LA-UR- 00-4843

Approved for public release;
distribution is unlimited.

Title: DAMAGE DETECTION IN BUILDING JOINTS BY STATISTICAL ANALYSIS

Author(s): Charles R. Farrar, ESA-EA
David W. Allen, Rose Hulman Institute of Technology
Sergio Castillo, University of Texas
Amanda L. Cundy, Montana State University
Robert E. McMurry, New Mexico State University

Submitted to: IMAC XIX: Conference on Structural Dynamics
February 5-8, 2001
Kissimmee, Florida

Los Alamos
NATIONAL LABORATORY

DISCLAIMER

DAMAGE DETECTION IN BUILDING JOINTS BY STATISTICAL ANALYSIS

David W. Allen[1], Sergio Castillo[2], Amanda L. Cundy[3], Charles R. Farrar[4], Robert E. McMurry[5]

[1]Rose Hulman Institute of Technology, undergraduate mechanical engineering student
[2]University of Texas, El Paso, graduate civil engineering student
[3]Montana State University, undergraduate civil engineering student
[4]Staff Member, Los Alamos National Laboratory, Los Alamos, New Mexico 87545
[5]New Mexico State University, graduate mechanical engineering student

ABSTRACT: Accelerometer data were acquired from a simulated three-story building driven by an electro-dynamic shaker attached to the base of the structure. Data were collected on the undamaged structure and after multiple damaged cases had been introduced to the structure. Operational variability was introduced by changing the shaker input levels. A statistical damage detection and localization method was implemented and applied to these data. The algorithm was shown to be insensitive to the operational variability and other sources of variability. This investigation was conducted as part of a conceptual study to demonstrate the feasibility of detecting damage in structural joints caused by seismic excitation.

NOMENCLATURE:

X = acceleration time history value
α = auto-regressive model coefficients
ε = residual error
m = number of data points
n = auto-regressive model order

1. INTRODUCTION

Recent earthquakes have shown that welded moment resisting steel connections are susceptible to failure [1]. Current methods of damage detection for joints in buildings subjected to earthquakes are quite costly and time-consuming visual procedures. If a damage detection method based on the measured vibration response can be developed, it can then be combined with current MEMS sensing technology, constituting a more economical and quantifiable damage detection method. Such a damage identification method can potentially provide significant economic and life-safety benefits. The focus of this study is to conceptually demonstrate a vibration-based damage detection system for structural connections.

In the research presented herein, baseline data sets measured on a structure in an undamaged state were compared in a statistical manner to data sets measured on the structure after various damaged conditions had been introduced to the structural connections. The structure tested was representative of a three-story frame structure.

The damage detection method used in this study was composed of a four-part process [2]:

1. Experimental scope definition,
2. Data acquisition and cleansing,
3. Feature extraction, and
4. Feature discrimination through statistical modeling.

Defining the scope of the experiment involves using driving motives of the experiment to define experimental control and variability [2]. During this stage, damage definition, flexibility of implementation and variability under which the structure was to be tested were considered. Damage definition should attempt to model the effect of damage in actual structures. Implementation flexibility governs the number, placement, and type of sensing devices to be used in the test. If the method used in the experiment is overly complicated or costly it will be impractical to implement. Variability was introduced in three forms: environmental, operational and testing variability. Each of these sources of variability must be carefully considered and the feature extracted for damage detection should be insensitive to all of them.

Possibly the most important aspect for implementing a damage detection strategy is to determine the appropriate damage-sensitive features to be extracted from the data. Features that are highly sensitive to damage while being insensitive to other variables must be chosen. The features extracted are used to develop a statistical model, which will discriminate between features from the undamaged and damage states.

A three-story frame structure was tested in different damage states. Then an Auto-Regressive (AR) model was fit to the collected data. Residual errors between AR predictions and the measured data were used as the damage sensitive features. Statistical process control charts were developed for actual damage detection. Results showed that the method developed could detect damage in most cases. The extracted features were insensitive to sources of variability, which resulted from test to test variability introduced by technicians and operational variability introduced by intentionally varying shaker input levels.

