Modeling and Compensation for Capacitive Pressure Sensor by RBF Neural Networks

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Abstract— Capacitive differential pressure sensor (CPS) is extremely used in industries. This sensor measures pressure and shows current. Accuracy of capacitive differential pressure sensor is limited because the ambient temperature has adverse effects on CPS output characteristic. In order to overcome this limitation, the output of this sensor is compensated by using RBF neural network and because of the importance of modeling of sensors and for having more correct read out, the model of this sensor is extracted by RBF neural network too. A test bench is designed and implemented to data acquisition in a real environment. The experimental results are being used to verify the performance of RBF neural network based on compensating and modeling of nonlinear system of CPS.

Keywords— Intelligent and smart sensors, Neural network, RBF, Capacitive pressure sensors, Compensation, Modeling.

1. INTRODUCTION

Pressure sensors have wide applicability in various systems including instrumentation, automobiles, biomedical, and process control systems. The capacitive pressure sensor (CPS), in which the capacitance of a chamber changes with application of pressure finds extensive applications because of its low power consumption and high sensitivity. However, its highly nonlinear response characteristics give rise to several difficulties including on-chip interface, direct digital readout and calibration. To compensate for the difficulties faced due to the nonlinear response characteristics of the CPS, several techniques have been suggested. A switched-capacitor charge balancing technique, a ROM-based look-up table method and a nonlinear encoding scheme have been proposed. The problem of nonlinear response characteristics of a CPS further aggravates the situation when there is change in environmental condition. As the output of a CPS is dependent on applied pressure as well as temperature, when the ambient temperature changes frequently, the situation becomes very complicated.

Artificial Neural Network (ANN) is widely applied to compensate for the above drift and to extract real model of sensors for correct read-out [1-4]. It has so strong ability to function approximation that it is used for sensor to model it and to compensate for the various nonlinear error [5]. However, it also has the drawbacks such as low convergence rate, being easy to fall into local minimum and so on [7], [5].

In this paper the compensation and the modeling of the CPS sensor by Radial Basis Function (RBF) Neural Network will be done. At first a test bench is designed and implemented to data acquisition in a real environment and these data are used for training and testing the RBF neural network for compensating and modeling of the CPS sensor. Two modeling techniques are proposed in this paper. In the direct modeling, the RBF is trained in parallel mode to estimate the output of the CPS. This model may be used for the purpose of on-line fault detection and quality control of the sensor during its production (modeling of CPS). In the inverse modeling, the RBF is trained in a series mode to estimate the applied pressure which is independent of ambient temperature (compensation of CPS).

2. CAPACITIVE PRESSURE SENSOR MODEL

The CPS has lower power dissipation and higher sensitivity than other types of pressure sensors. A CPS senses the applied differential pressure due to the elastic deflection of its diaphragm. In the case of a simple structure, this deflection is proportional to the applied differential pressure \( \Delta P \), and the sensor capacitance \( C(\Delta P) \) varies hyperbolically. Neglecting higher-order terms, \( C(\Delta P) \) may be approximated by

\[
C(\Delta P) = C_0 + \Delta C(\Delta P) = C_0(1 + \gamma) \tag{1}
\]

where \( C_0 \) is the sensor capacitance when \( \Delta P = 0 \), \( \Delta C(\Delta P) \) is the change in capacitance due to applied differential pressure, \( \gamma = \Delta P_N(1 - \alpha)/(1 - \Delta P_N) \), \( \alpha \) is the sensitivity parameter which depends upon the geometrical structure of the sensor, \( \Delta P_N \) is the normalized applied differential pressure.
given by $\Delta P_{p} = \Delta P/\Delta P_{\text{max}}$ and $\Delta P_{\text{max}}$ is the maximum permissible input differential pressure.

The problem that is discussed in this paper is the dependency of CPS on temperature. The sensor capacitance is a function of the applied differential pressure and the ambient temperature $T$. Assuming that the change in capacitance due to change in temperature is linear and dependent of the applied differential pressure, the CPS model may be expressed as

$$C(\Delta P, T) = C_0 f_1(T) + \Delta C(\Delta P, T_0) f_2(T)$$  \hspace{1cm} (2)

Where $\Delta C(\Delta P, T_0)$ represents the change in capacitance due to applied differential pressure at the reference temperature $T_0$ as given in equation (1). The function $f_1(T)$ and $f_2(T)$ are given by

$$f_1(T) = 1 + \beta_1(T - T_0)$$

$$f_2(T) = 1 + \beta_2(T - T_0)$$  \hspace{1cm} (3)

Where the coefficients $\beta_1$ and $\beta_2$ may have different values depending on the CPS chosen. The normalized capacitance of the CPS, $C_N$ is obtained by dividing (2) by $C_0$ and may be expressed as

$$C_N = \frac{C(\Delta P, T)}{C_0} = f_1(T) + \gamma f_2(T)$$  \hspace{1cm} (4)

3. DESIGN AND CONSTRUCTION OF BENCHMARK

To study the influence of temperature of the CPS characteristic we have to do some practical experiments. To this end a test bench is designed which helps us to gather data in order to study the influence of ambient temperature on the output of CPS. The schematic view of the system is shown in fig.1. The system is made up of a closed thermos which is thoroughly isolated. Performance of the heater and cooler is controlled in order to have constant value of temperature inside the box. Temperature value is changed from 0 to 50 by an increment of 2, and we change the value of $\Delta P$ by using the U-shaped glass from $-10$ mmH$_2$O to $10$ mmH$_2$O. It can be seen that in some low pressure values and some high pressure values the output of CPS is completely saturated.

