Bridge Monitoring Utilizing Smart Portable Sensing System

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Abstract

Natural Frequencies of structures is an elegant intrinsic property that is essential for many Civil Structural applications, as Structural Health Monitoring and Simulation Modeling. The physically tangible relation between the frequency of the structures and its dynamic characteristics was the impetus for using different time/frequency based methods to quantify this fundamental property. Unfortunately, the disruption effect of noise requires incorporating advanced sensors, that provide signals with a low noise-intensity, to accurately identify the fundamental frequencies of the structure. This article solves this bottleneck via exploiting the Stochastic Resonance (SR) phenomena to extract the fundamental frequencies of a bridge using an acceleration recorded by a conventional portable sensor as the sensor implemented in small portable accelerometer. The portable accelerometer device has an M9 motion coprocessor designed mainly for tracking human activities. Human activities have an exaggerated amplitude when it is compared to the structural responses. Therefore, if an iPhone device is used to record the response of the structure (for example a bridge) the structure response will be swamped by severe surrounding noise because of its small amplitude. Therefore, in this vein, the SR phenomena has been employed to use rather than suppress the noise to magnify the feeble bridge response in the recorded acceleration and hence identify the corresponding frequency. The fidelity of the proposed approach has been verified using the data of a field experiment. The bridge frequencies are identified first using conventional vibration analysis, thereafter, the portable accelerometer has been attached to the bridge rail to record the bridge vibration under the passing traffic. The recorded data has been processed using a new Developed Underdamped Pinning Stochastic Resonance (DUPSR) technique to quantify the bridge frequency.

Keywords: Stochastic Resonance, Bridge Health Monitoring, Identifying Bridge Frequency, Extraction of feeble bridge response

1. INTRODUCTION

Bridges are an integral part of transport facility, and its safety is essential for preserving the safety and the functionality of the roadway network. Most of the bridges on the transport network have an approximate age of 40 years, this in tandem with the unhindered use of highway facilities as well as the dramatic increase in freight volumes is conducive to suspecting the safety of these structures [1-3]. The FHWA has declared that approximately 11% of the bridges on the transport network has been classified as structurally defective bridges [1]. Further, and most perilous, there are almost 260 million trips over deficient bridges every day [1]. Therefore, the structural safety assessment of bridges on the road network has become an essential area of research. To this end, the Structural Health Monitoring (SHM) has emerged as an intriguing field of research, where anomalous structural behaviors are being predicted by monitoring the change in the dynamic characteristics of the structure [3, 4]. The intuitive SHM approach is to use the structural vibrations to quantify the dynamic properties of the bridge which are the focus of attention [5]. The fundamental frequencies of the bridge are considered an archetypal character that can be utilized in this vein [6-8]. The simplest approach for estimating the fundamental frequencies of the structure is the peak-picking (PP) method [9, 10], where the frequencies with the highest power in the signal spectrum are ascribed to the fundamental frequencies of the structure. The common technique for transferring the data from the time domain to the frequency domain is Fast Fourier Transform (FFT), which has been widely and successfully employed in many SHM studies [11-32]. However, FFT provides information in the frequency domain only, and cannot depict the signal's attribute along the sample's time. This regard is essential if several dominant frequencies occur at different time intervals, where it is necessary to discriminate between them. Therefore, some authors have investigated alternative techniques that are characterized by its mutual complementation of time and frequency domain analysis. Wavelet Transform has been introduced as a prominent tool in this domain, and it has been employed by many authors to identify the fundamental frequencies of the structures [33-35]. Further, some authors have successfully identified the fundamental bridge frequencies indirectly from a passing vehicle responses using the Wavelet Transforms [36, 37]. In another vein, Brincker, Zhang and Andersen [38] have introduced the Frequency Doman Decomposition (FDD) as an output only modal analysis technique, in which the frequencies and the mode shapes could be extracted from the vibration responses of the structure. The elegant property of this technique is its potential to detect close modes of vibrations. In tandem with these techniques, a number of studies have investigated several signal processing tools, as Discrete Fourier Transform (DFT) , Blind Source Separation (BSS), Hilbert-Hwang Transform (HHT), Empirical Modal Decomposition (EMD), etc. [39-42]. However, these techniques totally fail if the signal is contaminated by a severe background-noise, and hence non-specialized tools as smartphones are not practical to be used for SHM yet. The need and the appetite for smart phone industry, its wide spread, and its ease of use, was a strong motivation for the authors to investigate exploiting them for Structural Health Monitoring of civil structures. Therefore, the authors have investigated an alternative processing tool that possesses the capability to identify feeble signal disrupted by a fiercer background noise, by using rather than suppressing the noise. This phenomenon is known as Stochastic Resonance (SR).

