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Symbolic Encoding of Analytic Signals for Structural Monitoring of Power Systems

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Abstract—**This work aims to develop a novel non-destructive technique for real-time condition monitoring to enhance reliability and availability of fossil power systems during steady-state and transient operations. We focused on mechanical fatigue in plant components with the specific objectives of detection and identification of failure precursors, and compression of pertinent damage information to enable transmission over a wireless communication network. A symbolic encoding based technique is employed that utilizes analytic representation of ultrasonic signals for monitoring crack formation and propagation. The signal processing tools are implemented in MATLAB/Simulink environment, for which the direct code generation capability enables the algorithms to be executed on the microprocessor in real-time.**

I. INTRODUCTION

Currently, about 45% of the total electric power in USA is generated by fossil fuel plants. These plants, on the average, have a service life of 40 to 60 years; and about 70% of these plants are over 40 years old [1]. Therefore, extended operation of aging power plants would require prognostic condition monitoring to reduce the probability of forced outage that is largely caused by component failures at high temperature and pressure at supercritical steam conditions [2]. High temperature low cycle fatigue and creep at supercritical steam conditions are examples of structural failures in power plants [3]. Most high temperature components in power plants such as superheater and reheater tubes, and main steam and hot reheat headers undergo thermo-mechanical fatigue and creep [4],[5]. Unless appropriate and timely maintenance actions are taken, these structural defects may lead to forced outage and colossal loss of plant availability. Condition monitoring for power plants aims reliable prognosis of structural damage and estimation of remaining service life at an early stage of material degradation. The goal is to enhance plant reliability and availability without compromising generation efficiency and performance during steady-state and transient operations.

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Inspection techniques for power plants generally assume that the detection of a fault is sufficient. Thus, most efforts are placed on invention of sensors, or novel implementation of sensors. While this is adequate when a macro fault exists, i.e. a fatigue crack of sufficient length for detection, capturing progress of faults is not generally the goal of these technologies. The assumption is that a fault of sufficient size for detection exists, and thus can be located. Examples of such existing technologies are guided wave inspection, fiber optic sensing, acoustic emissions, eddy current testing, and electrically induced ultrasonic testing [6]-[9].

In this paper, we address detection of incipient structural damage and failure precursors in crucial power system components sufficiently in advance. This information is vital for real-time intelligent decision-making for optimization of plant operation and maintenance (O&M) scheduling. The method used here is a synergistic combination of symbolic signal processing and ultrasonic damage sensing. The core concept is built upon the principles of *Hilbert Transform*, *Symbolic Encoding*, and *Finite State Automata*. We aim to deduct material conditions from time series data of piezoelectric transducers. The information on gradually evolving thermo-mechanical fatigue is extracted as statistical patterns from time series data at the time scale of plant operation, and textural features in the observed data sets are mapped into the symbol space for damage identification.

This paper extends our previous work on *Hilbert Transform* analysis [10],[11] to two-dimensional analytic signal space partitioning, and presents an application to fatigue monitoring. This paper also reports dimensionality reduction of signals to suit efficient and error-corrected transmission of compressed data over a wireless communication network. The wireless sensing capability is essential to facilitate exchange of damage information among non-collocated components to enhance overall plant availability. The ensemble of distributed damage information at spatially disparate locations of the power plants can be inputs to the control and operation system for making O&M scheduling decisions in real time.

This paper consists of six sections including the present one. Section II elaborates the algorithm development and Section III details the implementation. Section IV describes the test setup and the results are presented in section V. The paper is summarized and concluded in section VI.

