A Practical Regime Prediction Approach for HUMS Applications

Shenliang Wu[1], Eric Bechhoefer[2], David He[1]

[1]Department of Mechanical & Industrial Engineering
The University of Illinois at Chicago
Chicago, IL, USA, 60607
davidhe@uic.edu

[2]Goodrich Sensors and Integrated Systems
Vergennes, VT, 05491

ABSTRACT

A number of aircraft parameters such as attitude, altitude, airspeed, torque, etc. are currently collected and used by health usage monitoring system (HUMS) to identify regimes. For each regime, a damage factor is assigned to each component that has usage. These damage factors are assigned by the original equipment manufacturers (OEMs) based on measured stresses in the aircraft when undergoing a given maneuver. Therefore, it is important that the regimes can be recognized correctly during the flight of the aircraft to avoid either underestimated or overestimated damages for the aircraft. A number of studies have shown the effectiveness of some newly developed regime recognition algorithms. As an extension to regime recognition to improve safety and/or reduce maintenance by predicting if the aircraft will be flown in a damaging way, a regime prediction approach is presented in this paper. This approach could be used to alert the pilot, who could then avoid flying the aircraft in those damaging regimes. Potentially, this extension could be used to alert if the power required is greater than the power available for some maneuvers such as heavy lift.

INTRODUCTION[1]

A number of aircraft parameters such as attitude, altitude, airspeed, torque, etc. are currently collected and used by health usage monitoring system (HUMS) to identify regimes for structural usage monitoring. Usage monitoring entails determining the actual usage of a component on the aircraft. This allows the actual usage/damage from a flight to be assigned to that component instead of the more conservative worst-case usage. By measuring the actual usage on the aircraft, the life of the components can be extended to their true lifetime. Usage monitoring requires an accurate recognition of regimes, where a regime is the flight profile of the aircraft at each instant of the flight. For each regime, a damage factor is assigned to each component that has usage. These damage factors are assigned by the original equipment manufacturers (OEMs) based on measured stresses in the aircraft when undergoing a given maneuver. It is important that the regimes can be recognized correctly during the flight of the aircraft to avoid either underestimated or overestimated damages for the aircraft.

Studies have reported the effectiveness of newly developed algorithms for regime recognition. Among them, three recent ones are summarized here. In the first paper [1], Teal *et al.* described a methodology for mapping aircraft maneuver state into the MH-47E basic fatigue profile flight regimes in a manner which ensures a conservative, yet realistic, assessment of critical component life expenditure. They also presented the use of wind direction and magnitude estimation and inertial/air data blending to obtain high fidelity airspeed estimation at low speeds. An accuracy rate of 90% based on time was reported. This method basically is a logical test. The system firstly identifies the maneuver based on flight dynamic data and general principles of tandem rotor helicopter flight which are derived from flight experience and mathematical models correlated with flight test results, then the aircraft maneuver state is mapped directly into one of the basic fatigue profile flight regimes. The method is subject to the main weakness of logical test in dealing with the noisy measurement. If the measured parameters were free of noise, logical tests would give accurate results. In the second paper, Berry *et al*. [2] presented an regime recognition scheme implemented as a hierarchical set of elliptical function (EBF) neural networks. Motivated to develop an automatic regime recognition capability as an enhancement to the US Army's Vibration Management Enhancement Program (VMEP), the EBF neural networks were devised to simplify neural net training and to improve the overall performance. The idea of using a hierarchical set of neural networks is to group individual regimes into regime groups, including an unknown regime group (regimes that cannot be

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[1] Presented at the American Helicopter Society 63rd Annual Forum, Virginia Beach, VA, May 1-3, 2007.