Stochastic Resonance (SR) is a model for weak response detection from the response of a global system. It is one of the firm mathematical models that is manifest in nonlinear systems whereby generally feeble input information (such as a weak signal) can be amplified and optimized by recruiting the noise in the signal. The approach was introduced by Benzi, Sutera and Vulpiani [43] as an explanation of the observed periodicity in the ice ages on earth. Since then, the approach has spurred interest, and many researchers have investigated applying this hypothesis in different disciplines [44].

This paper is investigate implementing the SR in the Civil Structural Health Monitoring domain. The article introduces a the Under Damped Pinning Stochastic Resonance as a model of analyzing structures responses (UPSR). Afterward, the approach will be implemented to extract the bridge frequency from an acceleration recorded using an iPhone device. The approach will be explored experimentally utilizing the data of two full scaled field tests.

2. UNDERDAMPED PINNING STOCHASTIC RESONANCE (DUPSR)

The conventional model of SR represents a heavily damped mass movement in a symmetric double potential well *V(x)*. The mass is moving due to a fluctuating force *f* contaminated by a noise having an intensity *D.* Thus the transition between the two potential minima is expressed by Kramers rate as follows [44]:

$$r_k = \frac{\omega_0 \omega_b}{2\pi\gamma} \exp\left(-\frac{\Delta V}{D}\right) \tag{1}$$

where ω_0 is the angular frequency at potential minima, ω_b is the angular frequency at the top of the barrier ΔV is the barrier height and *D* is the noise intensity. The application of a weak periodic force *f* will tilt the potential well up and down, however, the intensity of the force is not big enough to let the particle surmount the potential barrier and move from one potential to the other one. In contrast, the noise results in a fiercer hopping for the particle around the potential minima. By tuning the noise periodicity (or changing the potential geometry (*V(x)*)), the hopping induced by the noise can be synchronized with the weak periodic forcing. Since noise in most cases is the uncontrollable term, the SR invests its double potential well (*V(x)*) to synchronize the hopping between potential minima. The dynamical equation of this type of SR is shown in Eq. (2).

$$\frac{d^2x}{dt^2} = -V'(x) - \gamma\frac{dx}{dt} + \{s(t) + n(t)\} \tag{2}$$

where x is the targeted weak property, $V'_{(x)}$ is the derivative of the potential well (*V(x)*), γ is the system damping, and $\{s(t) + n(t)\}$ is the input signal mixed with noise, where $s(t)$ is the pure signal and $n(t)$ is the noise which is function of the intensity *D*. Conventional SR (CSR) models adopt a polynomial potential function $V_{(x)}$, which is adequate to represent bi-stable systems, as shown below [45];

$$V(x) = -\frac{a}{2}x^2 + \frac{b}{2}x^4 \tag{3}$$

The UPSR adopt a different potential well which has the capability to represent both mono-stable and bi-stable systems, further, this potential model showed to work properly with underdamped systems [45]. The potential function of the UPSR model is;

$$V(x) = V_0 - V_d\left(\exp\left(-\frac{(x+x0)^2}{L^2}\right) + \exp\left(-\frac{(x-x0)^2}{L^2}\right)\right) \tag{4}$$