Fig.5 shows the ideal input-output characteristics of the CPS which is independent of temperature and in all temperatures in range of 0°C to 50°C output current varies from 4mA to 20mA. Fig.6 shows the error between measured value and the actual one at the sensor output before compensation.
4. RBF NEURAL NETWORK

Radial-basis-function, RBF, neural network was proposed by J. Moody and C. Darken in the 1980s. At present it has been already proved that RBF network is also able to approach any continuous function by the random precision.

The structure of RBF neural model is shown in fig. 7, from that it can be seen that RBF network takes radbas function (Gaussian function) as transfer function. The independent variable of radbas is the Euclid distance between weighted value vector and threshold value vector $||dist||$, which is the product of the input vector and the weighted matrix row vector.

The input is product of threshold value matrix represented by letter b and Euclid between the input vector represented by letter P and the weight vector represented by letter W. The output is represented by letter a.

RBF network includes three layers, namely input layer, hidden layer (radbas layer with S1 neurons) and output layer (purelin layer with S2 neurons). The structure of RBF network is shown in fig. 8, in which R stands for the number of neuron of the input layer, S1 and S2 respectively stand for the number of neuron of the hidden layer and the output layer, W1 stand for the weighted value vector between the input
layer and the hidden layer, W2 stands for the weighted value vector between the output layer and the hidden layer, b1 and b2 respectively stand for the threshold value of hidden layer and the output layer, purelin is the linear transfer function.

Neural network need not to establish the analytical functions including non-target parameters which are then eliminated, but only need samples for training, through the training it can simulate the internal relations between the input and the output. Study samples are usually collected by the multi-dimensional calibration experiments. And network module is mostly realized by means of software program.

The selection of the number of hidden neurons in RBFs is problem-dependent and hence it is difficult to determine the optimal network configuration. Accordingly, the optimal numbers of hidden layer neurons are determined by trial and error and the number of nodes that give the minimum error has been selected for the structure. RBF structure is 2-11-1. From the process that is explained in section 3, 275 pairs of data are obtained which 60% of them are used for training and the 15% of them are used for validation and the rest is used for testing.

To speed up the training, the samples need to be normalized through the equation (10).

$$x'_i = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \times 2 \times 1$$  \hspace{1cm} (10)

In fig.10 the result of RBF neural network modeling is shown. It is clear that RBF output tracks the real output precisely.

Fig.8 Structure drawing of RBF network

5. MODELING OF CPS SENSOR

The modeling principle based on artificial neural network is that making use of the fundamental characteristics of neural network to enable the sensor to have correct model that can be used for getting output from every inputs in every temperature. The ideal model of this sensor is such as below:

$$I = 0.8. \Delta P + 12$$  \hspace{1cm} (9)

But this ideal model can be used just for situations that temperature does not change. If temperature changes in wide range, this model cannot be used.

The diagram of modeling principle is shown in fig.9. In the sensor module, the input signals are differential pressure ($\Delta P$) and temperature ($T$), the measured output is current represented by letter $I_{measured}$ and the output that is estimated by RBF is represented by $I_{estimated}$.

Fig.9 Diagram of modeling of CPS

ThCP1.8

Fig.10 Result of RBF modeling

Fig.11 Percentage of error in modeling
Fig. 12 shows the output of RBF neural network modeling and the measured output at $\Delta P = +6\text{mmH}_2\text{O}$. As it can be seen the CPS sensor is modeled accurately.

![Fig. 12 output of modeling system at $\Delta P = 6\text{mmH}_2\text{O}$](image)

6. COMPENSATION OF CPS

The temperature compensation principle based on artificial neural network is that making use of the fundamental characteristics of neural network to enable the sensor to have self-adaptive capacity, such as complicated nonlinear mapping, self-organization, self-learning, self-reasoning and so on.

Output of this sensor is dependent on both pressure and temperature and it should just depend on pressure because it measures pressure, but in the situation that temperature changes, the output does not show the exact pressure. By using the RBF neural network, the adverse effects of temperature on the output of the sensor is eliminated and the output of this sensor is compensated. The RBF structure that is chosen for this compensation is 2-13-1. The diagram of compensation principle is shown in fig. 13. In the sensor module, the input signals are differential pressure ($\Delta P$) and temperature (T), the measured output is current represented by letter $I_{\text{Measured}}$ and the output that is compensated by RBF is represented by $I_{\text{Compensated}}$ and the weights of RBFNN is updated via differences between the compensated current and the ideal one that is achieved by equation (9).

![Fig. 13 Diagram of modeling of CPS](image)

In fig. 14 the result of RBF neural network compensation is depicted. It is clear that, compensated output tracks the ideal output precisely except in some temperature there are some differences because the CPS goes to saturation states.

As it can be seen in fig. 14 after compensation all the output currents vary from 4 to 20 mA but before compensation because of the influence of temperature, output current just in 25°C varies from 4 to 20 mA and in other temperatures this range changes. The error between compensated output and isolated output is shown in fig. 15. The most amount of error is belonged to saturated points.

![Fig. 14 Result of RBF compensation](image)
7. CONCLUSION

Smart sensors should be capable of providing accurate read-out for the nonlinear influences of the environmental parameters on its characteristics. To achieve this object, RBF neural network has been proposed for modeling and compensating a capacitive pressure sensor operating in a harsh environment in which temperature can vary in wide range. The temperature compensation method based on RBF neural network overcome some adverse effects on measuring accuracy and stability of sensor brought by the other non-target parameters like temperature. In addition, the compensation and modeling based on RBF neural network have strong robustness, simplicity and versatility to be used for the other type of sensor as well.

REFERENCES