II. ALGORITHM DEVELOPMENT

In this paper, *Symbolic Encoding* technique is used for analysis of the time series data and *Finite State Automata* for compression of information into finite dimensional pattern vectors [12]. For preprocessing of the sensor data we also utilize analytic signal transformation, obtained by *Hilbert Transform* of the data, to discard the negative frequency components of the Fourier spectrum, providing a complex-valued signal. This technique is well suited for time-frequency analysis of non-stationary signals, for separation of frequency components in raw time series without any significant loss of pertinent information [10]. Once the analytic representation of the signal is obtained, it can be partitioned into non-overlapping segments using *Symbolic Encoding* to generate a symbol sequence from the signal. A fixed structure *Finite State Automaton* extracts the information for real-time monitoring of power plant components. Specifically, micro-structural anomalies can be captured as statistical patterns of the data. The evolving patterns are used to detect the damage and monitor the degraded components of the system. The procedure for crack formation and propagation monitoring using this concept requires the following steps:

Data Acquisition: Relevant ultrasonic signals are sampled at suitable rate to generate time series data. The period of data acquisition is significantly small compared to that of damage evolution. Data is acquired at various slow time epochs $t_0, t_1, \cdots, t_k$ starting from the nominal condition.

Preprocessing: *Hilbert Transform* is performed on time series data, and the complex-valued analytic signal is decomposed into phase and magnitude as explained below.

Given $x(t)$, a real-valued function whose domain is the real field $\mathbb{R}$, *Hilbert Transform* of $x(t)$ is defined as:

$$\tilde{x}(t) = \mathcal{H}[x](t) = \frac{1}{\pi}\int_{\mathbb{R}} \frac{x(\tau)}{t-\tau} d\tau \qquad (1)$$

That is, $\tilde{x}(t)$ is the convolution of $x(t)$ with $\frac{1}{\pi t}$ over $\mathbb{R}$, which is represented in the Fourier domain as:

$$\mathcal{F}[\tilde{x}](\xi) = -i \operatorname{sgn}(\xi)\, \mathcal{F}[x](\xi) \qquad (2)$$

where $\operatorname{sgn}(\xi) = \begin{cases} +1 & if\ \xi > 0 \\ -1 & if\ \xi < 0 \end{cases}$

Given *Hilbert Transform* of a real-valued signal $x(t)$, the corresponding complex-valued analytic signal is defined as:

$$\mathcal{A}[x](t) = x(t) + i\, \tilde{x}(t) \qquad (3)$$

$$\mathcal{A}[x](t) = A(t) \exp(i\, \varphi(t)) \qquad (4)$$

where $A(t)$ and $\varphi(t)$ are called the instantaneous amplitude and instantaneous phase of $\mathcal{A}[x](t)$, respectively. For a real-valued time series of N data points, the analytic signal of this data sequence yields a pseudo-phase plot. This phase plot is constructed by a bijective mapping of the complex domain onto the $\mathbb{R}^2$, i.e., by plotting the real and the imaginary parts of the analytic signal on the x and y axes, respectively. The time-dependent analytic signal in Eq. (3) is now represented as a (one-dimensional) trajectory in the two-dimensional pseudo-phase space.

Signal Space Partitioning: The phase and magnitude data of the nominal signal are transformed from the continuous domain to the symbolic domain by partitioning the pseudo-phase space into finitely many discrete segments [13]. Either a uniform partition or the maximum entropy principle can be used for partitioning.

In this paper, the analytic signal partitioning is based on maximum entropy principle which maintains the same number of data points in each segment of the partition, thereby maximizing the Shannon entropy [14]. In other words, the symbol probability occurrence is uniform. Let Ξ be a compact region in the pseudo-phase space, which encloses the trajectory. The objective here is to partition Ξ into finitely many mutually exclusive and exhaustive segments, where each segment is labeled with a symbol. The segments are determined by the instantaneous magnitude and phase of the analytic signal as well as based on the density of data points in these segments.

Symbol Generation: Once the partition is generated, it remains invariant in further analysis. Symbols are generated from phase and magnitude data at different time epochs based on this partition.

If the magnitude and phase of a data point of the analytic signal lies within a segment or on its boundary, then the data point is labeled with the corresponding symbol. Thus, a symbol sequence is naturally derived from the (complex-valued) sequence of the analytic signal. The set of (finitely many) symbols is called the alphabet Σ.

Pattern Representation: The nominal symbol sequence is utilized for construction of a *Finite State Automaton* using *Hidden Markov Modeling* techniques [12]. The structure of the *Finite State Automaton* remains fixed for all time epochs.

