Extracting a Whisper from the Din: A Bayesian-Inductive Approach to Learning an Anticipatory Model of Cavitation

Stephen W. Kercel

Oak Ridge National Laboratory*, PO Box 2008 MS 6011
Oak Ridge TN 37831-6011

kzo@ornl.gov

ABSTRACT

For several reasons, Bayesian parameter estimation is superior to other methods for inductively learning a model for an anticipatory system. Since it exploits prior knowledge, the analysis begins from a more advantageous starting point than other methods. Also, since "nuisance parameters" can be removed from the Bayesian analysis, the description of the model need not be as complete as is necessary for such methods as matched filtering. In the limit of perfectly random noise and a perfect description of the model, the signal-to-noise ratio improves as the square root of the number of samples in the data. Even with the imperfections of real-world data, Bayesian methods approach this ideal limit of performance more closely than other methods.

These capabilities provide a strategy for addressing a major unsolved problem in pump operation: the identification of precursors of cavitation. Cavitation causes immediate degradation of pump performance and ultimate destruction of the pump. However, the most efficient point to operate a pump is just below the threshold of cavitation. It might be hoped that a straightforward method to minimize pump cavitation damage would be to simply adjust the operating point until the inception of cavitation is detected and then to slightly readjust the operating point to let the cavitation vanish. However, due to the continuously evolving state of the fluid moving through the pump, the threshold of cavitation tends to wander. What is needed is to anticipate cavitation, and this requires the detection and identification of precursor features that occur just before cavitation starts.

INTRODUCTION

The ultimate objective of this research is to provide a basis for condition-based maintenance (CBM) of pumps through the detection of impending catastrophic failures. Catastrophic is meant in the mathematical sense. Whenever a system experiences a catastrophe it abruptly changes, or bifurcates, to a fundamentally different state. Some catastrophes, such as cavitation, are reversible. Other catastrophes, such as bearing failure, are irreversible. An irreversible catastrophe damages the system, and can only be reversed by repairing the damage.

In principle, a method that detects an impending reversible catastrophe should also work for irreversible catastrophes. The most cost-effective way to deal with a catastrophic failure would be to take corrective action just before the failure occurs. Is such an ideal goal practical?

The theory of anticipatory systems suggests that it is. An anticipatory system is one that inductively learns models of itself and its environment and then modifies its action based on predictions from the models. An interim goal of this research is to investigate the practicality of anticipatory systems by attempting to anticipate the catastrophe of bifurcation of a flowing fluid into a cavitating state.

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* Managed and operated by Lockheed Martin Energy Research Corporation for the U.S. Department of Energy under Contract DE-AC05-96OR22464.

Cavitation is defined as the emergence of vapor bubbles in a liquid at fixed temperature due to the occurrence of localized spots of low pressure. Cavitation degrades performance of fluid handling hardware and causes severe physical damage. By maintaining an operating point just below the migrating threshold of cavitation, the advantages of running a pump at the lowest practical input head could be obtained, while simultaneously avoiding the problems caused by cavitation.

ABSTRACTION OF MEANING

Detection of impending catastrophe from sensor data is a process of abstraction of meaning from sensor output. If a catastrophe is impending, a living creature abstracts the meaning that "something bad is about happen," given a flow of data from its senses, and awareness of its context from prior experience. Can this kind of abstraction be implemented in an artificial system? Note what is actually being asked. This project is *not* an attempt to create or even simulate a living creature; it is an attempt to artificially produce a valuable behavior observed in some living creatures.

Landauer describes the abstraction of meaning as being organized into a hierarchy [Landauer, 1998]. In increasing order of sophistication, the four levels of the hierarchy are data, information, knowledge and understanding. Qualitatively, information is when you can say it, knowledge is when you can do it, and understanding is when you can teach it. Fundamentally different types of processing are required within and between each level.

Data is the rawest or most elemental form of information. Observations of ontological events (real-world phenomena) produce a stream of epistemological atoms (data) according to some model of the measurement process. Conventional computer programs deal with data.

Information is data with an interpretive context. It is relatable to other collected data and to other available information. It can be processed to make new connections with other information or knowledge. The idea here is to find a formal space that is the best description of the data. Generally speaking, it is believed that conventional programs could deal with information, but most do not.

