ON-LINE LIFE PREDICTION OF A STRUCTURAL HOTSPOT

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ABSTRACT
Current aerospace practice follows an engineering model based on damage-tolerant reliability whereby structural components are regularly inspected and replaced. Under this practice, engineering designs are generally based on a physics-based fracture mechanics approach, in which the life of structural component is estimated using an assumed initial damaged condition. However, in a real time environment, keeping track of the damage condition of a complex structural component manually is quite difficult and requires automatic damage state estimation. The real-time damage state information can be regularly fed to a prognosis model to update the residual useful life estimation in event of a new prevailing situation.

The present paper discusses the use of an adaptive hybrid prognosis model, which estimates the residual useful life of a structural hotspot using information on the damage condition obtained in real time. The hybrid prognosis model has two modules: an off-line prognosis module that forecasts the future damage state, and an on-line state estimation module, which regularly predicts the current damage state and feeds into the off-line module in real time. Both the off-line and on-line modules are probabilistic models and use the concept of Bayesian inference based on input-output mapping through a Gaussian process.

INTRODUCTION
Aircraft maintenance must balance labor, logistic, and equipment budget constraints with the competing requirements of fleet readiness, reliability, and safety. Recently, stringent Diagnostic, Prognostic, and Health Management (PHM) [1, 2] capability requirements are being placed on new applications, like the Joint Strike Fighter (JSF), in order to enable and reap the benefits of new and revolutionary Logistic Support concepts. Although the PHM is the name given to the capability being developed by the JSF, to enable the vision of autonomous logistics and therefore meet the overall affordability and supportability goals, similar PHM systems can be developed and implemented for residual life prognostics and health management of any civil, mechanical or aerospace structure.

The usual practice for defining the structural life ceiling limits of any current aircraft structural component is based on either of the following three distinct approaches: safe-life, fail-safe, and damage-tolerant approach. Out of the above three approaches the damage-tolerant approach is quite popular in the aircraft industry, either for designing a new aircraft or maintaining an aging one. The damage-tolerant approach assumes the presence of initial defects, regardless of how small they may be, which will be eventually grow in service to be large cracks. Generally, inspection intervals are derived by using appropriate safety factors on the life spent to grow a crack from the detectable crack size to the critical crack length, which would provide a certain number of opportunities to find a crack. These safety factors are empirical or based on experience and will ensure that cracks will be detected at least once before reaching critical size. The United States Air Force also provides guidelines on crack size assumptions to calculate the crack growth lives needed to determine inspection intervals [3, 4]. Once the initial defect condition is known, any suitable crack growth model can be used with the available loading history data to estimate the future crack length and corresponding remaining life to reach that crack length. To work with different available crack growth models, there exist model dependent parameters that have to be fine tuned [5] to make consistent life predictions for the material selected, load histories and geometries to be analyzed.

It is noted that the accuracy of the residual useful life estimation at a typical fatigue cycle, depends on proper determination of the damage condition at that fatigue cycle. Manual inspection of the damage condition is generally uneconomical and also undermines the mission capability due to long overhauling time requirement. The current research on structural health monitoring [6, 7] can lead to a paradigm shift in condition based maintenance (CBM) and residual useful life (RUL) estimation procedures. The structural health monitoring based on a damage estimation approach will help to
automatically track the damage condition of a structure, rather than being manually inspected. This does not only economic and time saving, but also gives a real time measurement of the damage condition without any human interference.

The present paper uses a Gaussian process model based on Bayesian inference [9, 10] for predicting the damage condition at any given fatigue cycle. This is an on-line model, which maps the features of a piezoelectric sensor signal to the physical damage condition, in this case the crack length. Once the current damage condition is available, it is then fed to another Gaussian-process based prognostic model that estimates the residual useful life of the structural component from the point at which the on-line damage condition was available. The integrated on-line-off-line prognostic algorithm is validated on an Al-2024 T3 lug joint specimen undergoing constant amplitude loading.

THEORETICAL BACKGROUND

Hybrid Prognosis Concept

A hybrid prognosis model based on both physics and data driven based techniques is being developed at Arizona State University. A schematic of a future version of this hybrid prognosis model is shown in Figure 1.

