Some Features of Neural Networks based Intelligent Sensors and Design issues

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ABSTRACT
The need for intelligent tools for all stages of a product's lifecycle is becoming increasingly important with the increasing system complexity, shorter product life cycles, lower production costs, and changing technologies. This paper is a brief review of the features such as characteristic linearization, curve fitting, auto-calibration and fault diagnosis of Artificial Neural Networks (ANNs) based intelligent sensors and design issues for their development.

Keywords
Intelligent sensors, Artificial Neural Networks, sensor characteristic linearization and fault diagnosis.

1. INTRODUCTION
Sensors are fundamental elements in all the instruments and circuits which are extensively applied for measurements, as well as control, in scientific and industrial fields. For the industrial applications, low-cost sensors with high sensitivity and resolution, with linear characteristics are required [1]. Unfortunately, dynamic nature of the environment, aging, inherent noise in the sensor, missing data due to transients or intermittent faults, influences the sensor characteristics nonlinearly. It bas been observed that the regular mathematical approaches do not provide the acceptable non-linearity prediction results, since, an accurate mathematical model including all error sources is rarely known. Linearization could obviously be implemented either by means of a look-up table or a specific algorithm. However, in many cases, an accurate table may be too large to be realized [2], while the algorithm may be time consuming or may need a dedicated computing system. Thus a low cost precise schemes for compensation of several interfering parameters and linearization are the requirements which can be fulfilled achieved by ANNs [3].

ANNs are used to predict sensor drift because they are intrinsically capable to do so [4]. The primary advantages of ANNs are the ability to generalize results obtained from known situations to unforeseen situations, fast response time in operational phase due to a high degree of structural parallelism, reliability and efficiency [5].

They have robustness in presence of noise and are fault tolerant. Over the past four decades researchers have shown that ANNs do well at learning and adapting. Adaptation in ANN is usually based on the modification of interconnection strengths between computational elements according to a given learning algorithm. Constrained interconnection topologies may, however, place a priori upper limit on the ability to adapt. For non-linearity estimation and to obtain a direct digital readout of a sensor, an ANN based modeling technique has been proposed with quite satisfactory performance; with a consideration of change in the ambient temperature [6].

Field-programmable devices couple the benefits of a hardware implementation (mainly speed and parallelism) with the possibility of implementing ANN with dynamically re-configurable structures, enabling a system to modify its topology and adapt to changing situations.

A scheme for ANN based intelligent sensor is shown in figure 1. The output of nonlinear sensor is signal conditioned and passed to a precise the Analog to Digital Converter (ADC) so as to convert it into digital data, which is processed (linearized) by micro-controller, PC or Field Programmable Gate Array (FPGA) etc, based ANN. The processed output is reconstructed using Digital to Analog Converter (DAC).

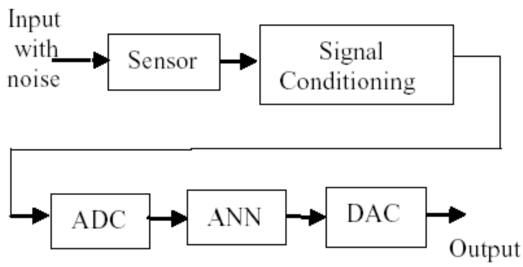

Fig. 1. Scheme for ANN based intelligent sensor

2. FEATURES OF INTELLIGENT SENSORS

2.1 Sensor Characteristic Linearization
The effect of change in environmental conditions on the sensors and subsequently upon there output is nonlinear in nature therefore a complex signal processing may be required to obtain correct readout. To solve this problem, modeling of the sensors using ANN can be done with satisfactory results. Direct modeling technique shown in figure 2, can be used to estimate the nonlinearity parameters of the sensor, whereas, inverse modeling technique shown in figure 3, can be used to estimate the applied input to the sensor, which is used to linearize the sensor, for direct digital readout. The purpose of the direct modeling is to obtain an ANN model of sensor in such a way that the outputs of the sensor and the ANN match closely. When there is a change in the environmental conditions, the ANN automatically compensates it based on the distributive information stored in its weights, making the sensor intelligent [6].

