MISSING SENSOR DATA RESTORATION FOR VIBRATION SENSORS ON A JET AIRCRAFT ENGINE

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ABSTRACT

Using array historical data, the readings from a sensor array may be shown to contain sufficient redundancy such that the readings from one or more lost sensors may be able to be accurately estimated from those remaining. This interdependency can be established by an neural network encoder. The encoder is also used in the restoration process. In this paper, we give some examples of sensor restoration for vibration sensors on jet engine and computer traffic data.

Key Words: neural network, auto-encoder, sensor restoration, auto-associative regression machine.

I. INTRODUCTION

In certain cases, sensor readings may be related in such a way as to allow restoration of one or more lost readings from those remaining. Using auto-associative regression machine auto-encoders [Reed & Marks], *missing sensor data* (MISED) *restoration* has been proposed as a method to estimate the readings of failed sensors by recognition or discovery of a constraint placed on the historical readings from the sensor array [Narayanan *et al.* 2002]. This paper presents example applications of this procedure.

II. BACKGROUND

Historical data from a sensor array can be used to train an auto-associative neural network encoder as illustrated in Figure 1. For N sensors, the auto-encoder with N inputs and N outputs, is trained to produce an identity mapping through a degrees-of-freedom bottleneck of $M < N$. If this identity operation can be achieved, there exists a (possibly nonlinear) relationship among the sensor readings. When one or more sensor values are lost, this redundancy can, in certain instances, be used to restore the missing sensor values.

The procedure for MISED is illustrated in Figure 2. The known sensors and initial guesses of the missing sensor values are placed into the auto-encoder. The output of the auto-encoder is subtracted from the distance to specify the error. The error is used to incrementally change the estimated values of the missing sensors and the feedback iteration is repeated. Numerous optimization algorithms can be used to find the missing sensor values that minimize the composite error of the encoder [Narayanan *et al.* 2002].

III. JET ENGINE VIBRATION SENSORS

A finite element emulation of jet engine developed at Boeing Phantom Works is used to illustrate MISED. Four vibration sensors are placed at disperse locations on the engine subjected to imbalances at three locations. Each sensor measures the vibration spectrum in the x, y and z directions. The frequency response consists of 500 points over 50 Hz each spaced by 0.1 Hz. Example plots of the vibration spectra magnitudes are shown in Figure 3.

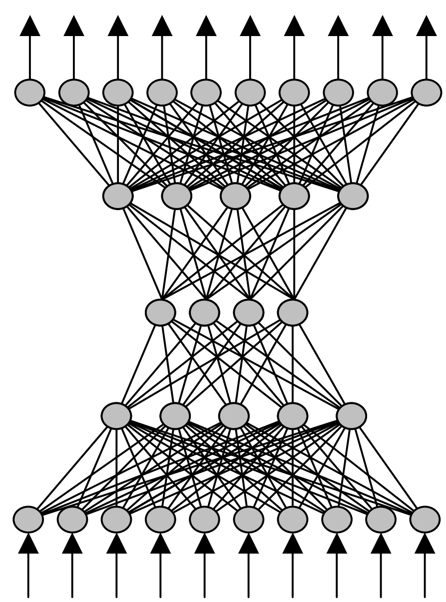

Figure 1: An example 10-5-4-5-10 neural network auto-associative auto-encoder.

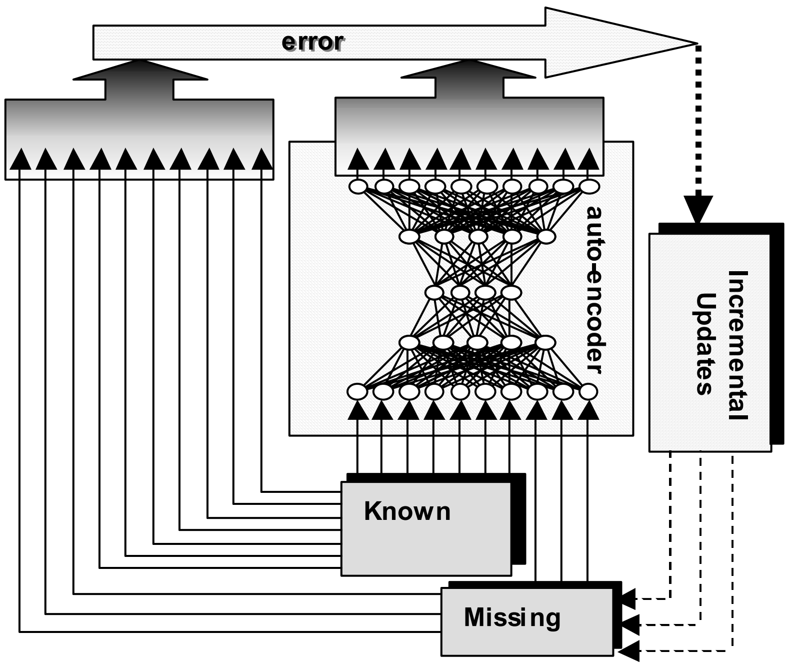

Figure 2: A methodology for restoring missing sensor data using a trained auto-encoder.