![Figure 1. A conceptual hybrid prognostic model (Source of the fighter plane image in figure is from http://www.jsf.mil).](image)

The overall prognosis model will have three different modules: an off-line physics-based module for baseline signal features and deterministic residual life estimation, an off-line data-driven module [10] for probabilistic residual life estimation and an on-line state-estimation module [11] for real time damage state estimation. All three sub modules will be finally integrated to develop a hybrid prognosis model. The off-line physics-based model will be based on a micro-meso-macro physics model, whereas the off-line data driven model and the on-line state estimation model will be based on Gaussian process approach with Bayesian inference. The off-line data driven model will implicitly model the macro level uncertainty that arises due to microstructure variability, loading uncertainty, etc., and complement the off-line physics based model for uncertainty in damage propagation and for any unmodeled exogenous influences. The physics-based model combined with a data-driven probabilistic model will be used for off-line prediction of residual useful life, whereas an on-line predictive model based on piezoelectric sensor signals will estimate the current damage state in real time and make this information available to the off-line module to reassess the residual useful life of the structural components based on the real time information. The present paper will only focus on the off-line data driven prognostics/forecasting model and the on-line state estimation model and their integration to estimate the residual useful life in real time.

Gaussian Process Time-Series Prediction

A Gaussian process [8, 9] approach that includes Bayesian uncertainty into the prediction model is used for both the off-line prognostics model and for on-line state estimation model. It is assumed that the crack length or the damage condition at a given fatigue cycle is a random variable and follows a Gaussian probability distribution. The gaussian process is a combination of such Gaussian distribution over the entire fatigue domain. The Gaussian process model projects the input space to an output space by probabilistically inferring the underlying nonlinear function relating the input and output. Once the Gaussian process is trained with a known input-output data set, it can predict the output crack length or its rate under the particular loading envelope. For on-line prediction, the model input space is trained using the features found from piezoelectric sensor signals, whereas the output space is trained with the corresponding crack lengths as parameters representative of the damage state. The off-line model is also based on the Gaussian process approach, however unlike the on-line model, the input space is based on the current (Nth cycle) damage state (or crack length) and future (e.g. N + ΔNth cycle) loading information. Once the damage state at a given instant of time is predicted from the on-line model, the probabilistic off-line model is used to estimate the residual useful life (RUL) of the structure.

The posterior distribution (ref. 10 for more details) of crack length $\alpha_{N+\Delta N}$ at the future $N + \Delta N$th cycle can be expressed as

$$f(\alpha_{t+\Delta t} | D, \mathbf{x}(\text{x}_t, \mathbf{x}, \mathbf{x}_{t+\Delta t}, \Theta) = \frac{1}{Z} \exp \left(-\frac{(\alpha_{t+\Delta t} - \hat{\alpha}_{t+\Delta t})^2}{2\sigma_{t+\Delta t}^2} \right)$$

(1)

where $Z$ is an appropriate normalizing constant and the mean and variance of the new distribution are, respectively, defined as:

$$\hat{\alpha}_{N+\Delta N} = \mathbf{k}^T_N \mathbf{K}_N^{-1} \mathbf{a}_N$$

$$\sigma_{t+\Delta t}^2 = \kappa - \mathbf{k}_N^T \mathbf{K}_N^{-1} \mathbf{k}_N$$

(2)

In Eq. (2) $\mathbf{a}_N$ is the $(1 \times N)$ training output vector, which in this case is the crack length. Also $\kappa$, $\mathbf{k}_{N+1}$, $\mathbf{K}_N$ are the
partitioned components of $N+1$th instances kernel matrix $K_{N+1}$ and they can be described as

$$\kappa = k(x_{id}, x_{id}) \text{ ; } k_i = k(x_{id}, x_{id})_{i=1,2,\cdots,N} \text{ ; } K_{ij} = k(x_i, x_j)_{i,j=1,2,\cdots,N}$$ (3)

In Eq. (3), $k$ is the assumed kernel function (ref. 8-11), which transfer the nonlinear function parameter to a linear high dimensional space based on some observations. It is noted that in high dimensional space, the original nonlinear data are linearly separable/distinguishable. There are many possible choices of prior kernel functions. From a modeling point of view, the objective is to specify a prior kernel that contains our assumptions about the structure of the process being modeled.