2. TEST STRUCTURE DESCRIPTION

The structure tested was a simulated three-story frame structure, constructed of Unistrut columns and aluminum floor plates. Floors were 0.5-in-thick (1.3-cm-thick) aluminum plates with two-bolt connections to brackets on the Unistrut columns. Floor heights were adjustable. The base was a 1.5-in-thick (3.8-cm-thick) aluminum plate. Support brackets for the columns were bolted to this plate. All bolted connections were tightened to a torque of 50 foot-pounds (70Nm) in the undamaged state. Four Firestone airmount isolators, which allowed the structure to move freely in horizontal directions, were bolted to the bottom of the base plate. The isolators were mounted on aluminum blocks and plywood so that the base of the structure was level with the shaker. The isolators were inflated to 20 psig (140 kPa).

The shaker was connected to the structure by a 6-in-long (15-cm-long), 0.375-in-dia (9.5-mm-dia) stinger connected to a tapped hole at the mid-height of the base plate. The shaker was attached at a corner on the 24-in (61-cm) side of the structure, so that both translational and torsional motion would be excited.

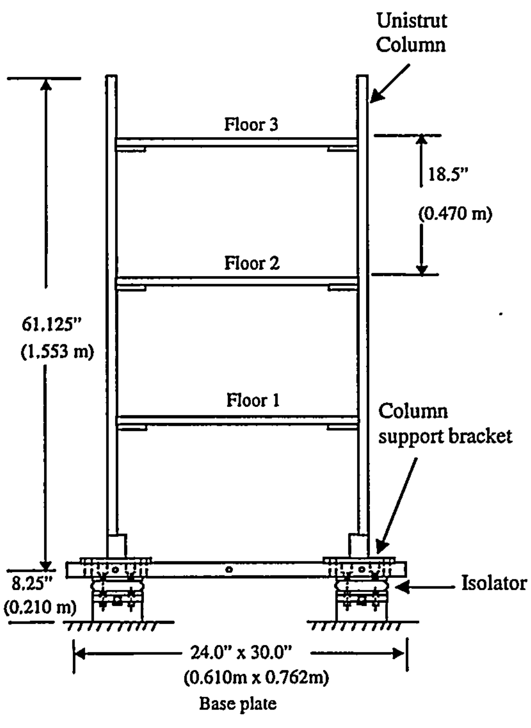

Figure 1. Assembled frame structure, out of plane shaking (not to scale).

3. DATA ACQUISITION AND CLEANSING:

The structure was instrumented with 24 piezoelectric accelerometers, two per joint (see Figure 2). Accelerometers were mounted on blocks glued to the floors and with wax on the Unistrut columns. This configuration allowed relative motion between the column and the floor to be detected. The nominal sensitivity of each accelerometer was 1 V/g. Additionally, a force transducer was mounted between the stinger and the base plate. This force transducer was used to measure the input to the base of the structure. A commercial data acquisition system controlled from a laptop PC was used to digitize the accelerometer and force transducer analog signals. A diagram of the data acquisition system is shown in Figure 3.

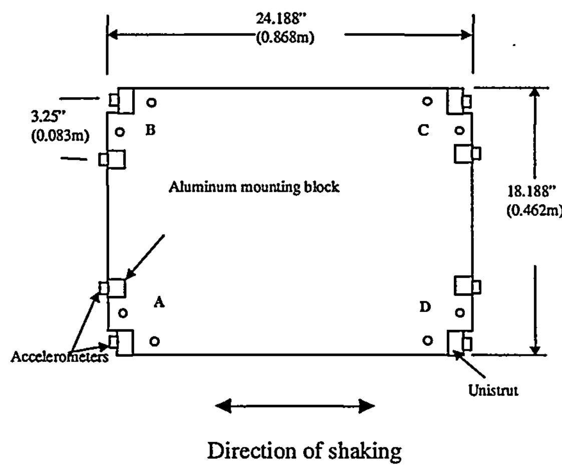

Figure 2: A typical floor plan showing sensor locations.

