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SENSOR ADAPTIVE LINEARIZATION AND TEMPERATURE COMPENSATION USING ANALOGUE PROCESSING ELECTRONICS

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ABSTRACT: This paper shows the application of an analogue-digital electronic neural processor to extend the linear output range of an angular position sensor, compensating the output drift due to temperature variations in a range of 60 K degrees. The system consists of two stages: the first one compensates temperature drifts; then, the second module extends the linear output range. The complete system gives a linear output, independently of the temperature in the range of 293-353 K, with an accuracy of 2 degrees. Low power and low size make these circuits valuable to implementing the "smartness" part of smart sensors.

INTRODUCTION

Temperature effects on sensors response must be corrected in order to extend its application range. Moreover, most of sensors show a linear response in a limited range of its span. The use of adaptive circuits based on artificial neural networks makes possible to modify the compensating circuit behaviour, tuning its parameters according to new requirements. Thus, selecting the suitable parameters, an adaptive electronic circuit will improve the operation of a sensor, extending the linear response independently of temperature drift.
Giant magneto-resistive devices (GMR) [1] are sensors that present a resistance which is dependent on its position within a magnetic field. This feature makes GMR sensors useful in angular position detection. However, this behaviour is linear in a limited range (Fig. 1). When a wider linear range is required, a conditioning circuit must be included in the signal processing path.

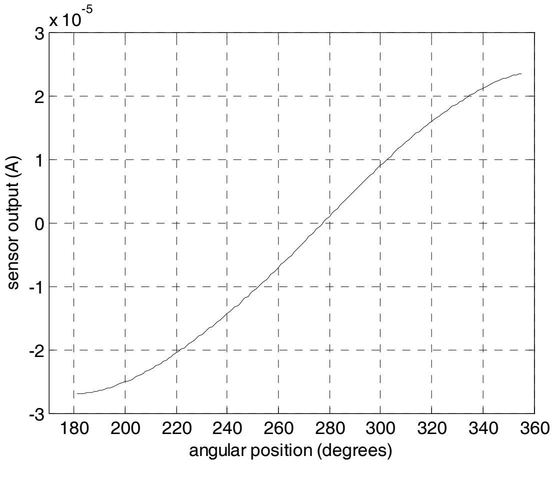


Fig. 1. Giant magneto-resistive sensor behaviour

Artificial Neural Networks (ANNs) are computing tools based on the operation of biological neurons [2]. ANNs are composed of small processing elements, called artificial neurons, highly interconnected and arranged in layers. The system operation is adjusted using a training process where input-output data samples from the desired task are iteratively presented, adjusting the network weights that connect inputs from a neuron layer with the preceding neuron layer outputs. When size, power consumption and speed are main requirements, electronic analogue implementation is a suitable selection for these systems [3] [4] [5]. Moreover, current-mode analogue circuits give better results at lower bias, reducing the power consumption [6].
As it was proposed in previous works [7] [8], implementation of reliable long-term and mid-term weights using digital registers as storage elements, combined with analogue processing electronics can improve dramatically the system features.
This paper shows the application of a current-based mixed-mode adaptive processing circuit applied to extending the linear range of a GMR sensor. Moreover, the system compensates the error drift due to temperature variations in a range of 60 K. Results show a minimum angular position accuracy of 2 degrees.
Next section shows the processing architecture, building blocks and processing stages. Following, its application of a GMR sensor is presented, showing partial results and final output, comparing to the original sensor behaviour.

PROCESSING SYSTEM FEATURES

The processing electronics is based on a current-mode circuit previously presented in [8]. Fig. 2a shows the blocks diagram of the adaptive processing element used in this work.