As it is mentioned earlier, for on-line state estimation model the input space $x_{(1,2,\cdots,N,N+\Delta N)}$ is made of sensor signal features, whereas the output space $a_{(1,2,\cdots,N,N+\Delta N)}$ is made of observed (or to be predicted) damage condition, here the crack length. It is noted that the input dimension “d” is the total type of features. For the present on-line prediction the type of features could be resonant frequency or variance of sensor signal observed from different sensor channels. For off-line prediction, the input space $\hat{x}_{(1,2,\cdots,N,N+\Delta N)}$ is a one dimensional data set, made only using the crack length data found from the on-line estimation model. In other word:

$$\hat{x}_{(1,2,\cdots,N,N+\Delta N)} = a_{(1,2,\cdots,N,N+\Delta N)}$$ (4)

Whereas, the output space of the off-line prognosis model is made from the crack growth rate. From the above information, Eq. (1) can be rewritten for the off-line model as:

$$f(d/dN_{\Delta N}/dN_{\Delta N}/dN_{\Delta N}, \theta) = \frac{1}{Z} \exp\left(\frac{(db/dN_{\Delta N} - db/dN_{\Delta N})^2}{2\sigma^2_{db/\Delta N}}\right)$$ (5)

Principal Component Analysis Based Sensor Signal Denoising

Although the raw sensor signals, as collected from data acquisition system, are filtered for the particular frequency band of interest, some environmental noise are still buried within the sensor signals. Principal component analysis (PCA) [12] is an orthogonal basis transformation that has been widely used in the signal/image processing community for the multivariate data analysis and dimensionality reduction, is used in the present case to denoise the piezoelectric sensor signal. Intuitively, PCA is a process that identifies the direction of the principal components where the variance of changes in dynamics is maximum. Assuming ‘M’ different observations and each observation with $\bar{M}$ samples, each input signal $y_p$ is a $\bar{M} \times 1$ vector. Then the centered $M \times M$ covariance matrix of the data set $\{y_p \in R^M | p = 1, 2, \cdots, M\}$ can be found as

$$C_M = \langle (y_q - \langle y_q \rangle)(y_q - \langle y_q \rangle)^T \rangle ; \quad q = 1, 2, \cdots, M$$ (6)

Then the covariance matrix is diagonalized to obtain the principal components and the diagonalization can be performed by solving the following eigenvalue problem:

$$\hat{\lambda} = \hat{C}_M \nu$$ (7)

The coordinates in the eigenvector basis are called principal components. The size of an eigenvalue $\hat{\lambda}$ corresponding to an eigenvector $\nu$ of covariance matrix $C_M$ equals the amount of variance in the direction of $\nu$. Furthermore, the direction of the first $m$ eigenvectors corresponding to the largest $m$ eigenvalues covers as much variance as possible by $m$ orthogonal directions. It is assumed that all the $M$ sensor observations taken at a typical fatigue cycle can be converted to $m$ equivalent observation, which consist the necessary dynamics of the structure at that fatigue cycle. The original (after band-pass filter) the observation space $Y_{M \times \sigma}$ can be reduced to $Y_{m \times \sigma}$ equivalent observation space by using the following transformation:

$$Y_{m \times \sigma} = \Phi_{M \times m}^T Y_{M \times \sigma}$$ (8)

Where, $\Phi_{M \times m}$ is the eigenvector matrix containing $m$ eigenvectors those found from the eigenvalue analysis described in Eq. (7). The transformed observation space $Y_{m \times \sigma}$ consists of $m \times 1 \bar{M}$ denoised sensor signals.

Damage Feature Extraction

Once PCA based sensor signal denoising is performed, it is assumed that the denoised sensor signal has minimal noise contents, and has only information pertinent to the dynamics of the physical system. From the denoised signal, two types of feature are extracted: one is based on resonant frequency of the denoised signal, and the other is based on the variance of the denoised signal. The scaled sensor signal features, those were feeded to Gaussian process input space of on-line state estimation model can be found using:

$$\hat{x}_{(1,2,\cdots,N,N+\Delta N)} = \frac{\sum_{k=1}^m (f e_{k,j} - f e_{k,0})^2}{f e_{k,0}}$$ (9)
where, \( f_c \) correspond either to resonant frequency or variance of denoised sensor signal; \( d \) is the dimension of input space and is equal to the total type of features; \( m \) is the total number of denoised signal considered according to ranked eigenvalue found in Eq.(7).

