Online Fatigue Damage Detection for Structures under Random Loading Using a Comparative Sensor-Data Approach

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ABSTRACT

Fatigue failure of metallic structures such as wind turbines towers or steel bridges is a problem that affects their remaining service life. The current industry standard of fatigue damage assessment is based on time domain cycle counting to estimate the cumulative fatigue damage which is compared to a reference value to detect fatigue failure. The stochastic nature of the fatigue process and the uncertainty in choosing the appropriate reference value limit the applicability of this approach. Fatigue crack detection is the focus of many structural health monitoring techniques. A novel sensor-data comparative approach for fatigue damage detection is proposed in this paper. This approach is based on online monitoring of the linear correlation between monitored and reference sensor-data. Fatigue failure is detected when the linear correlation is lost. The proposed concept is validated experimentally and the obtained experimental results prove the possibility of early detection of fatigue failure.

INTRODUCTION

Correlation analysis of sensor measurements has been used in the past few years in two different approaches. The first one aims to detect faulty sensors in a structural health monitoring (SHM) system such as the work presented by [1], [2] and [3]. Furthermore, [4] extend this approach to reconstruct the faulty sensor measurement based on a correlation model of monitoring data. The second approach is more concerned in structural fault detection and is proposed for example by [5] to monitor the rail-way crossing using correlation analysis of structural dynamic response and weather condition, [6] proposed the use of the cross-correlation analysis of vibration response for structural damage detection; similarly, [7] proposed the use of a statistical pattern matching technique

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to estimate the reliability of the corrected data and the potential structural damage. In both approaches, the detection of sensor or structure fault requires establishing a base or reference state.

Mechanical components/structures have design features which cause stress concentration such as holes, keyways, sharp changes of load direction, etc. These design features are common locations at which the fatigue process begins due to stress concentration at hot spots. Therefore, it is important to monitor these locations for fatigue failure. This paper proposes a novel method of online fatigue damage detection using correlation analysis of sensor data. The method requires stress measurement from the monitored location while the reference signal might be stress measurement from a reference location where fatigue damage is less expected to occur, or the input loading on the structure such as wind speed measurement (in case of aerodynamic loading). The signals from the monitored and reference locations are divided into data-blocks each with duration T. Furthermore, a fatigue damage index $\mathcal{D}$ is estimated from the stress signals per each data-block, while standard deviation of reference signals could be used for input loading, i.e. the standard deviation of wind speed. Finally, linear correlation between the obtained indices in terms of a scatter plot is examined. The structure is considered "healthy" as long as the linear correlation between the indices from the monitored and reference location exists, however, if the linear correlation is lost, the structure could be classified as "damaged". The proposed method could be applied online and the linear correlation is examined using a scatter plot and a simple linear regression. The reference state of the linear correlation could be established shortly after putting the structure into service. This state is monitored and updated online during the service life of the structure.

Early and reliable detection of fatigue damage helps avoiding unexpected structural failure by giving time for taking preventive measures, therefore, the proposed method focus on fatigue damage detection using online data-driven statistical approach.

LINEAR RELATION BETWEEN ESTIMATED FATIGUE DAMAGE INDICES

Consider a structure of n degrees of freedom (DOF) that is subject to the time-dependent external force $F_k(t)$ applied at the $k-$th DOF as shown in fig. 1. Also consider the strain measurements $\varepsilon_i(t)$, and $\varepsilon_j(t)$ at the $i-$th, and $j-$th DOF, respectively. It is possible to derive the linear transfer function between the applied force and the measured strain at the $i-$DOF such as

$$H_{ik}(s) \quad = \quad \frac{\varepsilon_i(s)}{F_k(s)}, \tag{1}$$

where $F_k(s)$ and $\varepsilon_i(s)$ are the Laplace transformation of the force $F_k(t)$ and the measured strain $\varepsilon_i(t)$, respectively; while s is the complex Laplace variable. The transfer function $H_{ik}(s)$ can be written in the following from

$$H_{ik}(s) = \gamma_{ik} \frac{\prod_{l=1}^{n_{ik,z}} (s - z_{ik,l})}{\prod_{l=1}^{n_{ik,p}} (s - p_{ik,l})}, \tag{2}$$

with γ_{ik} is a constant value, $z_{ik,l},\ l \in [1, n_{ik,z}]$ are the zeros with $n_{ik,z} \geq 0$ as the number of zeros of the transfer function $H_{ik}(s)$, and $p_{ik,l},\ l \in [1, n_{ik,p}]$ are the poles with

