Characterization of Real-world Vibration Sources with a View Towards Optimal Energy Harvesting Architectures

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ABSTRACT

A tremendous amount of research has been performed on the design and analysis of vibration energy harvester architectures with the goal of optimizing power output; most studies assume idealized input vibrations without paying much attention to whether such idealizations are broadly representative of real sources. These "idealized input signals" are typically derived from the expected nature of the vibrations produced from a given source. Little work has been done on corroborating these expectations by virtue of compiling a comprehensive list of vibration signals organized by detailed classifications. Vibration data representing 333 signals were collected from the NiPS Laboratory "Real Vibration" database, processed, and categorized according to the source of the signal (e.g. animal, machine, etc.), the number of dominant frequencies, the nature of the dominant frequencies (e.g. stationary, band-limited noise, etc.), and other metrics. By categorizing signals in this way, the set of idealized vibration inputs commonly assumed for harvester input can be corroborated and refined, and heretofore overlooked vibration input types have motivation for investigation. An initial qualitative analysis of vibration signals has been undertaken with the goal of determining how often a standard linear oscillator based harvester is likely the optimal architecture, and how often a nonlinear harvester with a cubic stiffness function might provide improvement. Although preliminary, the analysis indicates that in at least 23% of cases, a linear harvester is likely optimal and in no more than 53% of cases would a nonlinear cubic stiffness based harvester provide improvement.

Keywords: energy harvesting, vibration classification, vibrations

1. INTRODUCTION

In order to extract sufficient power for a given application, vibration energy harvesters (VEHs) are typically high Q (10-50) resonant oscillators. Thus, their operating bandwidth can be quite narrow. This has motivated an extraordinary amount of research work on methods to increase the operating bandwidth of VEHs [1–5]. Such methods include multi-mode dynamic structures, active frequency tuning by both mechanical and electrical means, and nonlinear dynamic structures. Of course, if the vibration source is dominated by a single stationary frequency, a linear oscillator based energy harvester is the optimal energy harvesting structure [6–9].

In the search for methods to improve the operating bandwidth of VEHs, careful examination and quantification of the types of vibrations that appear frequently in environments conducive to energy harvesting often becomes a secondary priority; to our knowledge, there has not been a systematic study of the prevalence of vibration sources geared towards determining which VEH structure would be most appropriate for a given source.

A typical approach to the treatment of vibration sources as seen in VEH research may involve any number of the following:

Oversimplification of the source description – of the sparse collections of vibration sources in the literature, many simplify the description of the vibrations down to only the spectral content of the vibration; that is, the component frequencies of a vibration signal and their amplitude, with limited discussion of vibration features[10,11]. Such simplifications omit key information about the vibration source, such as the consistency of the amplitude and frequency over the duration of the source signal, and the specific way in which those parameters vary over the length of the signal. The design of VEHs in

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the absence of such information is often suboptimal[12]. Beeby[13] does present the time varying nature of a limited set of vibration signals. One goal of this paper is to present and classify the important features of a broader set of vibration sources.

Create a vibration waveform for mathematical convenience – in some cases, it is mathematically convenient to subject a system model to a particular vibration waveform for the purpose of analytical analysis that might be difficult or impossible to carry out with more complex inputs. Such fabrications are often (but not always) performed with a source in mind – a single, stationary frequency of vibration for a machine source, for example, or a shifting frequency for a vehicle source – and may appear to be a plausible representation of some vibration source. Another mathematically convenient representation of source vibration is Gaussian white noise, band-limited white noise, or filtered white noise. However, when these vibrational input models are employed in the literature, a discussion regarding the conditions under which the proposed waveform accurately captures the salient properties of the source is often absent, rendering the applicability of such a source model unclear; in other words, the mathematically convenient source model may not be a valid model for the real sources upon which the model is based. The prevalence with which one may encounter the vibration source under consideration is also often ignored.; that is, a proposed waveform may model a real vibration signal very well, but such a signal may be so uncommon that the proposed waveform (and subsequent analysis) is of limited use [14–16].

Investigate a small sample of vibration sources – many studies simply look at a very small sample of vibration sources. Although this approach is, perhaps, more based in reality than creating a vibration signal for mathematical convenience, it makes it impossible to make broad claims about the nature of a vibration source and its relationship with the vibration waveform and, consequentially, the relationship between the nature of a vibration source and the expected performance of a particular VEH architecture [13,17].

The current study seeks to provide additional insight into the prevalence and characteristics of vibrations commonly encountered in the environment. A broad range of vibrations from the existing NiPS Laboratory "Real Vibration" database is classified using metrics that capture vibration properties that are relevant to VEH design. A preliminary analysis is then performed as a means to gain some initial insight into optimal architectures for common classes of vibrations.

2. METHODOLOGY FOR CLASSIFYING VIBRATIONS

The NiPS Laboratory "Real Vibration" database is a library of downloadable vibration signals collected from several types of acquisition kits [18].

One of the most commonly used acquisition devices, as reported by the signal metadata in the NiPS database, is an iPhone, and signals collected using an iPhone are uploaded via an iPhone application freely available to the public. Many of the vibration signals have been recorded and uploaded by unknown users, using the iPhone accelerometer as a sensor, and lack information on the conditions under which the vibration signal was recorded. Additionally, the specific iPhone model used to collect the data is generally not reported in the signal metadata, although all signals collected with an iPhone report a sampling frequency of 100Hz. Consequentially, many signals are not worth examination; there are numerous short signals on the database that clearly represent test uploads or calibrations, for example, or signals for which the reported sampling rate could not possibly resolve the source described in the metadata (e.g. attempting to resolve the sounds of an acoustic guitar). It thus stands to reason that an analysis that makes use of a database that freely allows for users to upload content as a source of vibration signals requires the judicious selection of a subset of signals hosted on the database in order to ensure that the analysis is capable of producing useful conclusions. Much of the efforts of this study concerned carefully examining each signal upload, using the associated sampling frequency and signal metadata to determine if the uploaded signal appears to be capable of capturing the salient vibrational characteristics of the source. As a result of this signal "qualification" process, many of the signals from the database were discarded from analysis in this study.