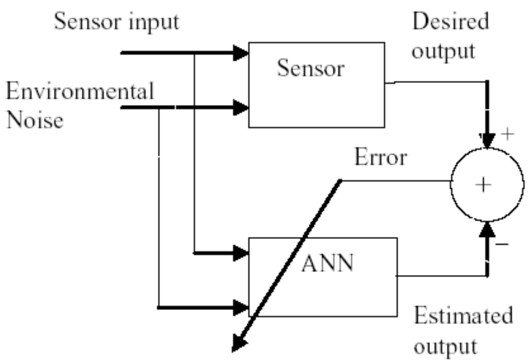

Fig. 2. Neural network based direct modeling of sensor

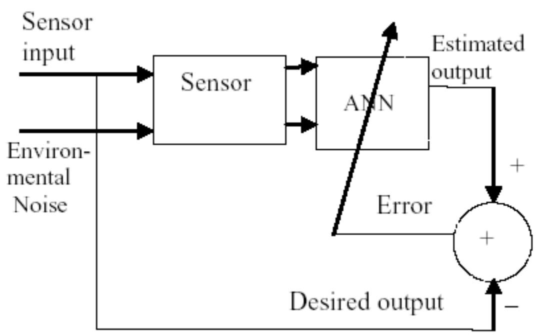

Fig. 3. Neural network based inverse modeling of sensor

2.2 Curve Fitting

Constant research is being carried out in the area of optimizing analog and digital methods for a transducer's characteristic interpolation or linearization. There are no rules to select the best curve-fitting method for a given set of data. The ANN is one of the most significant and optimal tools for function approximation and curve fitting, as compared to classical methods for data interpolation. The advantage of ANN based approach is its quality of approximations to measurement data with particular attention paid to the reduction of the required calibration set dimension to obtain a given accuracy [7].

2.3 Sensor Fault Detection

AI has been used in the field of electronic fault diagnosis. Various schemes used for fault diagnosis such as Rule-based system, Model-based system, Case-based reasoning, Fuzzy reasoning, ANN, Hybrid approaches, and IEEE diagnostic standards and automated diagnostic tools are described [8]. Fault dictionary approach can be used for identification of catastrophic faults in sensors. A "fault dictionary " is a priori generated by collecting signatures of different fault conditions. Neural classifiers trained on the fault dictionary examples have been successfully applied to the diagnosis problem providing satisfactory results [9-13, 21].

ANN based direct modeling may be used for the purpose of on-line fault detection and quality control of the sensor during its manufacturing process [6]. One of the reasons an ANN approach is chosen for fault detection is because of their ability to extrapolate and to predict the fault also in situations that were new or unseen in the learning phase [13,14]. A novel wavelet-based approach to the abrupt fault detection and diagnosis of sensors can be used. By the use of wavelet transforms that accurately localize the characteristics of a signal both in the time and frequency domains, the occurring instants of abnormal status of a sensor in the output signal can be identified by the multi-scale representation of the signal. Once the instants are detected, the distribution differences of the signal energy on all decomposed wavelet scales of the signal before and after the instants can be used to claim and classify the sensor faults [15].

2.4 Auto-calibration

Calibration of sensors through adaptive technique is another feature in intelligent instrumentation. It has been observed that in many cases supervision of the calibrator and error handling of the calibration process is a complex nontrivial task [16]. A fully automatic, fast and more precise calibration of sensor can be done with the help of ANN, to allow a non-expert user to carry out the calibrations with remarkable accuracy, protecting the hardware and rejecting faulty measurements. The optimal set points of the characteristic parameters can be identified and maintained so that the system behavior can be adapted to the specific realization, the components actually used, and the surrounding environment. [2]. The ANN based approaches are reliable in the determination of malfunctions. Also, malfunctions are predicted before the human expert or a traditional ruled system had traced a problem. It has been also used as a model of the human expert during all trials carried out for the development of a rule based system. Neuro-fuzzy network structure has been used for calibration of semiconductor array for gas measurements (artificial nose problem) [17].

