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Identification of sudden transitions in sensor data from rocket tests using wavelet transforms within an integrated health monitoring system

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ABSTRACT

Under a project undertaken at NASA's Stennis Space Center, an integrated framework has been developed for intelligent monitoring of smart elements. Integrated Systems Health Monitoring is an implementation of a monitoring system which is robust, user friendly, and adaptable. This paper focuses on smart sensors, and shows the advantage of utilizing an enhanced version of a previously developed intelligent system, DATA-SIMLAMT, called Enhanced DATA-SIMLAMT or EDATA-SIMLAMT. This new version contains additional properties and states for improved data interpretation. The additional properties are based on wavelets. The major advantage provided by adding wavelet analysis is the ability to detect sudden transitions as well as obtaining the frequency content using a much smaller data set then that required by the traditional Fourier transform method. Historically, sudden transitions could only be detected by a visual method or by offline analysis of the data. EDATA-SIMLAMT provides an opportunity to automatically detect sudden transitions as well as many additional data anomalies, and provide improved data-correction and sensor health diagnostic abilities. The newly developed system has been tested on actual rocket test data from NASA's Stennis Space Center.

1. Introduction

Integrated System Health Monitoring (ISHM) has now permeated its way into many civil, mechanical and aerospace structures/systems. Current interests in smart sensor networks that are reliable and robust have resulted in the development of numerous ISHM systems. Hence the need for intelligent sensors as a critical component for ISHM is well recognized by now. The purpose of such a system is to detect and measure certain parameters, and to use the information and knowledge obtained from the measured data, and any prior knowledge, to make intelligent, forward-looking decisions and initiate actions. Even the definition of what constitutes an intelligent sensor (or smart sensor) is well documented and stems from an intuitive desire to get the best quality measurement data that forms the basis of any complex health monitoring and/or management system. If the sensors (i.e. the elements closest to the measurand) are unreliable then the entire system works with a tremendous handicap. Hence, there is a desire to distribute intelligence down to the sensor level, and give a sensor the ability to assess its own health thereby improving the confidence in the quality of the data at all times.

Intelligent sensors started their history as new concepts in academia [10,26,18], but then parallel work in industry where sensors were developed with built in expert systems and look-up tables [2,33] moved them to real applications. The autonomous sensor was defined as a sensor that has an expert system with extensive qualitative tools that allow it to evolve with time into a better and more efficient system [8]. It differs from the above mentioned models by having a dynamic knowledge base as well as embedded qualitative and analytical functions that give it a higher degree of operational independence, self-sufficiency and robustness. The underlying philosophy behind the autonomous sensor is closest to Henderson's [11,12] logical sensor models that also endeavor to give more problem-solving capabilities to the sensor, but exclude any type of dynamic models. DeCoste [7] describes a system, called DATMI, which dynamically maintains a concise representation of the space of local and global interpretations across time that are consistent with the observations. Each of the observations are obtained from a sensor, therefore the number of observation are equal to the number of sensors in the system. Accuracy and validity of the observations are obtained by cross-referencing with possible and impossible states of the system. DATMI is designed for

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a complete control system comprising of multiple sensors and actuators, and is the basis for the formalized theory called DATA-SIMLAMT (*Dynamic Across Time Autonomous – Sensing, Interpretation, Model Learning and Maintenance Theory*) which is designed for and is applicable to each sensor in the control system [19].

The main challenge lies in the development of a standard format for intelligent sensors such that they can provide the measurement as well as the measurement quality for all types of sensors. Significant work has been done by the SEVA Research Group at Oxford in such standardization efforts [13]. Regular updates have shown considerable progress in the development of multiple sensor validity parameters that are independent of the type of sensor and set the stage for future standardization efforts [14]. Henry [15] showed the need for a 2-way communication for modern digital sensors that serve complex control systems. Schmalzel et al. [30] describe an architecture for intelligent systems based on the smart sensor communication standards such as IEEE 1451.X and lays the foundation for intelligent sensors that are truly standardized [20].

The key requirements of an advanced health monitoring system are that it should be able to detect damaging events, characterize the nature, extent and seriousness of the damage, and respond intelligently on whatever timescale is required, either to mitigate the effects of the damage or to effect its repair. These requirements have been discussed in some detail in earlier reports by Abbott [1]. According to Price et al. [28] a pure monitoring system is expected only to report damage rather than to formulate a response, but it is preferable that the ultimate objective of responding to damage be borne in mind from the outset. The statement of key requirements serves to sub-divide the problem as follows: detection of damaging events, characterization of the damage, prioritization of the seriousness of the damage, identification of the cause of the damage, formulation of the response and execution of the response. it can also be seen that there is a large demand for ISHM [25,31,5,9,24] with application in various fields like monitoring structural health, nuclear power, ship harbors, furnaces, turbine engines, thermal plants, etc.

