Bolted Joint Damage Assessment Using Chaotic Probes

Timothy R. Fasel[1], Matthew B. Kennel[1], Michael D. Todd[1], Erik H. Clayton[2], Mark C. Stabb[2], Gyuhae Park[3]

[1]University of California San Diego, 9500 Gilman Dr. Dept. 0085, La Jolla, CA 92093-0085
[2]Quartus Engineering, 10251 Vista Sorrento Parkway, Suite 250, San Diego, CA 92121-3771
[3]Los Alamos National Laboratory, MS T001, P.O. Box 1663, Los Alamos, NM 87545

ABSTRACT

Recent research has shown that ultrasonic chaotic excitation coupled with sensor-actuator or sensor-sensor cross-predictions can be used to identify incipient damage (loss of preload) in a bolted joint. In this study, a three-dimensional physics-based simulation is performed which models the behavior of a guided ultrasonic wave through a bolted metal lap joint. In order to mimic the physical experiment in the model, the waveform is directly applied via nodal displacement and 'sensed' using an average of the nodal strain over an area equivalent to that of a macro-fiber composite (MFC) piezoelectric patch. Multiple damage levels and locations are assessed by processing the MFC network responses with a statistical classification feature derived from notions of cross-prediction and interdependence. The effectiveness of this feature is compared for both experimental and computational data.

1. INTRODUCTION

Ultrasonic testing is currently the most widely used technique for joint and bond testing, especially in the aerospace industry [1]. This technique is limited, however, by a small inspection range and bulky test equipment that causes continuous health monitoring to be infeasible. There are also global techniques based on vibration testing and accelerometer response that operate at frequencies too low to be able to identify small changes in joint preload loss that we wish to categorize [2]. As an alternative, Guided Ultrasonic Waves (GUWs) operating in the tens to hundreds of kilohertz range are being increasingly used for in-situ monitoring purposes [3]. GUWs are able to identify incipient damage levels because of the small wavelengths involved but are suitable for continuous monitoring because relatively few actuators/sensors need to be used by exploiting the waveguide geometry of the structure.

Recently research has been done which uses GUWs with chaotic properties and state space reconstruction as an effective method of bolted joint health monitoring [4,5]. This idea evolved from earlier work in using chaotic excitation coupled with state space analysis to assess structural damage in the vibration-frequency domain [6,7]. In this study, chaotic GUWs are created by amplitude modulating a single frequency carrier wave using an envelope developed from a high speed chaotic process. In the GUW frequency range, the waveform appears as a narrowband, chaotically-modulated signal centered at the desired frequency. A center frequency of 80 kHz was chosen in this study because of the relatively minor dispersion that occurs for the particular experimental and computational models under consideration, and because the traveling modes are well-separated in phase velocity space.

2. THEORY AND BACKGROUND

2.1 Signal Creation

We first create a 1 Hz sine wave with a *dt*=0.02 so there are 50 points per period. A standard Lorenz chaotic signal can then be realized using the output of the *x* variable from the following three dimensional system:

$$\begin{aligned} \dot{x} &= \sigma(y - x) \\ \dot{y} &= (-xz + rx - y) \\ \dot{z} &= (xy - bz) \end{aligned} \qquad \textbf{(1)}$$

where σ=10, *b*=8/3, and *r*=28. This signal is integrated with a time-step *dt_lorenz*=*dt*R*, where *R* is a frequency ratio that can be modified. For this study we use a value of *R*=1/3 that creates a signal in which the significant frequency information (determined by a loss of 40 dB in power spectral density) is less than 1 Hz. A value of *R*=1/30 would result in significant frequency information being less than 0.1 Hz. The Lorenz signal is then normalized by subtracting the mean and dividing by the standard deviation of the signal. A modulated signal is then created using the following equations:

modulation_window = 1.0 + *modulation_depth*lorenz_signal*
modulated_sin = *sinwave*.**modulation_window* **(2)**

where in this study *modulation_depth*=0.4 and controls signal bandwidth. The chaotically modulated signal is then upconverted to the target carrier wave frequency by multiplying *dt*oscillation_frequency* which for this study is 80 kHz. In Figures 1a and 1b we can see the effect of changing the frequency ratio *R* as well as the *modulation_depth* on the power spectral density of the modulated sine wave. The chaotic GUWs are also smoothed in time at its boundaries with a trapezoidal window to facilitate launching with piezoelectric devices. The chaotic GUWs were launched over a 2 ms time length.