where, V_0 is a constant and will not be considered since it will turn into zero after differentiating the function as shown in Eq. (2), V_d is the depth of the pinning, L is the length between the two pinning $\pm x0$ is the center of each pinning. Unlike CSR, the potential function of the UPSR is governed by three parameters (i.e. V_d, *L* and *x0*) ascribing to efficient representation for mono-stable and bi-stable systems. Zhang, He and Kong [45] provide a numerical discretization for Eq. (2) considering the potential function given in Eq. (4). The numerical solution is illustrated in the following equation;

$$V'(x) = \frac{dV(x)}{dx} = -V_d\left(\frac{2(x+x0)}{L^2}\exp\left(-\frac{(x+x0)^2}{L^2}\right) + \frac{2(x-x0)}{L^2}\exp\left(-\frac{(x-x0)}{L^2}\right)\right)$$

$$x(0) = 0; \tfrac{dx}{dt}(0) = 0$$

For i = 2 : end

$$\begin{aligned}
k_{x1} &= \frac{dx}{dt}(i-1) \\
k_{y1} &= -V'\big(x(i-1)\big) - \gamma\frac{dx}{dt}(i-1) + \{s(i-1) + n(i-1)\} \\
k_{x2} &= \tfrac{dx}{dt}(i-1) + \tfrac{h}{2}k_{y1} \\
k_{y2} &= -V'\left(x(i-1) + \frac{h}{2}k_{x1}\right) - \gamma\left(\frac{dx}{dt}(i-1) + \frac{h}{2}k_{y1}\right) + \{s(i-1) + n(i-1)\} \\
k_{x3} &= \tfrac{dx}{dt}(i-1) + \tfrac{h}{2}k_{y2} \\
k_{y3} &= -V'\left(x(i-1) + \frac{h}{2}k_{x2}\right) - \gamma\left(\frac{dx}{dt}(i-1) + \frac{h}{2}k_{y2}\right) + \{s(i) + n(i)\} \\
k_{x4} &= \tfrac{dx}{dt}(i-1) + hk_{y3} \\
k_{y4} &= -V'(x(i-1) + hk_{x3}) - \gamma\left(\frac{dx}{dt}(i-1) + hk_{y3}\right) + \{s(i) + n(i)\} \\
x(i) &= x(i-1) + \frac{h}{6}(k_{x1} + 2k_{x2} + 2k_{x3} + k_{x4}) \\
\frac{dx}{dt}(i) &= \frac{dx}{dt}(i-1) + \frac{h}{6}\big(k_{y1} + 2k_{y2} + 2k_{y3} + k_{y4}\big)
\end{aligned} \tag{5}$$

where *h* is the calculation step which equals *R*dt* (*dt* is the time step and *R* is a rescaling factor). And *x* is the targeted weak property, in this case the weak signal. As previously noted, the weak signal will be extracted by tuning the potential function until the noise is synchronized with the weak signal *x*. This state (i.e. when the signal and the noise are tuned) is characterized by having the highest Signal to Noise Ratio (SNR). Therefore, Eq. (5) will be repeated several times for different potential parameters (i.e. V_d, *L, and x0*) until this condition is achieved. The SNR is calculated as follows [45];

$$SNR = 10\log_{10}\frac{A_s}{\sum_0^{N/2} A_i} \tag{6}$$

where A_s is the power of the targeted signal (i.e. the original one not the extracted *s(t)*), and $\sum_0^{N/2} A_i$ is the summation of the power of the input signal.