In consequent time epochs, the state probability vector, which is derived from the state transition matrix of the constructed *Finite State Automaton*, is considered to be the statistical pattern of the time-series data. In fact, the state transition matrix can be called the Perron-Frobenius operator and the state probability vector is the stationary probability distribution of this operator (i.e. the left eigenvector corresponding to the unity eigenvalue of the matrix.) Therefore, the pertinent damage information can be compressed as low-dimensional pattern vectors to suit efficient transmission over a wireless network.

Pattern Identification: Statistical characteristics of the data are defined by the state probability vectors of the automaton, and computation of these statistical pattern vectors at different slow time epochs are performed online from frequency counting of the automaton states.

Given a representative symbol sequence derived from the complex-valued analytic signal, this data-driven analysis method utilizes a D-Markov Machine to detect the change in the underlying dynamics of the observed system. The D-Markov machine starts with a state space structure where the states of the machine represent all the symbols

$\sigma_i \sigma_{i+1} \sigma_{i+2} \ldots \sigma_{i+D-1}$ which occur in the sequence. Given the cardinality, $|\Sigma|$, of the alphabet and the depth, D, the maximum number of states in the machine is given by $|\Sigma|^D$. The state machine moves from one state to another upon occurrence of a symbol. All sequences that have the same last D symbols lead to the same state (hence, the name D-Markov).

Damage Detection: At this point, the rich information embedded in the sensor signal is mapped to a finite dimensional statistical pattern vector for information compression. The changes in the signal relative to the nominal condition can easily be identified from the evolution of this pattern vector.

When the dynamics of the underlying system are highly similar, there will be minimal variation in the statistics of the symbol sequence, thus yielding state transition matrices with similar probabilities. A change in the dynamics will result in a different distribution of the symbols yielding distinctly different transition probabilities. One possible measure of this variation, which is used in this paper, is the angle between the state probability vectors at the nominal and off-nominal conditions. The measure is defined as:

$$\mathbf{d}_k = d(p_0, p_k) = \arccos\left(\frac{\langle p_0, p_k \rangle}{\|p_0\| \ \|p_k\|}\right) \qquad (5)$$

where $\langle p_0, p_k \rangle$ is the inner product of probability vectors p_0 and p_k for the nominal condition and the current signal at $t = t_k$, respectively, and $\|\bullet\|$ is the Euclidian norm of $\bullet$.

III. Algorithm Implementation

We have implemented the developed algorithms in MATLAB/Simulink environment. This implementation gives us a direct code generating capability so that the generated code can be executed in a computer or onboard a microprocessor of an electronic board. We have used a two-step procedure, where the data partitioning is performed in step 1 and the state probability vector computation is implemented in step 2.

Step 1: The first implemented step was to create a partitioning based on the nominal (reference) data of the component under test. This step can be done off-line after the data is collected by data acquisition hardware. However, the MATLAB/Simulink implementation was designed to create a partitioning method for both on-line and off-line application. During the implementation, we used two separate building blocks for *Symbolic Encoding* algorithms. One block performs the *Hilbert Transform* and the other block performs *Maximum Entropy Partitioning*.

Analytic signal space partitioning methodology was used to determine the partitions for the symbol sequence generation. This was based upon the *Hilbert Transform* of the observed real-valued data sequence as explained before. In algorithm implementation, we decomposed the sensor signal into its magnitude and frequency components by first mapping the signal to analytic space and then computing the instantaneous frequency from the time difference of instantaneous phase as seen in Figure 1. Note that unwrapping is required to have a continuous phase signal at $0/2\pi$ edges. Gain block is used to scale the signal based on the sampling rate of the data and the order of the filter used in analytic signal block.