Before recording each time history measurement, frequency response functions were calculated using five averages. A Hanning window was applied to the time histories used in this averaging process. The frequency response functions and corresponding coherence function plots were used to initially examine the data in a qualitative manner. This inspection was performed as part of the data cleansing process in order to determine if a problem with the sensing system had occurred.

Data that were analyzed in the feature extraction and statistical modeling portion of the study were the acceleration time histories. For this type of measurement, the time histories were sampled at a rate of 1024 samples/s. A uniform window was specified for these measurements.

A baseline undamaged data set was recorded before and after damage was introduced to the structure. Before acquiring each data set, the pressure on the air mounts was inspected, the bolt torques throughout the structure were verified and the accelerometers were also inspected for proper mounting. Damage was introduced by loosening or removing bolts at the joints as summarized in Table 1. Additionally, operational variability was introduced by varying the shaker input level.

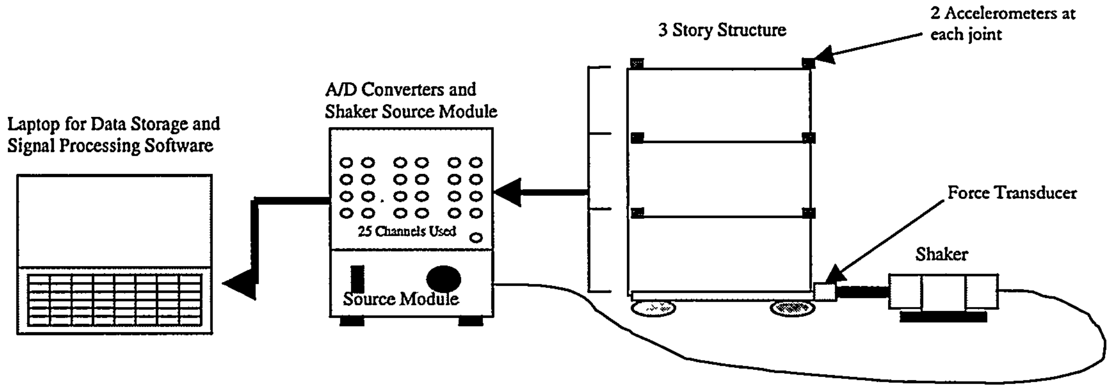

Figure 3: Schematic of Data Acquisition System and Test Structure.

Each time history was normalized by subtracting their respective mean values and dividing by their standard deviations. This data normalization process was used to minimize any shifts caused by DC offsets and to minimize shaker amplitude dependence.

4. FEATURE EXTRACTION:

Because of the accelerometer placement, the relative difference between adjacent column and plate acceleration time histories should demonstrate movement at the joint. If the plate is securely bolted to the bracket, both accelerometers should provide similar readings . If damage is introduced at a joint, the adjacent accelerometers should exhibit some quantifiable difference in their readings. For this reason the difference between the time histories measured on the column and on the plate at every joint was examined. An AR model was then fit to this difference. Residual errors between actual time history differences and predicted differences were computed. These residual errors were the damage-sensitive features developed for this study. Because the AR model is a linear predictive model, it was assumed that residual errors from this model applied to a nonlinear, or damaged, case would be greater than when the linear model was applied to the intact, linear structure. Also, it was assumed that the largest changes in residual error would be associated with the damaged joint. Statistical methods were applied to the residual errors to quantify when changes in this feature were significant.