3. DESIGN ISSUES FOR INTELLIGENT SENSORS:

3.1 Choice and Design of ANN

There are numerous ANN structures reported in the literature but most of them are highly application-specific. The basic feedforward multilayer perceptron (MLP) architecture remains the most widely applied and analyzed. The capability of MLP's, trained by error-back-propagation, to approximate nonlinear functions with any degree of accuracy, has already been shown in dozens of successful applications in the fields of pattern recognition/classification and image processing. In MLP networks, the neurons in a layer are connected to all the neurons in the following layer through unidirectional links represented by connection weights. The MLP requires the determination of the activation functions and the thresholds of the neurons, as well as of the connection weights. First, the activation function and the thresholds are defined by a recursive optimization procedure [3]. Then, the connection weights are computed by means of a learning algorithm such as back-propagation (BP). The MLP is selected in many applications due its simplicity and ease of training for small-scale problems. The Radial Basis Function Networks (RBF), which is a viable alternative to high nonlinearity in parameter, has simple architecture, fast learning rate and can achieve global minimum [19]. The RBF network has only one hidden layer and no weights connection between input and hidden layers. Each neuron of the output layer has a linear input-output relationship and performs simple summations. Thus, it does not give rise to proliferation of adjustable parameters when the dimension of the problem increases. The transfer function of the hidden neurons is set according to the characteristics of the signal to be processed.

ANN design mainly consists of defining the topology and the architecture of the networks. A major obstacle in using the ANN in many applications is the lack of clear methodology to determine the network topology before training starts and the slow training. It is then desirable to speedup the training and allows fast experimentation with various topologies. When a network topology has been selected, the specific neural model must be defined: the number of layers, the numbers of neurons per layer, and the interconnection weights. Sample guidelines are available in the literature for choosing the number of layers and the number of neurons within each layer [2]. MATLAB and the ANN toolbox may be used to characterize and optimize the ANN architecture. A routine can be developed to select the ANN structure, number of layers and number of neurons in each layer, that minimizes error between calibration and ANN modeled data.

The next step is to configure the network weights by applying a learning procedure may be *supervised* and *unsupervised* [18]. The weights configuration is obtained by optimizing a discrepancy function (e.g., a mean-squared error function) defined over the available examples. During learning, the error decreases as long as the network has unexploited degrees of freedom. On the other hand, learning in the long run (overtraining) has many side effects if the network is overdimensioned (in terms of the number of degrees of freedom) with respect to the application. In such case, the network may perform badly on new examples. This problem can be reduced by analyzing errors in both the learning and the test sets versus the number of learning cycles [18]. The learning procedure needs to be terminated as soon as a reasonable learning error has been achieved, before the network loses its generalization capability [2]. Network training time can be reduced with the appropriate implementation of fuzzy reasoning [17].

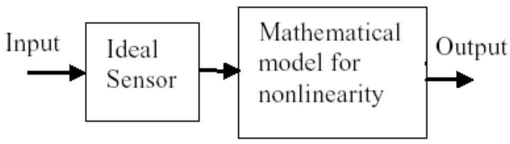

Fig. 4. Equivalent model of the nonlinear sensor

3.2 Mathematical Modeling and Simulation

The nonlinear sensors as shown in figure 4 can be expressed as a polynomial (Mathematical model for nonlinearity) whose coefficients can be estimated [20]. The estimated coefficients are the measure of sensor characteristics, which are helpful to identify the deviation in the characteristics due to environmental conditions and aging, etc. Mathematical modeling and of response curves of a sensor can be done using virtual instrumentation, in the initial stage. Graphical programming languages and tools such as, LabVIEW, SPICE etc. can be used to develop the virtual instrumentation station. The virtual instrumentation can also be used for the sensor testing and calibration. Simulation results can be presented to support the various techniques of modeling and simulation for the sensor.

3.3 Digital Hardware Implementation

Neural Networks can be implemented on a re-configurable computing platform, such as, FPGAs with performance speeds, fabrication area and precision closer to Application Specific Integrated Circuits [22,26-28]. The advancement of FPGAs in recent years, allowing millions of gates on a single chip and accompanying with high-level design tools has allowed the implementation of very complex networks [23]. It allows the fast design of complex systems with the highest performance/cost ratio [24]. FPGA implementation of the Flexible Adaptable-Size Topology architecture, ANN that dynamically changes its size is possible.