The process goes in an iterative manner by updating the potential parameters to attain the highest SNR ratio for the signal

3. EXTRACT THE BRIDGE FREQUENCY FROM AN IPHONE DEVICE.

The field test was carried out on a skewed prestressed bridge consists of three simply supported spans. The bridge is located on HWY 113 in Bartow County, Atlanta Georgia between Covered Bridge Rd and Dry Creek Rd. The bridge has a span of 21.3 m from the centers of the two supports. The bridge deck is a reinforced concrete slab rested on five pre-stressed reinforced concrete girders. The roadway facility consists of two-lane one-way traffic and one shoulder to the right side of the traffic. The bridge instrumentations were installed on the first span from the traffic direction as shown in Figure 1. Each girder was equipped with three Silicon Designs 2012-002 accelerometers spaced equally along the girder. The accelerometers were connected to a wireless sensor board to transmit the data to the DAQ station which lies under the bridge. Beside the accelerometers, a 90mm strain gages were installed and also were connected to wireless board. In the middle of the girders, magnetostrictive displacement sensors were installed to measure the displacement of the bridge. Further, the bridge's barriers were equipped with five laser emitters, which are utilized to exactly determine the time when a vehicle enters and exits the bridge [46, 47].

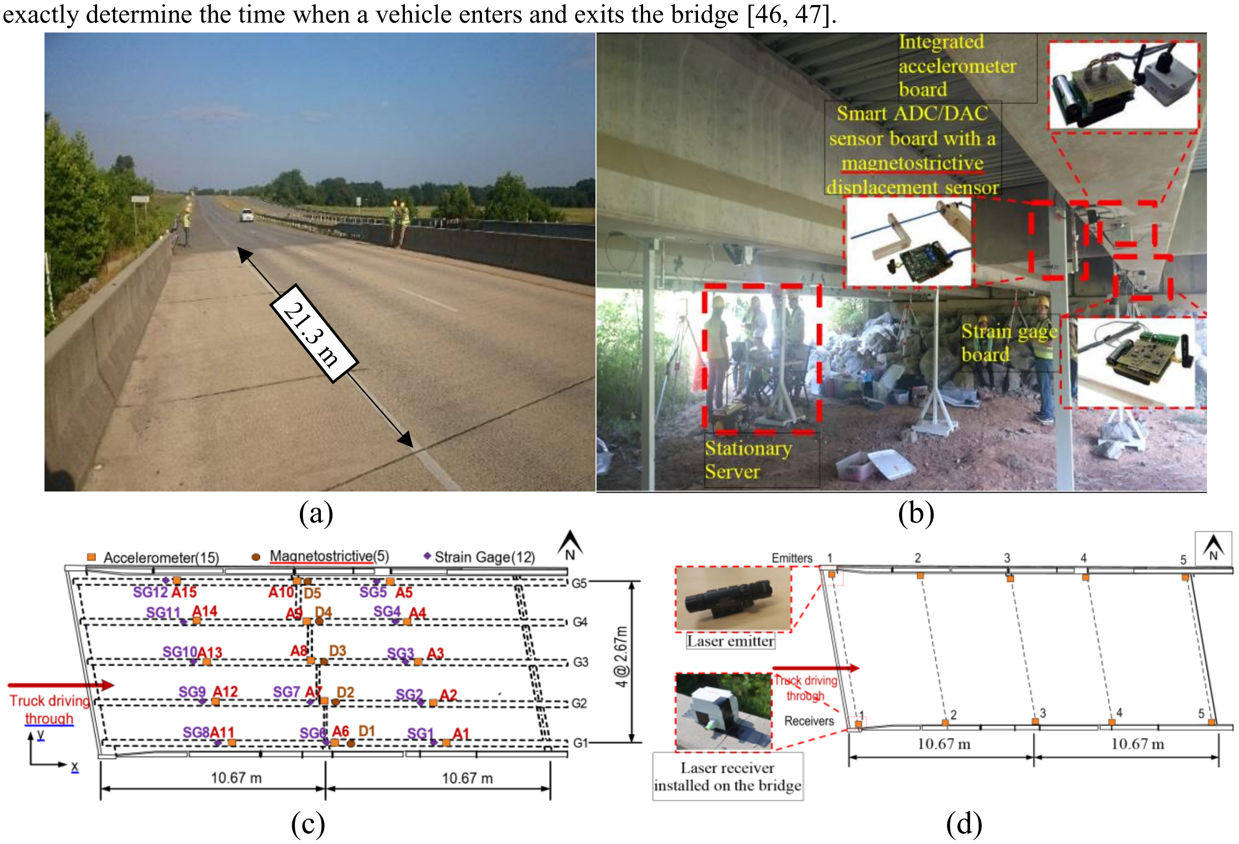


Figure 1 Field instruemtnation (a) Bridge Over View (b) Bridge Instruemntation (c) Location of the instrumentation on the bridge girders (d) laser emitters and recivers.

