Time Distribution Mapping: a Generic Transient Signal Monitoring Technique for Prognostic Methods

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ABSTRACT

The utilization of steady state monitoring techniques has become an established means of providing diagnostic and prognostic information for systems and equipment. This is mainly driven by both the wealth of available analysis techniques and the comparatively larger amount of data. However, steady state data is not the only, or in some cases, even the best source of information regarding the health and state of a system. Transient data has largely been overlooked as a source of system information due to the additional complexity in analyzing these types of signals. Time Distribution Mapping via the Sharp Transform allows for a fast, intuitive, generic quantification of deviations a transient signal from an established norm. Without regard to the type or source of the signal, referencing to an established Time Distribution Map can implicitly capture shifts mean, standard deviation, skewness, or even gross frequency shifts without need of additional processing. By quantifying and trending these shifts, an accurate measure of system heath can be established and utilized by prognostic algorithms. In fact, for some systems the elevated stress levels during transients can provide better, more clear indications of system health than those derived from steady state monitoring.

1. INTRODUCTION

Signal monitoring has advanced to the point where viable and accurate information regarding the health and state of a system can quickly and effectively be obtained using purely data driven techniques, Traditionally these techniques focus on steady state signals for both there availability and regularity. Transient signals however, provide a unique challenge and opportunity in regards to health information extraction. While the nature of these signals violates many of the assumptions necessary for steady state analysis, the elevated stress levels seen in these signals can provide faster, more accurate indications of heath in many systems.

By definition, a transient signal undergoes some significant statistical shift with regards to the pertinent time frame being analyzed. Specifically, this paper refers to these types of transient signals generated from systems and equipment undergoing a normal operational transient such as startup, shut down, or a load shift. One main difficulty in analyzing these signals is the lack of means of generically and intuitively quantifying the degradation of a transient signal. Without these, each signal analysis necessitates a case-specific algorithm for processing whose development generally relies on some engineering knowledge of the signal itself and its' attributes.

Time distribution mapping provides a generic, data driven means of quickly, intuitively, and accurately quantifying the degradation of a transient signal signature through the lifetime of a system. By using historical transient signatures to establish a nominal time distribution map, and transforming signatures into the same bin space as described in following sections, a residual can be created between these maps to provide measure of signature deviation which directly relates back to system heath. This additional measure of system health can be used either alone, or to augment existing information from steady state monitoring, providing more robust and accurate information regarding the overall state of the system. In fact, some systems, such as backup generators, may only have transient information on record as they are subjected to periodic pass/fail startup tests. The ability to utilize this information to better assess the current state of the unit, and predict future states of the unit could be invaluable, possibly leading to less frequent and more accurate decision-making regarding the unit.

2. BRIEF REVIEW OF GENERAL TRANSIENT ANALYSIS METHODS

Transient signature and signal analysis are generally thought to require complex, or at least specialized monitoring techniques due to the fact that many common statistical analysis methods are built on the implicit assumption that the signal being processed is steady state. Specifically, the key difference in processing a transient signal verses a steady state one is the necessity of a temporal aspect to the analysis. This section provides a brief review of some of the more common methods of transient analysis. This is not meant to be an all-inclusive list, but merely to highlight a few of general-purpose techniques that can be applied to a wide variety of signals and equipment.

The simplest techniques involve windowed tracking of statistical properties over the progression of the signal. These, along with more complicated techniques (Gabor Transform, Hilbert Huang Transform, Wavelet Analysis, etc.), capture particular aspects and features of a signal as it evolves over time. The general trade-off for most transient analysis techniques is between the resolution of the signal feature and time. The Gabor Transform most notably suffers from this trade-off. While the Hilbert Huang and to some degree Wavelet analysis do not directly suffer from this trade-off, there is some loss in direct physical meaning of the transforms.

Many of the traditional methods and algorithms for the analysis of transient signals are particularly suited for a specific type of signal or application. One common yet powerful tool, particularly in the case of oscillatory signals, is the Fourier transform. This method, extended by the Gabor Transform [Gabor 1946], can be used to identify evolutionary frequency shifts within a signal. Unfortunately when using frequency or time/frequency analysis, it is not always easy to discover and isolate the minute changes that may be significant in regards to the health of the system, but become over shadowed by less important but more constant frequencies shifts which are merely products of the transient. Physics models of the system can help to overcome this by providing a guide to the expected dominate degradation modes. When this type of physics model, or related information is not available however, the use of the Hilbert Huang Transform (HHT) can serve to help identify this same type of information [Huang 1998].

