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(54) **SENSOR RESPONSE RATE ACCELERATOR**

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(52) **U.S. Cl.** **702/190**; 702/189; 702/182; 324/340; 324/342; 340/855.6; 340/938; 340/549; 706/10; 706/18; 706/22
(58) **Field of Search** 702/190, 108, 702/117, 120; 324/340; 706/10, 12, 14–16, 18, 22, 23, 25–27

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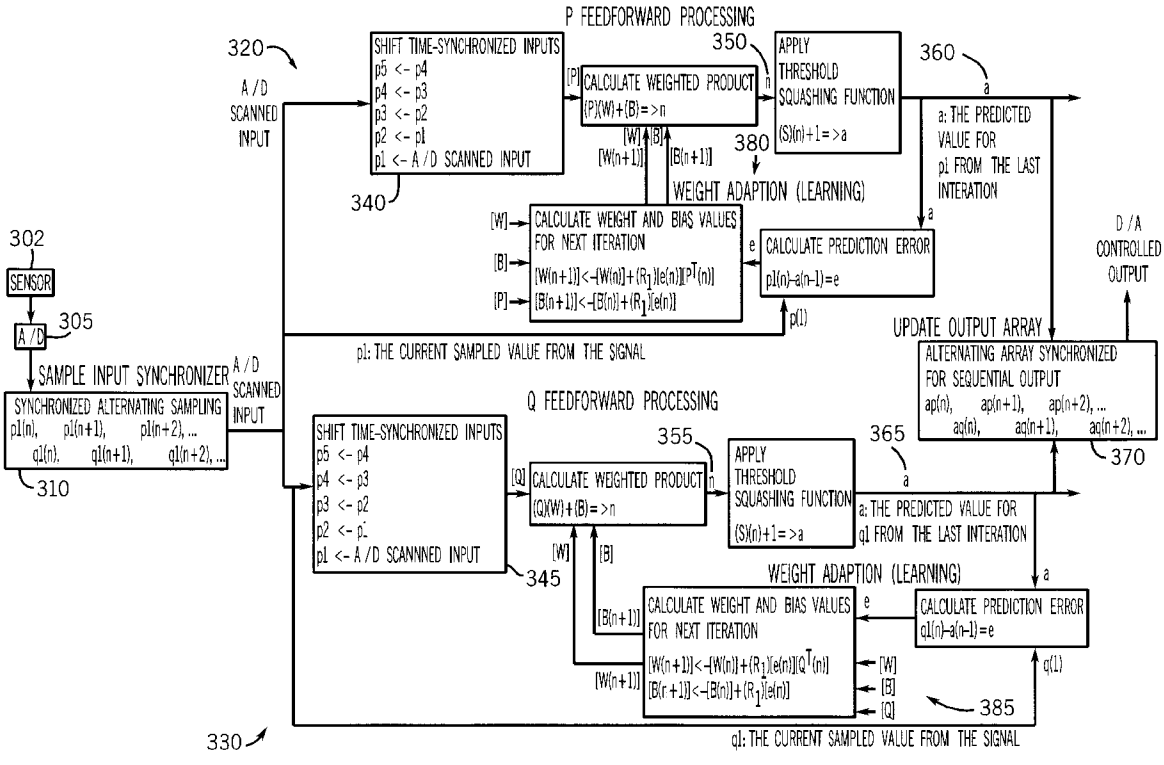
(57) **ABSTRACT**

An apparatus and method for sensor signal prediction and for improving sensor signal response time, is disclosed. An adaptive filter or an artificial neural network is utilized to provide predictive sensor signal output and is further used to reduce sensor response time delay.