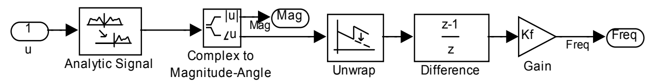

Figure 1. Analytic signal transformation and decomposing the signal to magnitude and frequency

In MATLAB/Simulink implementation, after *Hilbert Transform* the analytic signal is processed by the *Maximum Entropy Partition* block for phase-space partitioning as seen in Figure 2. N data points are buffered and sorted for partitioning. Based on the number of segments, k, we select the average of data points $N \cdot i/k$ and $(N \cdot i/k) + 1$, $i = 1, \cdots, k-1$ for borders of the partition. This assures that each segment has N/k number of data points, therefore the resulting partition satisfies maximum entropy criterion.

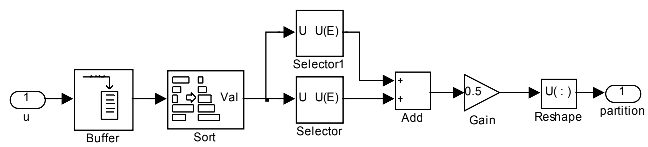

Figure 2. Maximum entropy partitioning

Step 2: The second implemented step of the algorithm was to analyze the sensor signals online and in real-time to detect incipient faults and anomalies in the signal. This was implemented separately in MATLAB/Simulink. The detection method uses statistical pattern representations of the data, obtained by a *Finite State Automaton* in terms of a probability vector.

In implementation, once again the data is mapped to an analytic signal using *Hilbert Transform*, and it was decomposed into the instantaneous magnitude and frequency components. Then the *Symbolic Filter* block, which consists of determining the statistical pattern of the data in terms of a probability vector and assigning a measure value to it, follows. The details are shown in Figure 3. We use StateFlow toolbox of MATLAB to create a finite state machine. By normalizing the column sum with the total number of transitions, we obtain the state probability vector. Given constant (known) state probability vector of the nominal case, the angle block measures the angle between the nominal and current vectors.

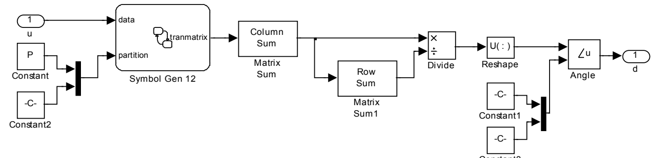

Figure 3. Generating a symbol sequence and computing the state probability vector of the corresponding signal. Probability vector is compared to the nominal case using an angle measure.

IV. Fatigue Crack Test Bed

Fatigue damage is one of the most commonly encountered sources of structural degradation during both nominal and off-nominal operations of power plants. The experimental apparatus, shown in Figure 4, is a special-purpose uniaxial fatigue testing machine that operates on the hydraulic power supplied by a hydraulic pump device, which moves under load control at speeds up to 12.5 Hz. The test apparatus is also connected to three computers dedicated for the tasks of data acquisition and control. The test specimens are subjected to tensile-tensile cyclic loading by a hydraulic cylinder under the regulation of computer-controlled electro-hydraulic servo-valves. The image data of the specimen surface from the optical microscope and the sensor data from the ultrasonic transducers are passed to the data analysis and damage estimation subsystem. The information from the optical microscope is analyzed to determine the fatigue crack length on the specimen surface. Data sets from the ultrasonic sensors are analyzed using the algorithm described in Section II for fatigue damage estimation even before the optical microscope detects a surface crack.