Unlike the Gabor transform, the HHT is not based on a preconceived parametric functional form. Whereas the Fourier transform can be thought of as deconstructing the signal into a series of sine waves to determine frequency, the HHT decomposes the signal into successive intrinsic mode functions (IMFs) based on the characteristics of the signal itself. By then applying the Hilbert Transform to these IMFs, analytic amplitude and an instantaneous frequency can be obtained for each IMF.Because of this, the HHT excels at highlighting the instantaneous dominant frequencies of a signal at any given point in time. By examining the multiple layers of Intrinsic Mode Functions (IMFs) and the instantaneous frequency of each, subtle frequency shifts which may evolve over time stand out, both in time and frequency over larger more dominate frequencies. These can be used is the form of the HHT, or as a guide to go back and reevaluated the simpler to calculate JTFS. Not only can the HHT provide frequency information, but information regarding power and amplitude as well. Though the HHT is typically computationally costly to calculate, the information it provides can be invaluable in the prognostic analysis, either from direct use or as a guide to identifying more simple trackable features.

The problem with each of these methods is that after suitable features have been found and extracted, some form of model must be additionally developed in order to quantify any degradation in these features. This is not always a trivial task, especially when the pertinent feature is represented by a certain signature based on the transient itself such as the rate of increase for the instantaneous frequency of a signals second IMF over a 3000 observation window. Time distribution mapping, as will be shown in this paper, can be used either directly on a signal or on these extracted features to solve this problem.

3. Time Distribution Mapping

A major drawback to all the previously discussed methods of transient signal analysis is the lack of widespread instant applicability. In other words, most techniques do not generalize across different systems or equipment without some additional knowledge and research into understanding the system. For example, although the Hilbert Huang Transform is highly adaptive and able to pick out subtle features in a given signal, there is no knowing in which level, and at what point in the decomposition an important feature will surface. With understanding of a system, one may infer, or expect to find features of interest at certain points, but these points will change between systems. This research seeks to provide and broadly examine generic processes for modeling and monitoring transient signals with the explicit goal of extracting a useable prognostic parameter.

Time distribution mapping via the Sharp Transform provides a novel method for expanding single or multiple signals into a non-uniform matrix space, or a similar cross-pattern space. In more general terms, this transform refers to taking successive measures of the empirical distribution of a signal throughout time and storing them in a serial temporally ordered fashion, thus creating a map detailing how the distribution of a signal evolves through time. For easy of interpretation and illustration, this section explains the algorithm for developing a model based on a single signal or variable. However, there is no reason that this transform could not be directly extended for the cross signal density of two or more.

The basics of this transformation rely on the creation and understanding of a signal's distribution, or probability density. An empirical measure of a signal's distribution over any given interval can easily be calculated by taking a simple histogram of the signal over that window. In order to become a true probability density, scaling based on the window size must be enforced, but as will become apparent later, this scaling can be factored out. All necessary processing can be accomplished with the un-scaled discrete distribution provided by the histogram. Unfortunately, the full temporal complexities of a transient signal cannot be expressed with a single distribution. Consider the transient signal below: this modulated oscillatory signal exhibits shifts in both amplitude and variance over the observed transient.