First, the bridge frequencies have identified using a vibration test. The test uses the ELECTRO-SEIS Long Stroke Exciter vibration shaker, wiliest the bridge acceleration was recorded. The scanning frequency was set to 100 Hz, while the frequency resolution was $6.25\text{x}10^{-3}$ Hz. The traffic was blocked during the test as recommended by Yang, Cheng and Chang [48]. The test was repeated twice, and the spectrums are illustrated in Figure 2. The average frequencies are listed in Table 1.

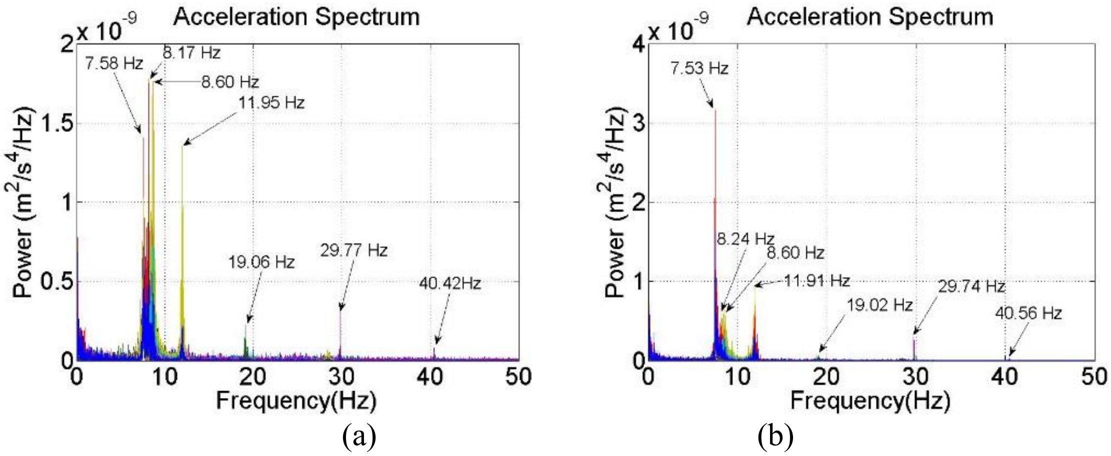
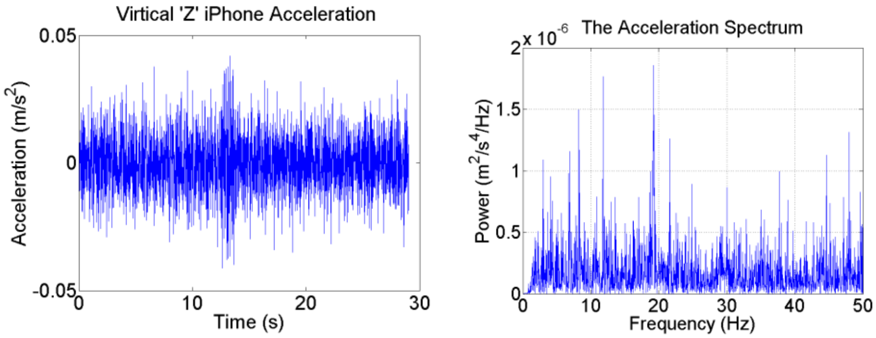


Figure 2 Acceleration Spectrum of the Bridge Vibration (a) Test 1 (b) Test 2

Table 1 Average bridge Frequency (Hz)

