High Accuracy Flight State Identification of a Self-Sensing Wing via Machine Learning Approaches

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ABSTRACT

Motivated by the supreme flight skills of birds, a new concept called "fly-by-feel" (FBF) has been proposed to develop the next generation of intelligent aircrafts. To achieve this goal, Stanford Structures and Composites Lab (SACL) has developed a smart wing which embeds a multifunctional sensor network on the surface layup of the wing [1]. By leveraging structural vibration signals recorded from multiple piezoelectric sensors in the sensor network under a series of wind tunnel tests, data-driven approaches are developed to identify the flight state of this smart wing, i.e. angle of attack (AoA) and airflow velocity. Different preprocessing techniques are used including extracting 38 features in both time and frequency domains and standardizing the raw signals. Various supervised learning algorithms were applied to effectively establish the mapping from the feature space to the practical state space. In addition, it is found that 1D Convolutional Neural Network (CNN) can directly learn features from standardized signals and achieve similar performance to other algorithms using manually designed features. Compared with previous study [2], we have successfully achieved 96.55% test identification accuracy with the airflow velocity resolution improved from originally 3 m/s to 0.5 m/s under the same AoA.

INTRODUCTION

Currently, flight state sensing for aerial vehicles relies heavily on traditional sensing

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devices such as the Pitot tube for measuring airflow velocity and the null-seeking pressure tube for detecting angle of attack (AoA). However, those devices have to be installed at certain locations of the aerial vehicle and it leads to increased structural complexity. To reduce the complexity as well as to enable autonomous flight control by self-sensing and decision-making, Stanford Structures and Composites Lab (SACL) has developed a smart wing that has a multifunctional sensor network installed on the surface layup [1]. This concept is called "fly-by-feel" (FBF), which is motivated by birds' excellent flight skills and aims to develop the next generation of intelligent aircrafts. The smart wing is intended to provide structural vibration signals from piezoelectric (PZT) sensors in the sensor network for identifying the flight states, i.e. AoA and airflow velocity condition of the aerial vehicle.

Researchers have attempted to attack the flight state identification problem from two perspectives. Kopsaftopoulos [3] [4] [5] has developed stochastic time-series models to characterize the structural dynamics and aeroelastic response under multiple flight states. Their physics-based model can achieve high accuracy in flight state identification of the current smart wing configuration. However, the physics becomes highly complex to establish a solvable model when the wing structure becomes complicated. Chen and his colleagues [2] have developed a data-driven approach for identifying the flight state of this smart wing. Their emphasis is on the study of feature selection techniques from the signal of a single PZT sensor on the wing. They applied supervised learning models using the selected features to identify the flight state with an airflow velocity resolution of 3 m/s.

This paper applies machine learning methods based on Chen's previous work [2] with the following improvements. The data from all 6 functional PZT sensors in the sensor network on the wing is used as input, which greatly augments the training data compared with the data from only one sensor used in the original work. Supervised learning algorithms like Decision Tree, Random Forests and Support Vector Machines (SVM) yield great classification performance being fed with a large feature pool extracted from the signals. Moreover, it is shown that 1D Convolutional Neural Network (CNN) offers comparable high accuracy by using directly standardized signals.

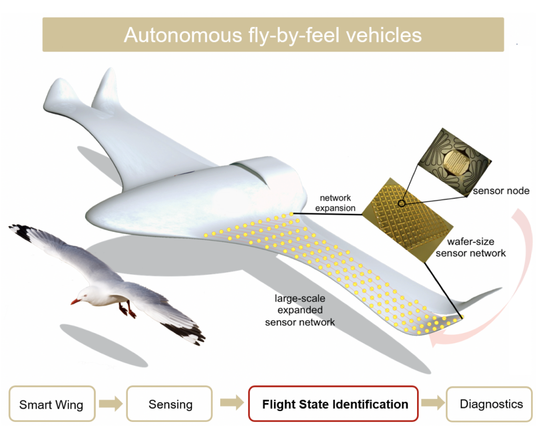


Figure 1. A smart wing which embeds a multifunctional sensor network on the surface layup.

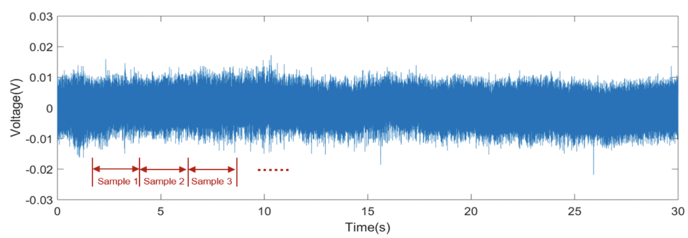


Figure 2. A segment of typical dataset from a piezoelectric sensor at AoA of 5° and airflow velocity of 25 m/s.