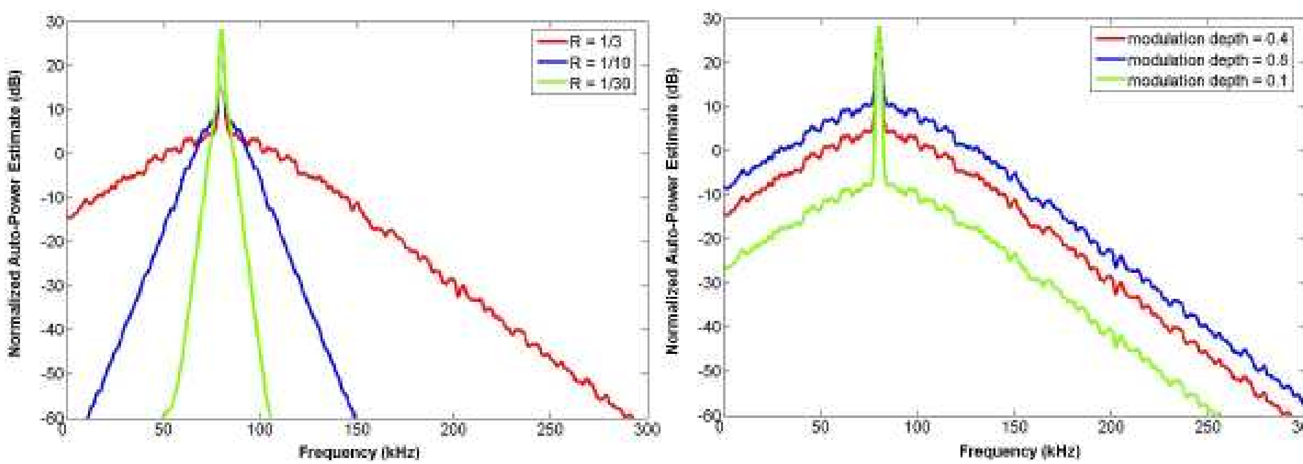

Figure 1: (a, left) Power spectral density of modulated signal using *modulation_depth*=0.4
(b, right) Power spectral density of modulated signal using *R*=1/3

2.2 Feature Extraction

Once this chaotic GUW is launched into the structure and detected after its interaction with the joint the primary task remains what feature(s) from the measured waveform may be extracted to assess the joint. We chose to employ a novel statistical classification technique with its basis in information theory. We modeled the discretely-observed output time-series *x(n)* with an autoregressive (AR) time series model using the following equation:

$$x(n) = \sum_{i=1}^{p} \alpha_i x(n-i) + e(n) \qquad \textbf{(3)}$$

where *p*=25 is the order of the AR model with associated coefficients α_i and residual error *e(n)*. These coefficients are estimated by minimizing the sum of the squared residual errors.

The idea behind the classification technique works as follows. First, a set of distinct 2 millisecond long input signals are created from a single data-generating process that has been previously described. For each of these input signals a structural response is recorded under various bolt preload states. For each of these responses we estimate AR coefficients. The sets of AR coefficients in the database of various damage conditions multiplied by the varying inputs forms the database. A new input signal (created from the same underlying process as the database input signals) is then applied to the structure when the bolt preload level is in an unknown state. Each set of AR coefficients in the training database is then used to estimate the structural response to the new input signal. The bolt condition of the set of coefficients that minimize the sum squared residual errors is counted as the "vote" for the models at that input. This process is performed using multiple input signals. The votes for each bolt condition are then summed and the condition with the plurality of votes is the estimated condition of the bolt preload level.

3. ANALYTICAL SIMULATION

Both the time and space magnitudes of an ultrasonic propagating wave make dynamic transient analysis computationally expensive with commercial off-the-shelf finite element software. Moreover, this computation cost can be substantially increased (many times over) with the inclusion of material and geometric nonlinearities like those which exist in our problem. In an effort to mitigate this issue, we essentially encapsulated the most relevant geometric nonlinearity, effective contact between overlapping regions, with several different linear models. Each linear model represented a different bolt preload (effective contact region) state and was analyzed independently with the appropriate input excitation. Figure 2 illustrates the contact region for each of the bolt preload configurations examined in this study. The elements within the pink region share degrees-of-freedom continuously through the overlapping region of the bars and those outside of the delineation do not. The simulated conditions correspond roughly with a "fully loose" bolt (BO) to "very tight" bolt (FF).