classified as any regimes in one of the first 10 regime groups). Regimes in each group are classified by an individual net in the hierarchical set. Regime recognition is carried out through a hierarchical process, e.g., if a regime cannot be classified as the first regime group by the top net in the hierarchy it will be passed to the lower level nets for further classification. In the paper, a total of 141 regimes of Sikorsky's S-92 helicopter were grouped into 11 groups, including "level flight", "auto", "climb", "dive", and etc. As reported in the paper, the EBF neural network regime recognition scheme gave near perfect classification results for "level flight" regimes. However, the results for classification of all regime groups didn't show a consistent effectiveness of the scheme. For example, for "level flight" group the classification rate is 97.85% but it is 33.18% for "turns" group. Because of the low classification rates for some groups, the scheme gave an overall rate of 76.21%. In addition to the requirement for a large amount of data to train a neural network, another variable that could affect the performance of the scheme is the way by which the regimes are grouped. Another limitation of neural network is that as it is a black-box methodology, little analytical insights can be gained to enhance the regime recognition process. The third paper [3] viewed regime recognition as a data mining problem, i.e., mining the measured parameter data and mapping them to a defined flight profile. Following the approach of data mining, a hidden Markov model (HMM) based regime recognition algorithm was developed and reported. The algorithm involves two major stages: model learning process and model testing process. The learning process could be implemented off-board. In this process, Gaussian mixture model (GMM) was used instead of unimodal density of Gaussian distribution in HMM. Once the learning process is completed, new incoming unknown signal could be tested and recognized on-board. The developed algorithm was validated using the flight card data of an Army UH-60L helicopter. The performance of this regime recognition algorithm was also compared with other data mining approaches using the same dataset. Using the flight card information and regime definitions, a dataset of about 56,000 data points labeled with 50 regimes recorded in the flight card were mapped to the health and usage monitoring parameters. The validation and performance comparison results have showed that the hidden Markov model based regime recognition algorithm was able to obtain an accuracy rate of 99.94% for all the 50 regimes recorded in the flight card data and outperformed other data mining methods.

It is clear that regime recognition can be done effectively, and this paper does not propose a new regime recognition algorithm. Instead, it is proposed that an extension to regime recognition can lead to improved safety and/or reduced maintenance by predicting if the aircraft will be flown in a damaging way. Regime prediction could be used to alert the pilot, who could then avoid flying the aircraft in those damaging regime. Potentially, this extension could be used to alert if the power required is greater than the power available for some maneuvers such as heavy lift.

The ability of regime prediction presented in this paper is built upon the integration of two major capabilities. The first capability is the ability to observe the rate of change in the flight parameters used in regime recognition by HUMS and predict their values by integrating these rates over time. The second capability is the ability to recognize reliably the regimes given the predicted parametric data. For example, in the IMD HUMS systems, there are 22 flight parameters that are used for regime recognition. Some are discrete, such as weight on wheels, where as most of continuous, such as angle of bank (AOB). If there was a damaging regime, say, right turn with AOB greater than 60 degrees, the AOB parameter could be input into a state observer. The state observer filters AOB and "observes" the 1st derivative of AOB. For any given time τ in the future, the AOB parameter can be estimated as:

$$E[\mathrm{AOB}] = \mathrm{AOB} + \int_0^{\tau} d(\mathrm{AOB})$$

If, 10 seconds in the future, the expected angle of bank, and other estimated parameters indicate that the aircraft will be in AOB greater than 60 degrees regime, an alert could be given. We can construct a state observer to predict the parametric data τ seconds into the future (1, 2, 5, and 10 seconds) and calculate the error between the predicted regime and actual regime at that time. We will focus on the error at state transitions, for example, when the aircraft enters a new regime, compared to when the predicted regime estimated a regime change, and if the predicted regime was correct.

The regime prediction approach presented in this paper was implemented by integrating a Kalman filter as the state observer with an HMM based regime recognition algorithm and validated with the flight card data of an Army UH-60L helicopter.

THE REGIME PREDICTION ALGORITHM

The flowchart of the proposed regime prediction algorithm is presented in Figure 1. As shown in Figure 1, the Kalman filter is used as a state observer and takes on-board HUMS flight parameters $\mathbf{X}$ as inputs to estimate the rate of change $d\mathbf{X}/dt$ over time. By integrating the estimated rate of change, one could obtain the estimated parameter values $\mathbf{X}_{t+\tau}$. These estimated flight parameters are then input into an HMM based regime recognition algorithm to predict the regimes τ time units from the current time point t into the future.

