

CAN CAVITATION BE ANTICIPATED?*

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ABSTRACT

The major problem with cavitation in pumps and hydraulic systems is that there is no effective (conventional) method for detecting or predicting its inception. The traditional method of recognizing cavitation in a pump is to declare the event occurring when the total head drops by some arbitrary value (typically 3%) in response to a pressure reduction at the pump inlet. However, the device is already seriously cavitating when this happens. What is actually needed is a practical method to detect impending rather than incipient cavitation. Whereas the detection of incipient cavitation requires the detection of features just after cavitation starts, the anticipation of cavitation requires the detection and identification of precursor features just before it begins.

Two recent advances that make this detection possible. The first is acoustic sensors with a bandwidth of 1 MHz and a dynamic range of 80 dB that preserve the fine details of the features when subjected to coarse vibrations. The second is the application of Bayesian parameter estimation which makes it possible to separate weak signals, such as those present in cavitation precursors, from strong signals, such as pump vibration. Bayesian parameter estimation derives a model based on cavitation hydrodynamics and produces a figure of merit of how well it fits the acquired data. Applying this model to an anticipatory engine should lead to a reliable method of anticipating cavitation before it occurs.

This paper reports the findings of precursor features using high-performance sensors and Bayesian analysis of weak acoustic emissions in the 100-1000kHz band from an experimental flow loop.

1. INTRODUCTION

The ultimate objective of this research is to provide a basis for condition-based maintenance of pumps through the detection of impending catastrophic failures. Catastrophic is meant in the mathematical sense. A system experiences a catastrophe when it abruptly changes, or bifurcates, to a fundamentally different state. Some catastrophes are irreversible, such as bearing failure. An irreversible catastrophe damages the system, and can only be reversed by repairing the damage. The most cost-effective way to deal with a catastrophic failure is to perform the repair *just before the failure occurs*.

Is such a fantastic idea practical? The discipline of anticipatory systems suggests that it is. An anticipatory system is based on inductive learning models of a system and its environment. To demonstrate that the models for an anticipatory system can be learned from sensory data, it is convenient to try to anticipate a reversible catastrophe, such as cavitation. A reversible catastrophe can be remedied and repeated simply by changing the operating point of the system.

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This paper reports our initial examination of a reversible catastrophe. The same catastrophe was repeated on the same system often enough that a statistically significant quantity of data was collected. From these data, we have made a preliminary identification of the signature of an incipient catastrophe. In principle a method that detects incipient reversible catastrophes should work for irreversible catastrophes as well, and the principle can be demonstrated without destroying hardware. The technique is to identify the non-linear mathematical model that underlies the process, locate its bifurcation point, and observe the proximity of the present operating point to the bifurcation point.

Bayesian parameter estimation was used to identify the model describing these data. It should be noted that through Bayesian analysis of experimental data it is often easier to obtain a non-linear differential equation describing a process than the function that solves the differential equation. The differential equation is much more than a "curve-fitted" estimate of a function. The processes in which we are interested are non-linear, and often do not have a solution in closed mathematical form. For example, consider the Lorenz equations. The solution is a function of applied energy, viscosity and several other things. At low energy the behavior is highly periodic. At higher energies it is chaotic. There is no closed form function that describes this behavior. However, the entire description is subsumed in the system of differential equations. The bifurcation point can be deduced from several of the parameters of the equations, and the present operating point can be determined from observed data. All this can be done with no description of the solution except the observation that it is whatever function happens to solve the system of equations.

In the present work, which is preliminary in nature, we have obtained a function that describes the acoustic emission (AE) signature of the cavitation bubble. In future research on the same data sets, and on similar data, we intend to obtain a better model by directly fitting the non-linear differential equation. This should produce a highly adaptive and inductive system for real-world data.

This type of analysis is completely unknown in the conventional practice of predictive or condition-based maintenance (CBM). The most advanced methods currently used in CBM are reported by Williams, *et al.*¹ They note that neural networks are completely unsuitable for CBM. In their words: "The field of neural nets is growing rapidly and is likely to yield useful results in the future but there is an element of 'suck it and see' about it."

These same authors note that vibration measurement gives very rich diagnostic information at low cost, and is most effectively done with piezoelectric accelerometers and model-based analysis. It is also noteworthy that in their discussion of modeling, they limit themselves to linear modeling. Although non-linear models are more difficult to identify, they contain the information needed to anticipate catastrophes.