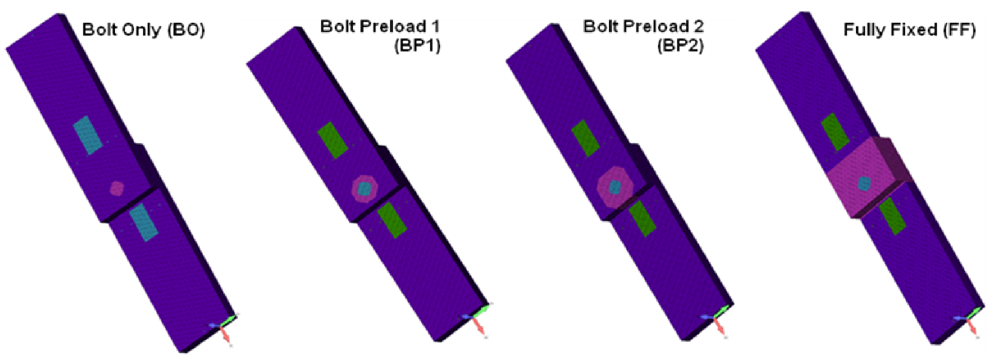

Figure 2: Depiction of fused surfaces (pink) for all 4 simulated bolt conditions

Using 29 distinct chaotic inputs, we generated response time history data from our detailed finite element models for 4 simulated bolt preload conditions. A typical input waveform and response time history for two conditions is shown in Figure 3.

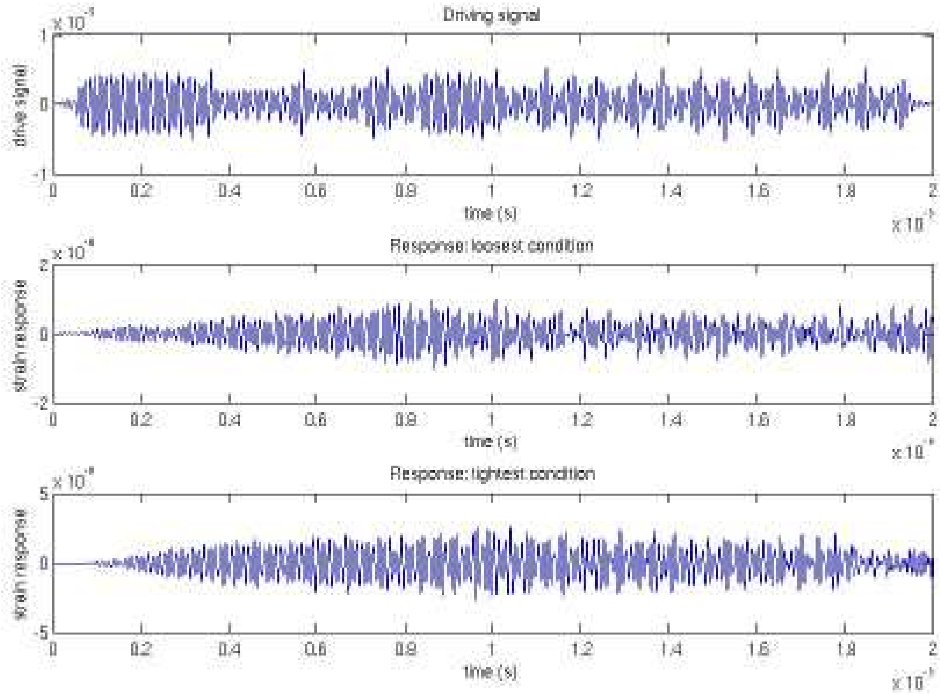

Figure 3: Simulated chaotic GUW input signal (top) and response time history as loosening occurs for BO (middle) and FF (bottom) bold conditions

To demonstrate proof-of-concept on classification, we randomly selected 15 of the 29 generated response time histories to be used as database training inputs; the other 14 formed test set inputs. The 'true' condition was selected randomly from the four conditions and our algorithm was asked to determine the actual condition based solely on knowledge it acquired from the 15 database training inputs. Table 1 shows the summed vote results. Each row is the actual condition of the bolt. Each column is the number of classification votes assigned to that condition. If the statistical classifier correctly identified every test condition the table would only have votes along the diagonal. The correct bolt condition was able to be identified in all cases.