The ANNs can be tested and validated first using simulation software such as ModelTech’s ModelSIM. Electronic Design Automation (EDA) tools such as Xilinx Foundation ISE can be used to synthesize and map (i.e. place and route) the FPGA based ANN. [22, 25]. The architecture implementing the algorithm can be mapped on a real current-generation FPGA (Xilinx 90 nm Spartan-3) [30]. Its effectiveness is then tested on the problem, where real-time performances are of paramount importance.

4. CONCLUSION

In traditional sensors, including those based on complex techniques for digital signal processing, operations performed on input signals usually follow strictly deterministic algorithms. With the universal approximation property and learning capability, ANNs have proven to be a powerful tool for the development of intelligent sensors.

The slow convergence of the tracking error is usually due to the smallness of the network size. Moreover, if the chosen size is too large, the computation burden increases. Common approach is to start with the smaller ANN size, and gradually increase it until satisfactory performance is achieved. Well-constructed ANNs have good interpolation properties. ANN algorithms are used as an alternative to the nonlinear and generalized linear regressions because the ANNs can model a nonlinear behavior of the transfer function better than the regressions. Also, its extrapolation capability can allow the drift compensation, auto-calibration and fault diagnosis of sensors to be made even in the situations that were unforeseen in the learning phase.

In the future, remarkable advantages and advancements of these techniques with hybrid systems and VLSI technology, might be achieved for the design of intelligent sensors based on knowledge and learning.

5. REFERENCES

[1] G. Bucci, M. Faccio and C. Landi, New ADC with Piecewise Linear Characteristic: Case Study – Implementation of a Smart Humidity Sensor, IEEE Trans, Instrumentation and Measurement, vol. 49, No. 6, pp. 1154-1166, Dec. 2000.

[2] C. Alippi, A. Ferrero and V. Piuri, Artificial Intelligence for Instruments and Measurement Applications, IEEE Instrumentation and Measurement Magazine, vol. 1, No. 1, pp. 9-17, March 1998.

[3] P. Arpaia, P. Daponte, D. Grimaldi and L. Michaeli, ANN – Based Error Reduction for Experimentally Modeled Sensors, IEEE Trans, Instrumentation and Measurement, vol. 51, No. 1, pp. 23-29, Feb. 2002.

[4] A. Sachenko, V. Kochan and V. Turchenko, Instrumentation for Gathering Data, IEEE Instrumentation and Measurement Magazine, vol. 6, No. 3, pp. 34-40, Sept. 2003.

[5] J. Pereira, O. Postolache, P. Girao, and M Cretu, Minimizing Temperature Drift Error of Conditioning Circuits Using Artificial Neural Networks, IEEE Trans, Instrumentation and Measurement, vol. 49, No. 5, pp. 1122-1126, Oct. 2000.

[6] J. C. Patra, A. C. Kot and G. Panda, An Intelligent Pressure Sensor Using Neural Networks, IEEE Trans, Instrumentation and Measurement, vol. 49, No. 4, pp. 829-834, August 2003.

[7] D. Pereira, J. M. S. Girao, P. M. B. Postolache, Fitting transducer characteristics to measured data, IEEE Trans, Instrumentation and Measurement, vol. 4, No. 4, pp. 26-39, Dec.2001.

[8] Fenton, B. McGinnity, M. Maguire, L. Ulster, Fault diagnosis of electronic system using artificial intelligence, IEEE Trans, Instrumentation and Measurement, vol. 5, No. 3, pp. 16-20, Sept. 2002.

[9] M. Catelani and A. Fort, Soft Fault Detection and Isolation in Analog Circuits: Some Results and a Comparison Between a Fuzzy Approach and Radial Basis Function Networks, IEEE Trans, Instrumentation and Measurement, vol. 51, No. 2, pp. 196-202, April 2002.

[10] V. C. Prasad and N. S. Babu, Selection of Test Nodes for Analog Fault Diagnosis in Dictionary Approach, IEEE Trans, Instrumentation and Measurement, vol. 49, No. 6, pp. 1289-1296, Dec. 2000.

[11] C. Alippi, M. Catelani, A. Fort and M. Mugnaini, SBT Soft Fault Diagnosis in Analog Electronic Circuits: A Sensitivity-Based Approach by Randomized Algorithms, IEEE Trans, Instrumentation and Measurement, vol. 51, No. 5, pp. 1116-1125, October 2002.