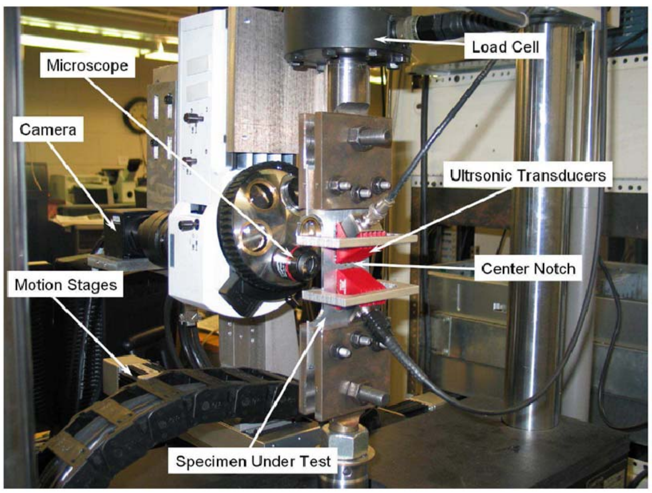

Figure 4. Fatigue damage test apparatus

The specimens used in the experimental apparatus were typical hourglass shaped flat plates that have a machined notch for stress concentration to guarantee crack propagation at the notch end. Specimens used in this study were made of 7075-T6 aluminum alloy [15]. These specimens with local stress concentration regions were designed to break in a reasonably short period of time to enhance the speed of the experiments. The test specimens were subjected to sinusoidal loading under tension-tension mode (where the maximum and minimum loads are 89.3 MPa and 4.85 MPa) at a frequency of 12.5 Hz. The direct component (*DC*) offset is provided in the load cycling to ensure that the specimen was always under tension.

The travelling optical microscope, shown as part of the test apparatus in Figure 4, provides direct measurements of the visible part of a crack. The growth of surface crack was monitored continuously by the microscope which took the images of the specimen surface at regular intervals. Furthermore, a piezoelectric transducer was used to inject ultrasonic waves in the specimen and an array of receiver transducers was placed on the other side of notch to measure the transmitted signal. The ultrasonic waves were generated as 10 MHz sine wave signals. The ultrasonic system was synchronized with the load cycling such that the waves are emitted during a very short portion at the peak of every load cycle where the stress is maximum.

Since the ultrasonic frequency (10 MHz) is much higher than the load cycling frequency (12.5 Hz), data collection is performed for a very short interval in the time scale of load cycling. The slow time epochs were chosen to be 500 load cycles (i.e., 40 sec) apart. At each epoch, the ultrasonic data points were collected for 50 cycles (i.e., 4 sec), which produced a string of 60,000 data points (i.e. sampling rate of 15 kilosamples/sec). These sets of time series data points collected at different slow time epochs were analyzed using *Symbolic Encoding* of analytic signals and an anomaly measure was calculated using the angle norm between state probability vectors of *Finite State Automaton* at these slow time epochs.

V. Test Results

Using the fatigue damage apparatus described in Section III, we have conducted 6 set of experiments. Each experiment consisted of sinusoidal load cycles till the crack starting at the notch site fully develops. Due to material characteristics and imperfections of each specimen, the experiments took different number of cycles to conclude. Each dataset had $60{,}000 \times N$ data points, where N corresponds to the number of slow time epochs. We want to discuss the results in terms of absolute number of working cycles and life usage.

For the first experiment conducted, the six triplets of plates in Figure 5 show two-dimensional images of a specimen surface, ultrasonic data and histograms of probability distribution at six different time epochs, approximately 1, 11, 22, 33, 38 and 43 kilocycles, exhibiting gradual evolution of fatigue damage. Note that the ultrasonic data were partitioned directly without *Hilbert Transform*. In each triplet of plates from (a) to (f) in Figure 5, the top plate exhibits the surface image of the test specimen as seen by the optical microscope. As exhibited on the top plates, the crack originated and developed on the right side of the notch at the center. Histograms in the bottom plates of six plate triplets in Figure 5 show the evolution of the state probability vector corresponding to fatigue damage growth on the test specimen at different slow time epochs, signifying how the probability distribution gradually changes from uniform distribution (i.e., minimal information) to delta distribution (i.e., maximum information). The middle plates show the ultrasonic time series data collected at corresponding slow time epochs. As seen in Figure 5, the visual inspection of the ultrasonic data does not reveal much information during early stages of fatigue damage but the statistical changes are captured in the corresponding histograms.