Each signal upload consists of 3 axes of vibrational data; linear acceleration of X, Y and Z, measured in units of g. Each of the 3 axes is treated as an independent signal for processing purposes. DC bias was removed from each signal axis by subtracting the mean value from the data. For each signal axis, spectrograms of using different cutoff frequencies and FFT window lengths were generated using the associated sampling frequency metadata, resulting in several spectrograms for each signal axis.

A discussion on the classification methodology requires establishing several definitions.

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2.1 Signal Sources

The "source" classification of a signal is a broad categorization of what kind of system produced the vibration.

The *Animal* source classification indicates that the vibration signal was produced by a living organism – typically a human, and typically during locomotion.

The *Machine* source classification indicates that the vibration signal was produced by something non-biological; typically, this is a machine or an appliance in operation.

The *Vehicle* source classification indicates that the vibration signal was produced by a vehicle – a machine capable of transporting human beings – during operation. The Vehicle classification supersedes the Machine classification when it can be determined that the machine which produced the signal is a vehicle during operation.

The *Structure* source classification indicates that the vibration signal was acquired from a static structure, such as a building, bridge, or tower.

The *Unknown* source classification indicates that it is not clear from where the vibration signal originates.

This vibration classifier is determined using both the title of the uploaded vibration file ("Airplane, light turbulence," for example) and the comments that are uploaded along with the vibration signal (continuing with the same example, "Boing [*sic*] 707, inflight light turbulence. Passenger armrest"). When the source of the vibration cannot be surmised with confidence, the signal is given the *Unknown* source classification.

2.2 Spectrogram Parameters

The entire NiPS database of vibration signals was downloaded and processed into spectrograms for each of the 3 axes, using several sets of parameters, generating several spectrograms per vibration signal.

There were two parameters that were varied in generating the spectrograms: the cutoff frequency (below which all spectral content of a signal was ignored) and the FFT (Fast Fourier Transform) "window" length.

A cutoff frequency was required in generating the spectrograms, as many of the signals contained high-amplitude, very low-frequency content that could not be removed by elimination of DC bias. It is suspected that this low-frequency content is caused by gradual changes in orientation of the acquisition device during recording; because the conditions under which the vibration signals were recorded are mostly unknown, one can only speculate as to a cause. Four cutoff frequencies were used to generate all spectrograms: 10Hz, 5Hz, 1Hz, and 0.25Hz.

The FFT window length was varied between 1s and 4s, resulting in a frequency resolution of 1Hz and 0.25 Hz, respectively. This was done to accurately resolve the small variations in frequency that one would expect in human walking data; consequentially, an FFT window of 4s was only used for signals that involve human locomotion.

In order to make dominant signals more apparent, a filtered technique was employed based in linear VEH theory. According to the Velocity Damped Resonant Generator (VDRG) model [19], the upper bound on average power output of a linear VEH subject to harmonic excitation is:

$$P_{avg} = \frac{A^2 m \zeta_e r^3}{\omega\left((1-r^2)^2 + \left(2r(\zeta_m+\zeta_e)\right)^2\right)} \tag{1}$$

where A is the input acceleration amplitude, m is the seismic mass, ζ_m is the mechanical damping ratio, ζ_e is the electrical damping ratio, and r is the frequency ratio; that is, the ratio of ω (the input frequency) to the harvester's natural frequency, ω_n. At resonance (i.e. $r = 1$), equation (1) reduces to

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$$P_{avg} = \frac{A^2 m\zeta_e}{4\omega(\zeta_m + \zeta_e)^2} \tag{2}$$

Using equation (2), it can be shown that the average power during resonance is maximum when $\zeta_m = \zeta_e$ [19].

Notice that the leading terms A^2 and ω in (1) and (2) are properties of the input alone. Determining dominant frequencies is a major component of the classification system presented in this study; thus, in order to make classification more straightforward, spectrograms filtered by only plotting frequency content that is greater than ½ the maximum value of A^2/ω in each FFT frame were plotted alongside unfiltered spectrograms; components of the input with large A^2/ω values have the potential to produce more power for a linear VEH than other signals within the input. This filtering process made "dominant" frequencies more distinct, resulting in easier classification of the signal. See 2.3 for more discussion on dominant frequencies, and section 3.1 for some example spectrograms and their classifications.

2.3 Signals with Distinct Dominant Frequencies

Knowledge of the frequencies at which the input power is concentrated has major implications on the design of a VEH architecture, and is therefore of critical importance in any classification scheme intended to shed light on the kinds of vibrations that could be encountered by VEHs.

A *dominant frequency* in the context of this study is a distinct frequency in the signal spectrogram at which the value of A^2/ω is large relative to other frequencies, that persists for a substantial duration of the signal. Because the filtered spectrogram is filtered by considering only values of A^2/ω that are greater than ½ the largest value of A^2/ω in each FFT frame, this definition implies that a dominant frequency is a thin (i.e. distinct), mostly continuous curve on the spectrogram extending for a substantial duration of the signal. Vibration signals may have zero, one, or more dominant frequencies. Note that the term *dominant frequency* is derived from the degree to which a particular frequency dominates (in terms of A^2/ω value) a single FFT window, and is thus somewhat of a misnomer; a dominant frequency needs to remain at a single frequency throughout the length of the spectrogram. See below.

The time-varying behavior of the dominant frequencies throughout the duration of the signal is also used for classifying the signal, as a VEH input with frequency content that is expected to shift with time has major implications on the design of a VEH. A dominant frequency is considered *stationary* if the frequency at which it occurs does not change much during the length of an input signal. It is possible for some, all, or none of the dominant frequencies of a signal to be stationary. See section 3.1 for some example spectrograms and their classifications.