21 Claims, 4 Drawing Sheets



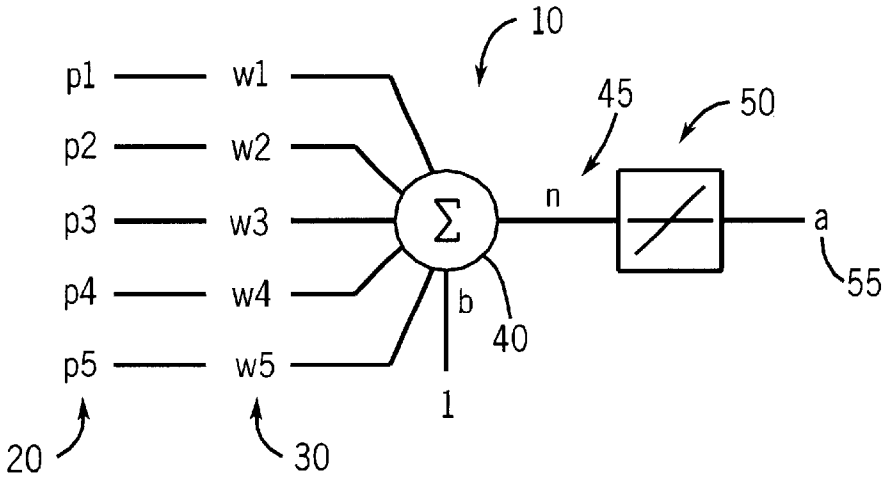

10
p1
w1
p2
w2
p3
w3
p4
w4
p5
w5
Σ
45
50
n
a
55
b
40
1
20
30

FIG. 1

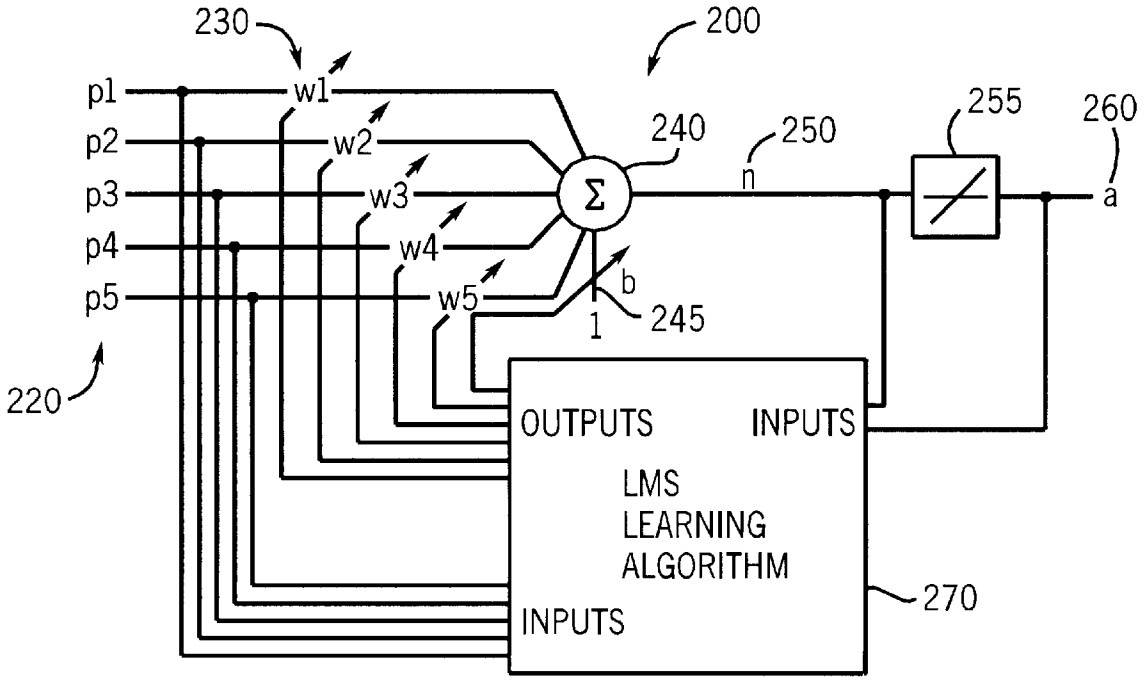
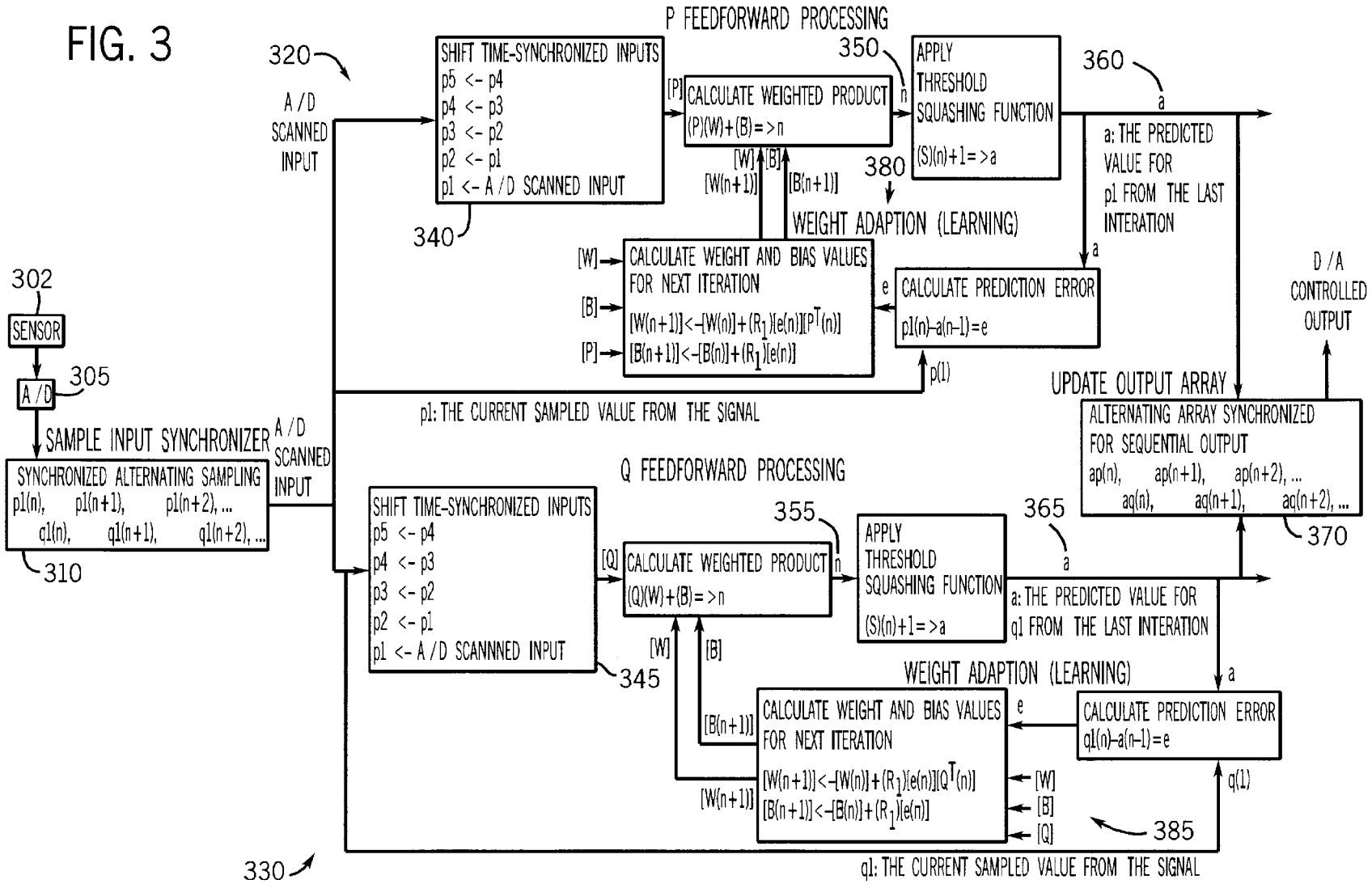

