Estimation of Surface Pressure and Strength of Flapping Wing Micro Air Vehicle

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Abstract
A combination of finite element modeling (FEM) and artificial neural network (ANN) is employed to estimate the surface pressure of flapping wing micro air vehicle. The ANN training patterns are prepared by varying the surface pressure distributions and calculating their associated strains through FEM. Through the well-trained network, the surface pressure can be estimated instantly by the strains measured during flapping. The maximum flapping frequency that represents the strength of flapping wings is then predicted using maximum strain criterion, in which the critical strain was measured using the standard ASTM specimens. The relation between the flapping frequencies and strains is a curve fitted by the data measured under lower and safer flapping frequencies.

Key words
Flapping Wing, Surface Pressure, Wing Beat Frequency, Artificial Neural Network, Finite Element Model

1. Introduction
While fixed-wing flight has advanced rapidly over past 100 years, nature’s flying animals, which have evolved over 150 million years, are still impressive. Based upon observation of flying animals such as birds and insects, most of the studies about flapping flight focus on wing motion and flexible airfoils [1]. Not too many researchers consider surface pressure and strength of flapping wings. Here, the strength means the maximum wing beat frequency since if the frequency is too high there is a risk for the wing bone failure. Although there are some studies concern about the wingbeat frequencies of migrating birds such as [2,3], their results cannot be applied to predict the strength of man-made flapping wings.

To estimate the surface pressure and strength of flapping wings, in this paper a four-bar linkage design was selected as the mechanism for the wing flapping [4]. The wing frame was made by carbon/epoxy fiber reinforced composites and the wing skin by LD-PE (Low Density Polyethylene) plastic. Through the measurement of flapping strains for lower and safer flapping frequencies, the surface pressure and strength of flapping wings can then be predicted with the assist of finite element modeling and artificial neural network. This prediction is then confirmed through the test of flapping to failure.

2. Mechanical Properties of Flapping Wings
The flapping wings studied in this paper consist of wing frame made by carbon/epoxy fiber reinforced composites, and wing skin by thin LD-PE plastic. Two different types of wings, wing-I and wing-II, are tested in the following experiments (Fig.1). The flapping mechanism is a four-bar linkage driven by electric motor (Fig.2). To know the elastic properties and static strength of wing frame, a series 230mm × 25mm specimens of carbon/epoxy fiber-reinforced composites are made and tested according to ASTM standards [5]. The elastic properties \( E_1, E_2, v_{12}, G_{12} \) are determined by the tension tests on the unidirectional \([0^\circ]_n\), \([90^\circ]_n\) and \([45^\circ]_n\) specimens. By conducting \([0^\circ]_n\) specimens to failure, the critical stress \(\sigma_c\) and critical strain \(e_c\) in fiber direction of carbon/epoxy fiber-reinforced composites can be measured. Through the standard procedure, the elastic properties and critical stress and strain of carbon/epoxy fiber reinforced composites used for the wing frame are measured to be

![Fig.1 Two different types of wings: (a) Wing-I, (b) Wing-II](image)

![Fig.2 Flapping mechanism](image)
The LD-PE plastic for wing skin with 0.1mm thickness is an isotropic material whose Young’s modulus $E$, Poisson’s ratio $\nu$ and density $\rho$ are measured to be

$$E = 1.5\text{GPa}, \quad \nu = 0.4, \quad \rho = 947.8\text{Kg/m}^3.$$ (2)

3. Finite Element Modeling of Flapping Wings

In this study, the finite element modeling was performed through the commercial finite element software ANSYS. The element SHELL91 was selected for the modeling of wing frame and skin whose mechanical properties have been measured and provided in Eq.(1) and Eq.(2). Boundary conditions are given by fixing all nodes at the wing root. The surface pressures are assumed to be in the form of two variables 2nd order polynomials, i.e.,

$$p(x, y) = a(x/L)^2 + b(y/H)^2 + c(x/y / L/H) + d(x/L) + e(y/H) + f,$$ (3)

in which $L(=0.187\text{m})$ and $H(=0.066\text{m})$ are the length and width of the wing. Mapped meshes are used for dividing elements and the element and node numbers are determined through convergence study. In this study, 4390 elements and 13399 nodes are used for the analysis of wing-I. The internal and boundary stresses, strains and displacements of the wings can then be obtained by running ANSYS.