PROBLEM STATEMENT

Collected from a series of wind tunnel tests with different flight states, the dataset includes conditions of AoA from 0° to 15° (incremental step of 5°) and airflow velocity from 0 to 25 m/s (minimum incremental step of 0.5 m/s). 60,000 data points are collected from every PZT sensor for each flight state.

The flight state identification problem is defined as a classification task [2]. One flight state, which includes a fixed AoA and fixed airflow velocity, is considered as one class. Given the signals with a period of 1,000 continuous time stamps, the classification task asks to which class, i.e. to which flight state the signal belongs. Two datasets are explored in this paper. One includes the signals under the same 15° AoA and different airflow velocities ranging from 20 to 28 m/s, with an interval of 1 m/s. The other includes the signals under the same 15° AoA and different airflow velocities ranging from 24 to 28 m/s, with an interval of 0.5 m/s. Since the second dataset has a higher airflow velocity resolution, the difficulty of the classification task is also increased. For each flight state, 60,000 data points are collected from every PZT sensor. Figure 2 shows a segment of typical raw data from the piezoelectric sensor under the flight state as AoA of 5° and airflow velocity of 25 m/s.

METHOD OF APPROACH

This paper is mainly focused on data-driven approaches to address the flight state identification problem. The machine learning methods applied to this problem are divided into two groups based on whether input is extracted features or the original time series data. One group requires manually designed features and the other is fed directly with the standardized signals. The first group contains Decision Tree [6], Random Forests [7], Support Vector Machines (SVM) [8] and Fully Connected Neural Network models [9]. The second group includes 1D CNN [10] and Long Short Term Memory (LSTM) Network [11]. Following is a brief review of all the methods applied in this paper.

Decision Tree and Random Forests

Decision Tree is a non-linear method. It is a decision support tool that uses a tree-like model of decisions to come up with an algorithm that only contains conditional control statements to split samples into regions. Formally, given node P (parent node) and covering region R_p, a split s_p on the jth feature with a threshold t is defined as

$$s_p(j,t) = (x|x_j < t, x \in R_p, x|x_j \geq t, x \in R_p) \tag{1}$$

The way to choose splits is to minimize the preset loss function. For each node, a conditional control statement is selected which decreases the loss function the most. Gini loss is a common loss function for Decision Tree. Given C as total classes and P_c as proportion of examples in R that are of class c, Gini loss is $\sum_c P_c(1 - P_c)$.

Random Forests algorithm is applied in order to avoid the overfitting of Decision Tree and increase the test accuracy. Instead of finding the best way to split according to all features, Random Forests only allows subset of features to be used at each split, which significantly decreases variance with sacrifice of a little increase in bias.

Support Vector Machines (SVM)

SVM is among the best "off-the-shelf" supervised learning algorithms. SVM uses hinge loss as the objective function. The intuition of SVM is finding a separating hyperplane to divide samples into correct spaces with maximum margin, which amounts to maximizing the minimum distance between samples and the hyperplane.

Neural Network

Different Neural Network models which have different input are built in this work. In this subsection it is referred to as the one fed with manually designed features, whose basic layer is the fully-connected layer. Rectified linear unit is used as the activation function which adds non-linear factors to the Fully Connected Neural Network. Softmax function is used as the last activation function to compute the probability of each class. Classification cross-entropy is used as the cost function. Moreover, L2 Regularization is used to mitigate overfitting. Gradient descent is used to upload weights and it is achieved by backpropagation. Specifically, Adaptive Moment Estimation (Adam) is used as the optimizer, which adjusts the learning rate during training process by taking into account the momentum in gradient descent. For all neural networks including CNN and LSTM, the default learning rate of Adam is used and the mini batch size is 128.

Convolutional Neural Networks (CNN)

A CNN model is built based on one-dimensional convolutional layers. The model is trained using standardized signals based on its ability of learning potentially useful features during training. Max-pooling layer is added in the model to make the model perform better. Figure 3 shows the 1D CNN architecture designed for the classification task.

Long Short Term Memory Network (LSTM)

LSTM is a type of recurrent neural network. LSTM model is trained by feeding in standardized signals instead of manually designed features. It is because the original data is in time sequence and LSTM is good at dealing with data in time or spatial sequence.