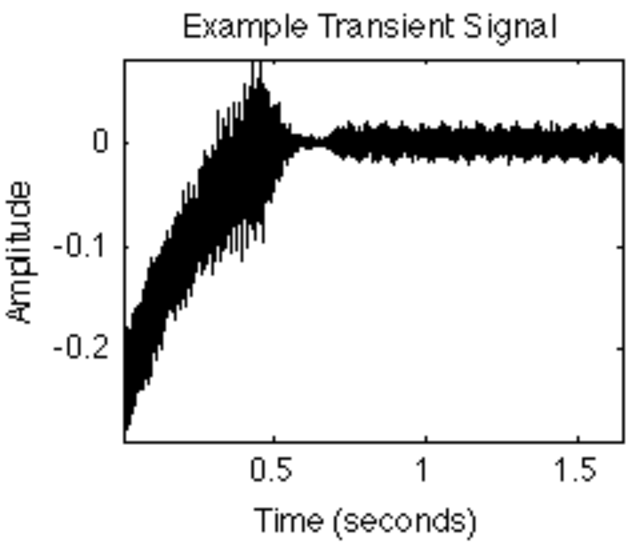

Figure 1 - Example Transient Signal

If one were to perform a standard series of tests on this data they could determine that it has a mean of -0.028, a standard deviation of 0.059 and upper and lower limits at 0.081 and -0.288 respectively. While most of this can be seen or estimated from a typical histogram such as the one shown below, none of this captures any of the highly temporal aspects of this signal.

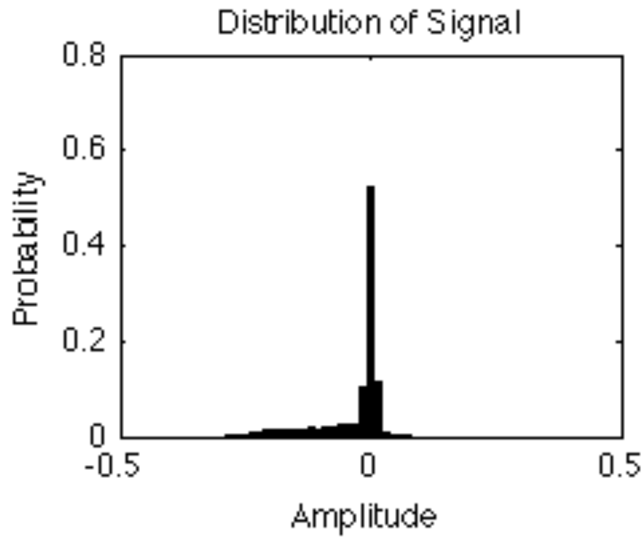

Figure 2 - Histogram of Example Transient Signal

However, if one were to calculate successive histograms of the signal through time and over smaller windows these temporal aspects are easily captured. Shown in the figure below is a series of histograms, each with 25 bins with varying bin locations based on the amplitude of the signal over each observation window. The selection of the number of bins as well as the window size can be altered based on the sample rate and time frame of the transient, but in general, a window size of greater than five times the number of bins is desirable.

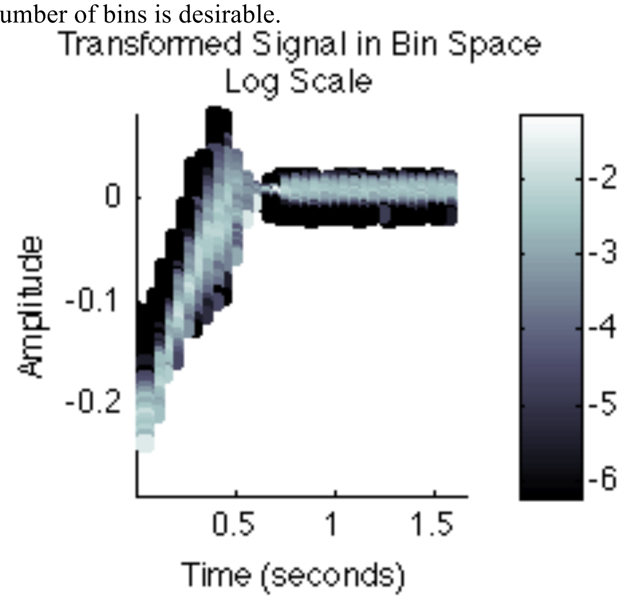

Figure 3 - Time Distribution Map of Oscillatory Transient Signal

This bin space map is able to capture both implicitly and explicitly many aspects of the signal as they evolve through time. Aspects regarding the mean, variance, and skewness as they evolve in time are all embedded within this ST map. Even gross changes in frequency are implicitly captured in the information of this map. That is not to say that by looking at this map a non-dominate frequency shift of five hertz in one of the upper peaks would be observable, but a frequency shift significant enough to change the distribution on the scale of the observable window could be detected. In fact, the most obvious, simplest, and yet most all encompassing statement that can be made is that any alterations in the localized distributions through time are captured with this method.