Neuroprocessor architecture

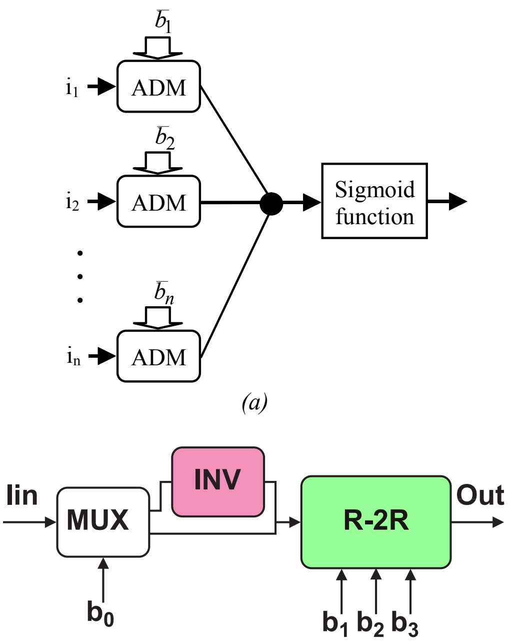
The analogue-digital multipliers (ADM in Fig. 2) [7] [8] multiply the analogue current inputs (i_i) to the 8-bit digital word $\overline{b}_i$ that represents the network weights. The first bit selects the sign operation, inverting the input current when its value is '0' (Fig. 2b). Fig. 3 shows the main circuit of the mixed-mode multiplier, based on a MOS R-2R current ladder [9] [10]. The arithmetic operation performed by this circuit is

$$out = 0.974865wp - 0.0136726p \qquad (3)$$

Once input currents are weighted and accumulated, the final output is achieved by means of a current conveyor (Fig. 4) [11], which performs the non-linear neuron operation. In order to achieve a valuable accuracy in simulations, current conveyor operation is simulated using a look-up table. Differences between the ideal hyperbolic sigmoid function and real circuit operation are shown in Fig. 5.

Temperature compensation circuit

Many sensors present an output drift due to changes in working temperature. Fig. 6 shows these effects for a GMR sensor at four different temperatures. A



(a)

(b)

Fig. 2. Neuroprocessor architecture. (a) main building blocks; (b) analog-digital multiplier architecture