Since the frame of the flapping wing was made by carbon/epoxy fiber reinforced composites, in order to retain the continuous characteristics of fibers some layers were folded to make the required shape of wing frames. Therefore, each part of Fig.3 may contain composite laminates with different stacking sequences, such as $[0]_4$ for regions A1, A3 and A7, $[90]_2$ for A8 and A11, $[0/90/0/90/0]$ for A2 and A6 (see Fig.4), $[0/34/0/34/0/34]$ for A4, $[0]_2$ for A5, $[90/34/90/34]$ for A9, $[34]_2$ for A10, and the isotropic LD-PE plastics are for the regions A12, A13 and A14. After designation of the material properties for each region of our model, the flapping wing was meshed as that shown in Fig.5. If the wing is subjected to a surface pressure with distribution given by the two variables 2nd order polynomials of Eq.(3) whose (Fig.6)

$$a = 10.98, \quad b = -24.07, \quad c = -4.47, \quad d = -31.84,$$
$$e = -23.31, \quad f = 3.45,$$ (4)

its stress contour analyzed by ANSYS model shown above is presented in Fig.7.
4. Artificial Neural Network

An artificial Neural Network is a parallel distributed processor made up of simple processing unit [6]. Similar to biological nervous systems, artificial neural networks can establish relations through neurons and their associated weights. In this paper, the popular used feedforward network, back propagation network (BPN), is utilized to develop a relation between the measured strains and surface pressures.

Generally speaking, there is no rule regarding the determination of neurons in the hidden layer, and the optimal number of neurons is concluded through test results. It is not necessary to have only one hidden layer. More hidden layers could simulate the highly nonlinear relationship between the input and output while sacrificing the speed of convergence. The convergence would be unstable when the hidden layers and neurons increase. In order to map the complex relation between input and output while maintaining a fairly simple architecture for stable convergence, back propagation neural network with two hidden layers is used in this paper.

Consider a four-layer network, the relation between input \( p \) and output \( q \) can be expressed as [7]

\[
q = f(W_4 f(W_3 f(W_2 f(W_1 p + c_1) + c_2) + c_3) + c_4),
\]

where \( f \) is the transfer function and \( W_i \) and \( c_i \), \( i = 1, 2, 3, 4 \) are, respectively, the weight matrices and bias vectors. If the target of output is \( d \), the mean square error \( E \) between target and output can be expressed as

\[
E = \frac{1}{2} \sum_{j=1}^{N_m} (d_j - q_j)^2 = \frac{1}{2} \sum_{j=1}^{N_m} e_j^2 = \frac{1}{2} e^T e
\]

where \( N_m \) is the neuron number of the output layer, and \( e \) is a vector of network errors. To minimize the error function Eq.(7), several different optimization methods such as the steepest descent method and LM (Levenberg-Marquardt) method, etc., can be used to update the neuron weights. To put the input and output data in the specified range, normalization is usually made. Table 1 shows parts of the training patterns with input and output vectors stated in Eq.(5), which are obtained through the finite element modeling stated in Section 3.

When the training patterns are well prepared, the artificial neural network can be trained by a proper optimization method. Since the architecture of artificial neural network includes the transfer function, the number of hidden layers, the number of neurons in each layer, and the convergence criterion, their selection becomes important for a well-trained network. In this paper, the output vector is specified in the range from zero to one through shifting and normalizing processes, and hence Log-Sigmoid function \( f(x) = (1 + e^{-x})^{-1} \) is selected to be the transfer function. As usual, two hidden layers with 40×20 neuron numbers are tried in this study to find the most suitable network. The convergence criterion is set to be \( E < 10^{-6} \). The training is performed by the commercial software Neural Network Toolbox built in MATLAB 6.5. After the training stage, several testing patterns also prepared through the finite element model are used to examine the wellness of the network.
5. Measurement of Flapping Strains

To estimate the flapping strength in nondestructive way, the flapping strains are measured under the lower and safer flapping frequencies. By the measured data of strains versus frequencies, the flapping strength may be estimated by extrapolating their relation to the failure frequency of flapping. Fig.9 is an illustrative result of the time variation of flapping strains $\varepsilon_{xA}, \varepsilon_{xB}, \varepsilon_{xC}$ under flapping frequency 6Hz for wing-I. Since the flapping mechanism designed for this test is a simple up and down flapping motion, the strain values at all wing points are periodical functions of time. The locations of A, B and C are, respectively, (0.0025, -0.038), (0.046, -0.003), (0.0995, -0.033) where the origin is at the wing root (Fig.1a).

![Fig.9 Time variation of flapping strains for wing-I](image)

To predict the flapping strength, only the largest strain in each flapping cycle is concerned in constructing the relationship between the flapping frequencies and measured flapping strains. Fig.10 is an illustrative result for flapping frequencies $\omega$ versus strains $\varepsilon$ at the root of wing-II, in which the small circle “•” denotes the average of the largest strains of all flapping cycles, and the horizontal bars above and below the small circle stand for the variation of largest strains from different flapping cycles. To best fit a curve for the data of strains-frequencies shown in Fig.10, the least square method was used. A straight line was assumed by $\omega = a + b\varepsilon$ and the unknown coefficients $a$ and $b$ was determined by minimizing the square error, which will lead to

\[
\sum_{j=1}^{n} (a + b\varepsilon_j - \omega_j) = 0, \quad \sum_{j=1}^{n} \varepsilon_j (a + b\varepsilon_j - \omega_j) = 0, \quad (8)
\]

where $(\omega_j, \varepsilon_j)$ are the data obtained from the experiments, and $n$ is the number of data points. By Eq.(8), the straight line fitted for the data shown in Fig.10 can be expressed by the following equation

\[
\omega = 0.8 + 886.6\varepsilon \quad (9)
\]

6. Estimation of Surface Pressure

To estimate the surface pressure through the simple strain measurement, in this study a combination of finite element modeling (FEM) and artificial neural network (ANN) is employed. In finite element modeling, known surface pressures are applied on the flapping wings and the strains of interested points are obtained through static analysis. The training patterns for the artificial neural network are then prepared by varying the surface pressure distributions and calculating their associated strains through FEM.