2.4 Signals without Distinct Dominant Frequencies

Many vibration signals do not have distinct, dominant frequencies. Many of these signals can be best described as white noise and filtered noise. For simplicity of classification, two classifiers were employed in this study to describe signals without distinct, dominant frequencies.

The *White Noise* classification applies to signals with distributed frequency content that spans the entire sampling range.

The *Filtered Noise* classification describes signals that have frequency content distributed over a specific band of frequencies, with relatively little content outside of that band.

A small subset of spectrograms could not be classified according to the proposed classifications scheme. If no appropriate descriptor exists for a spectrogram, then that spectrogram is classified as "NA."

2.5 Amplitude and Noise Tags

Vibrations with inconsistent acceleration amplitudes present unique challenges to nonlinear VEH designs, where both the amplitude and frequency of an input vibration have the capacity to dramatically affect the power output. In order to catalog vibrations with significant swings in amplitude without creating another classification dimension, an *amplitude tag* is applied to all vibrations that change at least (an arbitrarily selected) 50% over the length of the signal.

In the case of a signal with distinct, dominant frequencies, it is common to observe these dominant frequencies amidst significant levels of surrounding frequency content. The *noise tag* is applied to all signals that contain dominant frequencies that are embedded in significant, nearby frequency content. The noise tag is a statement about two, intimately related characteristics of a signal; firstly, it is, by definition, a statement about significant levels of frequency content

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outside of the dominant frequency or frequencies. Secondly, it is a statement about the difficulty of declaring a specific dominant frequency as "distinct;" when a dominant frequency is embedded in "noise," it obfuscates the dominant signal, often making it difficult to classify as "distinct" in the first place.

2.6 Classification Methodology

The entire NiPS database of signals was first downloaded, along with the signal metadata, by virtue of an automated script; at the time of execution, the script downloaded a total of 329 different signals, each with X, Y and Z channels. The script then fed the signal data and metadata into MATLAB so that spectrograms could be created for each axis of the signal. The metadata was packaged into a Comma Separated Value (CSV) file, with each line of the CSV file representing a single axis of a signal. Each line in the CSV file was associated with a particular set of spectrograms that varied in their cutoff frequencies and FFT window lengths.

The signals, with their associated metadata and spectrograms, were then manually inspected. Signals that were obvious test or calibration uploads (determined by their brevity and title) were discarded. Signals that were obviously erroneous, such as those attempting to resolve high-frequency phenomenon (as determined by the comments or title) using a slow (e.g. 100Hz) sampling rate, were then discarded. Signals that contained only extremely low-frequency content, such that their associated spectrograms only contained content at the cutoff frequency (10Hz, 5Hz, 1Hz, or 0.25Hz) were discarded. This process removed 218 signals, leaving 111 left for the study.

Each of the 111 signals contains X, Y and Z data, and each axis of each signal had 5 associated spectrograms. These spectrograms were manually inspected to determine which combination of the two spectrogram parameters (cutoff frequency and FFT window length) resulted in a spectrogram that accurately captured the nature of the vibration. One spectrogram was chosen for each axis of each signal, resulting in a total of 333 spectrograms requiring classification.

The classification of each spectrogram was performed manually, by visual inspection of both the spectrogram image file, as well as the (interactive) MATLAB-FIG file. Many spectrograms had obvious classifications, and many others were far more difficult to classify; see section 3.1 for some example spectrograms and their classifications, and section 4.2 for a discussion of classification subjectivity.

3. VIBRATION CLASSIFICATION RESULTS

3.1 Example Spectrograms

In order to better elucidate the classification procedure, this section contains several spectrograms from the study, and an explanation of how their classifications were determined.

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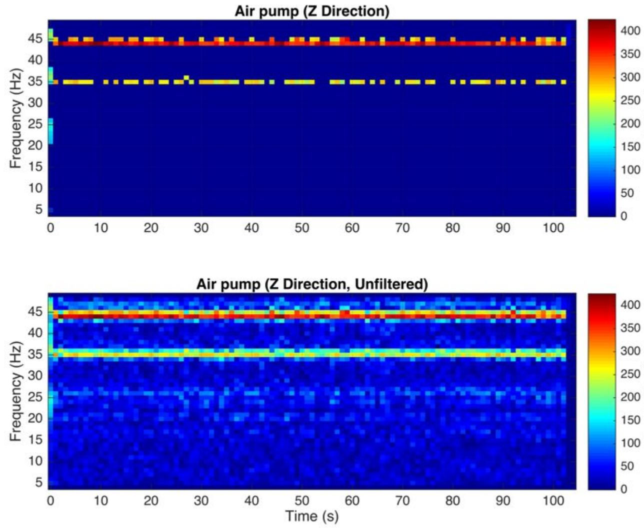

Figure 1 - Spectrogram of a Machine signal with the title "Air pump"

A spectrogram representing the signal from an air pump is shown in Figure 1. The top graph in the image, titled “Air pump (Z direction)” is a filtered spectrogram, created using the method discussed in section 2.2. The bottom graph in the image, titled “Air pump (Z Direction, Unfiltered)” is an ordinary spectrogram. The signal title “Air pump,” coupled with the comment “Fish air pump” collected from the signal metadata, indicates that the most appropriate source classification is Machine. Two, consistently high-amplitude signals are apparent in both the filtered and unfiltered spectrograms, and these two signals do not change in frequency with time. Thus, this signal is described as having two dominant, stationary frequencies. Although the amplitude of the 44Hz dominant frequency remains consistent over the length of the signal, the lower 35Hz signal has several periods of multiple seconds where the amplitude falls dramatically. Thus, this signal is given the amplitude tag, indicating inconsistency in signal amplitude. Finally, the filtered spectrogram makes it very clear that there are no *significant* levels of frequency content surrounding the dominant frequencies, so this signal does not receive the noise tag.