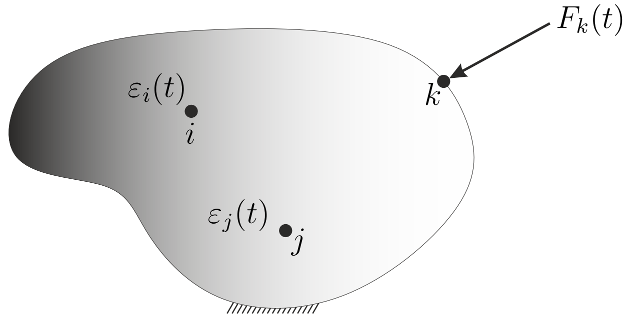

Figure 1. Illustration of the theoretical concept using strain measurement data at DOFs i and j.

$n_{ik,p} \geq 0$ as the number of poles of the transfer function $H_{ik}(s)$. Let $K_{ik} \neq 0$ be the static gain of the transfer function $H_{ik}(s)$, that is to say

$$K_{ik} = H_{ik}(s=0) = \gamma_{ik} \frac{\prod_{l=1}^{n_{ik,z}} (-z_{ik,l})}{\prod_{l=1}^{n_{ik,p}} (-p_{ik,l})}, \tag{3}$$

This allows to re-define the transfer function $H_{ik}(s)$ using the static gain K_{ik} and the normalized transfer function $\tilde{H}_{ik}(s)$ with unity static gain (i.e. $\tilde{H}_{ik}(s=0)=1$) such as

$$H_{ik}(s) = K_{ik}\tilde{H}_{ik}(s), \tag{4}$$

The static gain K_{ik} and the transfer function $\tilde{H}_{ik}(s)$ depend on many factors such as the location of the applied force $F_k(t)$ and the measured strain $\varepsilon_i(t)$, the geometry of the structure, material properties and not to forget the operational and boundary conditions. Using Eq. 4 it is possible to re-write eq. 1 such as

$$\varepsilon_i(s) = K_{ik}\tilde{H}_{ik}(s)F_k(s), \tag{5}$$

which gives a relation between the input force $F_k(s)$ and the measured strain $\varepsilon_i(s)$. This relation could be further simplified to get

$$|\varepsilon_i(s)| \approx K_{ik} \left|F_k(s)\right|, \tag{6}$$

with this simplification is valid only under the following condition

$$|s| \ll \min\left(|z_{ik,l}|, |p_{ik,m}|\right), \; l \in [1, n_{ik,z}], \; m \in [1, n_{ik,p}], \tag{7}$$

where $|\cdot|$ is the absolute value of the complex magnitude. The simplified eq. 6 can be also written in the time domain as

$$\varepsilon_i(t) \approx K_{ik}F_k(t). \tag{8}$$

The condition presented in eq. 7 implies that the frequency of the applied force is considerably lower than the lowest frequency that correspond to a zero or a pole of the normalized transfer function. If this condition is satisfied, the applied force will be marginally affected by the system dynamics and the measured strain can be derived directly from the applied force using the static gain K_{ik}. This condition is always valid in the case of static loading and can be extended to the case of quasi-static loading when the maximum frequency of the applied force satisfies the condition in eq. 7.

Moreover, [8] defines the transmissibility function $T_{ij,k}(s)$ between the $i-$th, and the $j-$th DOF as the ratio between the responses, this give

$$T_{ij,k}(s) = \frac{\varepsilon_i(s)}{\varepsilon_j(s)} = \frac{H_{ik}(s)}{H_{jk}(s)}. \tag{9}$$

The transmissibility function $T_{ij,k}(s)$ depends on the degrees of freedom i and j, in addition to the excitation location k. The transmissibility function could be simplified into

$$T_{ij,k}(s) = \frac{K_{ik}}{K_{jk}} \frac{\tilde{H}_{ik}(s)}{\tilde{H}_{jk}(s)} \tag{10}$$

if the conditions eq. 6 and eq. 7 are valid at both DOFs, i and j. The constant transmissibility allows to derive the following important relation in time-domain.

$$\varepsilon_i(t) \approx T_{ij,k}\varepsilon_j(t) \tag{11}$$

which gives a linear relation between the strain at the degrees of freedom i and j. It is worth to mention at this point that last equation is valid only for a linear system, that is to say, pure elastic deformation in the mechanical system.