230
200
p1
w1
p2
w2
p3
w3
p4
w4
p5
w5
Σ
240
250
255
260
n
a
b
1
245
220
OUTPUTS
INPUTS
LMS
LEARNING
ALGORITHM
INPUTS
270

FIG. 2

FIG. 3


P FEEDFORWARD PROCESSING
320
A/D SCANNED INPUT
SHIFT TIME-SYNCHRONIZED INPUTS
p5 <- p4
p4 <- p3
p3 <- p2
p2 <- p1
p1 <- A/D SCANNED INPUT
340
[P]
CALCULATE WEIGHTED PRODUCT
(P)(W)+(B)=>n
350
n
APPLY THRESHOLD SQUASHING FUNCTION
(S)(n)+1=>a
360
a
a: THE PREDICTED VALUE FOR p1 FROM THE LAST INTERATION
[W(n+1)]
[B(n+1)]
380
WEIGHT ADAPTION (LEARNING)
[W]
[B]
[P]
CALCULATE WEIGHT AND BIAS VALUES FOR NEXT ITERATION
[W(n+1)]<-[W(n)]+(R1)[e(n)][PT(n)]
[B(n+1)]<-[B(n)]+(R1)[e(n)]
e
CALCULATE PREDICTION ERROR
p1(n)-a(n-1)=e
p(1)
302
SENSOR
305
A/D
SAMPLE INPUT SYNCHRONIZER
SYNCHRONIZED ALTERNATING SAMPLING
p1(n), p1(n+1), p1(n+2), ...
q1(n), q1(n+1), q1(n+2), ...
310
A/D SCANNED INPUT
p1: THE CURRENT SAMPLED VALUE FROM THE SIGNAL
D/A CONTROLLED OUTPUT
UPDATE OUTPUT ARRAY
ALTERNATING ARRAY SYNCHRONIZED FOR SEQUENTIAL OUTPUT
ap(n), ap(n+1), ap(n+2), ...
aq(n), aq(n+1), aq(n+2), ...
370
Q FEEDFORWARD PROCESSING
SHIFT TIME-SYNCHRONIZED INPUTS
p5 <- p4
p4 <- p3
p3 <- p2
p2 <- p1
p1 <- A/D SCANNNED INPUT
345
[Q]
CALCULATE WEIGHTED PRODUCT
(Q)(W)+(B)=>n
355
APPLY THRESHOLD SQUASHING FUNCTION
(S)(n)+1=>a
365
a: THE PREDICTED VALUE FOR q1 FROM THE LAST INTERATION
WEIGHT ADAPTION (LEARNING)
CALCULATE WEIGHT AND BIAS VALUES FOR NEXT ITERATION
[W(n+1)]<-[W(n)]+(R1)[e(n)][QT(n)]
[B(n+1)]<-[B(n)]+(R1)[e(n)]
CALCULATE PREDICTION ERROR
q1(n)-a(n-1)=e
q(1)
385
330
q1: THE CURRENT SAMPLED VALUE FROM THE SIGNAL