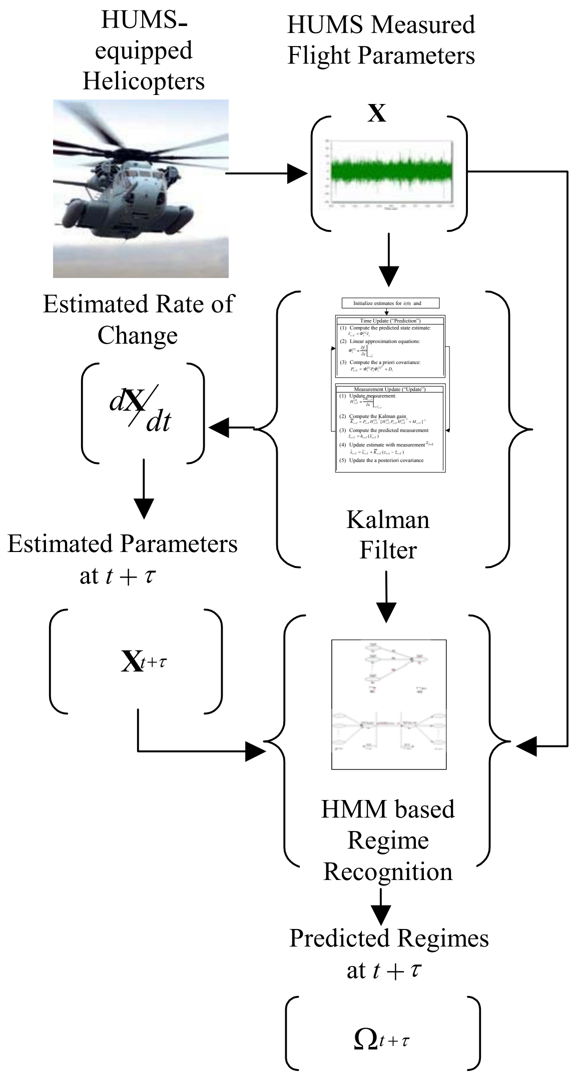

Figure 1. The flowchart of the regime prediction algorithm

Parameter Estimation

As shown in Figure 1, parameter estimation is a necessary step for regime prediction. To predict the regimes, parameters have to be estimated first. In our regime prediction algorithm, the Kalman filter [4] is used for parameter estimation. The Kalman filter is a kimematic model that functions as a state observer. The state observer reconstructs a state that is not directly measured. In this case, we are using the Kalman filter to derive in real time, the first derivative of a parameter. This is done by applying a filter coefficient to the difference between predicted and the observed data. The filter gain is set optimally based on the measurement and system variance. The estimation process by the Kalman filter is explained next.

Let $\mathbf{X} = \{a(1), \cdots, a(i), \cdots, a(q)\}$ be a set of flight pramemters, where q is the total number of the parameters. Since estimation of rate of change (ROC) for each parameter $a(i)$ is performed the same way, notation $a(i)$ is simplified as a in the following.

Deifne:

a_t = parameter value at time t

$\hat{a}_{t|t}$ = estimated a_t given the information at time t

$\dot{a}_t$ = ROC of the parameter at time t

$\hat{\dot{a}}_{t|t}$ = estimated $\dot{a}_t$ given the information at time t

$\hat{a}_{t|t-1}$ = estimate of a_t given the information at time t -1

$\hat{\dot{a}}_{t|t-1}$ = estimate of $\dot{a}_t$ given the information at time t -1

$\hat{P}_{t|t}$ = estimate of the error covariance given the information at time t

$\hat{P}_{t|t-1}$ = estimate of the error covariance given the information at time t -1

The parameter value and ROC can be described by a linear state space

$$\mathbf{A} = \begin{bmatrix} a \\ \dot{a} \end{bmatrix}$$

where $\dot{a}$ also can expressed as $\frac{da}{dt}$. We assume that in the time interval between $t - \tau$ and t the parameter undergoes a constant acceleration of δ whic is normally distributed with a mean of 0 and a standard deviation of σ. From Newton's laws of motion, we have

$$\mathbf{A}_t = \mathbf{\Phi}\mathbf{A}_{t-\tau} + \mathbf{G}\delta_{t-\tau}$$

where $\mathbf{\Phi} = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix}$ and $\mathbf{G} = \begin{bmatrix} dt^2/2 \\ dt \end{bmatrix}$.