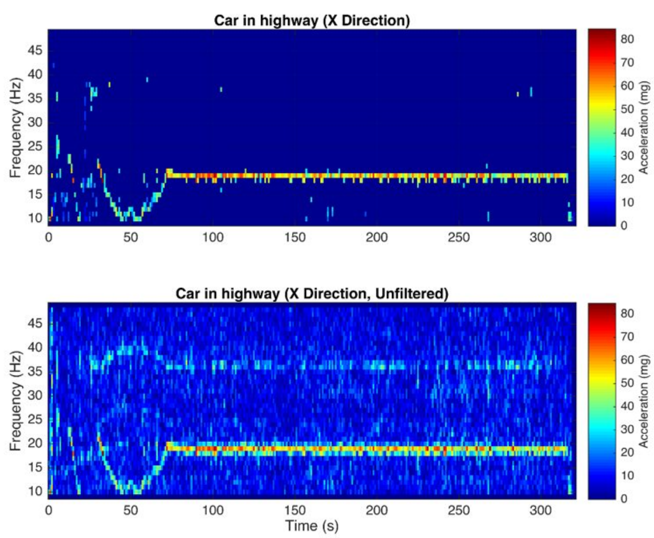

Figure 2 - Spectrogram of a Vehicle signal titled "Car in highway"

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Figure 2 is a spectrogram titled “Car in highway.” The metadata indicates a particular car model and driving speed, so this signal receives the Vehicle source classification. A single, dominant frequency is very apparent in the filtered spectrogram, and it is clear that it shifts frequency with time, eventually approaching a steady state frequency. This spectrogram is classified as having a single, dominant frequency that is nonstationary. Inconsistency in the signal amplitude means that this signal also receives the amplitude tag. Although some significant spectral content surrounds the dominant frequency during (what appears to be) a startup period, this additional significant content does not continue for a substantial portion of the signal, and thus this signal does not receive the noise tag.

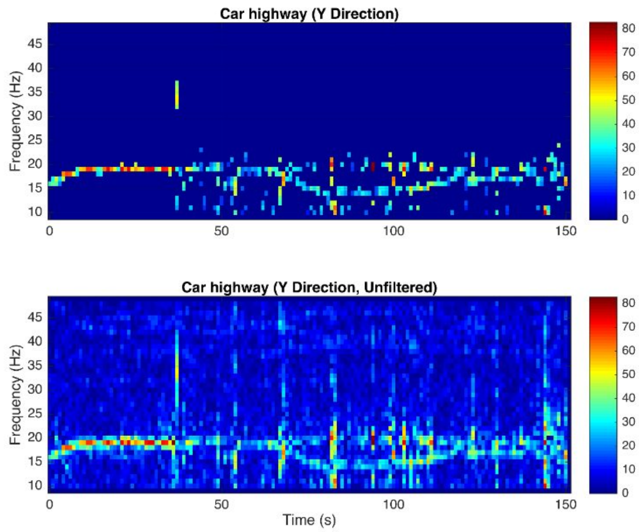

Figure 3 - Spectrogram of a Vehicle signal titled "Car highway"

Figure 3 is a signal from a vehicle source. One dominant frequency is consistent throughout the length of the signal, although it almost appears as if another dominant frequency appears approximately 70s into the signal, and merges with the first dominant frequency at approximately 120s. Because it is not clear that this frequency is indeed a second dominant frequency due to the abundance of significant nearby spectral content, this signal is classified as having a single, dominant, nonstationary frequency, and is given both the amplitude and noise tags.

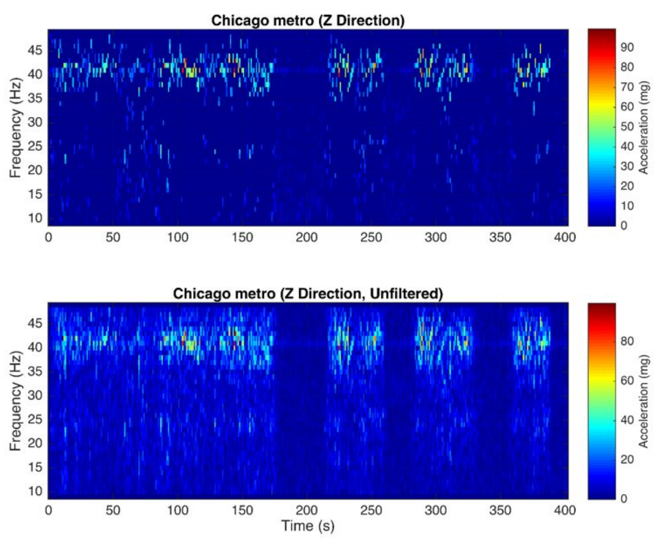

Figure 4 - Spectrogram of a Vehicle signal titled "Chicago metro"

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Figure 4 illustrates some of the difficulties of classifying signals according to a simplified schema. It is clear from the filtered spectrogram that significant levels of vibration content exist over a small band of frequencies. However, a faint, distinct line can be seen at approximately 41Hz that exists over the length of the signal. Is this a single, dominant frequency embedded in noise, or is this simply filtered noise? It was determined that the classification that best suited this signal is filtered noise, as content of significant amplitude exists over a band of frequencies for the duration of the signal, and the faint line at 41Hz does not appear distinct enough to be called dominant. This spectrogram received the amplitude tag, as large changes in amplitude exists throughout the duration of the signal.