Table 1: Test Cases

Description	Excitation Level (Volts) Random Vibration	Damage		# Data Sets/ Excitation Level
		Location	Amount	
Undamaged Set 1	2, 5, 8	N/A	N/A	10
Damage Case 1	2, 5, 8	1C	Removal of 2 bolts from plate	5
Damage Case 2	2, 5, 8	1C	Removal of 4 bolts from plate and bracket	5
Undamaged Set 2	2, 5, 8	N/A	N/A	10
Damage Case 3	2, 5, 8	3A	Removal of 2 bolts from plate	5
Damage Case 4	2, 5, 8	3A	Removal of 4 bolts from plate and bracket	5
Undamaged Set 3	2, 5, 8	N/A	N/A	10
Damage Case 5	2, 5, 8	1C, 3A	Removal of 2 bolts from plate from each location	5
Damage Case 6	2, 5, 8	1C, 3A	Removal of 4 bolts from plate and bracket from each location	5
Undamaged Set 4	2, 5, 8	N/A	N/A	10
Damage Case 7	8	1C	Untie Bolt (hand tied)	10
Damage Case 8	8	1C	Torque at 5 foot-pounds	10
Damage Case 9	8	1C	Torque at 10 foot-pounds	10
Undamaged Set 5	2, 5, 8	N/A	N/A	10

The AR model used in this study is :

$$x_i = \sum_{j=1}^{n} x_{i-j}\alpha_j + \varepsilon_i \tag{1}$$

where n is the model order, α's are coefficients that weigh previous relative response measurements, x, and ε is the residual error term. This model is then fit to the time history differences at each joint and alpha coefficients are derived by a least squares fit summarized below.

$$\begin{bmatrix} x_1 & x_2 & \cdots & x_n \\ x_2 & x_3 & \cdots & x_{n+1} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m-n} & x_{m-(n-1)} & \cdots & x_{m-1} \end{bmatrix} \begin{Bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{Bmatrix} = \begin{Bmatrix} x_{n+1} \\ x_{n+2} \\ \vdots \\ x_m \end{Bmatrix} \tag{2}$$

$$\{\alpha\} = \left([x]^T[x]\right)^{-1}[x]^T\{x\} \tag{3}$$

Where m is the number of data points that were fit. Alpha values are computed using data from one undamaged case and are then applied to data from the other cases, both damaged and undamaged models.

The order of the AR model, n, is determined by using a partial auto-correlation function [3]. Successive AR models of increasing orders are fit to the data and the magnitude of the last alpha values from these various models are plotted. The point at which the alpha values fall below a specified tolerance is selected as the order of the AR model. For this study the tolerance was set at $1/\sqrt{m}$. Figure 4 shows a plot of the last AR coefficient vs model order. Based on this analysis an AR model of order 44 was chosen.

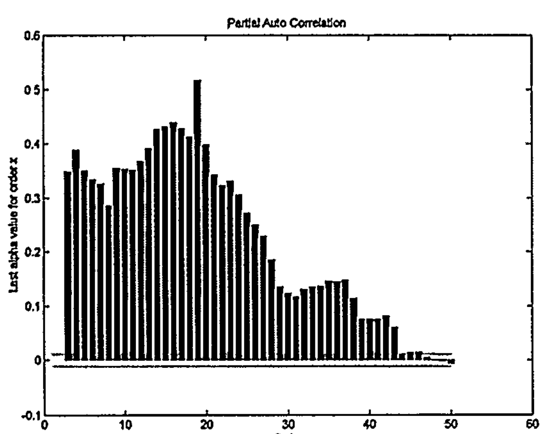

Figure 4: Partial auto correlation of an undamaged, low-level test. The order chosen for this AR model was 44.

5. STATSTICAL MODELING

Statistical process control (SPC) was used to establish when a significant change in the damage-sensitive feature had occurred. The residual errors of the AR model fit to the relative acceleration responses, $x(t)$, measured at each joint when the structure is in good condition will have some distribution with mean, μ, and variance, σ^2. If the structure is damaged the mean, the variance, or both might change. Statistical process control provides a framework for monitoring future residual error values and for identifying new data that are inconsistent with past data.