The linear relation in time domain as presented in eq. 8 or eq. 11 allows to derive the following concept. If the linear relation changes over time, or is lost, this is an indication of either a change in the operating or boundary conditions, a failure in the structure, or finally, a malfunction or a defect sensor. The change of operating conditions can be easily detected using data from other sensors. However, the detection of the change of boundary conditions, structural failure or defect sensor is the first step in structural health monitoring.

Monitoring the linear relation as in eq. 8 or eq. 11 can be done by periodic estimation of the sensors relation status over a pre-defined time duration T. This status could be the slope of the estimated linear regression, or the cross-correlation coefficient of sensors signals. In both methods, the collected sensor measurements per each data-block are compressed into a single scalar where its stability over time could be simply monitored.

Another possibility is to include the estimated fatigue damage index in the formulation. This could be done for example by monitoring the linear relation of the estimated fatigue damage index from the DOFs i and j, where one of the DOFs is the reference location and the other DOF is the monitored location.

The fatigue strength of a material depends primarily on the stress amplitude s of the loading cycles. The material fatigue strength could be illustrated with the help of the Woehler curve (known also as the $S-N$ curve) defined by

$$N\left(s, \bar{s}\right) s^m = K\left(\bar{s}\right), \tag{12}$$

with $N\left(s, \bar{s}\right)$ as the number of cycles to failure at the constant stress amplitude s and mean stress $\bar{s}$, m is the fatigue exponent that determines the slope of the $S-N$ line on a *log-log* scale, and $K\left(\bar{s}\right)$ is the fatigue constant that is proportional to the number of cycles a material can withstand before failure.

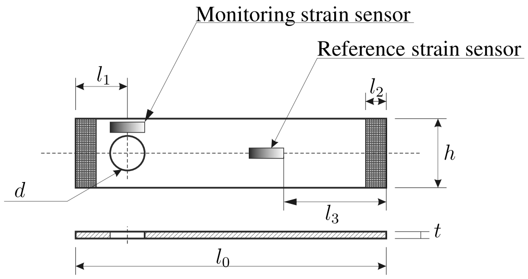

Figure 2. Specimen dimensions.

TABLE I. Specimen dimensions.

Dimension	Material	
	AlMgSi0,5	S235
l_0	$100mm$	$140mm$
l_1	$20mm$	$30mm$
l_2	$10mm$	$10mm$
l_3	$40mm$	$-$
h	$20mm$	$20mm$
t	$2mm$	$3mm$
d	$8mm$	$8mm$

The Palmgren-Miner Rule [9, 10] assumes a linear accumulation of the partial damage introduced by n_i cycles each with stress amplitude s_i. If N_i is the number of cycles to failure at the same stress level s_i, then the accumulated fatigue damage $\mathcal{D}(T)$ through the loading time history $s(t)$, $0 \leq t \leq T$ under the linear damage accumulation rule is given by

$$\mathcal{D}(T) = \sum_{i=1}^{N(T)} \frac{1}{N_i}, \tag{13}$$

with $N(T)$ is the number of all counted cycles during the loading period T. By using eq. 12, this last equation takes also the following form

$$\mathcal{D}(T) = \frac{1}{K} \sum_{i=1}^{N(T)} s_i^m. \tag{14}$$

According to this rule, it is assumed that the structural failure will occur when the accumulated fatigue damage $\mathcal{D}(T_{life})$ over the lifetime of the structure T_{life} reaches a critical level $\mathcal{D}_{cr}$. This critical level is often taken to be unity, namely $\mathcal{D}_{cr} = 1$.

Using eq. 11 along with eq. 14 allows to derive the relation between the fatigue damage indexes $\mathcal{D}_i(T)$, $n \in \{i, j\}$ estimated at the $i-$th and $j-$th DOF during the loading time duration T

$$\mathcal{D}_i(T) \approx (T_{ij,k})^m \, \mathcal{D}_j(T), \tag{15}$$

with m being the material fatigue exponent. This final equation gives also a direct linear relation between the fatigue damage estimated during the loading time T. Monitoring the stability of this linear relation over time allows, among others, the detection of structural damage, when the pair $\mathcal{D}_i(T)$ and $\mathcal{D}_j(T)$ deviate from the linear relationship.