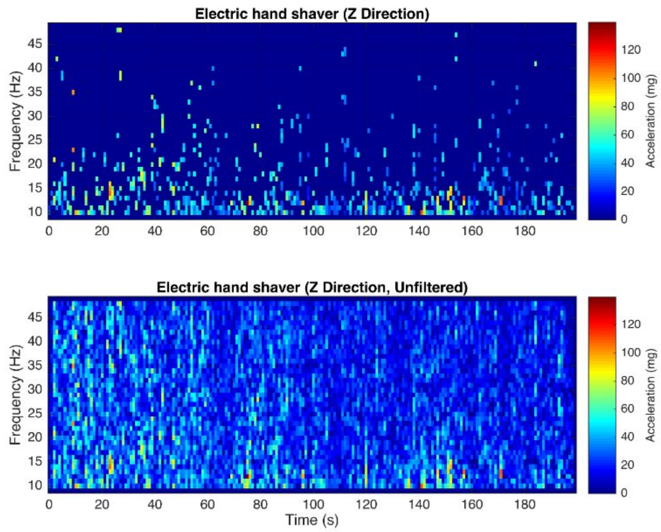

Figure 5 - Spectrogram of a Machine signal titled "Electric hand shaver"

Figure 5 constitutes an excellent example of what is considered a White Noise signal. In this case, the filtered spectrogram does nothing to assist in this classification, as the filtering method favors lower-frequency content. See section 2.2.

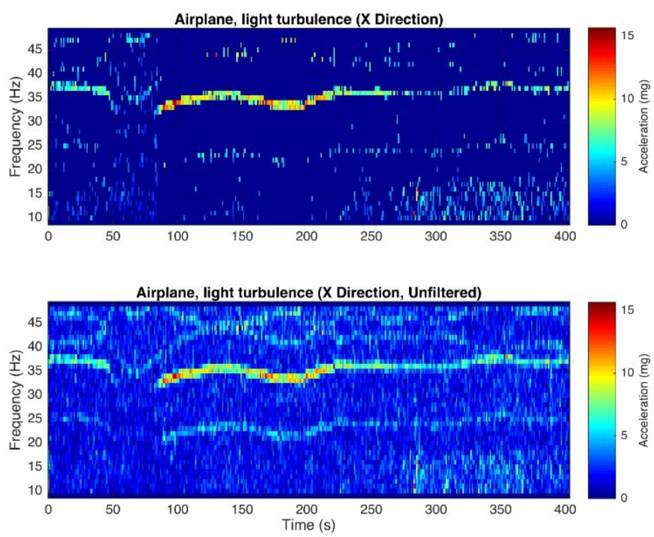

Figure 6 - Spectrogram of a Vehicle signal titled "Airplane, light turbulence"

Finally, Figure 6 is another example of a single, dominant frequency, embedded in significant additional spectral content (noise tag) with varying amplitude (amplitude tag). Although another, lower frequency trace appears at approximately

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22Hz, below the more significant one at 34Hz, the filtered spectrogram makes it clear that this signal should not be considered significant relative to the higher frequency one.

3.2 Breakdown of Signals by Source

A total of 333 spectrograms were analyzed for the study. A breakdown of all signals by source classification is presented in Figure 7.

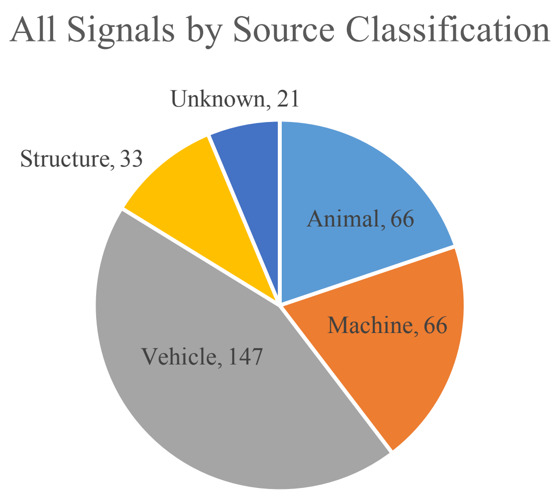

Figure 7 - All 333 signals from the study, sorted by source classification

The largest source category is Vehicle (147 spectrograms), while the smallest source categories were Structure sources (33 spectrograms) and Unknown sources (21 spectrograms). The number of Animal and Machine sources was identical (66 spectrograms).

3.3 Breakdown of Signals by Spectrogram Classification

A breakdown of all signals by spectrogram classification is presented in Figure 8.

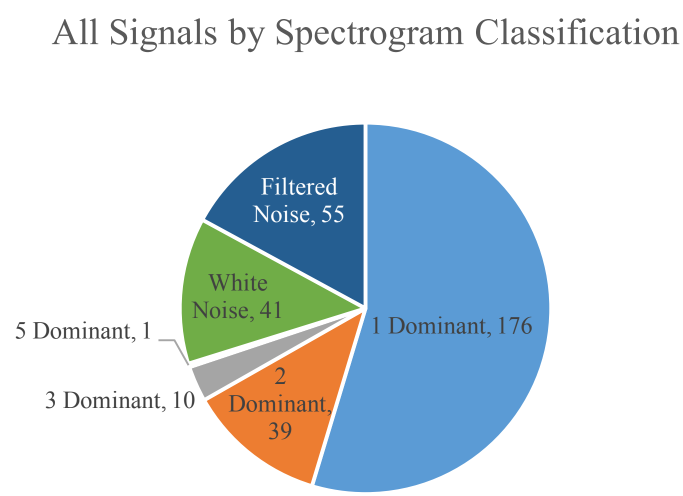

Figure 8 - All 333 signals from the study, sorted by spectrogram classification

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Most of the signals analyzed in the study can be classified as having a single, dominant frequency. Over a quarter of the total signals can be characterized as lacking a dominant frequency, and are better described by either the White Noise or Filtered Noise categories. A relatively small number of the signals could be classified as having more than one distinct, dominant frequencies.