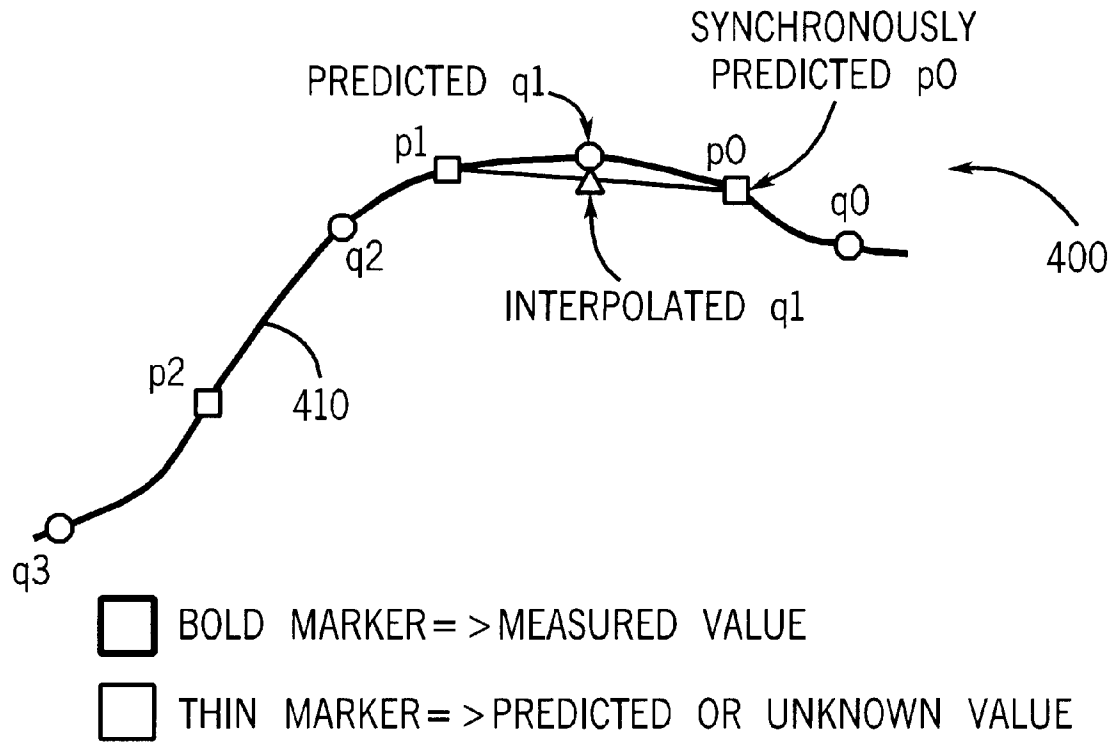
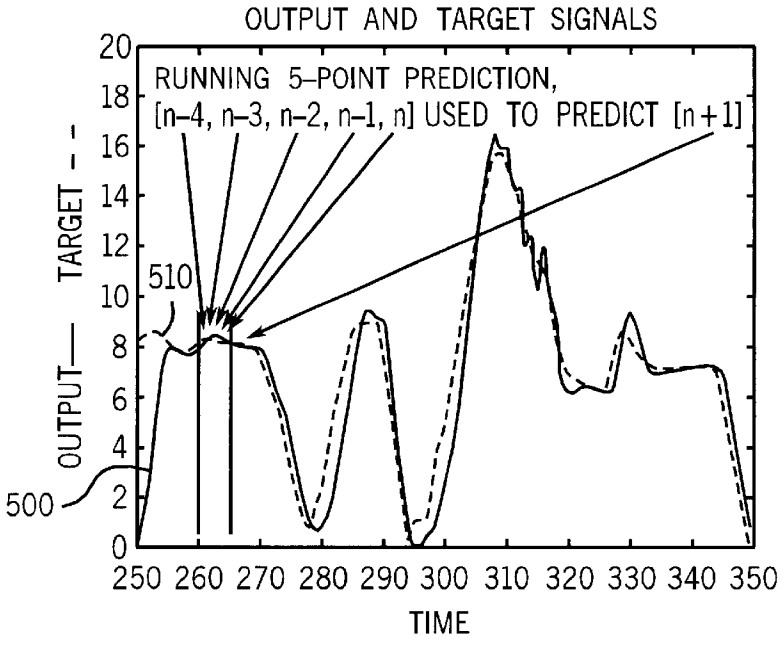

SYNCHRONOUSLY
PREDICTED p0
PREDICTED q1
p1
p0
q0
400
q2
INTERPOLATED q1
p2
410
q3
BOLD MARKER=>MEASURED VALUE
THIN MARKER=>PREDICTED OR UNKNOWN VALUE

FIG. 4

FIG. 5


OUTPUT AND TARGET SIGNALS
RUNNING 5-POINT PREDICTION,
[n-4, n-3, n-2, n-1, n] USED TO PREDICT [n+1]
OUTPUT— TARGET - -
510
500
20
18
16
14
12
10
8
6
4
2
0
250 260 270 280 290 300 310 320 330 340 350
TIME

