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Missing Sensors Restoration for System Control and Diagnostics

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Abstract-- Error free measurements are an essential requirement for system monitoring, diagnosis, and control. Measurements can be corrupted or interrupted due to sensor failure, broken links, or bad communication . Control, monitoring and diagnostics cannot operate effectively under these conditions. State estimation has been used in the past for sensors restoration. However, it requires accurate, observable and error free detailed system model. These requirements are often unattainable in hardware settings. In this paper, we propose a completely different concept based on auto-encoding and intelligent system search algorithms. The proposed technique is not model based, is hardware realizable, and is rapid enough for fast action of low inertia electromechanical systems. Hardware experimental results show the effectiveness of this technique for on-line control.

Index Terms—**Auto-encoder, missing sensors, particle swarm optimization, machine diagnosis, control.**

I Introduction

The diagnosis and control of complex drive systems is dependent on the quality and availability of measurements. For economical, reliability and operational reasons, most drive systems are monitored and control based on a small number of sensors' data. These measurements describe the status of the system and are often called the state variables. They may represent physical quantities such as current, voltage, speed, torque, position, frequency, flux, signal propagation; or they could be abstract mathematical variables of combinations of several quantities.

In modern systems, sensors data, analog or digital, are transmitted to a *control hub* that makes its decision based on the sensors data. In some complex control systems, the state estimation is used as a data-processing technique to provide the *best estimate* of the system state. It can also assign values to any missing data. Nevertheless, all state estimation techniques have strong drawbacks. For example, the system model must be available and accurate. In fact, an electric drives employing power electronics and variable load cannot be modeled accurately enough to detect or localize windings shorts. Although the parasitic parameters do not normally affect the control operation of the system, they are dominant in high frequency injection and time domain reflectometry [1-4].

In addition, the state estimation technique requires the model to be observable in the linear sense. In electric drives systems, sensors are placed in specific locations based on factors such as the practicality of mounting and accessibility. This can render the system unobservable. Furthermore, the state estimation method converges slowly, can become trapped in local minima, or produce ill-conditioned and therefore unreliable solutions.

In this paper, we propose a new concept based on auto-encoding with a multi-agent search algorithm known as *particle swarm optimization* (PSO). The proposed method is called *missing sensors restoration* (MSR).

2 General Description of Missing Sensors Restoration Algorithm

The MSR method is comprised of two modules, the auto-encoder and a PSO search algorithm.

Figure 1 shows the MSR algorithm. It consists of an auto-encoder and a feedback search loop employing PSO. The sensors data are initially evaluated to determine its integrity. If any of the sensors is missing or erroneous, the reading of the failed sensors is estimated by the auto- encoder. The auto-encoder is a neural network (NN) designed and trained to reproduce its input vector. The inputs to the NN are the sensors data. Thus, the NN is trained online by real measurements. Once trained, the NN develops a correlation among all sensors through its hidden layers. Since it is trained to reproduce its own input, the difference between the input and output of this NN is a measure of the encoding accuracy.

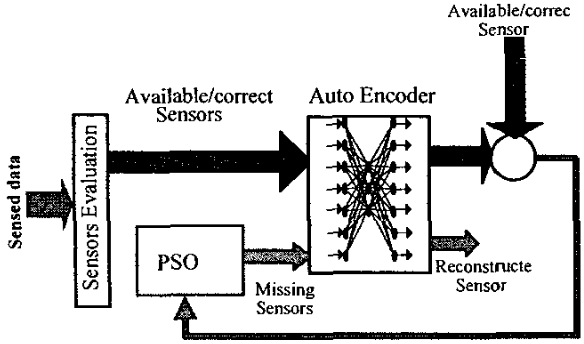

Figure 1: Missing Sensors Restoration Algorithm

When a sensor's data is missing, the output/input of the neural network are not images of each other. An error signal is generated based on the known sensors only. This error signal is used as a fitness signal for the PSO search algorithm. The search algorithm iteratively assigns values to the missing data until all output and inputs of the encoder are matched. The steady state value of the iteration provides the estimates of the missing sensor values.

3 Auto-Encoder

The layered perceptron neural network is known for its capability to reduce the dimensionality of a feature vector without compromising the systems accuracy. This is a non-linear dimensionality reduction that cannot be matched by other reduction methods such as the principal-component analysis. Figure 2 shows a schematic of a NN structure used to achieve dimensionality reduction.