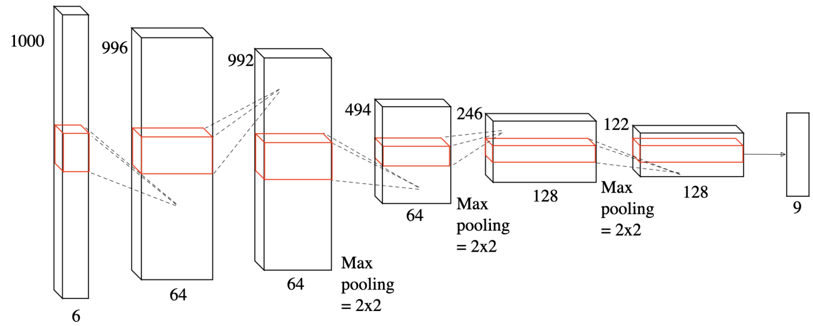


Figure 3. 1D CNN architecture that uses the standardized signal as input.

EXPERIMENTS

The dataset used to train machine learning models includes signals from 6 PZT sensors. 60,000 data points of each flight state class are split into segments of 1,000 data points as samples: 80% as training data, 10% as validation data and 10% else as testing data. Different preprocessing steps are performed for different groups of methods. For the group which requires feature input, the time-domain and frequency domain features proposed in the paper [2] are used. A large feature pool from both the time and frequency domains is created to extract enough useful information from the raw signal data. However, signals from all 6 sensors are processed rather than from a single sensor. The features include 25 in time domain and 13 in frequency domain, which are all explained in great details in Chen's paper [2]. For the group which is fed with time series data, the preprocessing is simply standardization, which is scaling the raw data so that it has zero mean and unit variance. The processed data will be fed into the corresponding machine learning algorithms discussed in previous sections to train the models. The Decision Tree and Random Forests algorithms are implemented by using Statistics and Machine Learning Toolbox provided by Matlab. The SVM is run by scikit-learn package from Python. Fully Connected Neural Network, CNN and LSTM Network are trained by using Keras library. All experiments are conducted on a MacBook Pro running macOS Mojave 10.14.5 with a 2.7 GHz Intel Core i7 Quad-Core CPU. All training processes are completed by using CPU solely.

RESULTS AND DISCUSSION

By using data from a single sensor, previous study [2] reached 98% classification accuracy on flight states that have 1° AoA and 3 m/s airflow velocity interval. In contrast, our study is focused on flight states with the same AoA. From Table I and Table II, we can see that by leveraging the data from all 6 sensors, almost all supervised learning models trained from manually designed features and the CNN which uses standardized signals as input achieve 100% test accuracy on flight states with 1 m/s interval. This task has a higher-resolution dataset and thus increased classification difficulty compared to the task performed by the previous study.

Figure 4 demonstrates the results from the Decision Tree algorithm, which reveal

TABLE I. PERFORMANCE OF SUPERVISED LEARNING ALGORITHMS WHICH USE MANUALLY DESIGNED FEATURES AS INPUT.

Supervised Learning Models	1 m/s velocity interval		0.5 m/s velocity interval	
	training accuracy	test accuracy	training accuracy	test accuracy
SVM	100%	100%	99.98%	96.55%
Fully Connected Neural Network	99.66%	99.62%	99.03%	95.79%
Random Forests	100%	100%	100%	92.91%
Decision Tree	100%	100%	99.66%	78.93%

TABLE II. PERFORMANCE OF SUPERVISED LEARNING ALGORITHMS WHICH USE STANDARDIZED SIGNALS AS INPUT.

Supervised Learning Models	1 m/s velocity interval		0.5 m/s velocity interval	
	training accuracy	test accuracy	training accuracy	test accuracy
Convolutional Neural Network	100%	100%	99.68%	94.83%
Long Short Term Memory Network	90.19%	95.79%	40.97%	39.08%

features which play more important roles than others. For example, feature x_1 and feature x_{153} appear several times in the tree. The feature x_1 represents the average of the 1st sensors signal magnitude and the feature x_{153} represents the counterpart of the 5th sensor. It indicates that average of signal magnitudes from different sensors make meaningful contributions to the classification. x_{26} and x_{35} , which corresponds to f_1 and f_{10} [2] of the 1st sensor, are also presented in the Decision Tree. They reflect vibration energy and power distribution in the frequency domain. Both time-domain and frequency-domain features are critical to the classification performance.