The process noise covariance matrix can be derived as:

$$\begin{aligned} \mathbf{D}_{t-\tau} &= \mathrm{cov}(\mathbf{G}\delta_{t-\tau}) = \mathrm{E}[(\mathbf{G}\delta_{t-\tau})(\mathbf{G}\delta_{t-\tau})^T] = \mathbf{G}\mathrm{E}[\delta_{t-\tau}^2]\mathbf{G}^T \\ &= \mathbf{G}[\sigma^2]\mathbf{G}^T = \sigma^2\mathbf{G}\mathbf{G}^T \end{aligned}$$

When $\sigma^2 = 1$, we have

$$\mathbf{D}_{t-\tau} = \sigma^2 \mathbf{G}\mathbf{G}^T = 1 \cdot \begin{bmatrix} dt^2/2 \\ dt \end{bmatrix} \begin{bmatrix} dt^2/2 & dt \end{bmatrix} = \begin{bmatrix} dt^4/4 & dt^3/2 \\ dt^3/2 & dt^2 \end{bmatrix}$$

At each time step of the estimation process, a noisy measurement of the true parameter value is made. Suppose the noise is a Gaussian noise $\mathbf{v}_t \sim N(0, \mathbf{M}_t)$, $\mathbf{M}_t \in \Re^m$. Then the measurement can be expressed as:

$$z_t = \mathbf{H}\mathbf{A}_t + \mathbf{v}_t$$

where $\mathbf{H} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^T$, and $\mathbf{M}_t$ is simply computed as the standard deviation of all measurements of a.

The workflow of the Kalman filter parameter estimation is shown Figure 2.

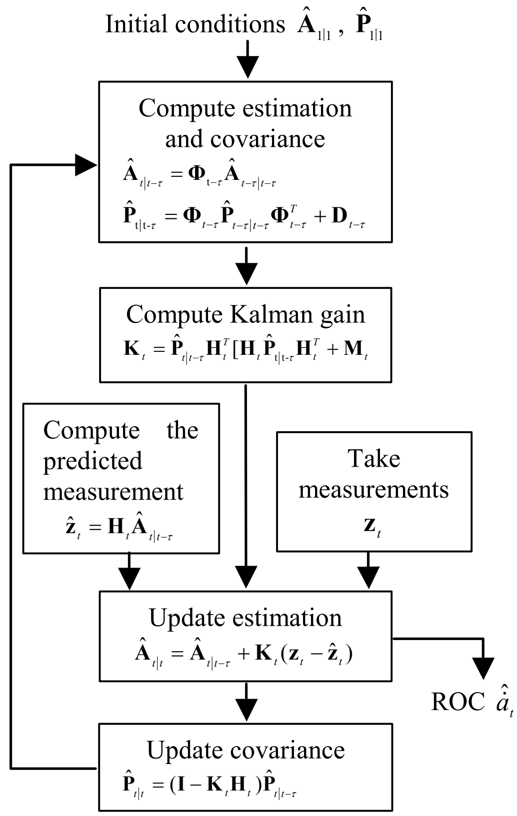

Figure 2. The workflow of the parameter estimation process

In Figure 2, the initial condition is initiated with following estimates: $\hat{\mathbf{A}}_{1|1} = \begin{bmatrix} a_1 \\ 0 \end{bmatrix}$, $\hat{\mathbf{p}}_{1|1} = \begin{bmatrix} 1 & 0 \\ 0 & 10 \end{bmatrix}$. In the prediction phase, previous $\hat{\mathbf{A}}_{t-\tau|t-\tau}$ is used to produce a prior estimate $\hat{\mathbf{A}}_{t|t-\tau}$ of the parameter and the *a priori* covariance matrix $\mathbf{P}_{t|t-\tau}$ corresponding to the estimate. The update phase is to take the updated measurements $\mathbf{z}_t$ to refine the estimate $\hat{\mathbf{A}}_{t|t-\tau}$ to a new and more accurate estimate $\hat{\mathbf{A}}_{t|t}$.

When ROC $\hat{\dot{a}}_t$ is derived from the Kalman filter, the parameter value can be predicted τ seconds into the future as:

$$\mathrm{E}[a_{t+\tau}] = a_t + \int_0^\tau \dot{a}_t dt$$

HMM Based Regime recognition

The proposed regime prediction uses an HMM based regime recognition algorithm to predict regimes τ time units into the future using the flight parameters estimated by the Kalman filter. There are a number of significant advantages of using HMM for regime recognition. For the most important one, an HMM has a computationally tractable mathematic structure and as a result it normally provides reliable and optimal solutions. As shown in the recent study [3], an HMM based regime recognition algorithm outperformed other methods including neural networks. The regime recognition function in our regime prediction algorithm is performed by the same regime recognition algorithm presented in [3]. A detailed description of the HMM based regime recognition algorithm can be found in [3].