EXPERIMENTAL VALIDATION

Two different specimen sets are used in the experiment, namely, aluminium (AlMgSi0,5) and construction steel (S235). Both specimen sets share the same design with different dimensions that takes into account the material properties and the limitations of the used shaker.

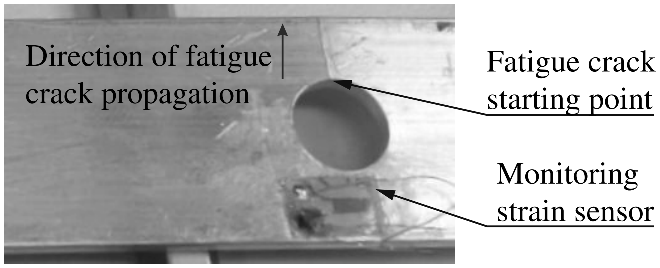

Figure 3. Fatigue crack starting point and propagation direction.

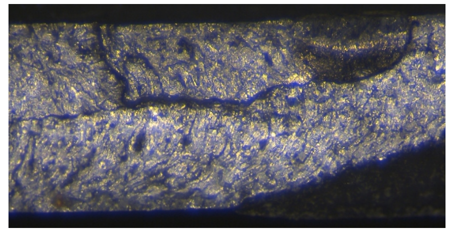

Figure 4. Microscopic photo of fatigue crack surface.

The experimental setup uses a shaker to apply a stochastic bending force on the right side of the specimen while being clamped in its left side. The applied bending force is monitored using a load cell located between the shaker and the specimen. Close to the specimen base, a through hole is present to introduce stress concentration on the hole lateral sides at which the fatigue cracks are expected to start. Strain measurement is achieved using strain sensors next to the hole and in a reference location in the upper part of the specimen.

All specimen had fatigue cracks in the opposite side to the monitoring strain sensors locations. These cracks started from the inner side of the hole and propagates towards the outer side of the specimen. Fig. 3 shows an example of the fatigue failure in aluminium specimen, and fig. 4 shows a microscopic photo of the fatigue crack surface.

RESULTS AND DISCUSSION

The experimental results are discussed considering two aspects. The first one is the correlation between the estimated fatigue damage at the monitored and the reference locations. The second aspect is the correlation between the estimated fatigue damage at the monitored location against the standard deviation of the applied loading force. The obtained experimental results for this last aspect are available in [11].

The fatigue damage estimated from the monitored location $\mathcal{D}^{RFC}_{monitored}$ and the reference location $\mathcal{D}^{RFC}_{reference}$ strain gauge measurements of one aluminium specimen are presented in fig. 5 as scatter plot. Fatigue damage values are estimated using the rainflow counting algorithm per each data-block (each of $480s$ duration). Furthermore, fig. 5 shows also the progress of the standard deviation per each data-block during the experiment of the monitored and the reference responses.

The scatter plot shows for the first part (first 2 days) a linear correlation between the monitored and reference fatigue damage rate values. Using the data collected for the first two days to estimate the linear regression between the monitored and the reference fatigue damage indices, the continuous line shown in fig. 5 is obtained.

By introducing the threshold δ, it is possible to define the tolerance region symmetric to the linear regression line where all points gathered in the first two days of the experiment are located within it. After three days, some points start to shift out-side the tolerance region (red colour). The number of points located out-side this region increase with time till 4.4 days ($T^{Identified}_{failure}$) where all points after this date are completely out-