**RESULTS AND DISCUSSION**

**Fatigue Test Experiment**

The real-time prognostic algorithm is validated on an AL-2024 T3 lug joint specimen under constant fatigue loading of 50N-2750N. A typical test setup is shown in Figure (2). The test setup includes a TESTRESOURCE desktop fatigue frame, a 48 channel NATIONAL INSTRUMENT PXI chassis based data acquisition system and a SONY high resolution camera for visual crack length measurement. Figure (3) shows a instrumented Lug joint with four piezoelectric sensor named as S1-S4 and one piezoelectric actuator named as A1. The sensor network is divided into two zones: Zone-1 consisting of sensors S1 and S2, and Zone-2 consisting of sensors S3 and S4. Three different lug joint named Sample-1, 2, and 3 are fatigue tested. The fatigue frame is stopped at different instances and piezoelectric signals corresponding to a narrow band actuator input (Ref. Figure 4) are taken at those stopping instances. The input signal has a central frequency of 230 kHz and sampled at 1 MHz. The corresponding sensor signal at a typical fatigue cycle from sensor S1 is shown in Figure (5). The acquired signal is filtered through a band-pass filter of cutoff frequency band 130 kHz-330 kHz. The typical filtered signal from sensor S1 can also be seen from Figure (5). As the fatigue frame was stopped, high resolution pictures of the lug joint was taken to find the corresponding crack length. The observed crack lengths for all the three samples are depicted in Figure (6). This crack length is used either for the prognosis algorithm validation or training the Gaussian process input-output space, which is discussed in details in the following section.

![Figure 2. Lug joint under fatigue loading](image1)

![Figure 3. Instrumented lug joint](image2)
Sensor Signal Denoising and Feature Extraction

For the on-line prediction sensor, signals from all four piezoelectric sensors are collected against the narrowband burst (Figure 4) actuation. For each four sensors, 100 observations were collected at different fatigue cycles and the corresponding signal features were denoised using principal component analysis as mentioned earlier. Figures (7) and (8) respectively show the covariance value of 100 observations before and after denoising. After the sensor signals were denoised, signal features were extracted that depict the damage state of the structural hotspot at a given number of fatigue cycles. For signal denoising, only the first eigenvector corresponding to the highest eigenvalue is considered. Hence with total number of signal samples considered ($M=1000$), and total number of eigenvector considered ($m=1$), the denoised observation space $Y_{m=1}$ described by Eq. (8) reduces to a $1 \times 1000$ denoised signal vector. Using this denoised signal the features are extracted using Eq. (9). Figure (9) and (10) respectively show the features based on change in resonant frequency and variance of the denoised signal at different fatigue instances. From the figure it is seen there is a good trend in signal features for both the sample-202 and sample-203. These features will be used further, to form the Gaussian process input space for on-line state prediction.
On-line Damage State Prediction

Based on the extracted signal features, Gaussian process algorithm is used to assess the corresponding damage state of the hot spot. The Gaussian process input and output space are respectively trained with signal features data and crack length data from the sample-203. However, the on-line state estimation algorithm is tested for the sample-202. The input space for both the training sample and test sample are fed with four types of signal features: resonant frequency based features from sensors S3 and S4, and signal variance based feature from sensors S3 and S4. However, it is noted that unlike the Gaussian process training input space, the test input space is fed with features, as they become available, in real time. The test output at a typical fatigue cycle has to be predicted using the $4 \times 1$ feature vector extracted at that fatigue cycle. The comparison between predicted damage state (crack length) and the experiment value is depicted in Figure (11). From the figure it is found there is a good correlation between experiment and prediction, when the crack length is larger than 5mm. The discrepancy between prediction and experiment increases as the crack length becomes smaller. This is possibly because the signal features are not sensitive to smaller damage condition. This problem can be solved by using high frequency input signals and nonlinear feature extraction techniques, which will be our future interest of study.