The top plate in plate triplet (a) of Figure 5 shows the image at the nominal condition (~1 kilocycles) when the anomaly measure is taken to be zero, which is considered as the reference point with the available information on potential damage being minimal. This is reflected in the uniform distribution (i.e., maximum entropy) as seen from the histogram at the bottom plate of plate pair (a). Both the top plates in plate triplets (b) and (c) at ~11 and ~22 kilocycles, respectively, do not yet have any indication of surface crack although the corresponding bottom plates do exhibit deviations from the uniform probability distribution. This is evidence that the analytic signals, based on ultrasonic sensor data, produce damage information during crack initiation, which is not available from the corresponding optical images.

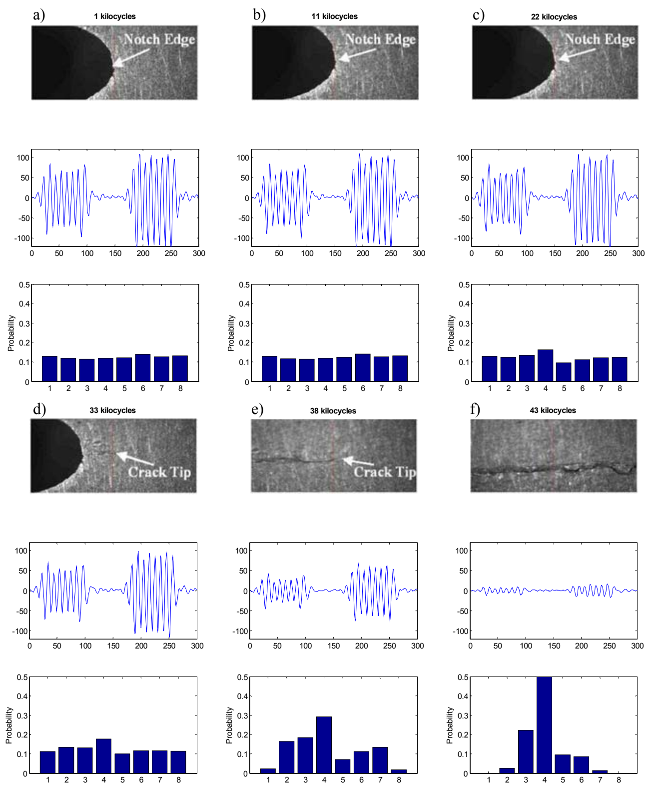

Figure 5. Pictorial view of the evolving fatigue crack damage, corresponding ultrasonic data and histograms of probability distribution

For the second set of experiments, the time series data obtained from the ultrasonic sensors were analyzed using the *Hilbert Transform*. Figure 6 depicts the analytic signal obtained from the time series data and the partitioning of the signal using the maximum entropy principle where real-axis was partitioned into 3, imaginary-axis was partitioned into 4 segments resulting in total 12 distinct symbols.

The next figure shows the probability distribution of the data in each segment. The results are obtained using a 12-state *Finite State Automaton* with depth $D = 1$. This represents the statistical properties of the data in a lower dimensional space. The damage characteristics are evaluated using changes in these histograms. The evolution of state probabilities is also given in Figure 7 where the signal statistics change drastically as damage progresses.