Once the concept of transforming and mapping signals in the new bin space has been established, it is next important to explain how these can be used to develop prognostic parameters to be used in the creation of Remaining Useful Life (RUL) estimations. The first thing required is multiple “good” or nominal transient recordings. Between three and ten of these exemplars make a good baseline for developing the ideal reference case. Development of this transformed reference map assumes that the transients in question exhibit similar behavior. If they do not, then multiple reference maps should be made for each category or pattern of transient. For example, load shifts from half to full load may not be the same as those from one quarter to full load, but all startups from zero to full load may be expected to look the same.

After the nominal transients are collected and appropriately grouped, they need to be divided into equally spaced segments based on the chosen window size. The selection of both the number of bins and the window size is highly dependent on the observed length of the transient, the sample rate, and the level of detail desired versus the robustness of the distributions. While it is intuitive that greater number of bins provides greater detail in the map itself, greater numbers of bins also require larger windows to develop full distributions, losing some of the time resolution of the map. In practice segmenting the transient signal into between approximately 30 and 100 windows and choosing a bin number about one tenth the window size seems to produce reliable results. Of course this is dependent on the available data and can be tailored to suit any needs. Also, in this discussion, the windows are treated as discrete and wholly separate from each other, there is no reason that the windows could not overlap or even “scroll”, over each observation in time. It is simply ignored for this discussion to simplify both computations and explanation.

Once the window size and number of bins has been determined a “master” bin map can be created. The maximum and minimum values inside each window observed over all the exemplar cases define the range of the bins for that time window. Unless there is special reason not to, the bin edges can then easily be defined as linearly spaced points between these ranges. This master bin map will now be the bin edges that will define the new bin space into which all subsequent transient signatures will be transformed into. The transformed maps of each of the exemplar cases based on these bin locations will then be averaged together to complete the creation of the reference map. With this reference map, and the master bin map, it is possible to create progressive bin space maps throughout the lifetime of the equipment, which can then be compared to create a measure of change that is relatable to degradation. By monitoring the summed square of the residuals between any given lifetime bin space map and the reference time distribution map, a quantitative value relatable to the overall degradation of the transient can be made. This can then be directly translated into a measure of health of the system based on the original signal. This value and its progression through time are then directly usable as a prognostic parameter for models estimating RUL.

It is possible for the prognostic parameter developed by this method to saturate if a signal experiences a mean shift greater than the span of the reference ST map, but this is easily overcome by simply developing a new reference ST and master bin map based on these new levels of degradation. In order to compare separate units, the residuals from the reference ST may need to be scaled by the residuals associated with the exemplar cases used to create it, but this is a trivial task and should not impair the results of the analysis.

This generic idea of mapping the progressive aspects of a signal over time through windowing and comparing them to a reference signal is the most widely applicable method of monitoring transients for degradation. Similar mappings of Joint Time Frequency Spectra (JTFS) or similar statistical evolutions can also use this methodology. Mapping of signals transformed into an empirical bin space is presented as the best generic test with the broadest number of implicit anomaly detections possible. This is not to say it is the best for every given application, but its’ broad range of applicability make it useful in many cases. Brief case studies of the development and use of this STDM modeling technique are provided in subsequent sections.

4. Proof of Concept Test Cases

The following sections provides multiple proof of concept case studies that solidify the hypothesis that not only are these techniques valid in processing transients with the goal of prognostic modeling, but that transients in general are valid and reliable sources of degradation and system health information. These experiments utilize other more traditional analysis methods to compare and validate the more novel transformation techniques for transient analysis presented in this paper.

4.1. Impeller Degradation Experiment

The first of these experiments analyzed the artificially induced degradation of small-scale neoprene horizontal pump impellers. The pumps were chosen as analogous representations of the large pumps found in many industry and power plants applications. The focus of this experiment was to identify correlations between monitorable features found during pump startup and the amount of degradation found in the system. Twelve separate impellers were degraded over time and failure was defined as the inability to self-prime.