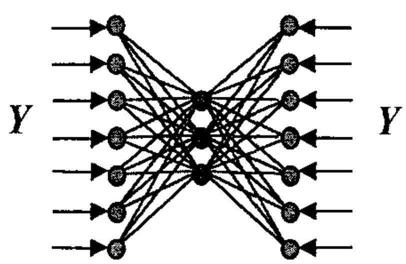

Figure 2: Auto-encoder.

This neural network has the same numbers of input neurons as output neurons. The number of hidden layer neurons is less than the number of the input or output layer's neurons. During the training process, the vector Y is presented simultaneously as the input and the output of the neural network. In other words, the neural network is designed to reproduce its own input vector. This is done by means of an attempting to map each input vector onto itself.

After the neural network is trained, the output of the hidden layer represents the extracted features of the input sensors. Hence, the hidden layer captures the correlations between all input sensors. Since the NN is reproducing its own input, it is performing two main operations: reduction and expansion. The reduction is the projection of the input vector onto the smaller dimension hidden layer space. In this process, the interrelationships of all input sensors are characterized through nonlinear combinations of all sensor values. Since the low dimension hidden layer space can reproduce the high dimensional input space through the hidden-to-output layer, the lower dimensional characterization of the hidden layer is sufficient to reproduce the higher dimensional input.

4 Particle Swarm Optimization

PSO is a multi-agent expandable search algorithm used here to construct the missing or unreliable data. PSO is an evolutionary techniques developed by Eberhart and Kennedy [5-7]. Unlike other evolutionary computation techniques, such as genetic algorithms and evolutionary strategies, PSO is inspired by social interactions between members of a swarm. PSO can be described as a group of birds searching the operating space for food. The best feeding place is equivalent to the optimal solution from the optimization point of view. Each individual bird is often called a "particle" and represents a solution. Each particle adjusts its motion in the operating space according to its own experience and that of its group members. Through cooperation and competition among potential solutions, particles can often find optima relatively quickly.

The basic operation of the PSO is described in Equations (1) and (2)

$$\vec{v}(k+1) = w \times \vec{v}(k) + c_1 \times rand() \times (\vec{x}_{SelfBest}(k) - \vec{x}(k)) + c_2 \times rand() \times (\vec{x}_{GroupBest}(k) - \vec{x}(k)) \quad (1)$$

$$\vec{x}(k+1) = \vec{x}(k) + \vec{v}(k) \quad (2)$$

where $\vec{x}$ is the solution vector of a single particle (position) and $\vec{v}$ is the velocity of the particle. *GroupBest* is the best position found among all the particles in the group, which is equivalent to the best experience of the particles as a group. *SelfBest* is the best point observed by the particle itself, representing its own best experience. c_1 and c_2 are acceleration constants represent the weighting in the directions of the *GroupBest* and *SelfBest* [5-7]. *rand( )* represents a uniform random number between *0* and *1*.

The simplicity of PSO is one of its most powerful features. Equations (1) and (2) are simple algebraic functions that are rapidly computed. The testing of a particle's solution is done by checking the solution against the objective of the operation without any need for gradient or higher order terms as with the classical single agent optimization techniques.

In our application, the positions of the particles in the operating space represent the values of the missing sensors. After converging the *GroupBest* is often the optimal solution.

5 Test System

Figure 3 shows the block diagram of the experimental setup, and Figure 4 shows a photo of the actual setup [8].

The test system consists of three main components– an electric drive to move a positioning head, an encoder to read the position of the head and a PC to implement the control algorithms. Other components are used to interface the electric machinery with the PC.

The positioning head is mounted on a load plate or stage. The axis along which the positioning head moves on a guide cylinder is the Y-axis. The guide cylinder houses a belt and the pulley system, which couples the positioning head to the motor. The axis along the Y-axis assembly is placed on two parallel guides is the X-axis. The X and Y axes each have a total travel length of 70cm along each axis. In this paper, all experiments were conducted on the X-axis of the setup.