Arguably, there are several available computational techniques that abstract information from data. Goldfarb's evolving transformation system is one example. It identifies class from exemplars of the class, providing a measure of distance between exemplars and distance between classes. It evolves transformation rules such that successive non-equivalent generations of formal spaces are produced until the one well suited to the data and the situation is found [Goldfarb, 1996]. Network thermodynamics is another example. It establishes a topology for models in a thermodynamic space and decides similarity between different data sets by measuring distances in the topological space. Since the topology can be changed, the nature of the space, and thus, the distance measure in the space, can evolve [Mikulecky, 1993]. Bayesian parameter estimation is well suited for converting sensor data to information. It can take prior knowledge (including associations observed in physical reality) into account. Most importantly, it provides a computed measure of how well a particular model describes the data [Jaynes, 1988].

(Note: In this context, distance is a more general concept than the geometric distances between vectors, such as Manhattan or Euclidean distances. Two exemplars are members of the same class or have a small distance between them if it requires little effort to transform one exemplar into the other. Two exemplars are members of different classes or have a large distance between them if it requires great effort, or it is impossible to transform one exemplar into the other. Geometric distance is a special case of this concept of distance.)

These computational methods all appear to be consistent with the need of a computing system in a complex environment to escape the trap of rigidity [Bellman, 1998]. All three allow for *model expansion*, or building a system whose grounding can be arbitrarily "deepened." All three can map current structures onto new foundations. In particular, Bellman's description of cooperation between observed data and theoretical models in the spirit of a Kalman filter, producing a running model of the current state and an error estimate, is the quintessence of embedded Bayesian induction.

Landauer's hierarchy has two more levels, knowledge and understanding. Knowledge is distinguished from the lower forms by requiring a knower that has *goals* for and about the knowledge. The goal may be to discover a regularity in the environment or a connection between phenomena. This is seldom achieved in practice because the goal is hard to define. Understanding is distinguished by perspective across problems in a domain. It requires principles that can lead to coherent stories being told as explanation. Present-day computer programs *do not* have understanding.

It appears that present-day research is barely beginning to grapple with the problem of synthesizing knowledge from information. Landauer says that knowledge can be synthesized from information structures via correlations with other activities. Bellman's conceptual categories are one approach to the problem. Kennedy's research in artificial immune systems also appears to be at this level in the hierarchy [Kennedy, 1998]. In order that it not attack itself, an artificial immune system needs to be able to distinguish between "self" and "non-self." Using evolving co-operating agents, the system has the *goal* of distributed self-preservation. The agents need a model of self and a model of context.

The process of learning a context from prior experience is sometimes called associative behavior. A system learns a causal connection by being exposed to repeated instances of the connection. [Allgood, 1994] The context or environment accommodates an entire class of system responses. [Rosen, 1987]

An anticipatory system emulates the mechanism by which living creatures anticipate and act in expectation of future events. An anticipatory system contains a model of itself, and of its environment. These co-operating models run faster than real-time, providing a prediction about the near future. The anticipatory system can use the prediction to change its own behavior. Since the internal models may be non-linear and feature emergent complex behavior, they may appear to be deceptively simple, and yet still be able to predict complex behavior such as bifurcation into catastrophe.

CAN WE REALLY DO THAT?

Engineers typically object that anticipatory systems violate causality. The popular view is that a conventional engineering system is influenced by past and present events and behaves causally. In contrast, an anticipatory system is influenced by future events and is therefore anti-causal.

The objection is not valid because no such contrast exists. Both conventional and anticipatory systems are attempts to make a decision based on incomplete knowledge. Neither is directly affected by events in reality; both make an estimate of the present state of reality from a limited description contained in data. Both invoke inductively derived models to make a guess about the future. The key distinction is that an anticipatory system modifies its behavior based on its expectation of the future, and a conventional system does not [Rosen, 1987]

To make a reasonable decision based on uncertain knowledge we must note that there is a crucial distinction between ontological facts (descriptions of specific *events that have occurred* in reality) and epistemological knowledge (the *meaning of the facts*, especially their predictive value). An amusing illustration of this distinction is provided by Sage; he points out that the same meteorological data used by environmental activists as "proof" of global warming are used with equal alarm and enthusiasm by those warning of an impending ice age [Sage, 1998]. At least one of these predictions is unreasonable.