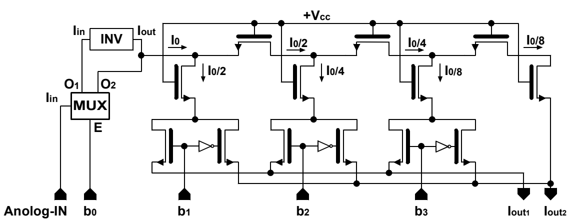


Fig. 3. Current- based analog-digital multiplier circuit

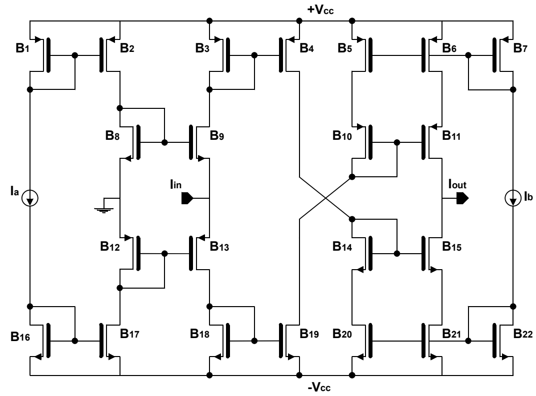


Fig. 4. Current-based hyperbolic tangent function

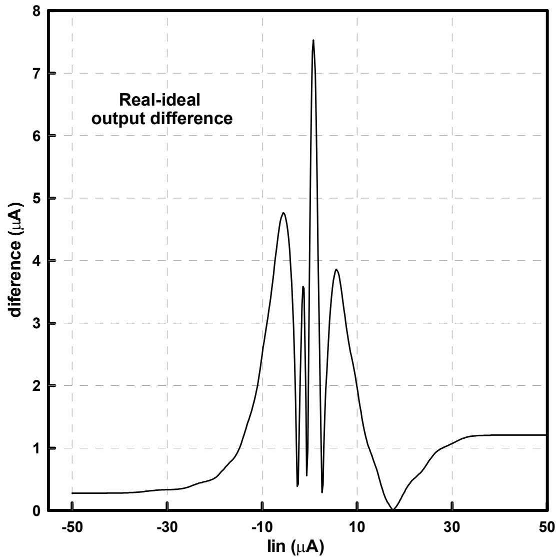


Fig. 5. Differences between real and ideal tanh function

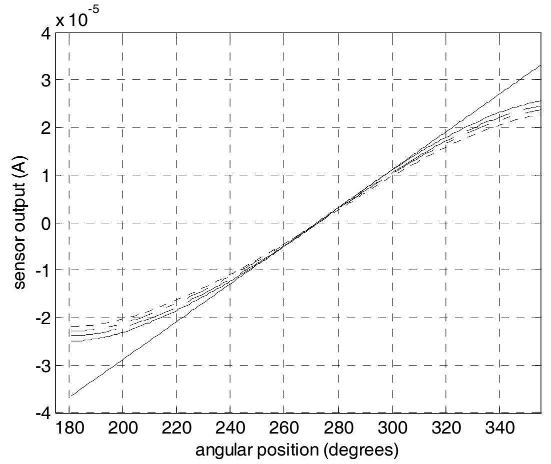


Fig. 6. GMR sensor output at 293 K (solid line), 313 K (dashed line), 333 K (dash-dot line) and 353 K (dotted line)

conditioning system could compensate this effect, giving the same output independently of the temperature.

The proposed temperature-compensation circuit is presented in Fig. 7. A multilayer perceptron (MLP) receives the actual temperature (from a linear diode-based temperature sensor) and sensor output as inputs, correcting the output drift and giving the expected sensor measure at a determined temperature as output. Hidden nodes architecture is as presented in Fig. 2, whereas the output node changes the non-linear output function for a linear output.

Network weights are tuned using a training process based on the classical perturbative learning algorithm proposed in [12]. We have verified that the network improves its performance simulating in the training phase a half of the hidden layer neurons with the inverse of the real non-linear operation function. Once the desired performance is reached, the inverted output function is replaced by the real one in the corresponding simulated processor, changing the sign of the corresponding neuron weights. A fast network re-training gives higher performances than using the actual output function in the training phase [13].

Linearization circuit

Once the temperature drift is compensated, an improved neural linearization circuit based on [8] (Fig. 8) gives the final linear output. The proposed MLP has a hidden layer with four processing elements, which block diagram is presented in Fig. 2. As in the case of the temperature compensation circuit, training process is based on the perturbative algorithm with modified output function in hidden neurons.

APPLICATION TO GMR SENSORS

Output temperature dependence (Fig. 6) is corrected using the neural network architecture presented in Fig. 7. The temperature-compensation circuit is trained in order to provide the sensor response at 293 K, independently of the working temperature in the selected range from 293-353 K. Fig. 9 shows the resulting compensated sensor outputs. As we can see, differences in the sensor output, working at the proposed 60 K degrees range are drastically reduced.

Fig. 10 shows the final corrected sensor output working at 293, 313, 333 and 353 K degrees. In this application, the expected (ideal) linear output used in the training phase is tangent to the linear characteristic of the sensor