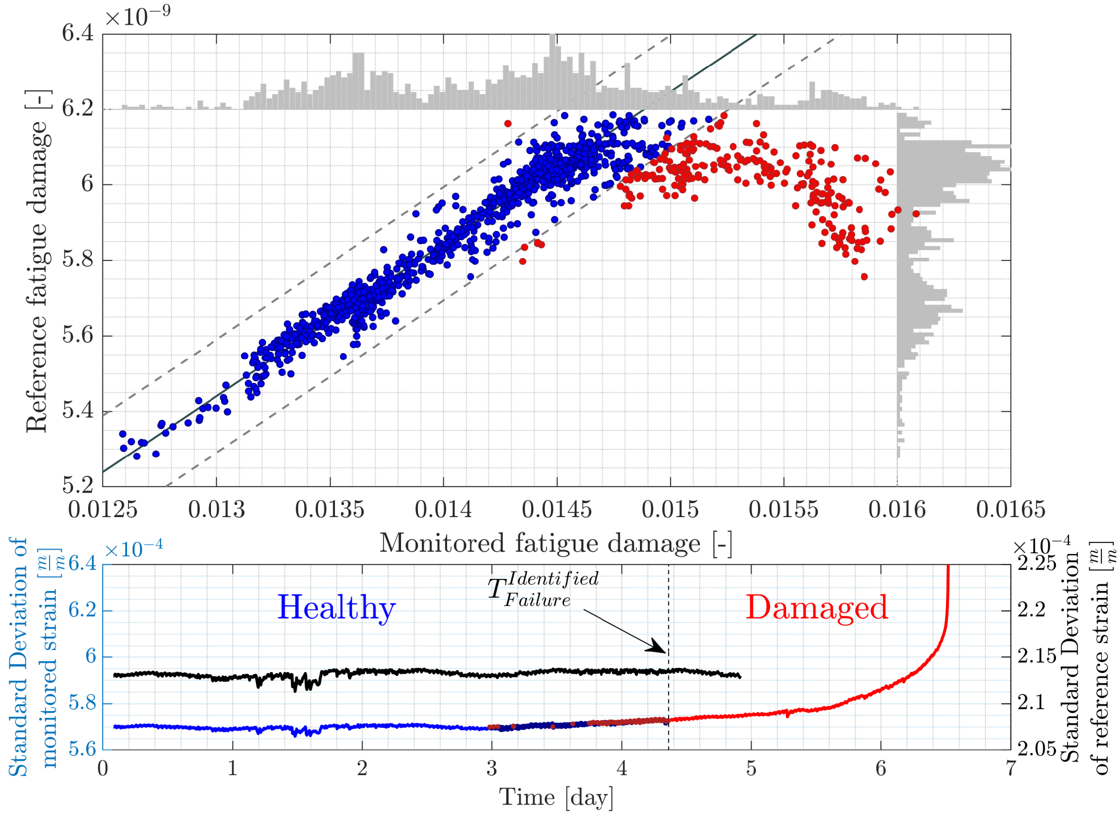

Figure 5. Fatigue failure detection of one Aluminium specimen using strain measurement as reference

side the tolerance region and basically located at one side. With time progress, the points deviates far from the linear regression. The deviation of the calculated fatigue damage from the monitoring sensor to the right indicates an increase in the estimated fatigue damage value from the monitored sensor, while at the same time, the estimated fatigue damage from the reference sensor keeps almost the same level.

The main feature that could be obtained from this strategy is the early detection of fatigue failure using a simple fatigue index. The threshold value δ that defines the tolerance region plays a key-role and it could be defined at the first period when the component is subject to the operational loading and is updated regularly.

CONCLUSION

The main advantage of the proposed approach over the accumulative fatigue damage monitoring method is the absence of the dependency on the critical accumulated fatigue damage value $\mathcal{D}_{cr}$ at which the failure occurs. On the contrary, the proposed approach is an adaptive one as it compares the fatigue damage at a defined monitoring position (hot spot) with high stress/strain level, calculated over a pre-defined time period, against a reference value such as the standard deviation of the input loading or the reference fatigue damage, both estimated for the same time period. The threshold value δ is set based on the collected data at the early stage when the system is considered as healthy.

The experimental results demonstrate the ability of the proposed approach in the early detection of the fatigue damage. Both ways of building the scatter plot either using a reference fatigue damage or using a statistical measure of the loading have demonstrated the ability of early fatigue failure detection.

This approach requires very good knowledge of the loading pattern on the component and the most critical locations at which the fatigue is highly likely to occur. This is related to the necessity to install a monitoring sensor next to the critical location to monitor it. Furthermore, it would be better to use a loading measurement sensor close to the monitoring one as a reference value rather than using the loading input which might be difficult to measure.

Finally, a simple classification method is used to setup the threshold δ. In a multi-loading case with dynamic operating conditions, a more sophisticated classification method is required which would be a good application for the advanced machine learning algorithms.

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