Conventional pump diagnostic analysis is based on simple curve fitting, Fourier analysis, and trending of vibration data.^{2,3,4} These methods are inadequate for several reasons. First, they discard most of the information generated by the sensor. Second, they make important decisions based on extrapolation, when it is well known that catastrophic pump failures are not predicted by extrapolation. Third, AE signatures of defective pumps are highly non-stationary, and Fourier analysis averages out the interesting features.

Greene and Casada note that conventional testing procedures themselves can cause pump failure.³ This further indicates the need for anticipatory measurements. These must be based on non-stationary models.

2. CAVITATION

Cavitation is the formation of vapor bubbles in a liquid whose local pressure falls below the vaporization point for the ambient temperature of the liquid. It is complementary to the idea of boiling, in which the local temperature rises above the vaporization point for the ambient pressure of the liquid. Cavitation is a problem for several reasons. As with boiling, it is turbulent and disrupts attempts to control flows. Also, when the vapor bubbles recondense to liquid, the bubbles collapse violently, creating damaging shock waves in the liquid.

Mathematical theory suggests that the AE signature should be most readily detectable in the 100-200 kHz band.^{5,6} Fluid viscosity will cause the signature to be damped. Decreasing natural frequency of the cavitation bubble cloud with increasing void-fraction will cause the signature to chirp downward in frequency. As seen in Section 5, this is exactly what the authors have observed experimentally.

3. ANTICIPATORY SYSTEMS

Of what use are these signatures? The objective of this research is to develop a system that will anticipate cavitation. The anticipation is based on the recognition of precursor features in non-cavitating fluid. This strategy is similar to the appeal to the "Doggie Existence Theorem," in mine detection.⁷ The argument being that if dogs can detect mines, then the problem is solvable. A slight generalization of the "Doggie Existence Theorem" is a common justification for the development of electronic systems that seek to emulate biological cognition. Assuming that biological percepts can be encoded, an electronic system should be able to emulate the process by which a biological system extracts features from sensory cues to identify the presence of a suspected effect.

Does the idea of computational emulation of a biological process actually provide a practical basis for a novel approach to extracting meaning from noisy data? Recent research by Landauer and Bellman suggests that, in principle it does.⁸ Biological systems process signs and symbols to gain awareness of their environment and their processing skill improves with experience. They commonly use the data inferred from these symbols to perform classification and grouping, and *they do not do so by identifying boundaries between classes*. The way that biological systems perform classification suggests that there exists a semiotic unifying principle of classification that is applicable to computational systems.⁹

Landauer and Bellman define semiotics as "the study of the appearance (visual or otherwise), meaning, and use of symbols and symbol systems." From their examination of classification by biological systems, they conclude that it would require a radical shift in how symbols are represented in computers to emulate the biological classification process in hardware. However, they argue that semiotic theory should provide the theoretical basis for just such a radical shift. Landauer and Bellman do not claim to have discovered the unifying semiotic principle of pattern-recognition, but they suggest that it must be inductive in character.¹⁰

Indeed, the development of a unified inductive-learning model is the key to artificial intelligence.^{11,12} Induction is defined as a mode of reasoning that increases the information content of a given body of data. The application to pattern-recognition in general is obvious. An inductive pattern recognizer would learn the common characterizing attributes of all (possibly infinitely many) members of a class from observation of a finite (preferably small) set of samples from the class and a finite set of samples not from the class. The problem arises due to the fact that the commonly used "learning" paradigms (neural

nets, nearest neighbor algorithms, etc.) are based on identifying boundaries between classes, and are incapable of inductive learning.

How then should induction be performed? The leading thinkers in machine intelligence believe it should somehow emulate the process used in biological systems. That process appears to be model-based. Rosen provides an explanation for anticipatory behavior of biological systems in terms of interacting models.

Rosen shows that traditional reductionist modeling does not provide simple explanations for complex behavior. What seems to be complex behavior in such models is in fact an artifact of extrapolating the model outside its effective range. Genuine complex behavior must be described by anticipatory modeling. In Rosen's words: "In particular, complex systems may contain sub-systems which act as predictive models of themselves and/or their environments, whose predictions regarding future behaviors can be utilized for modulation of present change of state. Systems of this type act in a truly anticipatory fashion, and possess many novel properties whose properties have never been explored." In other words, genuine complexity is characterized by anticipation.¹³