Dress shows how Rosen's modeling relation can be used to clarify the process of making reasonable decisions based on uncertain knowledge [Dress, 1999]. A natural system is an entity in physical reality. Its past behavior will affect its future behavior due to the inherent causality of reality. Attributes of its behavior can be perceived by an observer as a stream of encodings (epistemological atoms, sensory data, or percepts, correlated with the actual behavior of the natural system). A formal system is a purely epistemological construct at a higher level of abstraction than the encodings. It is iteratively constructed from the encodings, decodings and other knowledge. The formal system has logical internal connections such that it can make inferences based on its internal state and the encodings that it is receiving from outside itself. These inferences can produce decodings or predictions about the natural system.

Encodings and decodings are human activities that enable a natural system and a formal system to interact. The encodings emanate from measurement and influence the development of the formal system; the decodings emanate from the formal system and relate to some fact or observation in reality. Together, these encodings and decodings, experience-based judgments that interact with reality, form the basis of consciousness and anticipation.

Rosen distinguishes complex behavior from other types of behavior as being anticipatory in its nature. To the question of whether or not anticipatory systems can be constructed, he answers that they abound in the brains of animals. Since anticipatory systems exist in nature, there is nothing fundamental to stop us from constructing artificial anticipatory systems. [Rosen, 1987]

It may be objected that the emergence of a complex formal system from a stream of simple encodings violates the "Principle of Entropy." It is widely believed that entropy is a measure of *disorder*, and that every act of work must move in the direction of increasing entropy, each contributing its bit to our ultimate doom, the dreaded Heat Death of the Universe. However, entropy is *not* an ontological concept inextricably bound to some underlying disorder in the fabric of reality. Jaynes shows that entropy is itself an epistemological construct, measuring the *repeatability* of a process. [Jaynes, 1988] To perform an act of work repeatably, the act must move in the direction of increasing entropy.

The "Laws of Thermodynamics" are another set of epistemological constructs that abstract the cumulative effect of many microscopic events into a high-level description of the global behavior of a thermodynamic system. From the interaction of these epistemological constructs (the generalized principle of entropy and other thermodynamic measures) a prediction can be inferred. The prediction says that if you want a heat engine to run repeatably (an ontological statement about a succession of events in reality), energy must flow from hot to cold (an epistemological statement about the logical relationship between four abstractions). There is no justification for extrapolating this prediction about heat engines into an assertion that complexity cannot emerge from simplicity.

Far from prohibiting the synthesis of information from data, entropy actually helps to provide a practical method for performing this abstraction [Bretthorst, 1988]. The data that we have is a set of observations corrupted by noise, or measurement uncertainty. The knowledge we seek is the model of a process. Intermediate to finding the model, we postulate (whether based on physical insight, lucky guessing, or whatever other means) the mathematical form of a model and a set of parameters, and then compute the probability that this model, with these parameters, will produce these data. To compute the probability, we require an estimate to the probability distribution of the noise. We obtain this estimate by computing the entropy of the probability distribution of the error. The entropy is then maximized subject to the constraint of zero mean and a postulated variance.

The resulting probability value affords one other advantage. It is the probability that this model, with these parameters fits these observations. It serves as a computed measurement of the goodness of the guess. This gives us a basis for making a decision based on uncertain knowledge. This probability measure is "knowledge about the knowledge" that enables us make a judgment. Do we want to bet lives, safety, and vast sums of money on these predictions, or do we want to shop around a bit more in hopes of finding a better prediction?

ABSTRACTING CAVITATION SIGNATURES FROM SENSOR DATA

In assessing pump performance, the key observable conventionally used is the head of the flowing fluid (pressure normalized by specific gravity). At the pump inlet there is an inlet head, and at its outlet there is an outlet head. The difference between these is the net positive suction head (NPSH). The valuable thing that a pump does is to increase the head of a liquid flow; more NPSH implies more effective pumping action. Since the desired objective is typically to create some specified level of head at some point upstream of the pump, the lower the inlet head, the better. Unfortunately, lowering the inlet head lowers the internal pressure in the pump, and at some threshold of inlet head (given a desired NPSH and pumping energy), the pressure will drop sufficiently for vapor bubbles to form inside the pump.