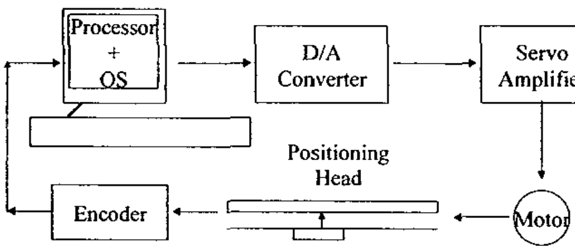

Figure 3: Main components of the lab setup

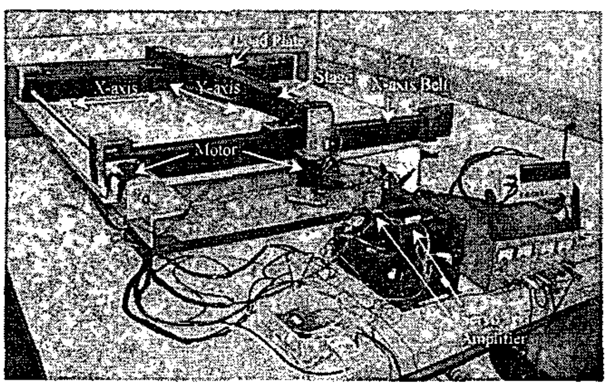

Figure 4: Photo of the lab setup.

The drive circuit consists of two motors and two servo amplifiers, one for each axis of motion. Direct current brush motors are used to drive the load in each direction. Two identical 25kHz H-bridge, PWM, DC-DC servo amplifiers drive the motors. A differential analog input is taken from the output of a D/A converter as the torque (current) reference command. The D/A converter takes current command input from the PC and outputs current reference command to the servo amplifier.

Two optical linear encoders having a resolution of 0.5 μm are fitted on each axis of the stage. They are used to read the position of the head on the XY stage. Optical encoders use quadrature-encoding technique to signal the direction and magnitude of motion. The linear encoders are interfaced with the PC via a quadrature-decoding card, through an ISA slot.

6 Sample of Experimental Results

The proposed MSR algorithm was tested by turning off one sensor in the control circuit. The sensor measures the rms voltage across the motor terminals. Other sensors measure current , speed, and reference and carrier frequencies of the PWM.

Several loading and operating conditions were considered. In each case, the rms voltage of the motor was identified in less than 10 ms using Pentium III processor. Figure 5 shows the error distribution of the MSR algorithm. As seen in these figures, the motor voltage was well restored and the worst case error was less than 6%. Higher accuracy is possible if faster processor is used, and more computational steps are allowed.

Although this case is a simple one-dimensional search problem, it shows how the proposed technique restores the missing information very effectively.

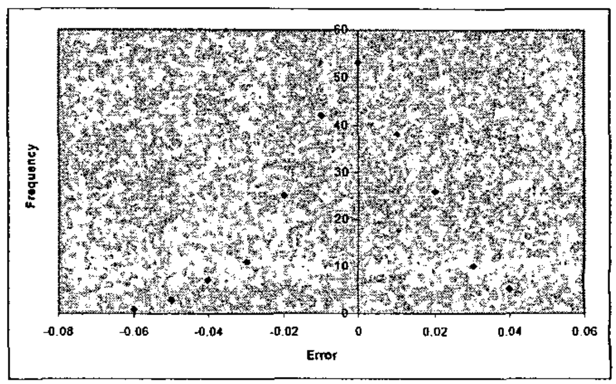

Figure 5: Error distribution of restored feature.

7 Conclusion

In this paper, we have proposed the combination of an auto-encoding with a PSO algorithm as a new method to restore missing sensors data. This technique does not require system models and is fast for on-line applications.

The proposed MSR algorithm was tested on a flexible shaft electric drives system. The initial results are very promising and the technique is being developed for multiple missing features.

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Biographies

Mohamed A. El-Sharkawi is a Fellow of IEEE. He received his B.Sc. in Electrical Engineering in 1971 from Cairo High Institute of Technology, Egypt. His M.A.Sc and Ph.D. in Electrical Engineering were from the University of British Columbia in 1977 and 1980 respectively. In 1980, he joined the University of Washington and is presently a Professor of Electrical Engineering. Dr. El-Sharkawi is the Vice President for technical activities of the IEEE Neural Networks Society. He is the founder of the international conference on the Application of Neural Networks to Power Systems (ANNPS), and a co-founder of the international conference on Intelligent Systems Applications to Power (ISAP). He is a founding Chairman of several IEEE task forces, working groups and subcommittees. He is a current or past member of the editorial board or associate editor of several journals. Dr. El-Sharkawi is the editor and co-editor of several IEEE tutorial books on the applications of intelligent systems. He is the author of a textbook on "fundamentals of Electric Drives" published by Brooks/Cole in 2000. He organized and taught several international tutorials on intelligent systems applications, power quality and power systems, and organized and chaired numerous panel and special sessions in IEEE and other international conferences. He has published over 160 papers and book chapters in these areas and holds 5 licensed patents. Dr. El-Sharkawi was the chairman of the IEEE International Electric Machines and Drives held in Seattle, May 1999.

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