In order to precipitate faults in the impellers, increasingly large notches were cut into each impeller vane between regular data collection runs of the pump. These notches are analogous to the type of degradation an impeller might suffer due to a spur or defect in the impeller housing or due to particulates in the fluid. The pump differential pressure, vibration, and inrush current were recorded at ~1.6kHz for analysis in this experiment.

The analysis of each of these signals via more traditional, means discovered multiple features within each that directly relate back to priming time of the pumps. It was discovered that the priming time was an acceptable features that could be used as an indication of overall impeller health, and could be used as a prognostic parameter.

For vibration, the most pronounced of these features was an increase in amplitude as well as a rise in the vane pass frequency prior to the water entering the impeller housing. While the rise in frequency can be viewed via a Joint Time Frequency Spectrum, both features are easily extracted using the Hilbert transform. The figure below shows how this rise in amplitude evolves over the life of the impeller.

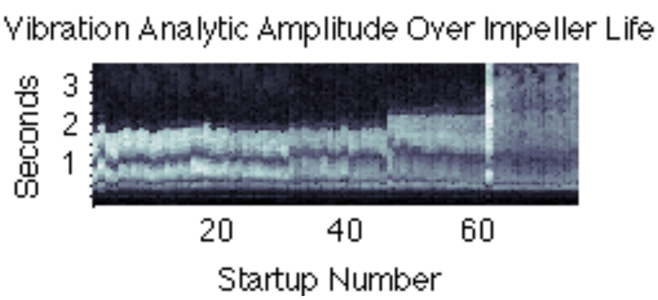

Figure 4 - Analytic Amplitude of Startup Vibration Over Single Impeller Lifetime

This figure shows that the elevated vibration amplitude reflecting priming time increases from approximately 1.8 seconds early in life, to around 3 seconds near the end of life. Extracting this time requires can be somewhat trivial task, but it still requires additional processing and model development.

Conversely, instead of calculating this amplitude and then making a model for extracting the amount of the elevated amplitude, nearly identical information can be extracted without special development through time distribution mapping via the transform detailed above. Using several start of life vibration signatures to create a master bin map, the residual mappings from the transformed bin space come out as a near exact echo of that information.

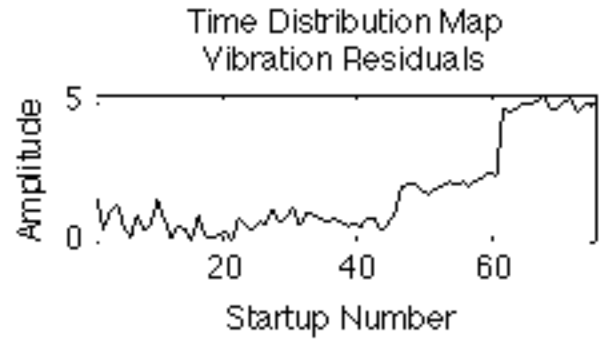

Figure 5 – Exemplar Impeller Bin Space Mapping Residuals

Each lifetime startup vibration signature is transformed into the same master bin space. The summed scaled residuals between these and the reference bin map implicitly extract the difference in priming time without a need to optimizing towards that goal.

Similar extractions can be done for both the inrush current and the differential pressure. Analysis shows that the current exhibits a drop in power prior to priming due to the lessened load, and unsurprisingly the differential pressure requires more time to reach its' maximum value. Information relating to these features can quickly be gleaned from the respective residuals of their separate time distribution maps as shown in the figure below.

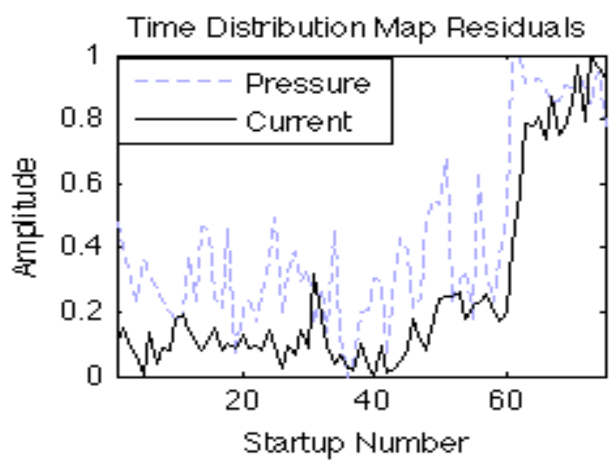

Figure 6 - Exemplar Bin Space Residuals From Additional Signals

Notice that despite the very different nature of the three signals, they all contain information related to the same system and as such the residuals of the bin space transformation have comparable information in them. The additional noise associated with the pressure residuals comes from the signal itself which exhibited significant noise. This is most likely do to voids in the sensing lines. The figure below presents the master bin maps created as the nominal startup signature for each signal.