When we try to restore we set the 11 points corresponding to the missing sensor to zero & try to reconstruct using the trained encoder NN. Using this way we would need about 50 NN's to train the whole frequency response.

To illustrate MISED, a 88-60-40-60-88 auto-encoder was trained with sensor data using standard error back-propagation. Eleven sequential points in the frequency response between 30Hz and 31 Hz was chosen. The neural network was trained on the real and imaginary parts of each point in the frequency spectrum. A sample training vector is shown at the top of Figure 4. Each eleven numbers correspond to the real part of the reading of sensor number 1 at sequential frequencies. The second eleven numbers correspond to the imaginary part. The next twenty two numbers correspond to the frequency components measured by sensor number two, etc.

The auto-encoder was trained with 5000 sensor readings obtained using the convex data enrichment procedure described by [Thompson *et al.*]. An additional 500 samples were used for testing. The neural network architecture used gave the lowest test error over those tested. The average RMS error for the testing data was less than 2% of the maximum. The maximum testing error was 10% of the maximum.

A second data set consisting of eight sensors placed at different locations and subjected to imbalances at three different locations were also used. Here too each sensor had a frequency response consisting of 500 points spaced over 50Hz. For the second data set, only the magnitude of each sensor vibration is used. Ten points corresponding to frequencies between 30Hz and 31Hz was tested. So with 10 points per sensor and eight sensors, there are 80 inputs.

Data enrichment was again used to create 5000 training data set and 500 test vectors. For the second data set, auto-encoder neural networks with different architectures were tried to reconstruct the missing sensors. The training and testing RMS errors were less than 3% of the maximum range of data.

The ability to restore lost sensor measurements was uniformly successful for one and two missing sensors. An example of restoring a single missing sensor is illustrated in Figure 4. Each missing sensor corresponds to 11 lost data points. Shown at the bottom of Figure 4 is the output of the auto-encoder for both known and missing sensor readings. The result is graphically indistinguishable from the desired response shown at the top.

For two lost sensors, worst case test results are shown in Figure 5. The maximum error, remarkably, is approximately 5% of peak. Restoration of three missing sensors is not possible because the number of known values would be reduced to 22. A necessary condition for MISED to work is that the number of known values must equal or exceed the number of degrees-of-freedom in the bottleneck – in this case 40. The

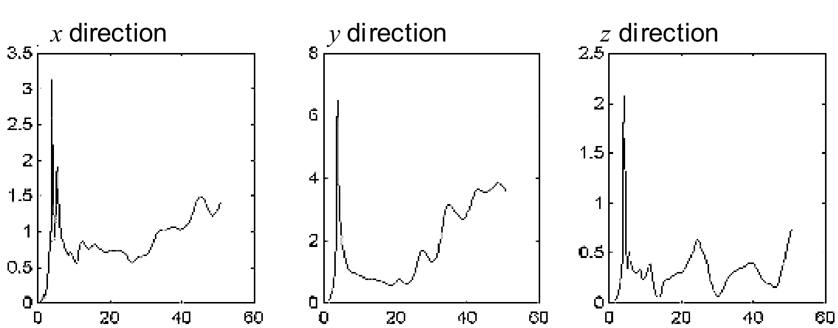

Figure 3: Example spectral magnitudes measured by vibration sensors. Frequency is in hertz.