If the mean and standard deviation of the residual errors are known are known, a control chart is constructed by drawing a horizontal line at μ and two more horizontal lines representing the upper and lower control limits. The upper limit is drawn at $\mu + k\sigma$ and the lower limit at $\mu - k\sigma$. The number k is chosen so that when the structure is in good condition a large percentage of the observations will fall between the control limits. In this study the values of k were determined in a heuristic manner from observations of numerous training data sets.

As each new measurement is made, it can be plotted versus time or observation number. If the condition of the structure has not changed, almost all of these measurements should fall between the upper and lower control limits, the exact percentage being determined by the choice of k. In addition, there should be no obvious pattern in the charted data; e.g. there should not be a repeated pattern of 5 observations above the mean followed by 5 observations below the mean. If the structure is damaged there might be a shift in the mean acceleration, which could be indicated by an unusual number of charted values beyond the control limits. Plotting the individual measurements on a control chart is referred to as an X–chart [4].

Note that observing an unusual number of observations outside the control limits does not imply that the structure *is* damaged but only that something has happened to cause the distribution of the current acceleration measurements to change. If data outside the control limits cannot be accounted for by operational or environmental factors, the structure should probably be inspected for damage.

To detect a change in the mean of the residual errors, an intuitively appealing idea is to form rational subgroups of size p, compute the sample mean within each subgroup and chart the sample means. The centerline for this control chart will still be μ but the standard deviation of the charted values would be $\sigma/\sqrt{p}$. Therefore, the control limits would be placed at $\mu \pm k\sigma/\sqrt{p}$. This type of control chart is referred to as an X-bar chart, see [4].

The subgroup size p is chosen so that observations within each group are, in some sense, more similar than observations between groups. If p is chosen too large a drift that may be present in the mean can possibly be obscured. An additional motivation for charting sample means, as opposed to individual observations, is that the distribution of the sample means can, by an application of a central limit theorem, be approximated by a normal distribution. For this study $p = 4$. Control limits were set at three standard deviations from the mean.

After observing numerous training data sets, the following threshold limits were established for classifying the residual errors from the AR predictions of the relative acceleration values at a joint. If a joint had less then 10% outliers, it was considered to be in control and undamaged. An example of such a condition is shown in Fig. 5. When the residual errors produced between 10% and 80% outliers, a change in the operational conditions had taken place, but damage was not present. An example of such a response is shown in Fig. 6. Those joints that had 80% outliers or more were considered to be damaged. Figure 7 shows the results from a damaged joint. This criterion could identify damage from the most severe cases down to hand tightening of bolts. However, this criterion could not identify bolts with torques of 5 and 10 foot-pounds, as these torques were tight enough to prevent relative motion of the joints for the applied excitation levels.

6. BLIND TEST RESULTS

A series of "blind" tests were performed in addition to the initial series of tests described above in Table 1. The "blind" tests involved one group member taking data and introducing damage and operational variability that was unknown to the rest of the group. After the data was recorded, the other group members then tried to locate the damage using the algorithms developed above. The operational variability included rotating the shaker position, such that it was shaking the base perpendicular to the accelerometer measurement directions. Variability also including setting masses on the floors of the structure. Very good results were obtained. In almost all cases there were no false-positive indications of damage caused by these sources of variability. Some joints did appear to be 10%-80% outlier range, indicating an operational change, but the threshold value previously set for damage indication was not exceeded. Ninety-seven percent of the joints examined in all test cases were correctly diagnosed!

7. CONCLUSIONS AND FUTURE WORK:

The damage detection method tested was successful in correctly identifying damage in almost all cases. The residual errors from AR models fit to the relative accelerations measured at a joint proved to be insensitive to operational variability in the system, and very sensitive to damage. This statement is based on the 97% success rate obtained in the blind tests that were performed, which included both operational variability associated with the undamaged structure and damage introduced at the joints.