Rosen defines a formal anticipatory system (AS) (a mathematical formulation that exhibits anticipatory behavior) as having five attributes. An AS, S_2 , must contain the model, M , of another system, S_1 . The AS, S_2 , must contain a set of observable quantities that can be linked mathematically to S_1 and an orthogonal set that cannot. The predictions of the model, M , can cause an observable change in S_2 . There must be some observable difference in the interaction between S_1 and S_2 when the model is present and when it is not. Finally, M must be predictive; based on present knowledge, M must change state faster than S_1 , such that M 's changed state constitutes a prediction about S_1 . The point of this discussion is that intelligent behavior is model-based and in the absence of models, there is no intelligent behavior. More to the point, these models must bear some resemblance to physical reality if the behavior of the intelligent system is to have utility in the real world.¹⁴

What is the best way to obtain the models required for an AS? The simple answer is to observe reality to a finite extent and then to generalize from the observations. To do so is inherently to add information to the data, or to perform an induction. It requires the generation of a likely principle based on incomplete information, and the principle may later be improved in the light of increasing knowledge. Where several possible models might achieve a desired goal, the best choice is driven by the relative economy of different models in reaching the goal.

4. BAYESIAN PARAMETER ESTIMATION

How might this be done in practice with noisy data? The most powerful method is Bayesian parameter estimation.¹⁵ Bayesian drops irrelevant parameters without loss of precision in describing relevant parameters. It fully exploits prior knowledge. Most important, the computation of the most probable values of a parameter set incidentally includes the measure of the probability. That is, the calculation produces an estimate of its own goodness. By comparing the goodness of alternative models, the best available description of the underlying reality is obtained. This is the optimal method of obtaining a model from experimental data, or of predicting the occurrence of future events given knowledge from the past, and of improving the prediction of the future as knowledge of the past improves.¹⁶ Bayesian parameter estimation is a straightforward method of induction.

Bayesian parameter estimation describes our best guess of the description of the signal as the weighted sum of several model functions. Its amplitude, or linear parameter, gives the relative contribution of each model function to the overall model. In addition, within each model function, there may be one or more nonlinear parameters. In this technique, the distinguishing feature of a physical effect is the list of model functions and their parameters. This is a somewhat more general concept of the "feature vector" of conventional pattern recognition.

There are as many amplitude parameters as model functions, but the nonlinear parameters in each model function must be searched for. All the nonlinear parameters are included in the argument of the probability function; the amplitude parameters are implicit in the number of model functions in the model (the model's dimensions). The time or sampling points are assumed to consist of a sequence of regularly spaced integers from 1 to the length of the data set. If we wish to scale the sampling points, simply include the scale factor as a (known) nonlinear parameter. Thus, the model for a single oscillatory term might be

$$\{1, \cos(\omega t), \sin(\omega t)\} \text{ or } \{1, \cos(2\pi\omega\kappa), \sin(2\pi\omega\kappa)\} \quad (1)$$

where κ is a scaling factor that converts the integer samples represented by t to microseconds, for example, letting ω represent the frequency in MHz. In the first expression, ω is the frequency in radians. Consider a model of linear chirp:

$$\{1, \cos(2\pi\omega\kappa + \alpha\kappa^2t^2), \sin(2\pi\omega\kappa + \alpha\kappa^2t^2)\}. \quad (2)$$

Here, there are three explicit nonlinear parameters (α , κ , and ω) and three implicit amplitude parameters. One of the nonlinear parameters is known, namely κ , the time-scale parameter. The two unknown parameters are α and ω , leading to a two-dimensional search or optimization problem in the ω, α -plane. Generally, if there are m unknown nonlinear parameters, the problem becomes a search in an m -dimensional space for the peak of the likelihood function. Should this prove too much of a computational burden, individual nonlinear parameters may be removed by integration in the usual manner—however, this may prove more difficult than a high-dimensional search.

A log likelihood is the log of the Student-t distribution. This assumes an integration over all the linear model parameters. The Student-t is computed from the projection of the data onto the orthogonalized model—which should be the same number as the projection of the data onto the model and the inner product of the data vector with itself as $S_t = [1 - (d.m/d.d)]^{(m-n)/2}$, where $d.m$ is the projection of the data onto the model, and $d.d$ is the projection of the data onto itself.

5. EXPERIMENTAL RESULTS

The observables measured in this experiment are the broadband AE signatures of a venturi chamber in a flow loop. The AE data are known to contain features of incipient cavitation and are suspected of containing features of impending cavitation.¹⁷ Previous experimenters have reported unmistakable features of incipient cavitation, but concluded that much richer information was being lost due to the limitations of the then-available hardware.