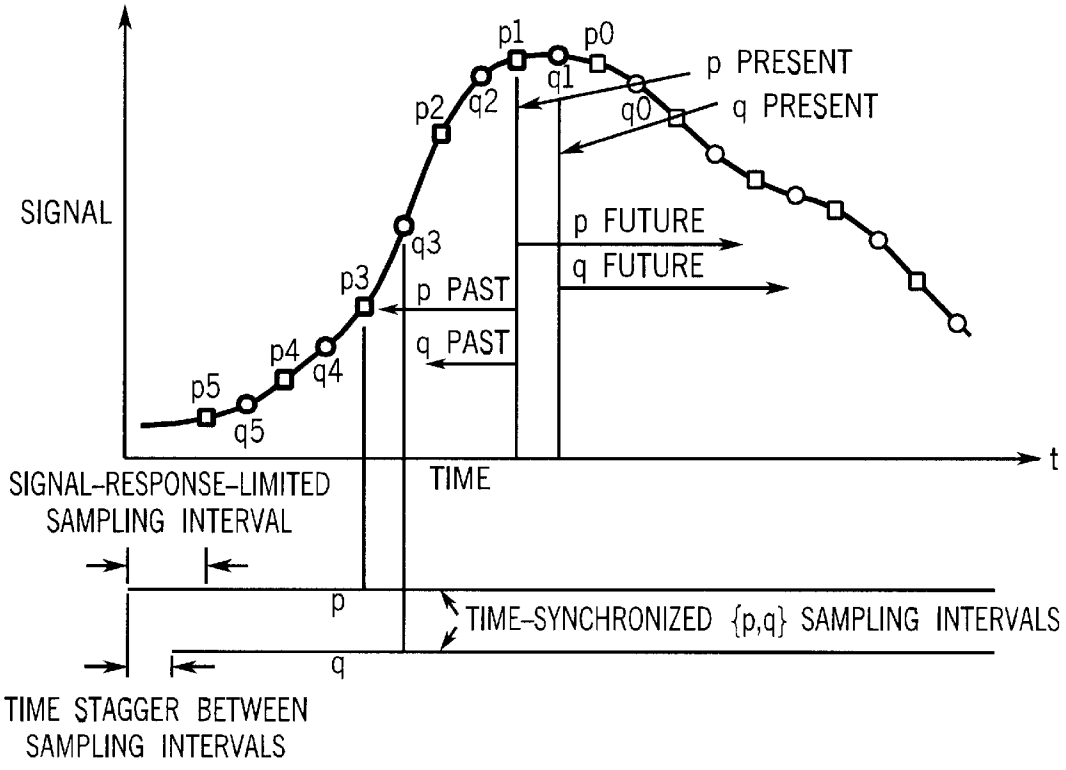

SIGNAL
p1
p0
p PRESENT
q1
q PRESENT
p2
q2
q0
p FUTURE
q FUTURE
q3
p3
p PAST
q PAST
p4
q4
p5
q5
t
TIME
SIGNAL-RESPONSE-LIMITED
SAMPLING INTERVAL
p
TIME-SYNCHRONIZED {p,q} SAMPLING INTERVALS
q
TIME STAGGER BETWEEN
SAMPLING INTERVALS
BOLD MARKER = > MEASURED VALUE
THIN MARKER = > PREDICTED OR UNKNOWN VALUE

FIG. 6

SENSOR RESPONSE RATE ACCELERATOR

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH OR DEVELOPMENT

The invention was made with U.S. Government support under contract no. W-31-109-ENG-38 awarded by the Department of Energy and the U.S. Government has certain rights in this invention.

FIELD OF THE INVENTION

The invention relates generally to the field of signal conditioning. More particularly, the invention relates to an interoperating collection of adaptive filters supporting sensor signal prediction and that prediction's application. The adaptive filter based sensor signal predictor(s) may be used to increase a sensor's rate of response.

BACKGROUND OF THE INVENTION

Many industrial control applications require a plurality of sensors. In some applications, the sensors have a response time that is inadequate to provide effective control of the system.

Sensor response time may be described as the period between changing physical conditions and a change in the sensor (electrical) output. Sensor sensitivity may be described as the amount of change necessary in the physical condition that is needed to initiate a similar change in the sensor output signal. Together, the response time and the sensitivity of the sensor control the output signal.

If a given sensor's response time is N (i.e., N=50 milliseconds) and its sensitivity is S (i.e., S=+/−10 parts per million, for a chemical sensor) then N milliseconds after an S part per million change is experienced, the sensor will produce an approximately proportional, measurable change in the generated electrical signal. A control system external to the sensor, relying on the sensor, receives no benefit in polling or sampling the sensor any faster than it can physically respond, because no change (or an inaccurate change) in the electrical signal will be detected. If, for example, the external control system requires a feedback signal at higher sampling frequencies than the frequency response of the sensor, the conventional or classic solution is to develop a new sensor with different (improved) physical response characteristics. Development of new sensors however, is costly and potentially not possible.

Therefore, there is a need for a method and apparatus for improving sensor response times by predicting sensor outputs. Further, there is a need for inexpensive electronic devices that serve as interfaces between a closed (black box) control system and a given (chemical, pressure, temperature, etc.) sensor. Further still, there is a need for sensor predicting devices that utilize adaptive filter or neural network prediction algorithms to monitor sensor short-range past response and are able to predict the short-range future response of the sensor. Further still, there is a need for sensor predicting devices utilizing adaptive filter or neural network prediction algorithms that employ adaptive error correction and optionally provide interpolated output in the short time period that is required by the external control system.

SUMMARY OF THE INVENTION

An exemplary embodiment of the invention relates to a system for improving the response time of a sensor. The sensor includes an input configured to sense an environmental characteristic and an output configured to provide an electrical signal representative of the input. The system also includes a sampling system configured to sample the sensor output at discrete time intervals and provide sampled sensor output signals. Further, the system includes an adaptive filter including a plurality of inputs and at least one output, the plurality of inputs configured to receive sampled sensor output signals, and at least one output of the adaptive filter configured to provide at least one estimated future sensor output based on the plurality of sampled sensor output signals provided to the plurality of inputs to the adaptive filter.

An exemplary embodiment of the invention also relates to a method of predicting the output of a sensor. The sensor has an input for sensing an environmental characteristic, and the sensor having a sampled output representative of the input at a discrete time interval. The method includes providing, to a plurality of inputs of an artificial neural network, a plurality of discrete sensor outputs. Each discrete sensor output is representative of a sensor input at a different discrete time interval. The method also includes generating at least one output of the artificial neural network. The at least one output being an estimate of at least one future sensor output.

Further, an exemplary embodiment of the invention relates to a method of predicting sensor output. The method includes adapting weights of an artificial neural network. The method also includes receiving, by the artificial neural network, a plurality of discrete sensor outputs from p discrete time intervals, up to the time n. Further, the method includes generating an output of the artificial neural network, based on the sensor outputs from the p discrete time intervals. The output is representative of the predicted sensor output at time n+1.