Future work should include more extensive testing of the different types of variability and their effects on the model. Also, more work is needed to establish the threshold values that are used to indicate damage. In actual applications it is doubtful if one will have the luxury of observing training data from a damaged condition. Therefore, the somewhat heuristic methods of establishing threshold values used in this study will have to be made more rigorous.

This study was undertaken to conceptually demonstrate a vibration-based damage detection system for structural connections in building subject to earthquakes. With the cost of current data acquisition technology it would be considered prohibitively expense to put two accelerometers at every joint in an *in situ* steel frame structure. However, current developments in MEMS sensing technology (see www.imi-mems.com) coupled with recent developments in wireless data acquisition and transmission systems [5] indicate that instrumenting every joint in a structure will be economically feasible in the near future. The results of this study show that there is the potential to identify and locate the damage at a joint if such an instrumentation system was put in place.

8. ACKNOWLEDGEMENT

The funding for this work was provided by The Department of Energy for the First Annual Los Alamos Structural Dynamics Summer School.

9. REFERENCES

1. "*Steel Moment Frames After Northridge: Special Issue of the J. of Structural Eng.*," David Darwin, Edt.,**126**, No. 1, 2000
2. Farrar, C. R. and S. Doebling, "The State of the Art in Vibration-Based Structural Damage Identification, A Short Course." Los Alamos Dynamics, Ltd. 2000.
3. Sohn, H, C. R. Farrar, N. F. Hunter and K. Worden "Applying the LANL Statistical Pattern Recognition Paradigm for Structural Health Monitoring to Data from a Surface-Effect Fast Patrol Boat," Los Alamos National Laboratory report LA-MS - ???, 2000.
4. Montgomery, D. C., *Introduction to Statistical Quality Control*, John Wiley & Sons, Inc., New York, 1996.
5. Straser, E. "A Modular, Wireless Damage Monitoring System for Strucutres," Doctoral Dissertation, Civil Engineering Dept., Stanford University, 1998.

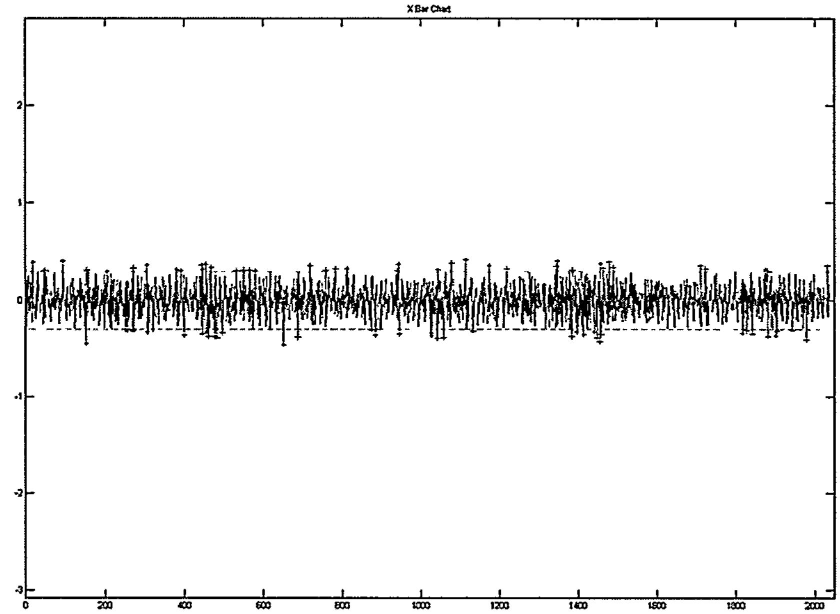

Figure 5. X-bar control chart corresponding to an undamaged joint. Plus marks indicate points outside the control limits.