The greatest limitation of most qualitative methods to analyze and interpret sensor outputs has been during sudden transitions in the signal. Traditional tools such as the Fourier transform e.g. FFT) cannot resolve sudden transitions well enough in the time and frequency domain. The reason is that the FFT describes a signal through an infinite sum of sinusoids of varying frequencies that extend over all time. One can try windowing the FFT, thus finding the frequencies during certain time windows; however, the time resolution is not great enough to find the specific time at which the sudden transition occurs. This paper focuses on the use of the discrete wavelet transform DWT) [6,21] to isolate features. The DWT has been used recently for many applications including image compression [32], pattern recognition [3], speech processing [16], signal detection [17] and model estimation [4].

The current version of DATA-SIMLAMT was refined using data provided by NASA's Stennis Space Center (SSC) acquired from rocket engine tests. The "enhanced" version of DATA-SIMLAMT, EDATA-SIMLAMT, includes two states added to the existing eight states. EDATA-SIMLAMT utilizes wavelet decomposition in order to detect sudden transitions in the test data. It also provides a reliable data fixing algorithm that utilizes a least mean squared algorithm. The performance of the algorithm is shown by evaluating the condition of sensor data acquired from rocket engine tests completed at NASA SSC.

2. Intelligent sensor phylosophy

This section provides an understanding of DATA-SIMLAMT *(Dynamic Across Time Autonomous - Sensing, Interpretation, Model Learning and Maintenance Theory)* [19] which is a theory that was developed for intelligent sensing systems. Its main building blocks are:

<u>Property</u> – is a parameter that has different state values based on the sensor performance, e.g. an amplitude check that monitors the amplitude of the current data point compared to the past few readings. It could have state values of (N)ormal or (H)igh signifying normal state of affairs or a potential problem.

<u>Concept</u> – is a set of properties with same state values, e.g. amplitude is (H)igh for a certain duration of time.

<u>Behavior</u> – is a set of concepts, e.g. a normal operation followed by duration of very high amplitude may signify a problem such as a spike.

<u>Envisionment</u> – is a known, hence pre-defined, concept/behavior similar to a known pattern in the pattern recognition problem, and is stored in the sensor's knowledge bases.

Numerous properties with their state values (at any given time) constitute a concept. A concept is defined as a period in time in which the properties have the same state values. A concept, as stated earlier, is defined by the eight properties and their unique state values. Two or more concepts, in a definite order, constitute a behavior, as shown in Fig. 1, and can be envisioned to be a pattern.

The symbolic table is a snapshot of the output of a sensor. The numeric sensor data is converted to the symbolic data set in real time and pattern recognition is then done. The lightly shaded segment has been identified as Previous_Noise(Low) concept and the heavily shaded portion has been identified as Amplitude(High) concept. Together, in that order, the behavior of Spike (Present) has been identified that would cause the sensor to take appropriate action. In this case, it could be to send a predicted value to the main controller rather than the actual data which is probably faulty. Such sensor output interpretation is the part of a larger system that has numerous behaviors coded in as well as has the ability to learn new ones.

The governing Integrated System Health Monitoring (ISHM) vision for an entire process needs to be in an environment conducive for embedded intelligence and decision making. Such an overall system for the rocket test stand has been designed at Stennis Space Center, using the G2 environment from Gensym, Inc.[1] G2 software offers the opportunity to develop layered behaviors analogous to hierarchical autonomous architecture. This work is focused solely on the single sensor level. The central system collects the data from the sensors and external programs; then applies it to the model for the system contained in its knowledgebase.

The intelligent sensor spoken of in this paper is foreseen to be a major component in the ISHM vision. An intelligent sensor is anticipated to provide additional information than that of a traditional sensor. The information provided by an intelligent sensor can include actual data, corrected data, validity of the data, health of the sensor, etc. (see Fig. 2).

The intelligent sensor embodiment shown in Fig. 2 provides a possible scenario where the input data from a physical sensor is analyzed by various routines. The outputs of the routines provide information which forms a basis for a structured output from the intelligent sensor. The output from the sensor could consist of the raw data, actual or corrected, and health information about the data and the sensor itself. This health information could be in the form of a Condition Assessment Sheet (CAS) which shows a confidence factor level of the data.

The intelligent sensor is developed in two forms: Physical Intelligent Sensor (PIS) and Virtual Intelligent Sensor (VIS). A PIS is an actual sensor with an embedded microprocessor, while a VIS is a software based sensor that functions as a PIS where it is impossible

[1] [Online]. Gensym, Inc. Burlington, MA. Available: http://www.gensym.com.