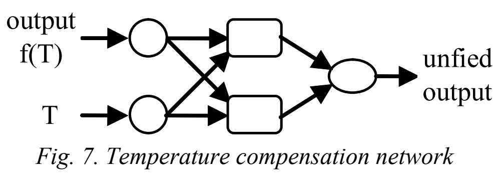


Fig. 7. Temperature compensation network

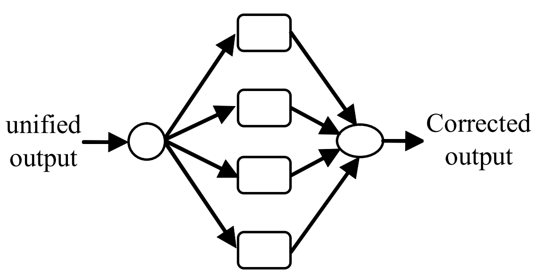


Fig. 8. Sensor output linearization system

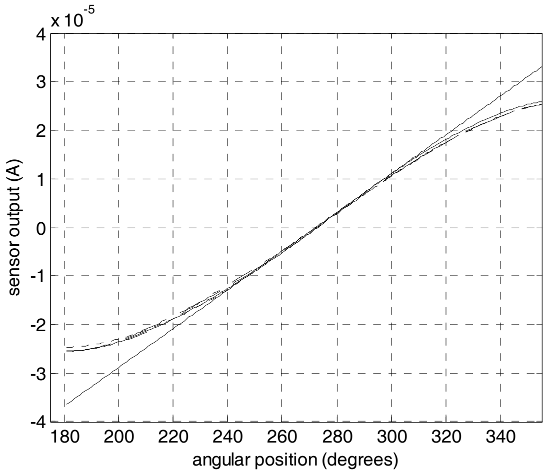


Fig. 9. Temperature compensated sensor outputs

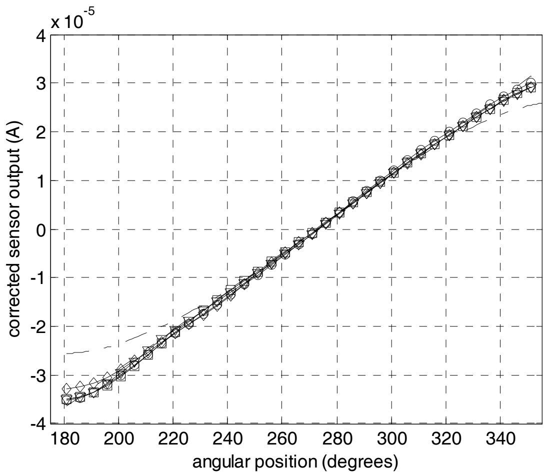


Fig. 10. Linearized sensor outputs for sensor at 293 (circles), 313 (triangles), 333 (squares), and 353 (diamonds) kelvin degrees, compared to the actual sensor output at 293 K degrees (dash-dot line)

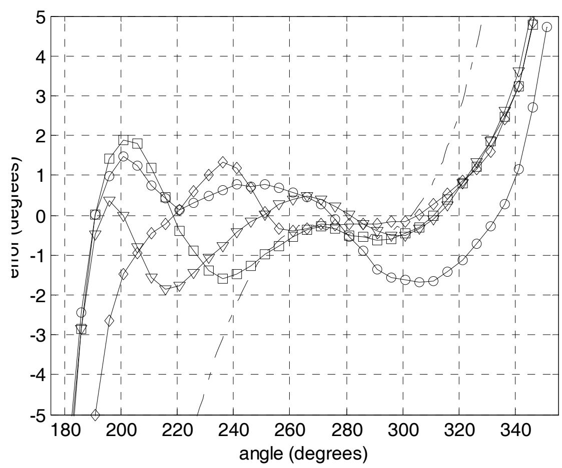


Fig. 11. Corrected sensor output errors compared to the ideal linear response. Markers are as in Fig. 10

at 293 K, in the middle of the output range (Fig. 9). As we can see in Fig. 10, resulting outputs are closer to the ideal linear output than the actual sensor output at 293 K degrees, represented in the figure with a dash-dot line.

The goal of this work is to linearize the GMR sensor behaviour, giving the angular position with an error lower than 2 degrees, independently of the temperature. Fig. 11 presents the achieved errors at the selected temperatures, compared to the actual sensor error at 293 K degrees.

CONCLUSIONS

This work presents a mixed analogue-digital circuit designed to linearize the behaviour of GMR sensors, compensating the temperature dependence of its response. The system consists of two stages. In the first one, temperature drifts are corrected, giving an output similar to the sensor response at 293 K. The second stage extends the linear range of the sensor at this temperature, assuming a maximum error of 2 degrees in the measured angular position. Table 1 shows the linear ranges achieved using the proposed compensation system. We can see that the global system improvement is higher than 55%, compared to the linear range of the non-corrected sensor output at the reference temperature (293 K). Moreover, according to the table values, it seems possible a wider extended linear range selecting a more suitable linear output target.

TABLE 1. Extended linear range

Temperature (K)	Extended range (angular deg). Err<2	%
293	205-342	83
313	186-327	88
333	209-326	56
353	197-328	75
Global behaviour	**209-326**	**56**

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