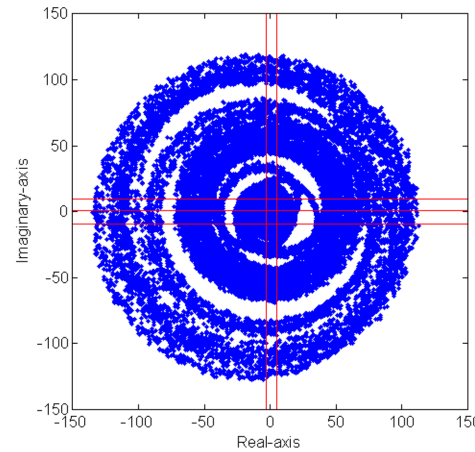

Figure 6. Analytic signal and its partitioning

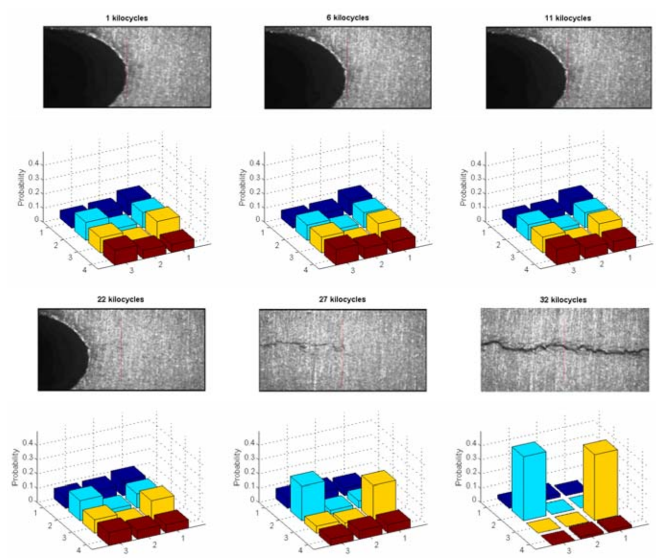

Figure 7. The probability distributions corresponding to different conditions of crack formation and propagation. Also shown is the evolution of probabilities as damage progresses

We assign a measure value for the change in the probabilities. The angle between the vectors is used in this paper. Figure 8 summarizes the results of all 6 datasets. It is seen that the algorithms described herein can capture the damage patterns very effectively. However, due to the disparities in the damage for each specimen the results cannot be compared easily in these graphs. Plotting the measure with respect to the life usage can give us a better understanding. Figure 9 compares the results on a normalized scale where the x-axis is the life usage of specimens. As seen in the figure, first 60% of the life (0.6) is the crack initiation stage. Here, there are only minor changes in the data statistics. After 60%, there is a rapid acceleration in measure corresponding to the crack formation stage. Around 0.85, we observe a fully formed crack.

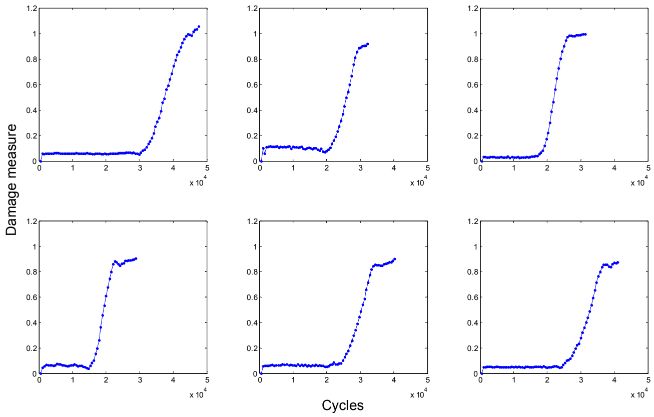

Figure 8. The measure shows the evolution of damage as a function of loading cycles

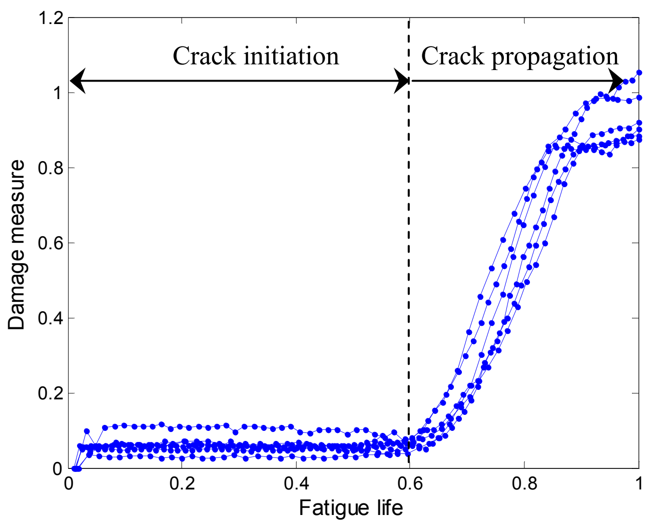

Figure 9. Calculated damage measure versus the life span of specimens

VI. Summary and Conclusions

In this paper, we have demonstrated structural monitoring using *Symbolic Encoding* of analytic signals for fatigue damage detection in power plants. We have used MATLAB/Simulink blocks to implement the algorithms, which can be used to create a C code to be executed onboard a microprocessor. The outputs of the ultrasonic transducers are connected to a signal conditioning unit which prepares the sensor signal for the A/D converter. The PIC microcontroller is used to read the digitized sensor signal.