To search for features of impending and incipient cavitation in AE data, the experiment reported in this paper began where the work of Neill *et al.* left off. The authors used a flow loop at Oak Ridge National Laboratory (ORNL) that is routinely used for calibrating various flow devices. The source of AE signatures was a venturi chamber inserted into the flow loop. The venturi chamber was designed specifically for this experiment and is similar to the one described by Neill *et al.*

The authors used a Vallen Systeme AMSY4-MC6 AE monitor (Vallen ID number 40900) to collect the data. A complete set of AE signatures at various flow rates was collected with broadband piezo-electric AE sensors (Vallen SE-1025-H, usable frequency response from 10 kHz through greater than 400 kHz). Another complete set of AE signatures at various flow rates was collected with narrowband piezo-electric AE sensors (Vallen SE-9125-M, usable frequency response from 20 kHz through 200 kHz). The sampling rate was 10 million samples per second. The dynamic range was approximately 80 dB. This paper includes highlights of the experimental data.

A typical example of the time-domain signature of a cavitation event seen in the AE data is shown in Figure 1. This type of signature occurs very frequently at high flow rates (thousands of instances per second at flow rates above 20 gallons per minute (gpm)). This is a particularly clean instance from the unrefined raw data of the many cavitation events observed at 30 gpm and is used to derive a model of the cavitation event. The amplitude is normalized to 1 at the peak value of the signature. The time-axis is in units of μsec .

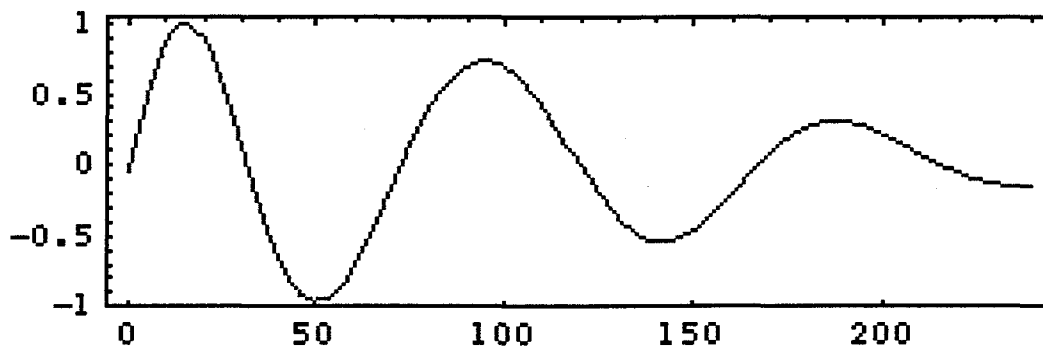


Figure 1. AE signature at 30 gpm.

A linear-chirped damped sinusoid is easily fitted to these data. The model is $\{e^{-\gamma t} \cos(\omega t \kappa + \alpha \kappa^2 t^2), e^{-\gamma t} \sin(\omega t \kappa + \alpha \kappa^2 t^2)\}$. Assume $\kappa=1$. Bayesian parameter estimation computes that the most probable nonlinear parameter values are $\omega = 0.0877091$, $\alpha = -0.000923205$, and $\gamma = 0.00553404$. As shown in Figure 2, this provides a very good first order fit to the data. The damped chirp model is used in the subsequent analyses in this paper. The utility of a more sophisticated model (nonlinear chirps and other decay envelopes) to describe these data will be investigated in future research.

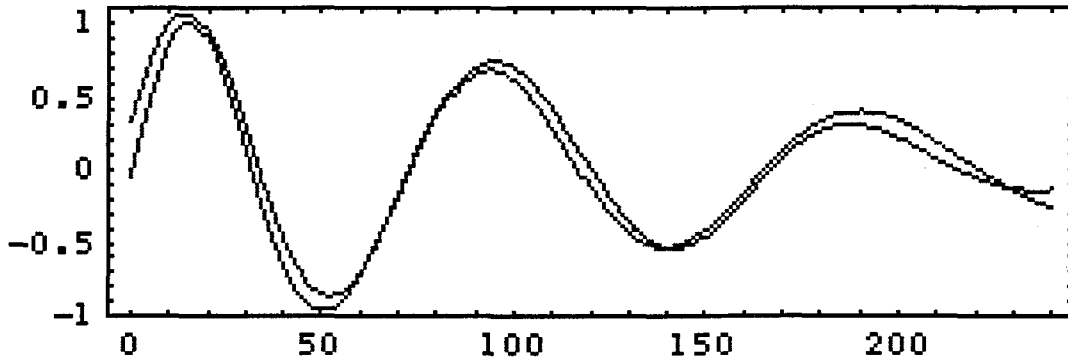


Figure 2. Fitted damped chirp model and observed data.