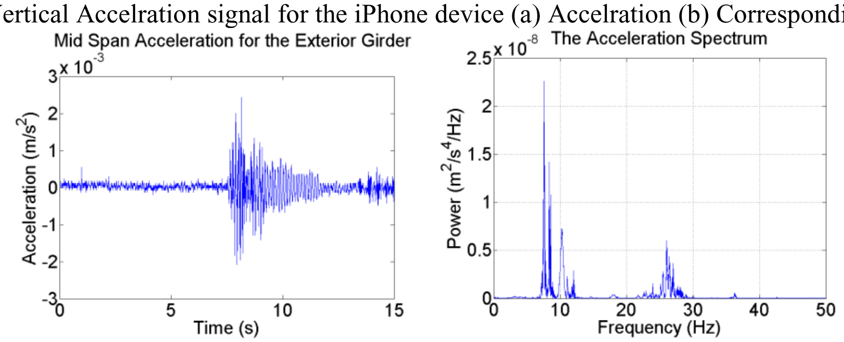
1st	2nd	3rd	4th	5th	6th
7.56	8.4	11.93	19.04	29.76	40.49

The phone used to record the bridge response is iPhone 6s, which has an M9 motion coprocessor connected to an accelerometer, compass, gyroscope, and barometer for a wide range of activity tracking. To record the acceleration, the authors used the VibSensor® program from the App Store®. The program records the iPhone sensors reading at 6 degrees of freedom, rotation about three axes and displacement at three axes. The device has been simply placed over the bridge barrier and has been fixed using a duct tape to maintain relatively consistent movement between the device and the bridge. The data has been recorded during normal traffic operation. A sample for the recorded z acceleration is illustrated in Figure 3 As shown in the plot, the spectrum is raucous and is showing many peaks, making it difficult to identify the bridge frequencies. Prior the implementation of the UPSR technique, the quality of the recorded signal will be estimated by identifying the intensity of the noise in the signal. The noise intensity will be represented by the Signal to Noise Ratio (SNR). The signal SNR can be calculated applying Equation (6), where As is the power of the original pure signal and $\sum_0^{N/2} A_i$ is the summation of the power of the corrupted signal. The pure signal is the acceleration that was recorded at the mid-span by the Silicon Designs accelerometers, while the corrupted signal is the signal recorded by the iPhone. It is noteworthy to mention that higher SNR refers to a pure signal, while corrupted signal provides lower SNR values. The SNR for this signal has been found equal to -80 dB. This is evident in the acceleration plots, where the magnitude of the bridge acceleration is perturbing between ± 0.003 m/s^2, while the iPhone acceleration record fluctuates between ± 0.03 m/s^2 which is conducive to the plausibility of the calculated SNR value. The Silicon Designs accelerometers provides a signal with SNR up to 90dB. This numbers demonstrate the dramatic difference between the sensitivity of the two devices.



(a) (b)

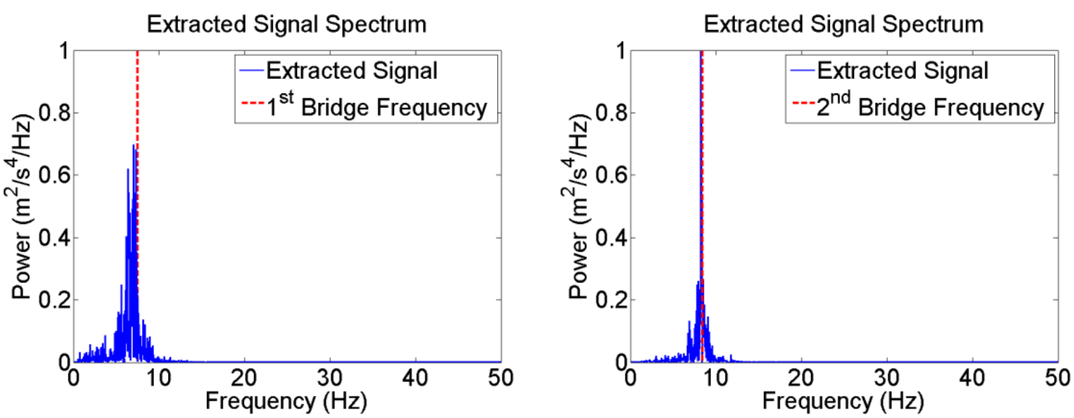
Figure 3 Vertical Accelration signal for the iPhone device (a) Accelration (b) Corresponding Spectrum