3.4 Breakdown of Individual Source Classifications

Perhaps most the most important results concern how the signals were characterized for each source. Figure 9 shows the breakdown of characterizations for the Animal sources analyzed in the study.

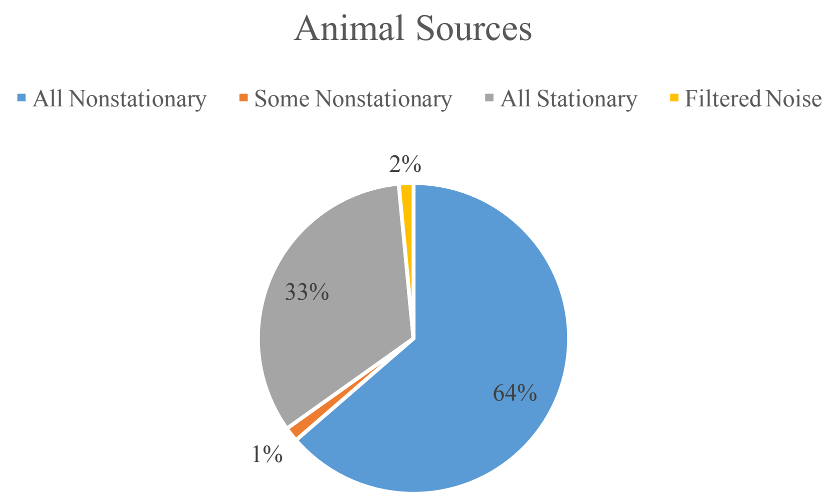

Figure 9 - Breakdown of Animal sources

The majority of Animal signals can be described as having dominant frequencies that are nonstationary. A considerable portion of the Animal signals can be described as having dominant signals that are stationary.

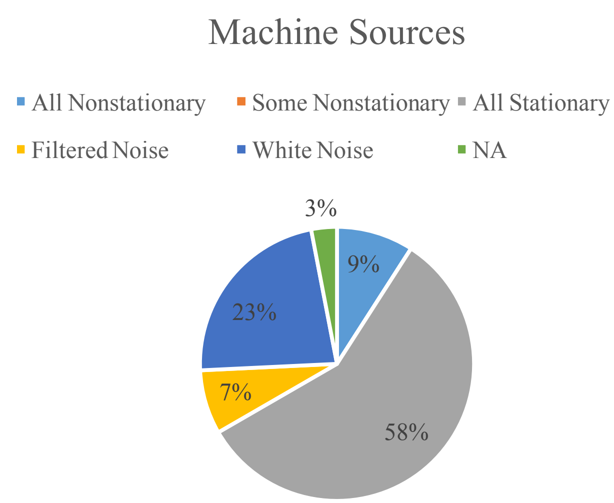

Figure 10 - Breakdown of Machine sources

Figure 10 shows the breakdown of characterizations for Machine sources. 58% of the Machine sources analyzed contained dominant frequencies that remained stationary with time. 30% of the Machine sources generated spectrograms that could

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best be described as "noise;" 23% received the "White Noise" classification, and 7% received the "Filtered Noise" classification.

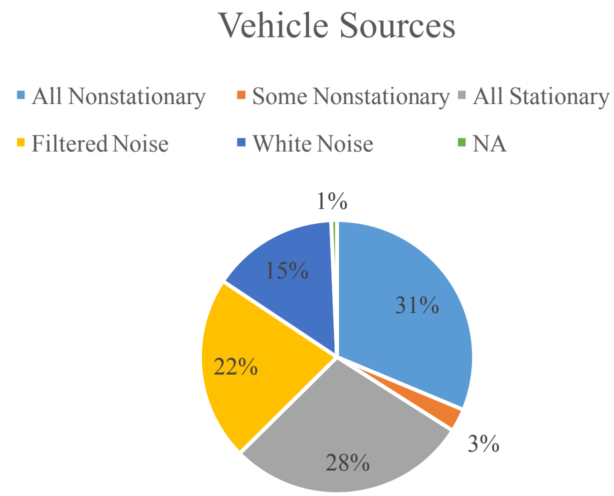

Figure 11 - Breakdown of Vehicle sources

Figure 11 shows the breakdown of characterizations for Vehicle sources. Vehicle sources have the most variability in their characterizations; no one category dominates over the others. Dominant frequencies constitute the largest combined category, making up 62% of the classifications. The largest single category is "All Nonstationary," consuming 31% of the total characterizations. This is, perhaps, no surprise; as a vehicle accelerates and decelerates, it is reasonable to assume that the vibrational characteristics will vary with time. "All Stationary" is the second largest category. This may be explained by steady-state vehicle motion; a car moving at constant speed on a highway, for example, may not have any vibrational characteristics that change over the length of the signal.

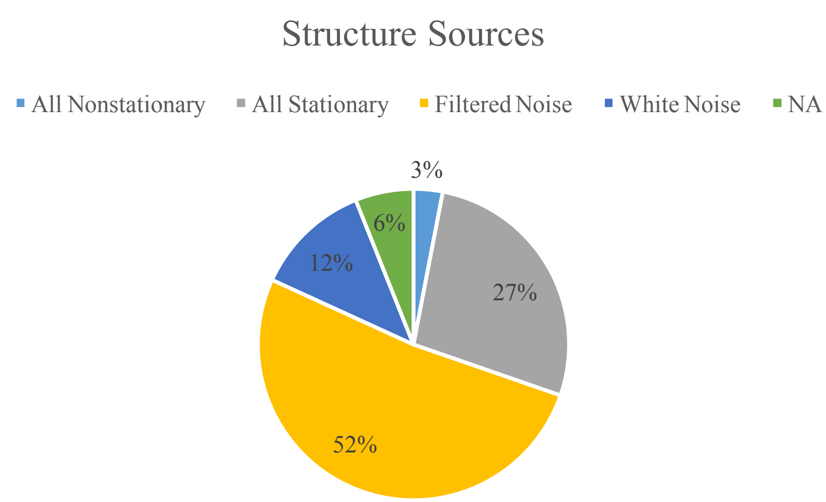

Figure 12 - Breakdown of Structure sources

Figure 12 shows the breakdown of characterizations for Structure sources. The majority (64%) of the signals derived from Structure sources can best be described as "noisy;" 52% fall under the Filtered Noise category, and 12% fall under the

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White Noise category. 27% can be described as having dominant frequencies that are stationary with time. This leaves a mere 3% that can be described as having dominant frequencies that change in time.