VALIDATION OF THE ALGORITHM

In this paper, the proposed regime prediction algorithm was validated using the Army UH-60L flight card data. Data was collected during a flight test and provided by Goodrich. During the flight test, the pilots annotated detailed flight cards with actual event times as maneuvers were conducted during the flight. The on-board pilots maintained a detailed log of the maneuvers, flight conditions, and corresponding event times encountered during the mission flight. A total of 50 regimes were conducted with annotation in the flight test. A limited amount of non-annotated actual fight data was used prior to the fight test to check the functionality of the HUMS system. The recorded data was downloaded and processed after the flight test.

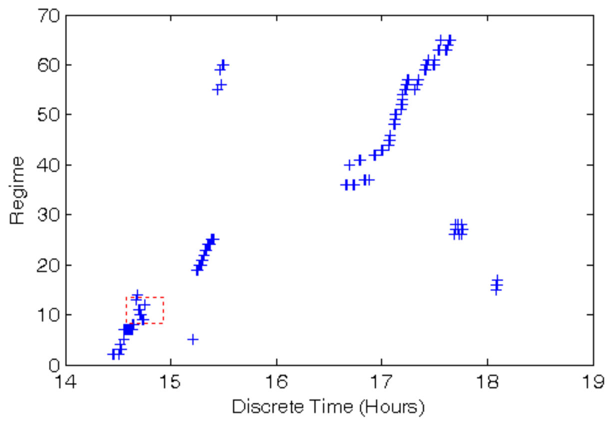

Figure 3. Regime evolution of UH-60L

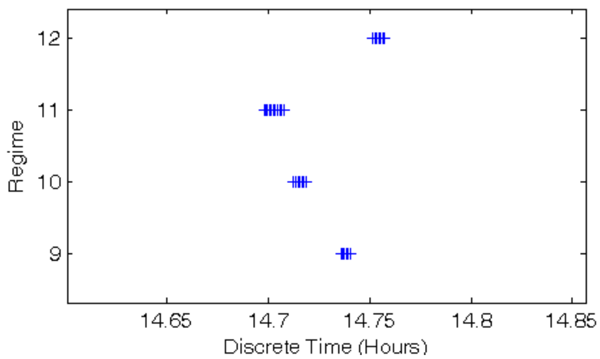

Figure 4. Zoom-in of regime evolution

For the Army UH-60L helicopter, a total of 90 preliminary regimes were defined by OEM, and they were denoted by number from 1 to 90 in the system. Each regime with associated time information was recorded by pilot and data of 22 basic aircraft parameters were collected from sensors mounted on the aircraft, or sensors added to Goodrich's IMD-HUMS for regime recognition. These parameter data was used for the identification of events, control reversals, and regimes. The parameter monitoring was performed during the whole ground-air-ground (GAG) cycles, from rotor start to rotor shutdown, and takeoff to landing. A plot of sampled regime sequence is shown in Figure 3. Figure 4 zooms in the part of the regime sequence.

In preparing the data for the validation test, all parameter data was down sampled to 8 Hz and only continuous parameters were observed by the Kalman filter to estimate their first derivatives. The list of the parameters used is provided in Table 1.

Table 1. List of the parameters

Parameter No.	**Parameter Description**
1	Airspeed Vh Fraction
2	Altitude Rate
3	Angle of Bank
4	Lateral Acceleration
5	Normal Acceleration
6	Pitch Attitude
7	Radar Altitude
8	Roll Attitude
9	Turbine Temperature
10	Torque
11	Corrected Normal Acceleration
12	Vertical Acceleration
13	Yaw Rate
14	WOW Delayed

The flight card data with all recorded parameter values were used to train the HMM based regime recognition models. Estimated parameter values were input to the trained HMM regime recognition models to obtain the predicted regimes. The predicted regimes were then compared with the flight card recorded regimes to compute the prediction accuracy.

Let c_i be the total number of times that regime i is correctly predicted, n_i the total number of times that regime i to be predicted, and N the total number of regimes, then the prediction accuracy is computed as a ratio as follows:

$$\text{Prediction Accuracy} = \frac{\sum_{i=1}^{N} c_i}{\sum_{i=1}^{N} n_i}$$

The validation test was conducted for different prediction horizon τ values: 1, 2 5, 7, 10, 15, and 20 seconds. The results are provided in Table 2.