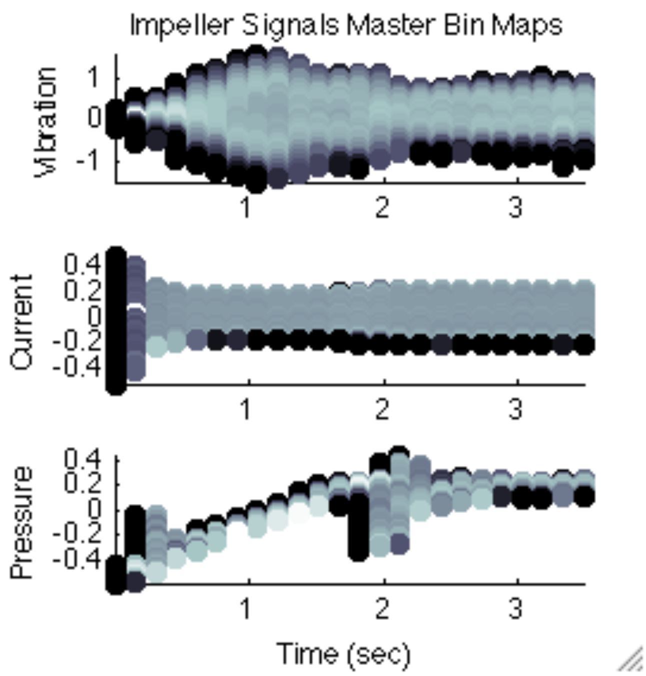

Figure 7 - Transformed Impeller Signals' Mater Bin Maps

Where as differential pressure exhibits a degradation of a significantly mean shifting signal, both the current and vibration signals have an alteration in their variance shifts. Additionally, the current signal is highly modulated on the 60Hz electrical carrier wave, yet transformations of each of these signals into similarly windowed bin spaces is able to quickly provide the pertinent degradation information.

The residuals from each of these mappings can be combined together to create a more robust measure of overall priming time, and by inference, impeller health. Due to the lack of available comparison data regarding the true lifetime or rate of wear time of these impellers, direct estimation of Remaining Useful Life (RUL), as would be more traditional in prognostic applications [Hines 2009], could not be made, and it would be meaningless to attempt with this data. Instead a percentage of current life consumption (CLC) model is inferred such that with the addition of a known lifetime run, a RUL estimate model could be made. The figure below represents the CLC chart with standard error uncertainty bounds on each calculated point.

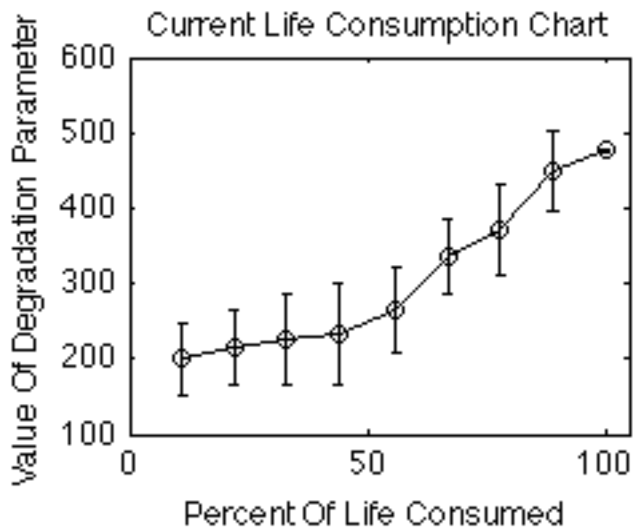

Figure 8 - Impeller Current Life Consumption Chart

This figure is read by calculating the optimally weighted combination of the rescaled bin map residuals on the vertical axis, then estimating the corresponding percent of life consumed on the horizontal axis. It has been show that utilizing genetic algorithms to find an optimal linear combination of trendable parameters can increase both the robustness and accuracy of a prognostic parameter [Coble 2011]. Using this technique to combine the residuals shows how the process of transforming signals into a non-uniform time/bin space can directly lead to trendable prognostic parameters.