3.5 Amplitude Tag

Recall that another important piece of information relevant to VEH design is the time dependence of the vibration amplitude, and that this information is conveyed in this study by virtue of an *amplitude tag*. The amplitude tag can be applied to all classifiable signals; that is, signals not classified as "NA."

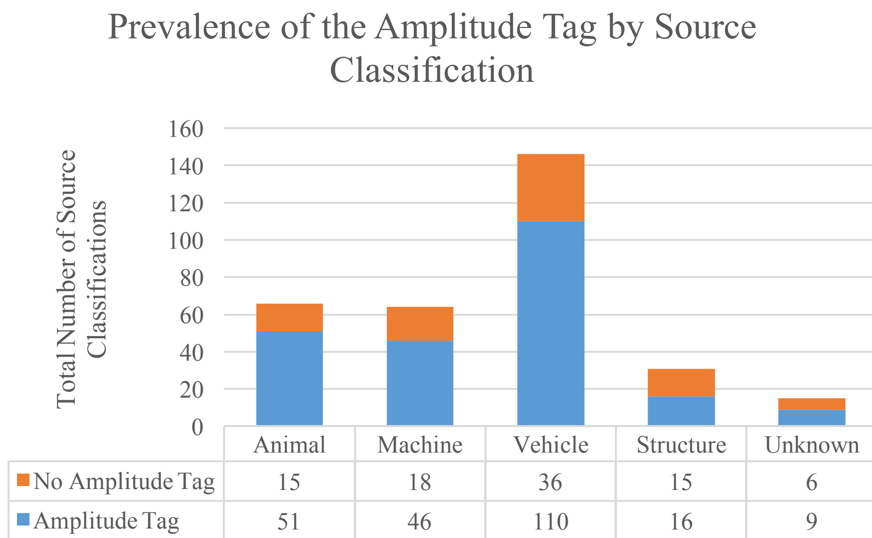

Figure 13 - Prevalence of the amplitude tag, broken down by source classification

Figure 13 displays the frequency with which the amplitude tag was applied to signals, sorted by source classification. It is very clear that time-dependence of vibration amplitude is common in real-world vibration signals, regardless of source.

3.6 Noise Tag

Recall that the noise tag is applied to all signals that contain dominant frequencies that are embedded in significant, nearby frequency content; therefore, it is only meaningful when applied to signals with dominant frequencies.

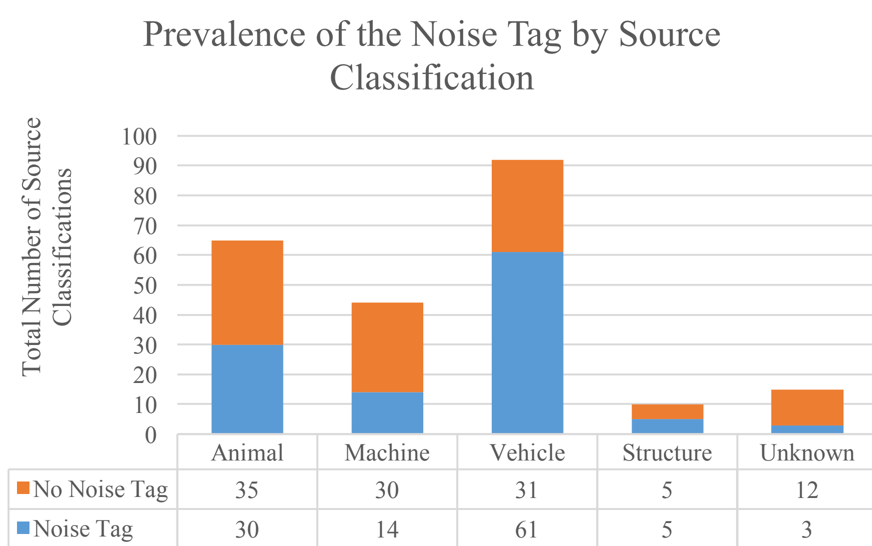

Figure 14 - Prevalence of the noise tag, broken down by source classification

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Figure 14 displays the frequency with which the noise tag was applied to signals that can be classified as having dominant frequencies. It can be surmised from the figure that, even in the case of a signal best described as having dominant frequencies, it is very common for those dominant frequencies to be embedded in significant, nearby frequency content.

4. DISCUSSION

4.1 Classifications and Relationship to VEH Design

The study classified a broad range of vibrations from an existing database in order to inform the VEH researcher of the prevalence and characteristics of vibrations seen in real world environments.

The study of 333 signals from the NiPS Real Vibrations database resulted is several interesting conclusions about the available dataset:

The majority of signals do not maintain constant amplitude excitations. This appears to be the case regardless of the source classification.

No single vibration classification appears to describe a single source classification universally. With the exception of the Unknown source classification (not discussed), the greatest portion that any single signal classification consumes within a single source is 64% (All Nonstationary, Animal). This suggest that proper modelling of a signal from a known source requires more information than simply the source classification of the signal.

Most Animal sources are best described as having distinct dominant frequencies that move with time. 65% of the signals with the Animal source classification have a dominant component that moved in time. Additionally, nearly half of the Animal signals were embedded in significant levels of noise, as indicated by the number of signals given the noise tag.

