation of the center of gravity from its ideal geometric position.

3. Diagnostic of the stabilizer

The traditional method for analyzing diagnostic parameters for the servomotor is through Fourier transformation [3], which has a number of significant drawbacks [4] not allowing its implementation for automatic diagnostics of electric drives operating under dynamic loads. In contrast, methods such as the wavelet transformation [5] has no such constraints, and allow one to identify the current state of the drive.

To analyze the state of the drive, the current signal and the phase voltage of the new faultless drive are considered as reference. Troubleshooting is performed at the characteristic frequencies [6-9] (Table 1) by comparing the current spectrum with the reference spectrum using artificial intelligence.

Table 1. Fault identification scheme

Fault	Signal frequency
Commutation	$2 \cdot k \cdot p \cdot f_r$
Rotor	$2 \cdot p \cdot f_r, \quad k \cdot f_r \pm 2 \cdot p \cdot f_r$
Main power pulsation	$k \cdot f_s$
Stator	$k \cdot f_r$

where f_s - the frequency of the current supplied to the bridge, f_r - the rotational frequency of the rotor; $k = 1, 2, 3$ - the harmonic number of the current; p - the number of poles.

To analyze the current state of the drive, it is necessary to recalculate the resulting Fourier transform frequencies into a wavelet scale [10]. As a maternal function, any type of wavelet can be selected. In the course of experimental studies on various servomotors with and without load, the regularity is shown in Fig. 3.

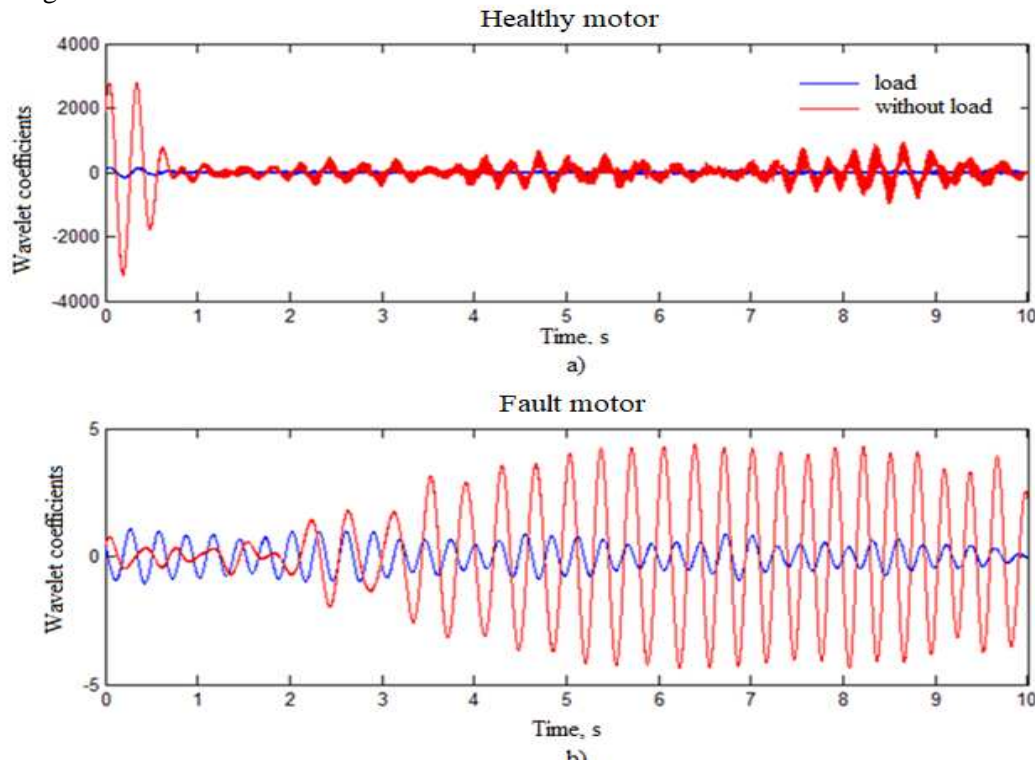


Figure 3. Wavelet stator current signal: (a) healthy motor, (b) faulty motor

From these graphs it is seen that the wavelet coefficients of a serviceable unloaded engine on characteristic scales have insignificant fluctuations at drive's start-up, then the process is practically linearized. When a load occurs, the oscillatory process at the start of the engine is more obvious, however it decreases with a certain periodicity and get repeated after a certain time interval. In general, the process can be considered as stable since there is no significant increase in the amplitude of the oscillations with time.