Figure 3 shows a typical frame of data captured at 30 gpm with the narrowband sensor. From the audible crackling from the venturi chamber, we know that severe cavitation was occurring. Figure 3 shows a little over 2000 μsec of data with maximum amplitude of approximately 20,000 μV . [Note: In Figure 3, 5, 7, and 9 the vertical-axis is the raw AE sensor output in μV .]



Figure 3. Several cavitation events at 30 gpm.

Likelihood is computed for each set of 240 data points in the signature data as the model (used as a matched filter) is swept forward one sample at a time. The nonlinear parameters and then the linear parameters are calculated for the model and the goodness of the fit is determined by computing the $\text{Log}(\text{likelihood})$ in dB. As shown in Figure 4, the signature of Figure 3 includes four events that are very likely damped chirp events. Similar data are shown in Figures 5 and 6 at a 20 gpm flow rate.

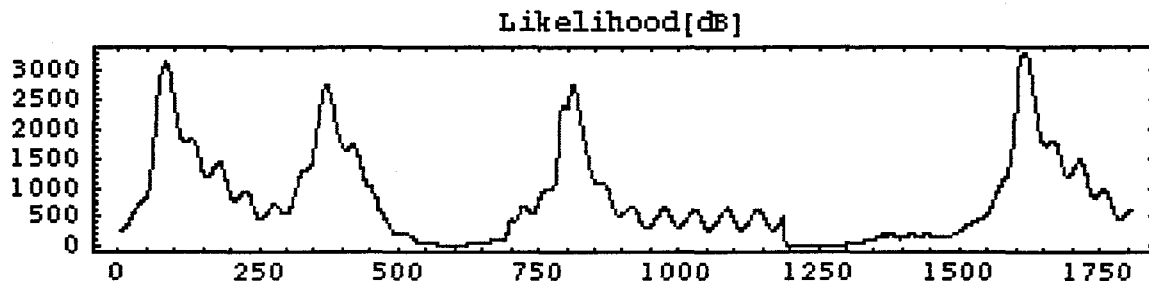


Figure 4. Likelihood of damped chirp events in the signature in Figure 3.

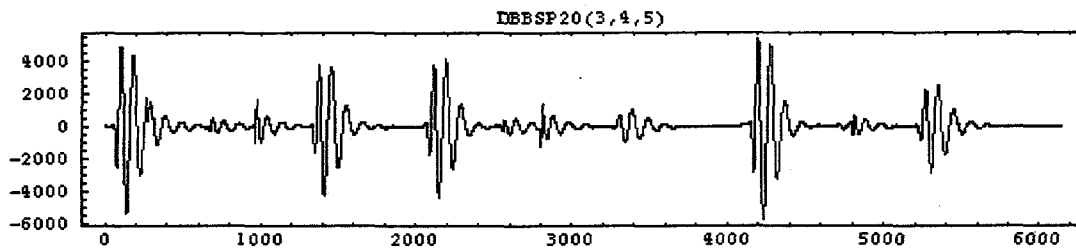


Figure 5. Several cavitation events at 20 gpm.

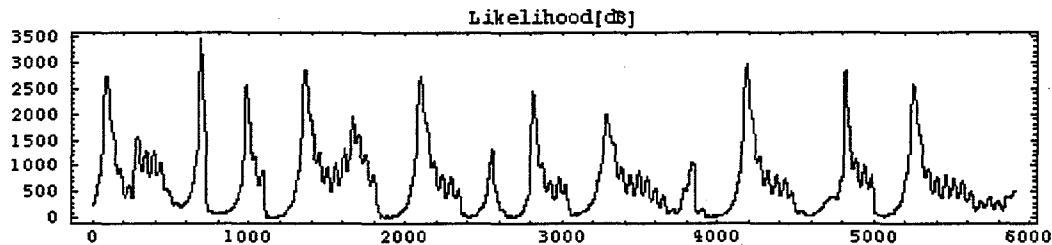


Figure 6. Likelihood of damped chirp events in the signature in Figure 5.

At flow rates below 18 gpm, damped chirp features are very rare occurrences. As Figures 7 and 8 show, a typical data set collected at 17 gpm is practically indistinguishable from the electronic noise of the experimental setup. [Note: The noise floor of the electronics is 1 μ V rms.]