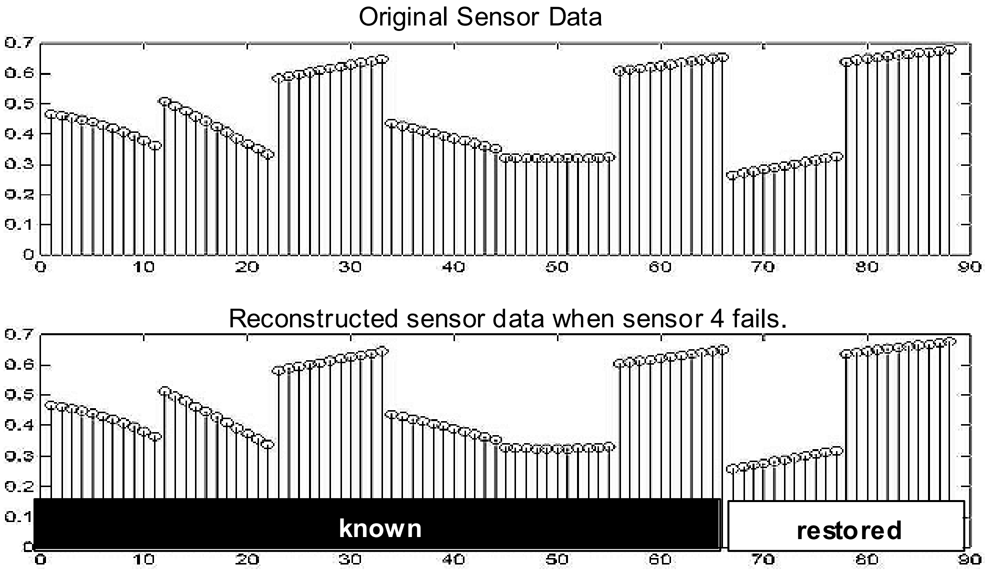

Figure 4: Original (top) and restored missing sensor data.

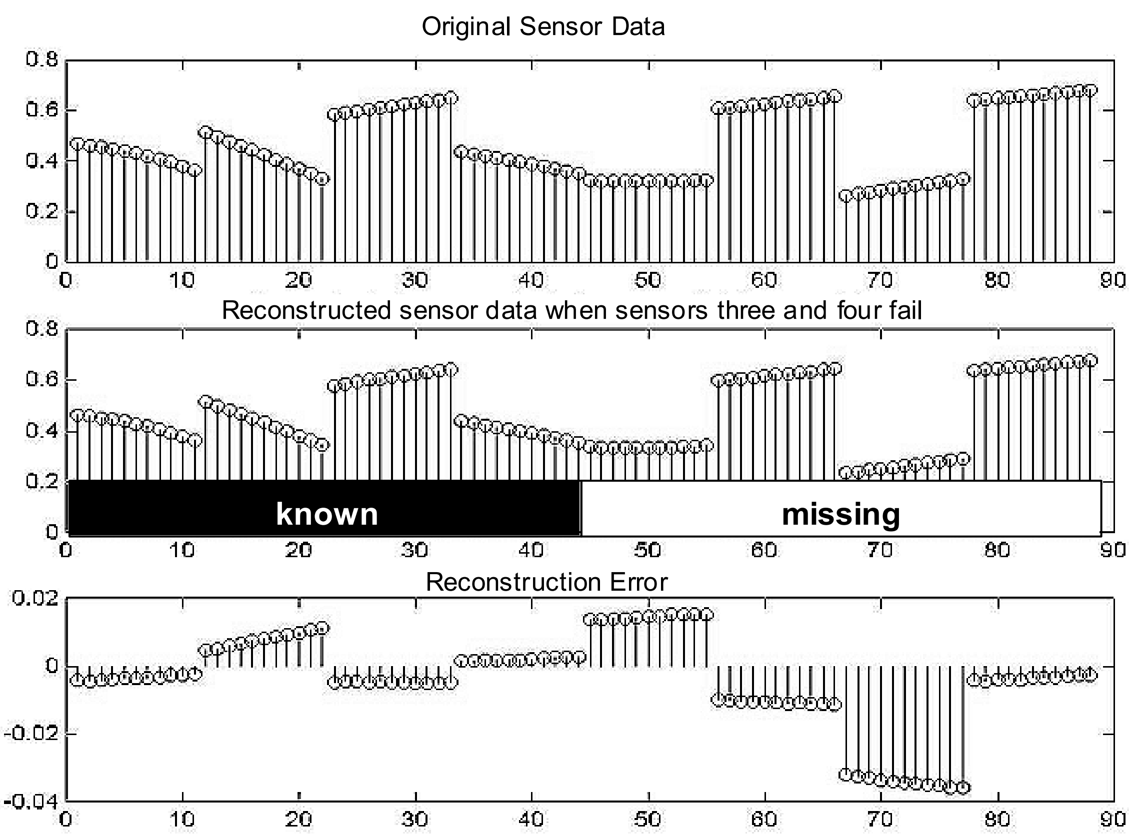

Figure 65: Restoration of two lost vibration sensors corresponding to 44 points of data.

performance of MISED will degrade, consistent with the results of Oh *et al*. [5] who show effects of uncertainty are magnified as the number of known sensors diminish.

IV. ACKNOWLEDGEMENTS

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V. REFERENCES

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