Table 1: Classification "vote" distribution of simulated lap joint data

Actual Condition	***Votes***				**Outcome**
	BO	**BP1**	**BP2**	**FF**	
BO	**204**	0	6	0	Correct
BP1	0	**182**	28	0	Correct
BP2	0	17	**193**	0	Correct
FF	0	0	0	**210**	Correct

4. EXPERIMENTAL SETUP

4.1 Single bolt lap joint

The single lap joint used in the following study is shown in Figure 4. The actuation signal is sent to one of the attached MFC patches and the structural response is measured by the other MFC patch. Due to the symmetry of the problem it does not matter which patch is used as the sensor and which as the actuator. Either configuration will yield similar results.

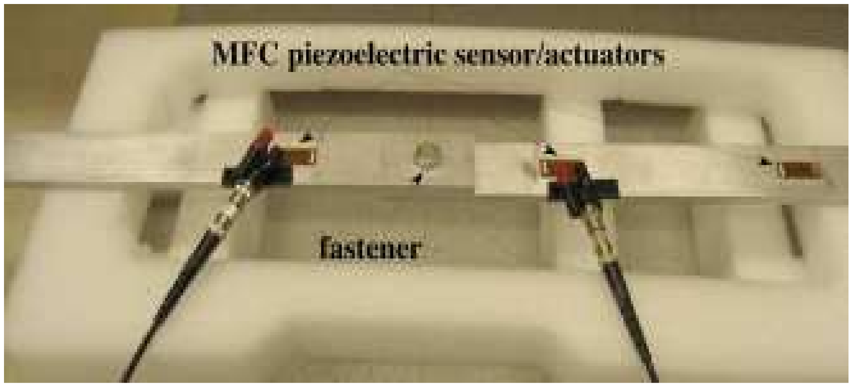

Figure 4: Single lap joint experiment

Table 2: Classification "vote" distribution of experimental lap joint data

Actual Condition	*Votes*				Outcome
	Condition 1	Condition 2	Condition 3	Condition 4	
Condition 1	**175**	4	0	46	Correct
Condition 2	0	**79**	122	24	Incorrect
Condition 3	0	0	**188**	37	Correct
Condition 4	1	0	74	**150**	Correct

In this study we took data at each step of a bolt sequence in which the bolt condition is: 'loose' (Condition 1), 'finger-tight' (Condition 2), 30 in-lb (Condition 3), and 120 in-lb (Condition 4). This sequence is then repeated three times to simulate assembly and disassembly of the joint in a real structure. The first two assembly/disassembly sequences were used to create a training database. The third sequence structural responses were used as test inputs. Table 2 shows the vote results for the 4 conditions.

The damage level of the bolted joint was correctly assessed by the algorithm in all cases but Condition 2, which was estimated by vote-counting to be in Condition 3. The difference between ‘finger-tight’ and 30 in-lb is only approximately 1/16 of a bolt turn so this result is not surprising. In this experiment it was difficult to maintain the boundary conditions of the lap joint and it is believed that this led to inflated number of incorrect votes.

4.2 Multiple bolt portal structure

A test bed with more reliable end boundary conditions should result in a greater percentage of correct classifications. We also wished to test a structure that had multiple bolted connections and so the portal structure shown in Figure 5 was employed. The actuating MFC is placed asymmetrically to remove the symmetry of the structure and to make individual bolt damage state identification more possible.