The coefficients of the wavelet transformation of a faulty motor are much lower than those of a healthy motor and have constant oscillations, which increase when the load appears. The values of the wavelet coefficients on scales that are not characteristic of the introduced fault have the form shown in Fig. 4.

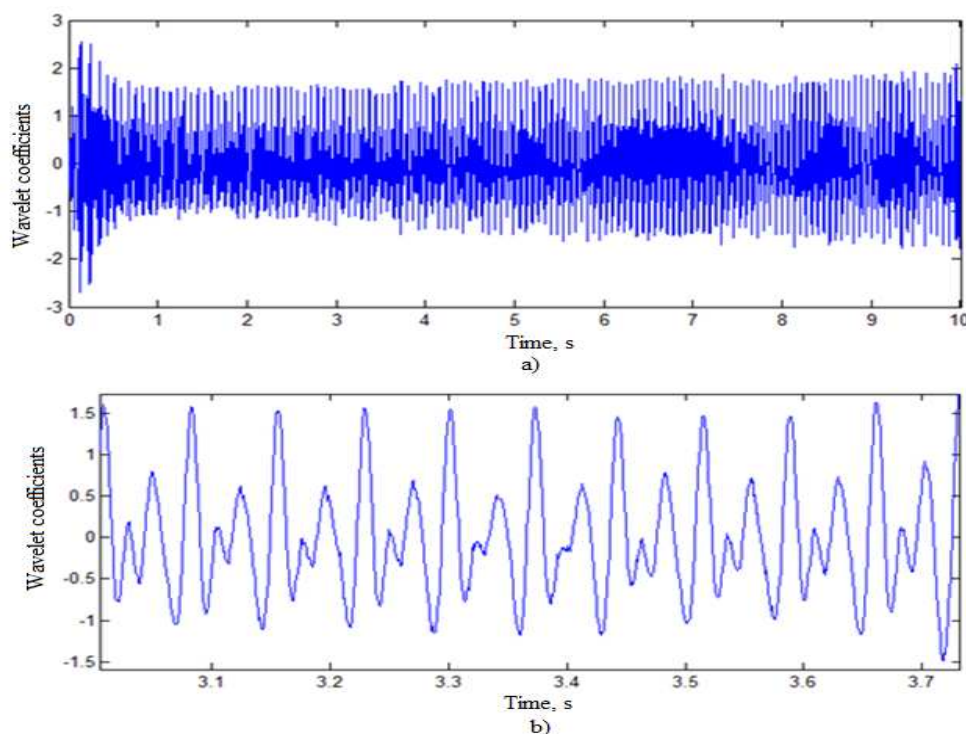


Figure 4. The wavelet coefficients of the feeding tension of the serviceable and faulty engine at an uncharacteristic scale: (a) a real signal in the increased scale

Figure.4 shows that the signal has a high density and low values of wavelet coefficients, while the signal is regular and completely repeated at a specified frequency. This type of signal is characteristic of all frequencies regardless of the technical state of the engine. Thus, according to the results of the analysis, one obtains five characteristic signals for diagnosis. Signals of characteristic frequencies for serviceable unloaded and loaded engines are shown in Fig.1.a, uncharacteristic signal for "normal status" in fig.2, while faulty loaded and unloaded engine "defective" in fig.1b.

4. Neural Network Condition Classification

The automatic determination of the technical state of an electric drive can be done using neural classification [11-14]. As the initial data, the wavelet coefficients are used at a characteristic scale for the failure and normal status signal. As an input, a matrix containing five values of characteristic signals is given. The output of the network is the class of the diagnosis: "11" is not loaded properly, "12" is fully loaded, "21" - defective and not loaded, "22" - defective and loaded.

Figure 5 shows the neural classification structure. The network contains four layers: three hidden and an output. The hidden layer has five neurons with a tangential activation function; the output one is a linear neuron.