Most Machine sources are best described as having distinct dominant frequencies that are stationary, and a substantial portion can best be described using noise. 58% of the Machine sources analyzed contained dominant frequencies that remained stationary with time, and 9% contained dominant frequencies that moved with time. 30% of the Machine sources generated spectrograms that could best be described as "noisy;" that is, 23% received the "White Noise" classification, and 7% received the "Filtered Noise" classification.

No single classification dominates the description of Vehicle vibrations. Signals with the Vehicle source classification expressed the most variety in their signal classifications.

Most Structure sources can be described by some type of noise. The White Noise and Filtered Noise signal classifications constitute a combined 64% of signals that also have the Structure source classification. Nearly all of the remaining signals were classified as having stationary dominant frequencies. Of the signals classified using dominant frequencies, half received the noise tag.

In the case of the single dominant, stationary frequency, it seems unlikely that a novel structure could provide any substantial increase to the maximum power output over a harvester based on a linear oscillator (i.e. characterized by the VDRG model). In fact, it has been shown that for the case of a simple harmonic input, a properly designed linear harvester represents the limiting case of harvester power output[8,9]. Of all the signals in the study, approximately 23% are characterized by a single dominant, stationary frequency.

If the signal can be classified as having multiple dominant, stationary frequencies, then it may be possible to harvest more power from such a signal than could be harvested by a well-designed linear harvester. For example, a multi-mode or wideband harvester might outperform the standard linear oscillator in certain cases. Of all signals in the study, approximately 6% are characterized by multiple stationary frequencies.

For signals with dominant frequencies that move in time, a tunable harvester would appear to be an appropriate architecture choice, depending on the amount that the frequencies move with time, the characteristic frequency with which the frequencies move, and the tuning power costs of the harvester. Wideband harvester architectures could also provide benefit for this class of signal; harvesters with multiple vibratory modes, for example, or harvesters that employ nonlinear dynamical structures have the potential to provide an increase in power over a linear counterpart with a single resonant peak.

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Much research has been focused on wideband harvesters exhibiting a nonlinear stiffness function, usually characterized by a cubic stiffness function. Thus, it is worthwhile to investigate how often – in the sample set characterized here – this architecture might provide a significant benefit over a standard linear harvester design. As previously mentioned, such nonlinear harvesters may provide a potential improvement in cases with multiple dominant frequencies or a single moving frequency. Hoffman[14] showed a significant improvement for a single moving frequency using a monostable or bistable nonlinear harvester. In the same study, a bi-stable harvester showed very little improvement for multiple stationary frequencies. However, nonlinear harvester architectures represented a significant improvement for an input consisting of band-limited noise. Daqaq[15] has shown that the shape of the potential function does not affect the power that can be harvested from white noise. Therefore, it is reasonable to conclude that the categories where a significant improvement could be made from a nonlinear harvester are single dominant nonstationary frequency, filtered noise, and multiple dominant stationary frequencies. Taken together, these comprise approximately 53% of the total signals. It should be noted, however, that such nonlinear structures have a strong amplitude dependence and the majority of signals analyzed have shifting amplitudes. Thus, the real percentage of signals for which a nonlinear design would represent an improvement over a linear design will be somewhat lower.

4.2 Study Limitations and Future Work

There are numerous limitations to the study:

Small number of useful signals. The majority of the signals obtained from the NiPS database appeared to be of such low quality that they were deemed invalid for analysis; nearly 2/3 of the database was rejected for this reason.

Uncertainty in measured data. Of the signal data that appeared to be useful to the study, the majority were measured using an iPhone as the data acquisition system. This raises several concerns as to the validity of the data; namely, it is unknown if the uploader is qualified to be making careful measurements of the vibration signals, the iPhone sampling rate is limited to 100Hz in the database, there are no specifications regarding the recording conditions (mounting and placement of the iPhone, events that occurred during recording, etc.), the iPhone model used for recording is unknown, and at least one source [20] states that the maximum resolution of a particular iPhone accelerometer model is 18mg. Thus, many of the signals that passed the crude quality check may not be valid representations of the phenomena that was intended for recording.

Subjectivity of analysis. One inescapable consequence of having a human visually examine spectrograms for the purpose of signal classification is the subjectivity of the resulting classifications; although efforts were put in place to prevent obvious misclassification (such as fixing the definition of a particular signal classification before classification began), in many cases, two observers may disagree on the classification of a particular signal. For example, a signal that appears to be characterized by a single dominant frequency embedded in noise to one observer may appear to be better characterized as filtered noise to another observer.

Future work would include a comparison of the maximum power output of various VEH architectures subjected to the signals in the study, with a particular interest in determining if specific VEH architectures are well suited to signals with specific classifications. In this way, it can be determined whether a given VEH architecture is well suited for particular application, or if complex VEH architectures are capable of outperforming simpler (e.g. linear) architectures when the input signal falls under a specific classification.

5. CONCLUSIONS

333 vibration signals from the NiPS Laboratory “Real Vibration” have been characterized and classified by key vibration characteristics. A primary goal of this classification is to provide insight into the design of vibration energy harvesters (VEHs). Determining the prevalence of vibration signals for which standard VEH architectures are optimal is of particular interest. The vibrations were classified by source (i.e. machine, animal, vehicle, structure, unknown). The signals were further characterized by the number of dominant frequencies, whether these frequencies are stationary or move with time, or whether the signal was best characterized by noise, either broadband or band limited. Although VEH simulations for the different categories have not been performed, an initial qualitative analysis would indicate that a standard linear oscillator harvester is likely the best design for at least 23% of the signals and that harvesters with the common cubic nonlinear stiffness function could offer an improvement at most 53% of the time; this is an initial conclusion and more study is required to refine this result.

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