Table 2. Regime prediction accuracies at different prediction horizons

Prediction Horizon (second)	Predication Accuracy
0	0.99430
1	0.99173
2	0.98345
5	0.96284
7	0.95180
10	0.93057
15	0.89439
20	0.86396

Note that in Table 2, the regime prediction accuracy for 0 prediction horizon is basically the regime recognition accuracy obtained by the HMM based regime recognition algorithm.

From Table 2, it is not surprised to see that as the prediction horizon increases, the accuracy for regime prediction decreases. This decrease in prediction accuracy is due to the increase in parameter estimation errors by the Kalman filter. Figure 5 shows the increase in parameter estimation errors computed as root mean squared error (RMSE) at different prediction horizons.

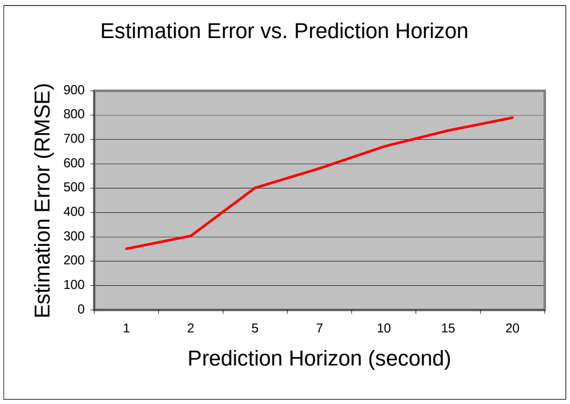

Figure 5. Parameter estimation errors vs. prediction horizon

From Figure 5, we can see that as the prediction horizon increases the total RMSE increases dramatically.

For HUMS regime prediction applications, we want to predict when the aircraft will enter severe or extreme regimes which would account for a large damage factor on the component. These severe or extreme regimes include regimes related to severe pullout, extreme maneuver, and pullout to 3.0 G. Unfortunately, the flight card data do not include these regimes. For this study, we will use surrogate maneuvers to represent extreme and sever maneuvers. These surrogate regimes and maneuvers are shown in Table 3.

Table 3. Regimes and corresponding maneuvers

Regime	Maneuver
Regime 10	Right Sideward Flight
Regime 11	Left Sideward Flight
Regime 25	Level Flight up Between 0.9 and 1.0 Vh
Regime 44	Rudder Reversal in Autorotation
Regime 50	Longitudinal Reversal in Partial Power Decent
Regime 57	Level Left Turn 60 d AOB
Regime 61	Level Right Turn 60d AOB
Regime 65	Descending Left Turn, 60d AOB

A summary of regime prediction accuracies for those regimes listed in Table 3 is provided in Table 4.

Table 4. Prediction summary for regimes in Table 3

Prediction Accuracy		Prediction Horizon (second)			
		1	2	5	7
Regime No.	10	0.9896	0.9845	0.9430	0.9223
	11	0.9963	0.9707	0.9487	0.9304
	25	0.9979	0.9959	0.9896	0.9855
	44	0.9922	0.9766	0.8906	0.8672
	50	0.9926	0.9559	0.9044	0.8897
	57	0.9972	0.9944	0.9861	0.9805
	61	0.9937	0.9874	0.9686	0.9560
	65	0.9950	0.9900	0.9751	0.9652
		10	15	20	
Regime No.	10	0.8860	0.8446	0.7254	
	11	0.9084	0.8938	0.8755	
	25	0.9793	0.9689	0.9585	
	44	0.8281	0.8047	0.7422	
	50	0.8603	0.7868	0.7206	
	57	0.9721	0.9582	0.9443	
	61	0.9308	0.8994	0.8679	
	65	0.9502	0.9254	0.9005	

From Table 4, we can see that even though the prediction accuracy varies for different regimes, it can reach 90% when the regimes were predicted less than five seconds into the future. For regimes that are characterized by 60 degrees of AOB turns (regime 57, 61, and 65), prediction accuracy can be over 93% even when the regimes were predicted 10 seconds into the future.

In addition to how well the regime prediction algorithm is able to predict those severe regimes, one would also be interested in knowing whether it could predict when the aircraft is flown entering into a severe regime from other regimes. Table 5 shows whether it was predicted when the aircraft was flown from other regimes entering into the server regimes listed in Table 3.