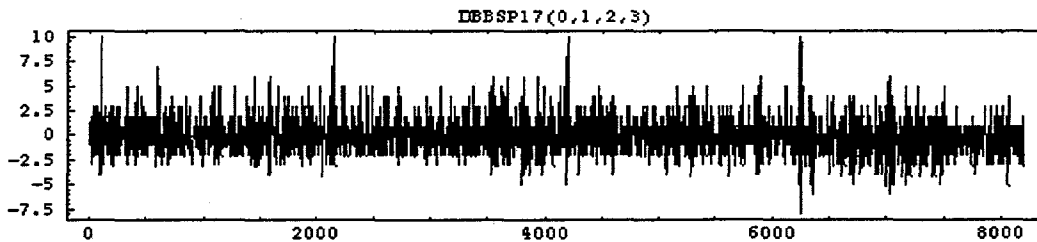


Figure 7. Typical data set at 17 gpm.

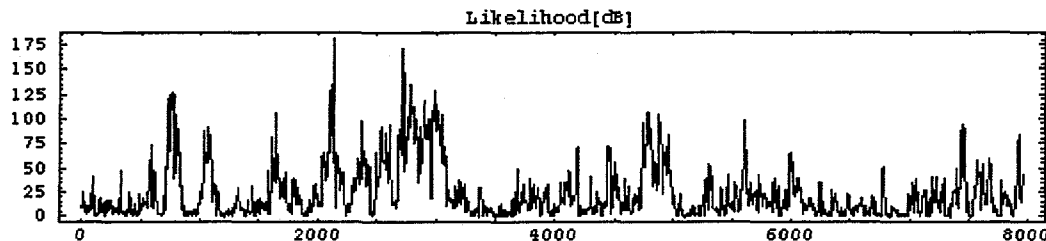


Figure 8. Likelihood of damped chirp events in the signature in Figure 7.

Compare Figures 7 and 8 with Figures 9 and 10. Figure 9 is a typical time domain signature with the sensors mounted on the venturi section, but with zero flow through the flow loop. This is the AE signature of the noise from the environment plus the experimental apparatus itself. As seen in Figure 10, if the log likelihood measure is below 750, it is very unlikely that a damped chirp feature is present in the data.

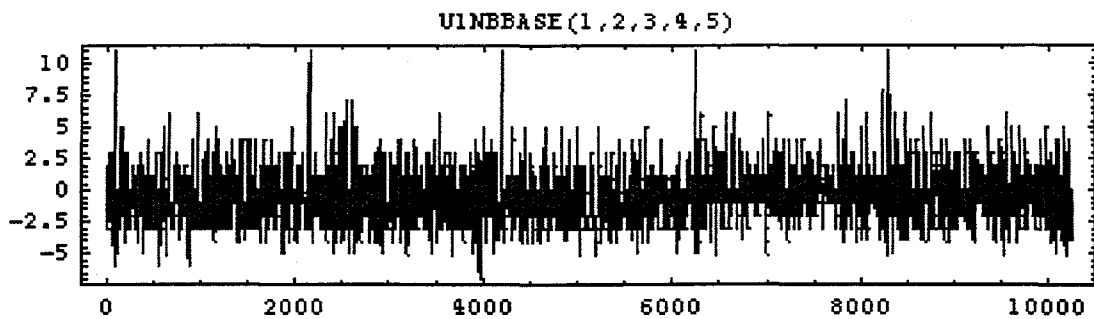


Figure 9. Typical data set at zero flow.

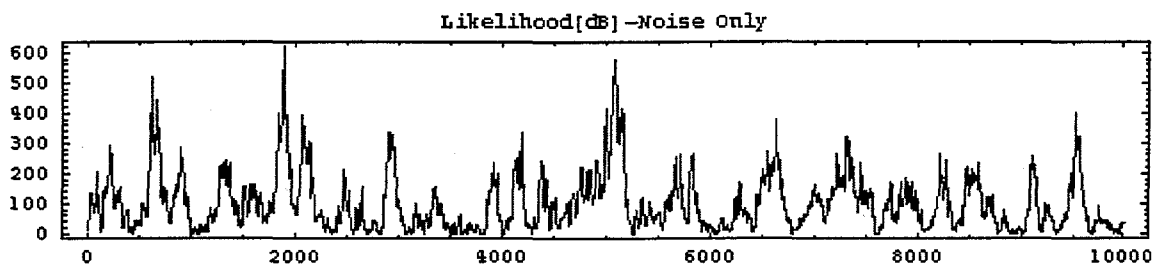


Figure 10. Likelihood of damped chirp events in the signature in Figure 9.

Although damped chirps are rare at 17 gpm, they do occur occasionally. Figure 11 (time domain shown higher, likelihood shown lower) shows the only events captured at 17 gpm with the broadband sensors that do not look just like noise. bursts are apparent in the time domain data, a stronger burst near the beginning, and a weaker one just after the strong one. Both are only a little stronger than the background noise.