Further still, an exemplary embodiment of the invention relates to a method of accelerating the output of a sensor. The method includes receiving by a first neural network a plurality of sensor outputs at discrete evenly spaced time intervals less than and including time n. The method also includes receiving by a second neural network a plurality of sensor outputs at discrete evenly spaced time intervals less than and including time n+m, where 0<m<1. The method further includes generating, by the first neural network, a predicted sensor output that is an estimate of the sensor output at time n+1. Further, the method includes generating, by the second neural network, a predicted sensor output that is an estimate of the sensor output at time n+1+m.

BRIEF DESCRIPTION OF THE DRAWINGS

The invention will become more fully understood from the following detailed description, taken in conjunction with the accompanying drawings, wherein like reference numerals refer to like parts, in which:

FIG. **1** is an exemplary block diagram of an artificial neuron model;

FIG. **2** is an exemplary block diagram of an artificial neuron model showing the feedback adaptation mechanism;

FIG. **3** is a block diagram of a sensor signal prediction system including two artificial neural networks;

FIG. **4** is an illustration of an exemplary interpolation process used for improving sensor response time;

FIG. **5** is an illustration of the actual sensor response versus the predicted sensor response using an exemplary 5-point prediction; and

FIG. **6** is an illustration of a predicted sensor signal utilizing time off-set predictive filters.

DETAILED DESCRIPTION OF EXEMPLARY EMBODIMENTS

A method and apparatus configured to perform sensor predictions utilizing an adaptive filtering, such as an adaptive filter or an artificial neural network (ANN) is disclosed.

Artificial neural network (ANN) systems are somewhat unique from recognized heuristic algorithms and expert systems. Scientists pioneered artificial neural networks as a method of simulating human brain activity. Today, ANNs show great promise as computing devices and may receive great attention from scientists and engineers to solve problems that are traditionally problematic for machines, in particular, problems involving unknown nonlinearities. For example, ANNs are ideal for pattern recognition tasks, prediction tasks, and automatic control tasks. Most significantly, ANNs have the ability to "learn" specific tasks, and "adapt" to specific environments. An ANN learns by comparing its output to a known output. The ANN has a set of adjustable internal weight settings that may be adjusted to minimize the error between the ANN output and the known output. ANNs are similar to, related to, and in some cases the same as some adaptive filtering techniques. Thus, it should be noted that although one exemplary embodiment shown and described is an artificial neural network model, the disclosure is not limited to ANNs, but includes other adaptive filtering techniques, or methodologies.

Referring now to FIG. **1**, a single neuron ANN **10** is depicted. Exemplary ANN **10** includes a plurality of j inputs ($p_1, \ldots, p_j$) **20**. Each input p_i **20** is multiplied by a weight W_i **30** ($w_i=w_1, \ldots, w_j$). The weighted inputs are added together at a summation stage **40**, along with a bias b, to produce an output n **45**, where

$$n = \sum_{i=1}^{j} (P_i W_i) + b \tag{1}$$

In the exemplary embodiment of ANN **10**, output n is passed through an activation stage or function **50** to produce an output a **55**. Activation function **50** may be any of a variety of activation functions, including, but not limited to, a linear function, a logistic function, a hyperbolic tangent function, a discontinuous function, such as, but not limited to, the sign function, or other activation functions, squashing functions, sigmoidal functions, Gaussian functions, etc.

In a particular exemplary embodiment, ANN **10** includes an activation stage that is a linear function where $a=C_1n+C_2$ such that C_1 and C_2 are constants, and is therefore known as an ADALINE (adaptive linear element) network such that

$$a = C_1\left(\sum_{i=1}^{j} (P_i W_i) + b\right) + C_2 \tag{2}$$

An ANN, such as ANN **10**, or any of a variety of other ANNs or adaptive filters, such as, but not limited to, multi-layer perceptron networks, back propagation networks, radial basis function networks, adaptive linear filters, and the like, may be used to provide approximations of nonlinear functions or approximations between nonlinear associations between input and output.

In an exemplary embodiment, an ANN, such as ANN **10** may be used in a system to predict sensor output and/or improve sensor response time through sensor output prediction and estimation.

Referring now to FIG. **2**, an exemplary artificial neural network **200** is depicted including an adaptive learning mechanism. Artificial neural network **200** receives inputs **220** ($p_1, p_2, \ldots, p_5$). In an exemplary embodiment, p_1 may be the most recent sampled sensor input and p_2, p_3, p_4, and p_5, may be previously sampled inputs retrieved from a memory. Each of inputs **220** are multiplied by a set of weights **230** ($W_1, W_2, \ldots, W_5$) respectively. Inputs **220**, multiplied by weights **230**, are summed at a summation stage **240** along with a bias b **245** to produce an output **250** n. Output **250** n is provided to activation stage **255** to provide a network output **260** a, each of inputs **220** and outputs **250** and **260** are provided as inputs to a least means squared (LMS) learning algorithm **270**. LMS learning algorithm **270** calculates the error between the current sampled signal value p_1 and the previous iteration's predicted value a to adaptively correct the weight values ($W_1, W_2, \ldots, W_5$). A particular exemplary learning law (algorithm) that may be applied is the Widrow-Hoff LMS error minimization method. The error is calculated as

$$e=(a(n-1)-p_1(n)). \tag{3}$$

The weight values are then updated for the next iteration following the Widrow-Hoff rule

$$W(n+1)=W(n)+2\alpha e(n)p^T(n),\ b(n+1)=b(n)+2\alpha e(n) \tag{4}$$

where

$$p(n) = [\ p_1 \quad p_2 \quad p_3 \quad p_4 \quad p_5\ ], \tag{5}$$

$$W(n) = \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{bmatrix}, \tag{6}$$

and $0<\alpha<1$ is the learning rate. The error correction is completed each iteration and may be capable of achieving a small fraction of a percent error within a few iterations. This type of adaptively correcting algorithm may also be categorized as an adaptive filter that may be put into the framework of a neural network or provided as a software implemented algorithm.