In our training patterns, the surface pressures are varied by randomly choosing the polynomial coefficients $a$, $b$, $c$, $d$, $e$ and $f$ from the range of $(-30, 30)$. By this loading variation, the strains at the measured points locate in the following ranges:

\[
-8.5 \times 10^{-5} \leq \varepsilon_{xA} \leq 7.1 \times 10^{-4},
\]

\[
5.7 \times 10^{-5} \leq \varepsilon_{xB} \leq 6.4 \times 10^{-3},
\]

\[
-3.2 \times 10^{-4} \leq \varepsilon_{xC} \leq 8.7 \times 10^{-4}. \quad (10)
\]

![Fig.11 Estimated surface pressure of wing-I under flapping frequency 6Hz](image)
different flapping frequencies 4Hz, 6Hz and 9Hz are input to get the estimated surface pressures. Table 2 shows the results of this estimation and Fig.11 is a plot of surface pressure for the case of flapping frequency 6Hz. Using this estimated surface pressure as the applied load acting on the flapping wings, the calculated strains presented in Table 2 show that most of their values are within 10% error of the original measured strains, which is acceptable.

### 7. Estimation of Flapping Strength
To estimate the flapping strength, i.e., the maximum allowable flapping frequency, two commonly used failure criteria are considered in this study. One is maximum stress criterion and the other is maximum strain criterion, which can be expressed as

\[ \sigma < \sigma_c, \quad \varepsilon < \varepsilon_c \]  

where \( \sigma_c \) and \( \varepsilon_c \) are the critical stress and strain in the fiber direction of carbon/epoxy fiber-reinforced composites, and \( \sigma \) and \( \varepsilon \) are the responded stress and strain in the fiber direction.

#### Maximum stress criterion
To predict the failure frequency of flapping through the maximum stress criterion, we need to establish the relation between flapping frequency and maximum stress, which may need the assist of the estimated surface pressure. Following is the procedure for getting their relation: (i) When the flapping frequency is given, the strains at points A, B and C can be measured; (ii) Input these measured strains into the well-trained neural network, the surface pressure on the flapping wing can be estimated; (iii) Apply this estimated surface pressure on the flapping wing, the stress contour can be plotted through FEM and the maximum stress can be found. For example, when the flapping frequency is 6Hz, the surface pressure is estimated as

\[ p(x, y) = 5.26(x/L)^2 + 3.34(y/H)^2 - 1.59(xy/LH) - 17.74(x/L) + 0.34(y/H) - 6.49. \]

By applying this pressure on wing-I, the maximum stress calculated by ANSYS is found to be 265MPa occurred at wing root. With this procedure, a plot like Fig.10 can be drawn for \( \omega-\sigma \) by a series of flapping experiment and a curve fitting line can be obtained as follows for wing-I,

\[ \omega = 1.606 + 0.0197\sigma \]  

in which the units of \( \omega \) and \( \sigma \) are Hz (times/sec) and MPa. With this relation and the critical stress given in Eq.(1), the failure frequency of flapping for wing-I is estimated to be 18.8Hz. To verify our estimation, several specimens of wing-I was flapped by frequencies higher than 20Hz. However, none of them fails, which means that our estimation by maximum stress criterion is too conservative and the wing-I is too strong. To get the failure frequency of flapping, we modify wing-I to wing-II to lower its strength. Moreover, to improve the strength estimation we consider the following maximum strain criterion.

#### Maximum strain criterion
Unlike the maximum stress criterion, when employing the maximum strain criterion we do not need to estimate the surface pressure which may avoid the error resources from the inverse analysis. Therefore, it is suggested to use this criterion to predict the flapping strength. By the relation established in Eq.(9) and the critical strain given in Eq.(1), the failure frequency of flapping for wing-II is estimated to be 18Hz. By actually flapping wing-II to failure, the failure frequency of flapping was measured to be 18.7Hz which is close to our estimation. Also, the fracture occurs at the wing root which is the maximum stress location predicted by ANSYS simulation.

### 8. Conclusions
In this study the surface pressure of flapping wings was estimated by a well-trained artificial neural network through the measurement of strains at certain points of the wing frame. Moreover, the strength of flapping wings is successfully predicted by the maximum strain criterion. Although this test is done only for a specific flapping wing, we believe the same concept can be applied to the other flapping wings which need further studies.

#### Acknowledgement
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#### References
Table 1 Partial training patterns for strains v.s. surface pressures

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Table 2 Surface pressures estimated by neural network with strains as input data

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