Table I shows that when the velocity resolution becomes 0.5 m/s, the Decision Tree

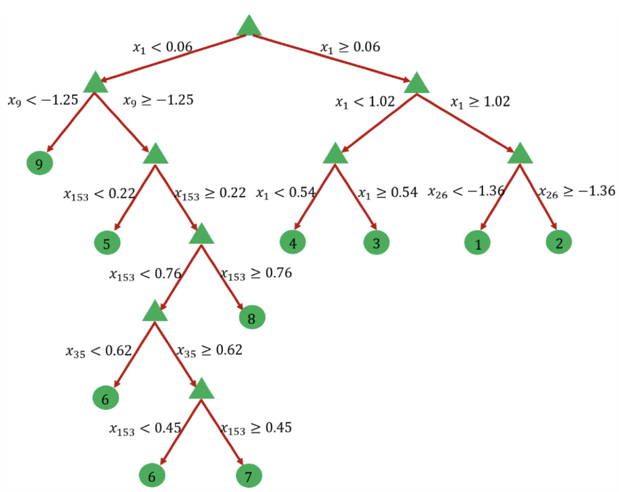
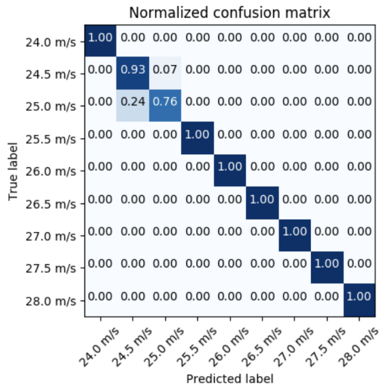
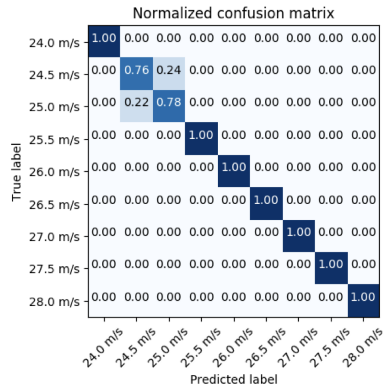


Figure 4. The Decision Tree trained from the dataset which has 1 m/s velocity interval between flight states.



(a) linear SVM



(b) 1D CNN

Figure 5. Confusion matrix by using (a) linear SVM using feature data and (b) 1D CNN using standardized signals

tends to overfit, while other models maintain decent classification performance. Both SVM and Fully Connected Neural Network work well and have leading test accuracy, but it is now hard to achieve 100%. One thing to note is that SVM with the linear kernel actually outperforms the other types, which means that the extracted features improve the linear separability of the data.

1D CNN reaches similar accuracy in the higher resolution classification task compared with the best models which use manually designed features as the input. It suggests that 1D CNN is able to capture potential features of the original data during the training process, and thus can skip the feature selection process. Figure 5 illustrates the confusion matrices from the results of performing linear SVM and 1D CNN. It is expected that misclassification happens between adjacent flight states. Since misclassification only happens between flight states with 24.5 m/s and 25 m/s for both methods, there is some extent of ambiguity between signals under the condition of these two airflow velocities and 15° AoA, which do not exist under other velocities and the same AoA. It would be interesting to dig in this phenomenon to find a reasonable physical interpretation. As for LSTM network, it has a reasonable test accuracy on 1 m/s resolution task, while the test accuracy drops significantly on the higher-resolution one. One possible cause is that the 1,000 data points from one sample might be too long for LSTM. LSTM might work better for samples with shorter data length, just like 1D CNN which can learn features from subsets of data points.

CONCLUSIONS

In this work, several data-driven approaches with different data preprocessing steps are proposed for the flight state identification problem. By taking advantage of vibration signals measured from multiple PZT sensors on the sensor network of the smart wing developed in SACL, the algorithms are able to improve flight state classification resolution from 3 m/s airflow velocity interval and 1° AoA interval to 0.5 m/s interval with the same AoA. The trained supervised learning models achieve 100% test accuracy in the 1 m/s resolution classification task and 96.55% test accuracy in the 0.5 m/s case. Moreover, it is discovered that 1D CNN being fed only with the standardized signal reaches 94.83% test accuracy in the 0.5 m/s case, which is comparable to the decent performance of models which requires manually designed features as input. It indicates that 1D CNN is able to acquire the effective features from the original time series data directly. In future work, the machine learning models developed in this paper will be deployed onto the smart wing during runtime. We will also redefine the flight state identification problem as a regression task and attempt to train regression models to provide an accurate estimate of the flight state.

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