Referring now to FIG. **4**, an exemplary graph **400** of a sensor output **410** is depicted. In one embodiment, a single ANN may be used to predict a sensor output one time increment into the future. For example, values p_1, p_2 and prior values of p may be used to predict the point p_0. Point p_0 may be exactly the same time step ahead of p_1 that p_1 is ahead of p_2. In order to predict a value prior to p_0, a prediction may be made for p_0 by the ANN and a separate value, between p_1 and p_0 may be established by interpolation. In FIG. **4**, the interpolated point is designated as interpolated q_1. This may be suitable for high-speed operations where computational capability is limited but where small error introduced by the interpolation is acceptable. In the exemplary illustration of FIG. **4**, a single value interpolated between p_1 and p_0 is shown, however, many values could be calculated using simple linear interpolation or other interpolation mechanisms, such as quadratic interpolation, hyperbolic interpolation, and the like.

In another exemplary embodiment, multiple ANNs may be used to eliminate the error introduced by the interpolation mechanism. The use of multiple predicting ANNs requires that the ANNs receive sensor input off-set in time and synchronized with one another. The examples shown and

described herein show only two networks used to double an effective sensor response rate, but the number of neurons and the scaling/acceleration are limited only by processing power and A/D sampling speed.

Referring now to FIG. **6**, sample values p_1 through p_5 may be used as inputs to the first neural network to predict the value of p_0. Off-set in time inputs q_1 through q_5 may be used to predict output q_0 in the future. The p and q values are off-set by a fixed amount controlled by the device, sampling rate, and the new p_1 and q_1 values are sampled independently with the same off-set.

Referring now to FIG. **3**, a block diagram/flowchart depicts a system including two simultaneous executing networks predicting and accelerating the incoming signal by a factor of two. It should be noted that any number of networks may be applied in a similar manner as that illustrated in FIG. **3** which will increase the acceleration of the predicted sensor output. A sample input synchronizer **310** receives an incoming signal from an analog to digital (A/D) converter **305** which is coupled to an analog sensor **302**. A/D converter **305** samples analog sensor **302** signal and provides the sampled output to sample input synchronizer **310**. Sample input synchronizer **310** alternately copies to the p network **320** an input p_1 and then to the q network **330** an input q_1. The P network may normally be executed first to calculate p_0. Previous signals $p_1, \ldots, p_4$ are shifted in inputs by a shift time-synchronized inputs mechanism **340** and **345**. For example, in shift time-synchronized inputs mechanism **340**, p_1 is assigned the latest sampled input from sample input synchronizer **310**, p_2 is assigned the previous value of p_1, p_3 is assigned the previous value of p_2, p_4 is assigned the previous value of p_3 and p_5 is assigned the previous value of p_4. The neural network processing takes place by calculating the weighted product n **355** and applying the threshold squashing function to produce the predicted output a **360** and **365**. Outputs a are provided to a synchronized output controller module **370** which alternates in synchronized sequential output of the two networks. The alternating synchronized output may be supplied to a D/A controller to provide an analog output, or further may be provided to any of a number of data acquisition systems, stored in a memory, or the like.

As described earlier, output a **360** and input p_1, the current sampled value from the sensor, are provided to the weight adaptation or learning algorithm **380** for the networks where adjustments are made to weights W and bias b. Similarly, output a **365** and input q_1 are provided to the weight adaptation or learning algorithm **385** to make weight W and bias b adjustments for the q network.

Referring now to FIG. **5**, an exemplary graphical representation of the capability of an exemplary system, such as a system utilizing ANN **200**, used to predict the sensor output at a time one sampling ahead of the sampled sensor output, is plotted. Line **500** depicts the sampled output using an ANN, such as ANN **200** and line **510** depicts the actual sensor output sampled. It can be seen that there is a time, approximately between time **250** and **255** where line **500** is substantially different than line **510** because the ANN does not have enough sampled historical data points to make an accurate prediction. In an exemplary demonstration, when approximately five time points have been sampled, the ANN is able to make relatively accurate predictions of time steps one time step ahead of the sampled.

The sensor response rate accelerator as described above, in an exemplary embodiment, may be part of a suite of signal conditioning algorithms that are all embedded on a microcontroller (a sensor interface). The microcontroller (sensor interface) may include correcting/conditioning software or hardware for supplying a conditioned signal to an external controller system. The signal conditioning software or hardware may include the described prediction and acceleration algorithms along with, but not limited to, scaling (gain) algorithms, offset adjustments, integration (or smoothing) algorithms, derivative calculation (rate of change), threshold detection, and the like.

It should be noted that a variety of embodiments may be employed without departing from the spirit and scope of the invention, as to the configuration of the ANNs, the interpolation mechanism, the information processing device, and the A/D converter. For example, in one embodiment of the invention the A/D converter may be part of the sensors system and not a part of the computer whereby the computer receives a sampled signal from the A/D converter. Similarly, the ANN may be a program running in the memory of the computer, or, alternatively, the ANN or multiple ANNs may be embodied in dedicated hardware devices, such as dedicated neural processing hardware. Furthermore, the interpolation mechanism may be incorporated into the system as software running on the computer, or as software running on another dedicated device.