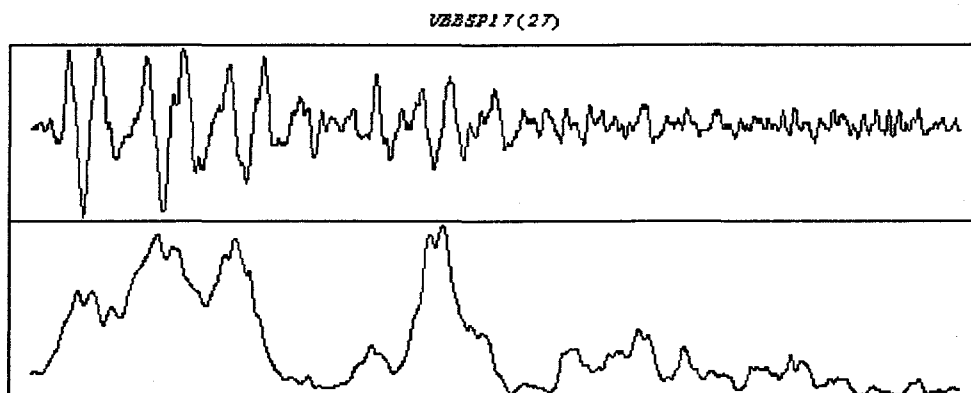


Figure 11. A possible damped chirp at 17 gpm.

Figure 12 shows more details of the log likelihood plot from Figure 11. It is noteworthy that the weaker burst between times 700 and 900 is more likely to be a damped chirp than the stronger burst between times 200 and 400. If the "threshold of cavitation" is between 17 and 18 gpm, it is possible that the very weak damped chirp (amplitude on the order of 10 μ V) in the 17 gpm data is a precursor to the very strong damped chirp (amplitude on the order of 10 mV) signature in the data at 18 gpm and above. This needs to be investigated in more detail in subsequent research.

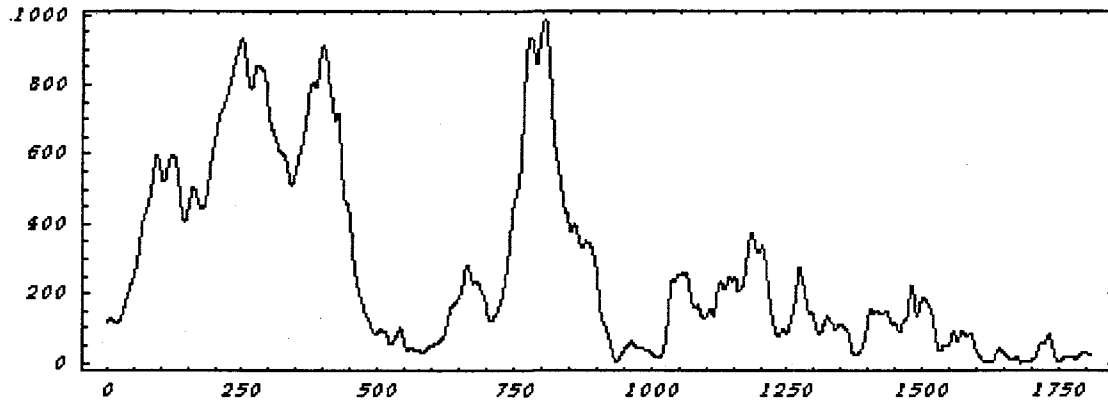


Figure 12. Log likelihood of damped chirp at 17 gpm.

Comparing the 17 gpm data with the zero flow data, it appears that a crude way to distinguish between the presence and absence of damped chirps is to use the log likelihood of 750 as a threshold. The damped chirp appears to be a cavitation signature, although this remains to be confirmed by further investigation. Weak damped chirps (amplitudes of approximately $10 \mu\text{V}$ with this experimental setup) with a high log likelihood (greater than 750) appear to be a useful cavitation precursor.

In future work, a less crude (and more reliable) method of deciding whether or not the cavitation signature is present would be a Rosen anticipation engine. The interacting models in the Rosen anticipation engine would be derived from experimental data similar to these and the theory already described. Such a system would inductively learn the signature of cavitation, with the effectiveness of the learning improving over time as the anticipation engine gains experience.

A bit of interpretation of the data yields some useful guidance at this point. The dominant frequencies of the damped chirps are in the digital frequency range of $0.08 \leq \omega \leq 0.1$ radians. The sampling rate is 10^7 samples per second, meaning that the digital frequency of π corresponds to 5 MHz. Thus, the underlying dominant frequency of the physical chirps is in the range of 127-159 kHz. This is well within the flat response range of the broadband AE sensors. It is also in the resonance peak of the narrowband sensors whose sensitivity in the resonant band tends to be 5-15 dB greater than the sensitivity of the broadband sensors. This suggests that at flow rates below 17 gpm, we should see occasional weak high-likelihood damped chirps with the narrowband sensors. We did.