The avoidance of cavitation is a major unsolved problem in pump operation [Neill, 1997]. Cavitation causes immediate degradation of pump performance (an epistemological evaluation of an observed abrupt drop in dynamic head in response to a decrease in NPSH at a given flow rate) and ultimate destruction of the pump (an ontological event attested to by the broken pieces of the pump all over the room). However, the most efficient (hence, least expensive) point at which to operate a pump is with a combination of input and output head and driving energy just outside the threshold of cavitation.

It might be hoped that a simple method to minimize pump cavitation damage would be to adjust the operating point until the inception of cavitation is detected (conventionally decreed to have occurred when a 3% drop in dynamic head is observed) and then to slightly reset the operating point to let the cavitation vanish. However, due to the complexity of cavitation inception, this is not effective. The threshold of cavitation depends on the relationship several parameters that evolve over time, causing the threshold of cavitation to migrate. Even in the short term, hysteresis, and other non-repeatable behaviors are present. Once a pump just begins to cavitate, if the inlet head is ramped up a bit, it will still cavitate. If the inlet head is increased until the cavitation finally stops, and is then gradually decreased, the pump will start to cavitate at a different point from the one at which it started before. What is actually needed is some means to anticipate cavitation from some straightforwardly observable quantity.

The insights provided by the physics of cavitation include both good news and bad news. The good news is that practically everything that can be said about the properties of the cavitation bubble is captured in the Rayleigh-Plesset equation. [Brennen 1995, equation 2.12] This generalized differential equation gives the instantaneous bubble radius, R(t), in response to the driving pressure far from the bubble, $p_{\infty}(t)$ for a specified set of fluid parameters. The bad news is that it is a non-linear differential equation, and has no solution in closed form. Many insights into the nature of cavitation have been uncovered by comparisons between experimental observations and approximate solutions of the Rayleigh-Plesset equation for specific situations. [Brennen 1994, Brennen 1995]

In the most simplified case, the solution of the Rayleigh-Plesset equation predicts a non-stationary oscillating response in which the contracting part of the bubble represents a catastrophic collapse. In reality the oscillation does not occur. As the bubble approaches zero radius, it becomes unstable to non-spherical perturbations; it shatters into a cloud of even smaller bubbles during the first collapse. This generates powerful shock waves that produce the acoustic emission. The cloud will then expand and collapse, and this will also produce powerful shock waves.

Our experiment investigated these acoustic emissions. The idea was to find out what the cavitation features and precursors look like, describe them with a Bayesian-derived model and use the model to extract these same features from noisy and cluttered signals. Based on this strategy, we observed acoustic emissions from a Venturi chamber instead of a pump. The Venturi chamber was designed to produce cavitation in a controlled manner while minimizing other effects, and was installed in a flow calibration loop of the ORNL metrology group. Both the conventional physical insights on cavitation and our experimental acoustic emission data are reported in detail in another document [Allgood, 1999].

CONCLUSIONS

In the initial phase of our research, using Bayesian induction we have found a model of cavitation that may be usable in an anticipatory system. The cavitation signature is a damped chirped oscillation, and this is consistent with expectations from pre-existing theory. Bayesian analysis finds a strong fit between the model and the data at high flow rates. At low flow rates, the Bayesian model sees occasional damped chip oscillations that have a surprisingly good fit to the model, considering that they are much weaker than other features in the data.

At this writing, we are just about to start the next phase of this research. Using the same data sets, collected in the first phase and new data to be collected in the second phase, we intend to obtain a more general model by estimating the parameters by direct fit to the Rayleigh-Plesset equation. A further goal of the next phase is to use the model in an anticipatory system to detect impending cavitation.

ACKNOWLEDGMENT

This research was performed at Oak Ridge National Laboratory, managed by Lockheed Martin Energy Research, Inc., for the US Department of Energy under Contract No. DE-AC05-96OR22464. This research was a joint effort with AEPTEC Microsystems, Inc., and supported under their SBIR No. N98-114.

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