4.2. Motor Aging Experiment

Another experiment conducted to verify the robustness of the bin space mapping technique was an accelerated induction motor aging experiment. In this experiment, 5HP motors were subjected to cyclical thermal stresses and tested between each cycle. Several sensors were recorded during each test startup to monitor the overall state and health of the motor. These included current, voltage, vibration and acoustic signals, each sampled at a frequency of just over 10kHz.

As these motors aged, it became apparent that the dominate failure mechanism was due to bearing fatigue. As there is much work already in the literature regarding the steady state quantification of bearing degradation, this experiment was not meant to replace those techniques, but instead to augment them through transient analysis and to verify the validity of the empirical non-uniform bin space transformation and the associated mapping technique.

To conserve space, not all of the signals analyzed will be fully illustrated here, but instead a brief overview of the signals is given, highlighting the different types of signals.

The first signal analyzed is the acoustic signature. This signal exhibits a shift in frequency and amplitude over the life of the signal. Directly and reliably extracting this requires both the Hilbert transform and significant filtering of the returned parameters. Although contain similar informational aspect relating to the degradation of the bearing itself, the more easily visually distinguished is the startup dominate frequency signatures which is shown in the figure below.

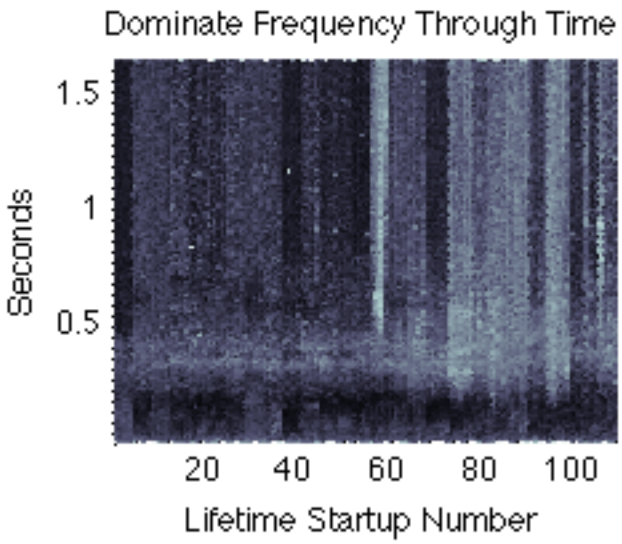

Figure 9 - Acoustic Dominate Startup Frequency Over Motor Lifetime

The vertical axis in this chart represents the amount of time after the energizing the motor, where the lifetime startup number is on the horizontal axis. The lighter tones represent the higher frequencies, and notice how these become more dominate towards the end of life, especially in the time before approximately 0.5 seconds after energizing.

Now examining the residuals from the time distribution map of the transformed bin space, this increasing deviation is easily extracted.

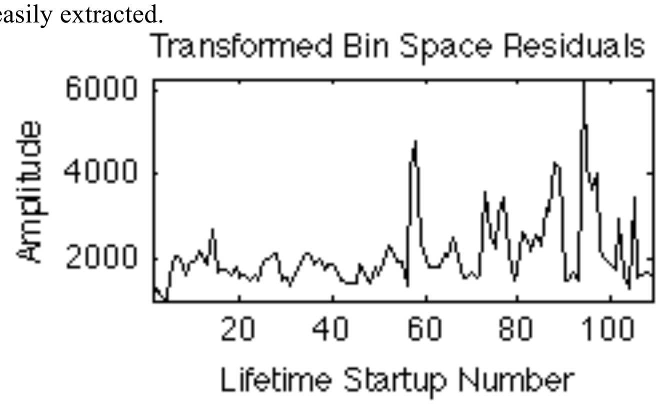

Figure 10 – Startup Acoustic Transformed Bin Space Residuals

These residuals actually seem to reflect a combination of the information from the frequency as well as the amplitude shifts over time. This is not only to be expected, but in many cases desirable as it automatically combines different aspects of the signal degradation into a single easily monitored value.