Table 5. Detected regime transitions

Regime Transition	Prediction Horizon (second)						
	1	2	5	7	10	15	20
11 => 10	Y	Y	Y	Y	Y	Y	N
14 => 11	Y	Y	Y	Y	Y	Y	Y
24 => 25	Y	Y	Y	Y	Y	Y	Y
43 => 44	Y	Y	Y	Y	Y	Y	/
49 => 50	Y	N	N	N	N	N	N
56 => 57	Y	Y	Y	Y	Y	Y	Y
60 => 61	Y	Y	Y	Y	Y	Y	Y
63 => 65	Y	Y	Y	Y	Y	Y	Y
64 => 65	Y	Y	Y	Y	Y	Y	Y

Note that in Table 5, an entry "Y" indicates that the regime transition was predicted and an entry "N" indicates that the regime transition was not predicted. A sign "/" indicates that transition from regime 43 to 44 did not exist when the regimes were predicted 20 seconds into the future because regime 44 was recorded for only 16 seconds on the flight card.

Also note that the results in Table 5 were generated by assuming that anytime interval between the two regimes in a regime transition on the flight card is recognized as the first regime. For example, for regime transition 11=>10, there was a time interval in which no data were recorded on the flight card. It was assumed that regime 11 was flown in this time interval.

From Table 5, we can see that when the regimes were predicted 1 second into the future, all the transitions into those severe regimes could be predicted. Except for transition from regime 49 to 50, when the regimes were predicted up to 15 seconds into the future, all the transitions into those severe regimes could be predicted.

For transition from regime 49 to 50, it was not predicted when regimes were predicted more than 1 second into the future. The reason for that was because there were only 0.126 seconds between regime 49 and regime 50. Therefore, when the regimes were predicted more than 1 second into the future, the predicted parameters were updated with a slower rate since the rate of change was estimated based on larger time intervals. For example, when the regimes were predicted 2 seconds into the future, it took 0.75 seconds to recognize that it was in regime 50.

Overall, from the flight card validation test results, we can see that the regime prediction algorithm presented in this paper predicted all 50 regimes in the flight card data with over 99% accuracy when the regimes were predicted 1 second into the future and over 93% accuracy when 10 seconds into the future.

In general, the regime prediction accuracy is inversely impacted by the errors of the parameter prediction but not affected by the performance of the HMM based regime recognition algorithm. Therefore, the real challenge toward further increasing the regime prediction accuracy for prediction over 10 seconds into the future lies in using more accurate models for parameter estimation.

Another issue in regime recognition and prediction is sampling frequency. Because of the inertia of the aircraft, instantaneous maneuvers are not possible. The aircraft, as a system, has a "bandwidth" (ability to complete an maneuver) of perhaps 1 to10 Hz. Thus, if the acquisition system is sampling the aircraft at 20 Hz, all maneuvers could be reconstructed from the parametric data. This also suggests that by sampling at greater than 20Hz, and constructing the appropriate system model, rate data can be reconstructed from a state observer, such as the Kalman filter. In our validation test, the data were sampled as a rate of 8Hz. It is expected that for data with higher sampling frequency, the performance could be better.

CONCLUSIONS

In this paper, a regime prediction algorithm was presented as an extension to regime recognition to improve safety and/or reduce maintenance by predicting if the aircraft will be flown in a damaging way. The regime prediction algorithm consists of two major components. The first component is a state observer to observe the rate of change in the flight parameters and predict their values by integrating these rates over time. This component was implemented based upon the Kalman filter. The second component is a regime recognition algorithm that takes the estimated parameters to predict reliably the regimes seconds into the future.

The regime prediction algorithm was validated using the flight card data of an Army UH-60L helicopter. The validation results with regime prediction up to 20 seconds into the future were provided. The regime prediction results showed that the regime prediction algorithm presented in this paper predicted all 50 regimes in the flight card data with over 99% accuracy when the regimes were predicted 1 second into the future and over 93% accuracy when 10 seconds into the future. However, as the regimes were predicted more than 15 seconds into the future, the accuracy was reduced to below 90%. In general, the regime prediction accuracy is inversely impacted by the errors of the parameter prediction and not affected by the performance of the HMM based regime recognition algorithm. To further improve the regime prediction accuracy for prediction over 15 seconds into the future one needs to search for more accurate models for parameter estimation.

The significance of the regime prediction algorithm presented in this paper is that not only could it be used to alert the pilot, who could then avoid flying the aircraft in those damaging regime, but also potentially, could it be used to alert if the power required is greater than the power available for some maneuvers such as heavy lift.

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