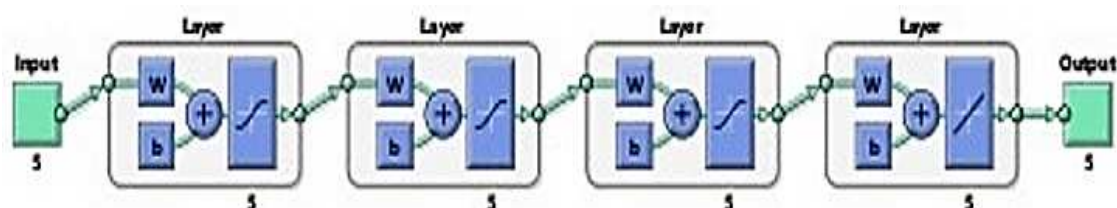


Figure 5. Neural network for electric drive technical condition and mode operation classification

To train the neural network, the Levenberg-Marquardt algorithm [14-18] is used, which is designed to optimize the parameters of nonlinear regression models. The result of training is shown in Fig.6

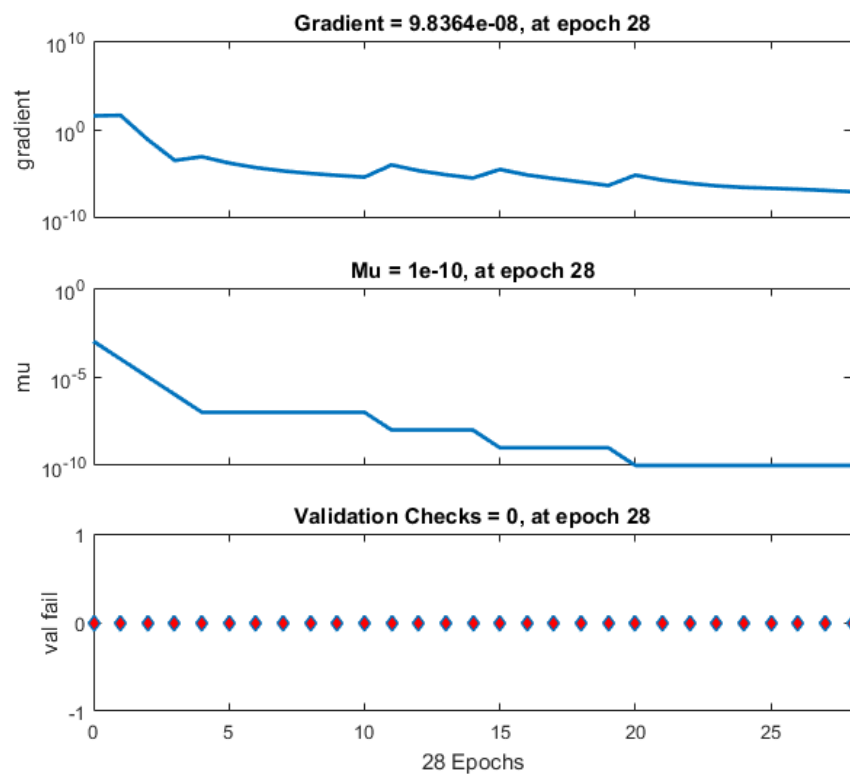


Figure 6. Neural network training result for technical condition and operation mode determination
The simulation results are provided in table 2.

Table 2. Results of neural network for technical condition and operating mode classification

Signals	Network Results
Healthy off-load, (Fig.3,a)	11
Healthy loaded, (Fig.3,a)	12
Uncharacteristicsignal (Fig.4)	11
Faulty off-loaded, (Fig.3,b)	21
Faulty loaded, (Fig.3,b)	22

5. Conclusion

The paper discussed the stabilizing mechanism of an inspection drone operating based on a gravitropism process. The technical status of the stabilizer was assessed using wavelet transformation and neural network classification. Theoretically, the results of artificial intelligence diagnostic of the stabilizer conditions was achieved. However, and due to the noise created by the springs, these results might alter. Springs are sensitive components and unreliable in certain conditions. Temperature, pressure and humidity change the stiffness of the mechanism as well. Hence, some constraints were adopted while modelling this case study.

The presented results can be used for orientation purpose and later physical implementation and assessment.

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