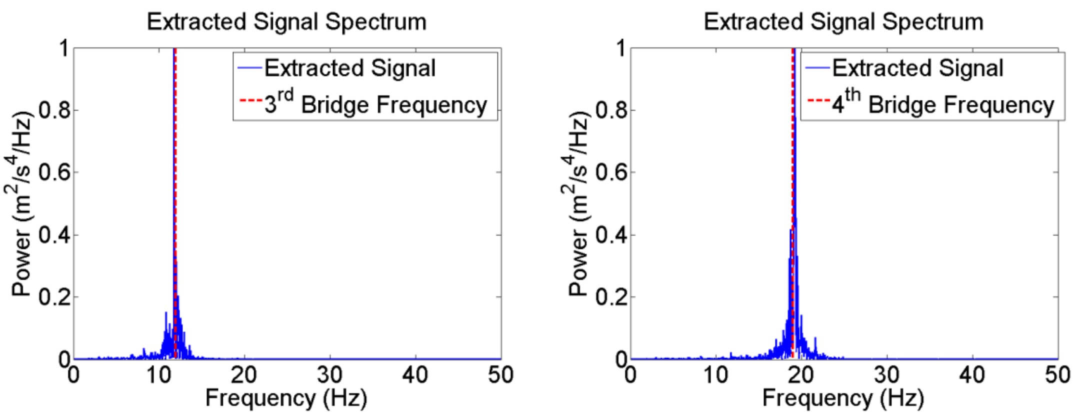
(a) (b)

Figure 4 Vertical Bridge Accelration recorded using the Silicon Designs accelerometer (a) Accelration (b) Corresponding spectrum.

The signal has been processed using proposed UPSR method. The values of V_d, $x0$ and L have been increased until several peaks have become evident in the plot. The values of $x0$ and L that provides the highest SNR have been used to extract the corresponding signal, and hence identify the signal frequency. The spectra of the extracted signals are plotted in. The first frequency is deviated a from the original bridge frequency, while the second and the third frequencies showed good agreement with the bridge frequency. The signal of the selected potential parameters has been extracted and its spectrum is shown in Figure 5(d). This peak refers to the fourth frequency for the studied bridge. As the figures show, the approach successfully identified the first four bridge frequencies. It is evident that the first frequency has the highest error, the authors presume that this is due to the location of the iPhone, where this spot is excreted more by lateral modes of vibration. However, a good interpretation for this attribute is persist.



(a) (b)



(c) (d)

Figure 5 Extracted frequencies from the DUPSR plot

4. CONCLUSION

This paper presents a new technique that employs the Stochastic Resonance phenomena to extract the bridge frequencies from a noisy signal collected with a commercial iPhone device. Stochastic Resonance is a phenomenon refers to the detection of a feeble property in a raucous domain by the aid of noise. The article has explored the UPSR in extracting a weak signal disrupted by a sever background noise, and the results have revealed a successful identification for the frequency of the signal. The technique fidelity has been asserted using the data of a full scale field test. First, a vibration test was conducted to extract the fundamental bridge frequencies. Afterward, the iPhone was placed on the bridge rail and was fixed by a duct tape. The iPhone recorded the bridge acceleration while regular traffic was traversing the bridge. The recorded signal has been processed using the developed DUPSR technique and successfully identified the first four frequencies of the bridge. The first frequency has shown to be subjected to appreciable error which may be a factor of the device location, however the error is less than 6%. The results of this study is conducive to the fidelity of the DUPSR technique in identifying the feeble information from a raucous response.

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