On-line-Off-line Residual Life Estimation

The discussed estimated on-line damage states are finally fed into a prognosis model, to forecast the residual life of the structural hotspot. As mentioned before, the prognosis model is also a probabilistic model based on the Gaussian process approach. For the off-line forecasting model the future mean and variance of the damage state rate is predicted using Eq. (5). It is known from the linear fracture mechanics that the crack growth rate at the future fatigue cycle ($N + \Delta N$ cycle) is a
function of the stress intensity range or, in other words, a function of the future cycle \((N + \Delta N)^{th}\) cycle minimum load, maximum load, and current cycle \((N^{th})\) cycle damage condition or crack length. From this physical concept, the Gaussian process function mapping can be performed between inputs: \(N + \Delta N^{th}\) cycle loading information and \(N^{th}\) cycle damage condition, and the output: the \(N + \Delta N^{th}\) cycle crack growth rate. Gaussian process prognosis model is a multivariate mapping with as many damage affecting variables can be fed into it. However, for the crack growth estimation results shown in Figure (12) only \(N^{th}\) cycle damage state information (crack length) is taken as the Gaussian process input space. The reason for not considering loading information into Gaussian process input space is that the loading has constant amplitude and statistically leads to a stationary ergodic process. It is noted that the \(N^{th}\) cycle crack length predicted from the on-line state estimation model is feeded to the off-line prognosis model. Once the \(N + \Delta N^{th}\) cycle fatigue cycle rate is predicted, linear integration is performed to estimate the \(N + \Delta N^{th}\) cycle crack length.

![Figure 12. Residual useful life estimate for sample-202.](image)

The estimated crack length is then feeded back to the Gaussian process off-line module to predict the rate at a future fatigue cycle, and using this new predicted rate the corresponding new crack length is estimated. The off-line prediction is continued as long as the critical crack length of the component is reached. The difference between the number of cycles at which the off-line model estimated crack length becomes critical and the number of cycles at which the last on-line damage state information was available, gives the RULE of the component. A typical result showing residual useful life estimate, with on-line damage state information available at 164 kcycles is shown in Figure (12). It is noted that the on-line state estimation is performed in an outer loop (called the structural health monitoring loop), in which continuous damage state information is inferred from the piezoelectric sensor signals and feeded into the inner off-line prognosis loop. The outer on-line and inner off-line loop continues to run as long as the component survived the failure or allowed to retire. Figure (13) shows the mean square error between forecasted crack length and that found from experiment. The individual fatigue cycles, where the error bar is shown are those fatigue cycles, up to which the on-line predicted crack growth data are available. The predicted crack growth data are not necessarily the same as the real crack growth data found using the high resolution camera. Also it is seen from Figure (13) that as more on-line data are available there is a clear trend in reduction of the mean square error. The slight discrepancies at fatigue cycle 169 kcycles and 171 kcycles are possibly due to accumulated error caused by the error in on-line state estimation. This can be evident from Figure (11), that there is a discrepancy between on-line prediction and experiment at fatigue cycle 168 kcycles and 171 kcycles. In addition, the mean square error can be further reduced by providing a large amount of off-line test data for training the Gaussian process model, which is also one of our future work.

![Figure 13. Mean square error between estimated crack growth and experiment result at different fatigue cycle.](image)

CONCLUSIONS

An adaptive on-line-off-line life prediction model is developed to estimate the residual life of a structural hotspot in real time. The major conclusions may be summarized as follow:

1. Both the on-line and off-line models are based on a Gaussian process approach based on probabilistic Bayesian inference.
2. The on-line-off-line prognostic model is validated on a structural hotspot, i.e., an Al 2024-T351 lug joint.
3. The real time estimation of damage states is based on piezoelectric sensor signal features.
4. The signal features are found using resonant frequency or variance of the denoised sensor signal.
5. Sensor signal denoising is performed using principal component analysis.
6. The on-line damage state prediction shows that there is a good correlation between experiment and prediction when the crack length is larger than 5mm. The prediction error for crack lengths smaller than 5mm can be reduced by using higher frequency active sensing and using better feature extraction algorithms such as nonlinear kernel principal component analysis (KPCA), which will be part of a future study.
7. Once the current damage state is predicted, it is fed to the Gaussian process based off-line forecasting model, to estimate the residual useful life (RUL), based on the new damage information available.
8. The off-line forecasting model is a probabilistic mapping between the input: the current crack state, and the output: the future crack growth rate.
9. It is found that there is a good correlation between residual life estimation from on-line-off-line prognostic model and real (experiment) life.
10. It is also found that the error between forecasted crack length and real (experiment) crack length reduces as more on-line data are available to the prognostic model.

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