Another interesting signal to apply this transformation and mapping technique to is the supply voltage of the motor. This signal has properties such that, on gross inspection alone, make it appear to be a steady state signal, despite the fact that it is produced during a transient. Yet upon examination of the residuals for the signal, we see a similar clear progression as the overall motor system degrades.

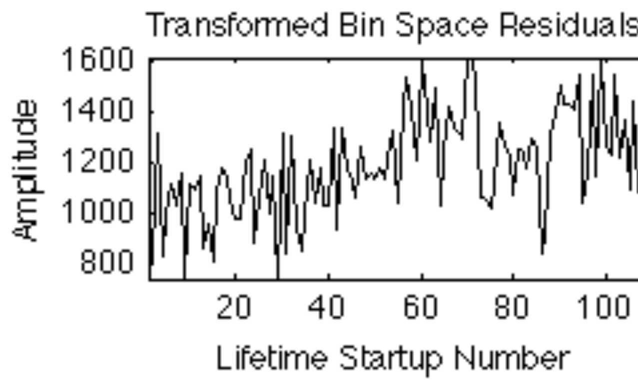

Figure 11 - Startup Supply Voltage Transformed bin Space Residual

In order to find this same level of information about the deviation in this signal through traditional algorithms several levels of demodulation or decomposition of the voltage would be required.

In fact, all of the signals show progressive trends as the motor is aged, but the degree of their increase and the noise level obviously are signal dependant. Again this is expected as the signals all relate to the same system, but are capturing different aspect of the system.

Another useful aspect of the developed transform is that since the bin maps have a temporal aspect, information regarding when in the transient as well as what type of deviations occur can be obtained. The figure below shows the progression of the motor vibration signature's residuals through the transient time.

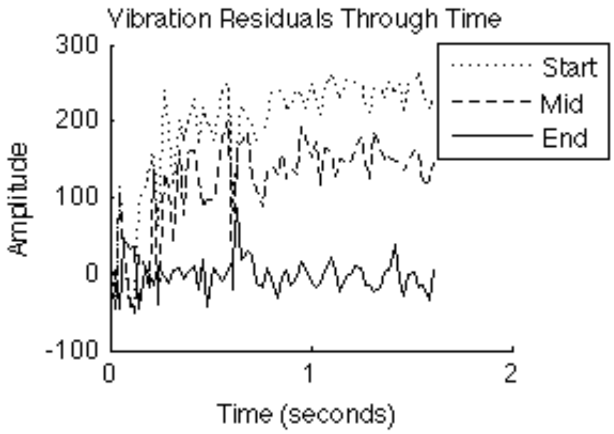

Figure 12 - Startup Vibration Transformed Residuals in Time

Here the horizontal axis represents the time from energizing the motor and each line represents a particular lifetime startup at the beginning, middle, and end of life. This provides information showing that in fact for vibration, the largest differences in startup come after the one-second mark. This is unlike the each of the other signals, which exhibit their largest changes prior to that time. The reason for this can be traced back to the increased steady state level of vibration through out the life of the motor.

Each signal provides easily monitored and trended residuals that can be quickly implemented by a myriad of prognostic methodologies to create Remaining Useful Life predictions.

5. CONCLUSION

The work presented in this paper shows time distribution mapping and the transformation of a signal into a non-uniform bin space based on the empirical aspects of a transient signature to be a clean and elegant method of generically quantifying the degradation of a transient signature. This method is able to simultaneously capture several types of statistical shifts within a signal without need to explicitly search for any one in particular. Furthermore, this transformation and subsequent mapping is shown to be robust over various forms of non-stationary signals. It is this indifference to modulation or signal source that allows it to quickly analyze and quantify a myriad of signals for a single application without the need to tailor individual algorithms to each specific signal. By capturing both statistical and temporal aspects of a signal simultaneously, time distribution mapping via the developed transform is shown to be a versatile and generically applicable tool to aid in transient analysis and to augment existing techniques.

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