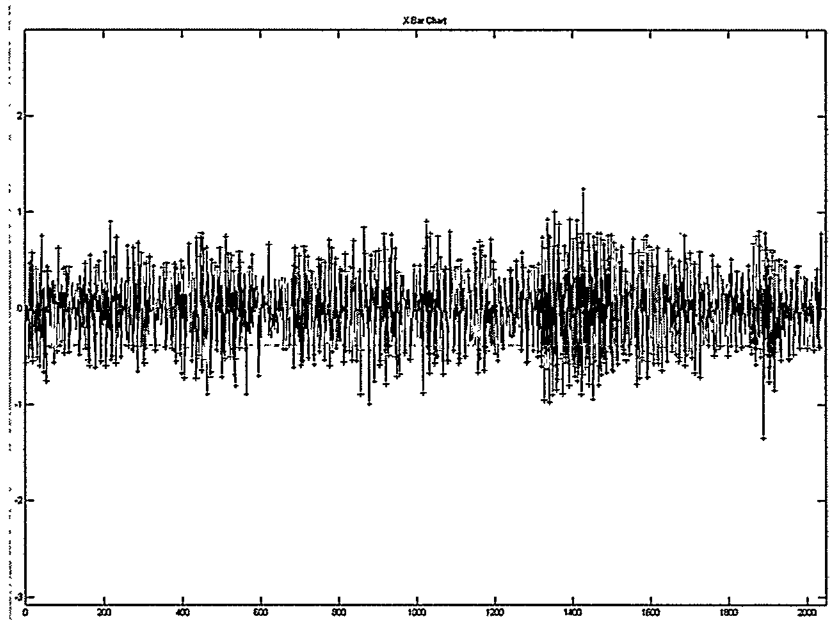

Figure 6. X-bar control chart corresponding to an undamaged joint nut with operational variability present. Plus marks indicate points outside the control limits.

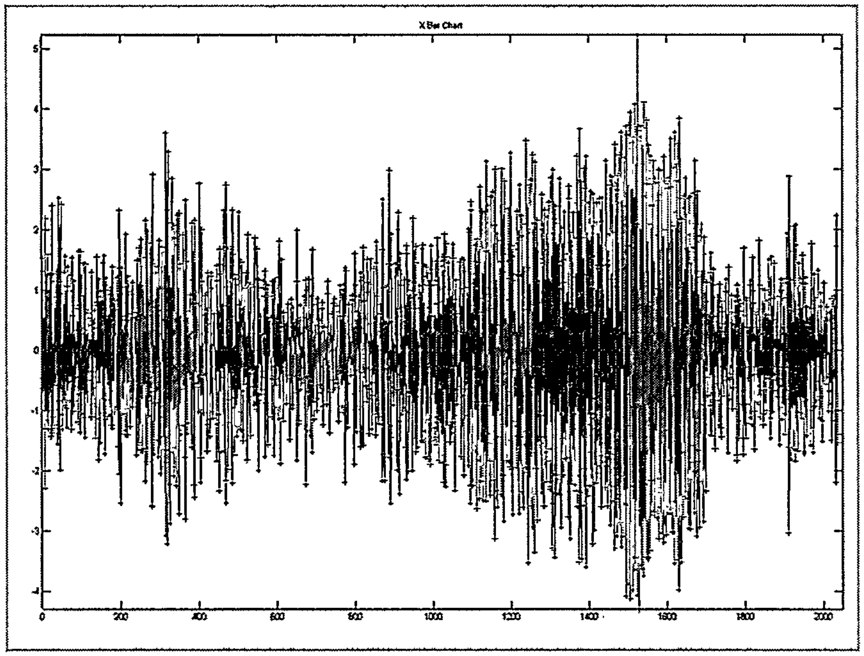

Figure 7. X-bar control chart corresponding to a damaged joint. Plus marks indicate points outside the control limits.