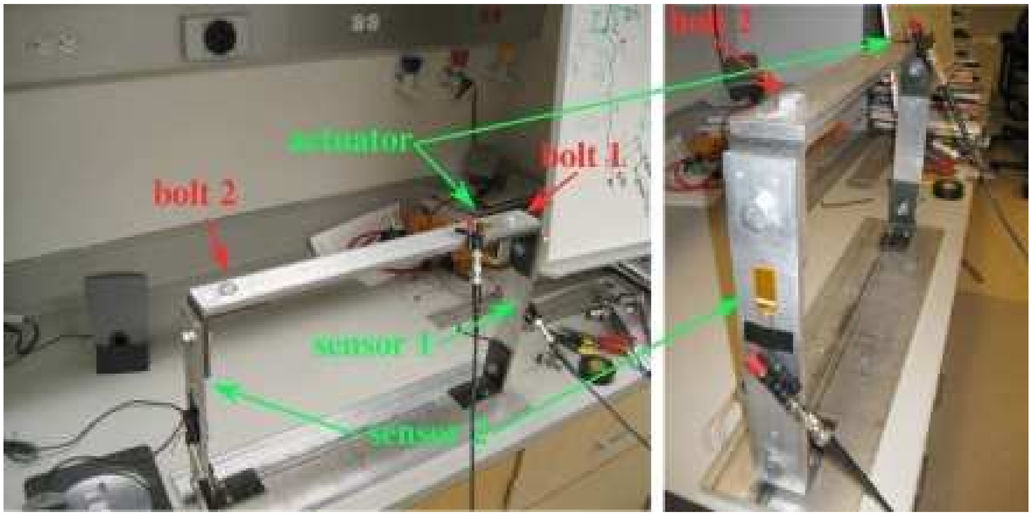

Figure 32: Multiple-joint frame structure experiment

Table 3: Test conditions of the multiple-joint structure

Case	Bolt 1 Condition	Bolt 2 Condition
1	Tight	Tight
2	Finger Tight	Tight
3	Loose	Tight
4	Tight	Finger Tight
5	Tight	Loose
6	Finger Tight	Finger Tight
7	Loose	Loose
8	Tight	Tight
9	Finger Tight	Tight
10	Loose	Tight
11	Tight	Finger Tight
12	Tight	Loose
13	Finger Tight	Finger Tight
14	Loose	Loose
15	Tight	Tight
16	Finger Tight	Tight
17	Loose	Tight
18	Tight	Finger Tight
19	Tight	Loose
20	Finger Tight	Finger Tight
21	Loose	Loose

Table 3 shows the damage cases that were considered in this study. 'Tight' indicates 120 in-lb, 'finger tight' indicates nominal preload (less than 30 in-lb), and 'loose' indicates no preload. While there are thus 7 “conditions” defined, as indicated, there are only 3 damage levels for each bolt.

Table 4: Classification "vote" distribution of multiple-joint frame data

Damage Case	MFC 1(Bolt 1)			MFC 2 (Bolt 2)		
	Tight	Finger Tight	Loose	Tight	Finger Tight	Loose
15	**225**	0	0	**225**	0	0
16	0	**152**	73	**225**	0	0
17	2	115	**108**	**225**	0	0
18	**225**	0	0	0	**134**	91
19	**225**	0	0	0	98	**127**
20	1	**140**	84	0	**196**	29
21	0	3	**222**	0	1	**224**

Similar to Section 4.1, the last 7 cases were used as test cases against the training database created using first 14 cases. The vote chart for each MFC sensor is shown in Table 4. The bold numbers in each row indicate the true condition of the bolt. Therefore a correct classification is made if the bold number is the largest in its row. As such, the correct classification was made in each case except for bolt 1 in damage case 17. The 'tight' condition was classified correctly for almost every test signal whereas the distinction between 'finger tight' and 'loose' is less clear.

Table 5: Classification Distribution Multi-joint Experimental Data

Damage Case	MFC 1(Bolt 1)		MFC 2 (Bolt 2)	
	Tight	Loose	Tight	Loose
15	**225**	0	**225**	0
16	0	**225**	**225**	0
17	2	**223**	**225**	0
18	**225**	0	0	**225**
19	**225**	0	0	**225**
20	1	**224**	0	**225**
21	0	**225**	0	**225**

If we were to combine the categories 'finger tight' and 'loose' into a general 'loose' category in an attempt to make a purely healthy/unhealthy joint status determination, we have proper classification with each damage case. This simple classification works so well that votes for individual test responses choose the correct joint configuration greater than 99% of the time, as can be seen in Table 5.

5. SUMMARY

This study has shown the structural health monitoring capability of chaotically modulated ultrasonic waves that are imparted to a structure through a piezoelectric patch. The classification damage detection scheme was shown to be effective in identifying bolt preload configuration in simulations and experiments on single and multi-bolt structures. This is only one method of identifying structural health using chaotic guided ultrasonic waves (CGUWs). There are other damage detection methods based on state space reconstruction which are able to identify incipient levels of damage due to bolt preload loss. These methods have the ability to detect and locate small levels of damage due to the frequency regime of the excitation signal. It will be preferable to standard ultrasonic SHM techniques such as time-of-arrival and wave attenuation for specific applications because it is easily implemented for complicated geometries.

However, there is still work to be done in several areas to improve the efficacy of the method. A more rigorous consideration of many possible damage features to be extracted from the data will need to be completed. A more complex three-dimensional finite element model that can both verify experimental observations and predict simulated damage conditions will need to be developed.

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