Key contributions of this effort are:

- A synergistic combination of physics of failures has been used in conjunction with advanced tools of signal processing utilizing a non-destructive ultrasonic method of damage sensing.
- Textural features in the time-series data has been mapped into a symbol space for damage identification and the information on gradually evolving failure has been extracted as statistical patterns.
- An experimental apparatus, which is designed to study the growth of fatigue damage in mechanical systems, has been used for algorithm validation.
- It has been experimentally demonstrated that analytic signals, based on ultrasonic sensor data, produce damage information during crack initiation, which is not available from the corresponding optical images.
- Statistical pattern changes in probability distributions of the observed time series data sequences at different slow-time epochs have been identified to capture the gradual evolution of microstructural changes in poly-crystalline alloys.
- A novel wireless data acquisition module has been developed with expansion capabilities for stand-alone wireless mesh networking to enable simultaneous monitoring of non-collocated components.

References

[1] C-K. Weng and A. Ray, "Robust Wide Range Control of Steam-Electric Power Plants," *IEEE Trans. on Control Systems Technology*, Vol. 5, 1997, pp. 74-88

[2] Electric Power Research Institute, *Remaining Life Assessment of Superheater and Reheater Tubes*, Report No. EPRI CS-5564, Project 2253-5, May 1988

[3] R. Viswanathan and J. Stringer, "Failure Mechanisms of High Temperature Components in Power Plants," *Trans. ASME, Journal of Engineering Materials and Technology*, Vol. 122, 2000, pp. 246-255

[4] S. L. Mannan and M. Valsan, "High-temperature Low Cycle Fatigue, Creep–fatigue and Thermomechanical Fatigue of Steels and Their Welds," *International Journal of Mechanical Sciences*, Vol. 48, 2006, pp. 160-175

[5] Electric Power Research Institute, *Advances in Materials Technology for Fossil Power Plants*, Report No. EPRI 1011381, October 2004

[6] J. L. Rose, "A Baseline and Vision of Ultrasonic Guided Wave Inspection Potential," *Journal of Pressure Vessel Technology*, Vol. 124, 2002, pp. 273-282

[7] R. M. Measures, *Structural Monitoring with Fiber Optic Technology*, Academic Press, San Diego, 2001

[8] J. Blitz and G. Simpson, *Ultrasonic Methods of Non-Destructive Testing*, Springer-Verlag, New York, 1991.

[9] R. Zorgati, B. Duchene, D. Lesselier, D, and F. Pons, "Eddy Current Testing of Anomalies in Conductive Materials," *IEEE Tran. on Magnetics*, Vol. 27, 1991, pp. 4416-4437

[10] M. Yasar and A. Ray, "Trend Detection and Data Mining via Wavelet and Hilbert-Huang Transforms," *Proceedings of American Control Conference*, 2008, pp. 4292-4297

[11] M. Yasar, A. Purekar, and D. Sheth, "Real-time Hardware Implementation of Symbolic Health Monitoring for Aircraft Engine Components," *Proceedings of American Control Conference*, 2010, pp. 2224-2229

[12] A. Ray, "Symbolic Dynamic Analysis of Complex Systems for Anomaly Detection," *Signal Processing*, Vol. 84, 2004, pp. 1115-1130

[13] D. Lind and M. Marcus, *An Introduction to Symbolic Dynamics and Coding*, Cambridge Univ. Press, Boston, MA, 1995

[14] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, John Wiley, 1991

[15] Electric Power Research Institute, *Creep-FatiguePro: On-Line Creep-Fatigue Damage and Crack Growth Monitoring System*, Report No. EPRI TR-100907, Project 1893-11, July 1992