[12] Z. Czaja and R. Zielonko, Fault Diagnosis in Electronic Circuits Based on Bilinear Transformation in 3-D and 4-D Spaces, IEEE Trans, Instrumentation and Measurement, vol. 52, No. 1, pp. 97-102, Feb. 2003.

[13] A. Bernieri, G. Betta, A. Pietrosanto and C. Sansone, A Neural Network Approach to Instrument Fault Detection and Isolation, IEEE Trans, Instrumentation and Measurement, vol. 44, No. 3, pp. 747-750, June 1995.

[14] Y. Maidon, B. W. Jervis, P. Fouillat and S. Lesage, Using Artificial Neural Networks or Lagrange Interpolation to Characterize the Faults in an Analog Circuit: An Experimental Study, IEEE Trans, Instrumentation and Measurement, vol. 48, No. 5, pp. 932-938, Oct. 1999.

[15] Han Qiu Zhang, Yong Yan, A wavelet-based approach to abrupt fault detection and diagnosis of sensors, IEEE Trans, Instrumentation and Measurement, vol. 50, No. 5, pp. 1389-1396, Oct. 2001.

[16] F. L. Pena and R. J. Duro, A virtual Instrument for Automatic Anemometer Calibration With ANN Based Supervision, IEEE Trans, Instrumentation and Measurement, vol. 52, No. 3, pp. 654-661, June 2003.

[17] S. Osowski, T. H. Linh and K. Brudzewski, Neuro-Fuzzy TSK Network for Calibration of Semiconductor Sensor Array for Gas Measurements, IEEE Trans, Instrumentation and Measurement, vol. 53, No. 3, pp. 630-637, June 2004.

[18] J. A. Freeman and D. M. Skapura, Neural Networks: Algorithms, Applications and Programming Techniques, Reading, MA: Addison Wesley, 1992.

[19] R. Zhu, Y. Zhang and Q. Bao, A Novel Intelligent Strategy for Improving Measurement Precision of FOG, IEEE Trans, Instrumentation and Measurement, vol. 49, No. 6, pp. 1183-1188, Dec. 2000.

[20] D. Patranabis, Sensors and Transducers, Wheeler Publishing, New Delhi, 1997.

[21] Nello Zuech, Handbook of Intelligent Sensors for Industrial Automation, Addison-Wesley publications, 1992

[22] K. R. Nichols, M. A. Moussa, S. M. Areibi, Feasibility of Floating-Point Arithmetic in FPGA based Artificial Neural Networks, wolfman.eos.uoguelph.ca/~saraibi/PUBLICATIONS_dr/current-pub-list.html.

[23] H. S. Ng, K.P. Lam, Analog and digital FPGA implementation of BRIN for optimization problems, IEEE Trans, Neural Networks, vol. 14, No. 5, pp. 1413-1425, Sept. 2003.

[24] L. M. Reyneri, Implementation issues of neuro-fuzzy hardware: going toward HW/SW codesign, IEEE Trans, Neural Networks, vol. 14, No. 1, pp. 176-194, Jan. 2003.

[25] Xilix University Worshop at IIT Bombay, 30th Sept. – 1st Oct., 2003.

[26] H. Hikawa, A digital hardware pulse-mode neuron with piecewise linear activation function, IEEE Trans, Neural Networks, vol. 14, No. 5, pp. 1028-1037, Sept. 2003.

[27] D.C. Hendry, A. A. Duncan and N. Lightowler, IP core implementation of a self-organizing neural network, IEEE Trans, Neural Networks, vol. 14, No. 5, pp. 1085-1096, Sept. 2003.

[28] C. T. Yen, W. Weng, Y. T. Lin, FPGA Realization of a Neural-Network-Based Nonlinear Channel Equalizer, IEEE Trans, Neural Networks, vol. 51, No. 2, pp. 472-479, April 2004.

[29] Y. Maeda, T. Tada, FPGA implementation of a pulse density neural network with learning ability using simultaneous perturbation, IEEE Trans, Neural Networks, vol. 14, No. 3, pp. 688-695, May 2003.

[30] Bill Okubo, Maximize Your Success with Spartan-3 Design, Xcell journal: The Authoritative Journal for Programmable Logic Users, No. 47, Fall 2003. (www.xilinx.com/publications/xcellonline/),