While the detailed drawings, specific examples, and particular formulations given describe exemplary embodiments, they serve the purpose of illustration only. The materials and configurations shown and described may differ depending on the chosen performance characteristics and physical characteristics of the sensor prediction systems. For example, the type of neural network or training methodologies used may differ. The systems shown and described are not limited to the precise details and conditions disclosed. Furthermore, other substitutions, modifications, changes, and omissions may be made in the design, operating conditions, and arrangement of the preferred embodiments without departing from the spirit of the invention as expressed in the appended claims.

What is claimed is:

1. A system for improving the response time of a sensor, comprising:

a sensor including an input configured to sense an environmental characteristic and an output configured to provide an electrical signal representative of the input;

a sampling system configured to sample the sensor output at discrete time intervals and provide sampled sensor output signals;

an adaptive filter including a plurality of inputs and at least one output, the plurality of inputs configured to receive sampled sensor output signals, and at least one output of the adaptive filter configured to provide at least one estimated future sensor output based on the plurality of sampled sensor output signals provided to the plurality of inputs to the adaptive filter, the adaptive filter including an artificial neural network, the artificial neural network including a set of weights that are adapted using a learning law;

a processing unit including the adaptive filter; and

a program configured to be run by the processing unit, the program configured to provide a plurality of estimated future sensor outputs based on the at least one estimated future sensor output provided by the adaptive filter and based on the plurality of inputs to the adaptive filter,

wherein the plurality of estimated future sensor outputs represent sensor outputs at time intervals between the at least one estimated future sensor output and the sampled sensor output signals input to the adaptive filter.

2. The system of claim 1, wherein the processing unit includes the sampling system.

3. The system of claim 1, wherein the adaptive filter is a program configured to be run by the processing unit.

4. The system of claim 1, wherein the adaptive filter is a hardware device of the processing unit, having programmable characteristics.

5. The system of claim 1, wherein the program includes linear interpolation.

6. The system of claim 1, wherein the learning law is a least mean square learning law.

7. The system of claim 1, wherein the artificial neural network is an ADALINE network.

8. The system of claim 1, wherein the artificial neural network is a multi-layer neural network.

9. The system of claim 8, wherein the multi-layer neural network is a back propagation neural network.

10. The system of claim 1, wherein the artificial neural network is a radial basis function network.

11. The system of claim 1, further comprising:

at least two artificial neural networks, each of the artificial neural networks configured to provide an estimated future sensor output representative of different discrete times.

12. The system of claim 1, wherein the adaptive filter includes at least two outputs, each of the outputs configured to provide an estimated future sensor output representative of different discrete times.

13. A method of predicting sensor output, comprising:

adapting weights of a first artificial neural network,

receiving, by the first artificial neural network, a plurality of discrete sensor outputs from p discrete time intervals, up to the time n;

generating an output of the first artificial neural network, based on the sensor outputs from the p discrete time intervals, the output representative of the predicted sensor output at time n+1; and

generating an output of a second artificial neural network, based on the sensor outputs from k discrete time intervals, the k discrete time intervals being offset from the original k discrete time intervals by a time m, where 0<m<1, such that the generated output predicts sensor output for a time n+1+m.

14. The method of claim 13, further comprising:

estimating k sensor outputs between the time n and n+1, based on the sensor output at time n and the estimated sensor output at time n+1.

15. The method of claim 13, wherein the adapting is carried out in an off line training period.

16. The method of claim 13, wherein the adapting is carried out adaptively on line during use.

17. The method of claim 13, wherein the training is based on the optimization of an objective function.

18. A method of accelerating the output of a sensor, comprising:

receiving by a first artificial neural network a plurality of sensor outputs at discrete evenly spaced time intervals less than and including time n;

receiving by a second neural network a plurality of sensor outputs at discrete evenly spaced time intervals less than and including time n+m, where 0<m<1;

generating, by the first neural network, a predicted sensor output that is an estimate of the sensor output at time n+1; and

generating, by the second neural network, a predicted sensor output that is an estimate of the sensor output at time n+1+m.

19. The method of claim 18, further comprising:

updating the weight values of the first neural network based on the actual sensor output at time n and the estimated sensor output at time n; and

updating the weight values of the first neural network based on the actual sensor output at time n+m and the estimated sensor output at time n+m.

20. A method of synthetically accelerating the output response rate of a sensor, comprising:

receiving by an adaptive filter predictor a plurality of sensor outputs at discrete evenly spaced time intervals less than and including time n;

receiving by a second adaptive filter predictor a plurality of sensors outputs at discrete evenly spaced time intervals less than and including time n+m, where 0<m<1;

generating, by the first adaptive filter predictor, a predicted sensor output that is an estimate of the sensor output at time n+1;

generating, by the second adaptive filter predictor, a predicted sensor output that is an estimate of the sensor output at time n+1+m; and

synchronizing the inputs and outputs of the two adaptive filter predictors to provide synthetic sensor output data at a rate faster than the sensor can physically respond.

21. The method of claim 20, wherein the first adaptive filter predictor includes a first neural network and the second adaptive filter predictor includes a second neural network.

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