For example, consider the data set shown in Figure 13, observed at 14 gpm with the narrowband sensors. Note that the two bursts most likely to be damped chirps are barely stronger than the noise and that the matched filter does not show a strong response to the much stronger signal that is unlikely to be a damped chirp.

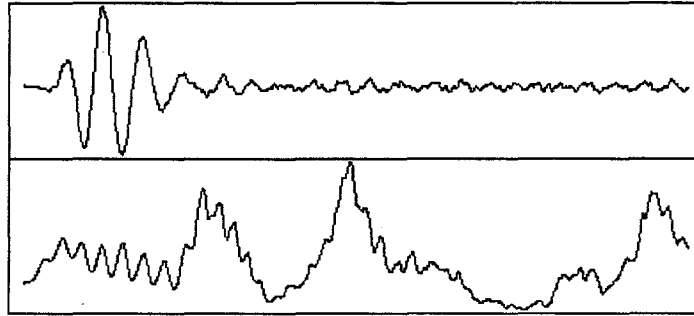


Figure 13. Likely damped chirps at 14 gpm in narrowband data.

Figure 14 shows more details of the log likelihood plot. It is noteworthy that three very weak damped chirps (amplitude below $10 \mu\text{V}$) in the 14 gpm data are very likely to be damped chirps. It is also noteworthy that the strong burst at the beginning of the time domain signal is unlikely to be a damped chirp. Among other things, this illustrates that Bayesian parameter estimation does not confuse strong undesired signals with the damped chirp. Similar results are seen at 13 gpm, but the events are rarer and weaker than at higher flow rates.

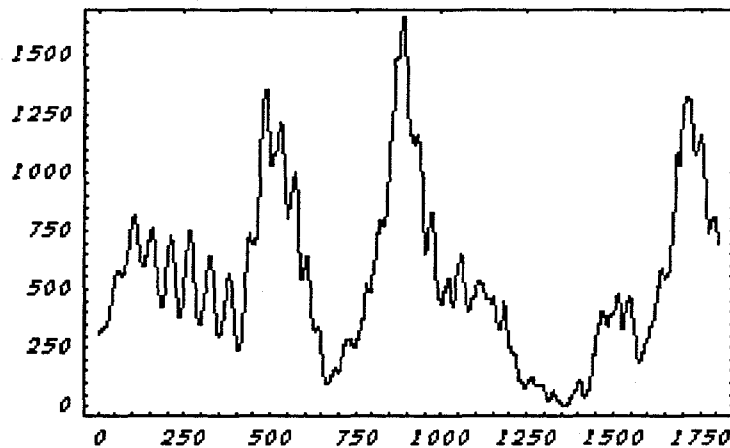


Figure 14. Log likelihood of damped chirps at 14 gpm.

6. CONCLUSIONS AND FURTHER RESEARCH

The foregoing analysis is very preliminary and needs to be validated both by further analysis of the extensive data collected during the initial phase of this research and by the collection of additional data. However, several preliminary conclusions appear to be reasonable. First, that damped chirp AE signature seems to be a distinguishing feature of cavitation. Second, above the "threshold of cavitation" strong damped chirps are common occurrences. Third, below the "threshold of cavitation" weak damped chirps are rare (but not non-existent) occurrences. Fourth, the amplitude of the damped chirps drops abruptly at the "threshold of cavitation," consistent with the concept that the inception of cavitation is a catastrophic bifurcation. Fifth, damped chirps are easy to detect and hard to confuse with other

signatures when Bayesian parameter estimation is used. Sixth, at flow rates well below the threshold of cavitation, occasional damped chirps are observed with weak amplitudes (virtually indistinguishable from noise by the eye), but high log likelihood measure.

These conclusions have utility in two aspects of cavitation detection. First, it appears that the sudden appearance of strong damped chirps in response to a small increase in flow rate is a strong and reliable indicator of the inception of cavitation. Second, weak damped chirps at low flow rates appear to be cavitation precursors. This suggests that the Bayesian-derived damped chirp may be well suited to be a model in the anticipation engine in a formal Rosen AS. These data and their Bayesian analysis illustrate the principle that Rosen's formalism can be used on real-world data to anticipate catastrophic occurrences.

ACKNOWLEDGMENTS

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