Closed-Loop, Neural Network Controlled Accelerometer Design

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ABSTRACT

In this paper, a closed-loop, smart transducer design is proposed, based on artificial neural network (ANN) techniques. The design aims to improve the performance of open-loop, off-the-shelf capacitive acceleration sensors and increase their robustness to manufacturing tolerances. A "model reference" control strategy was adopted for the design of the smart transducer. Multilayer perceptron (MLP) type networks were chosen for implementing the control strategy. While a static MLP was used for the feedback arrangement, a tap delayed lines MLP was necessary for implementing the controller due to the dynamic nonlinear behaviour exhibited by the sensing device. A dynamic version of the back-error propagation algorithm was used for training the networks. The resulting closed-loop transducer had a dynamic range of ±10g and a stable behaviour for input stimuli up to ±100g.

Keywords: micromachined accelerometer, neural network, model reference control

1 INTRODUCTION

Recent advances in micro-electro-mechanical system (MEMS) technologies have made possible silicon inertial sensors of very small size and with low power consumption [1]. Such features permit a wide range of possible applications where motion/movement-controlled systems are used. The class of acceleration sensors considered here, as a basis for the design of 'smart' transducers, are those with a capacitive type of pick-off. The pick-off method has the advantages of high output levels, low sensitivity to temperature drift, and, most importantly, can be readily used in force-balancing configurations (closed-loop operation). In spite of the advances in micromachining, no sensor is perfect in its manufacture and capacitive sensors are no exception [1,2]. These devices not only exhibit non-idealities such as offset, drift, non-linearity and noise, but also the magnitude of these non-idealities can vary.

In this paper, a closed-loop, smart transducer design is proposed, based on artificial neural network (ANN) techniques. It has been shown that these techniques can be used as a representation framework for modelling and controlling nonlinear dynamic systems [2,3]. The design presented here aims to improve the performance of open-loop, off-the-shelf capacitive acceleration sensors and increase their robustness to manufacturing tolerances. A "model reference" control strategy [3] was adopted for the design of the smart transducer. The work presented here follows a previous successful development of a neural network controlled open-loop hardware transducer prototype. Although this prototype exhibited good measuring performance, it can only be used in static-low frequency applications and has a dynamic range limited to ±3g. Furthermore, there are conditions in which the sensor latches up. This can only be corrected by depowering the device. It is intended here to extend the use of the transducer over the 0-100Hz frequency range, by applying electrostatic feedback. Multilayer perceptron (MLP) type networks were chosen for implementing the control strategy. While a static MLP was used for the feedback arrangement, a tap delayed lines MLP was necessary for implementing the controller due to the dynamic nonlinear behaviour exhibited by the sensing device.

2 THE SENSOR CONTROL STRATEGY

2.1 The Closed Loop Transducer Structure

The small size of the sensing element allows electrostatic actuation to be used as a form of feedback. Thus, the inertial force acting on the proof mass is balanced by an opposing electrostatic force. The idea of integrating the sensing element within a closed-loop structure is not new. Previously, simple linear PI control has been attempted but this fails to solve the latch-up problem [4]. Nevertheless, the PI approach has been used in many devices described in the literature [4] since it does improve the sensor performance compared to open-loop operation.

In contrast to the linear control approach, the novel transducer design proposed here uses the nonlinear mapping capabilities of neural networks for controlling the sensing element and linearising the electrostatic forces. A block diagram representation of the proposed system is given in Figure 1.

The neural network controller performs a dynamic mapping, in order to compensate for the frequency dependent nonlinearities exhibited by the sensor.

The feedback neural network (FNN) has two functions. Firstly, it calculates the square root of the output voltage,

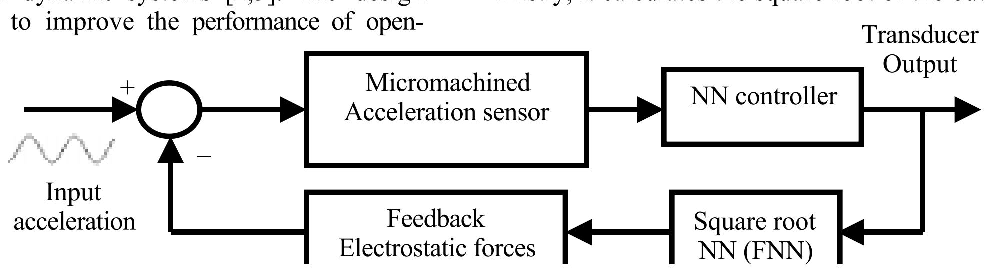

Figure 1. Block diagram of the closed-loop, smart transducer

providing a linear feedback relationship between the system output and the electrostatic forces acting on the electrodes. Secondly, the network demodulates the output signal in order to apply the feedback to only one electrode at a time: the bottom electrode will be activated if the proof mass has moved towards the top electrode and vice-versa.

2.2 The Model Reference Control

The model reference control strategy consists of specifying the desired performance of the closed-loop system through a stable reference model which is defined by its input-output pair $\{a_r(t), x_r(t)\}$. The control system attempts to make the system output $x_s(t)$ match the reference model output asymptotically, i.e.:

$$\lim_{t \to \infty} \left\| x_r(t) - x_s(t) \right\| \leq \varepsilon$$

for some specified constant $\varepsilon > 0$. The error defined above is used to train the network acting as the controller [3]. This approach is related to the training of inverse system models: when the reference model is the identity mapping, the two approaches coincide. In general, the training procedure will force the controller to be a "detuned" inverse, in the sense defined by the reference model. In the design presented here, the model reference represents an ideal, linear acceleration sensor model, having a sensitivity of 1V/g over its entire dynamic and frequency ranges.

The block diagram of the controller training scheme is presented in Figure 2. The model reference, in this configuration, provides the feedback voltage to the sensing element, while the controller is trained to minimise the error between the transducer output and the model reference output. Details of both FNN and controller network training and performance are presented in the following section.

3 NEURAL NETWORK IMPLEMENTATION OF SMART TRANSDUCER

3.1 The Feedback Neural Network

As stated above, the FNN has the role of providing a linear relationship between the output voltage and the feedback electrostatic forces acting on the seismic mass.

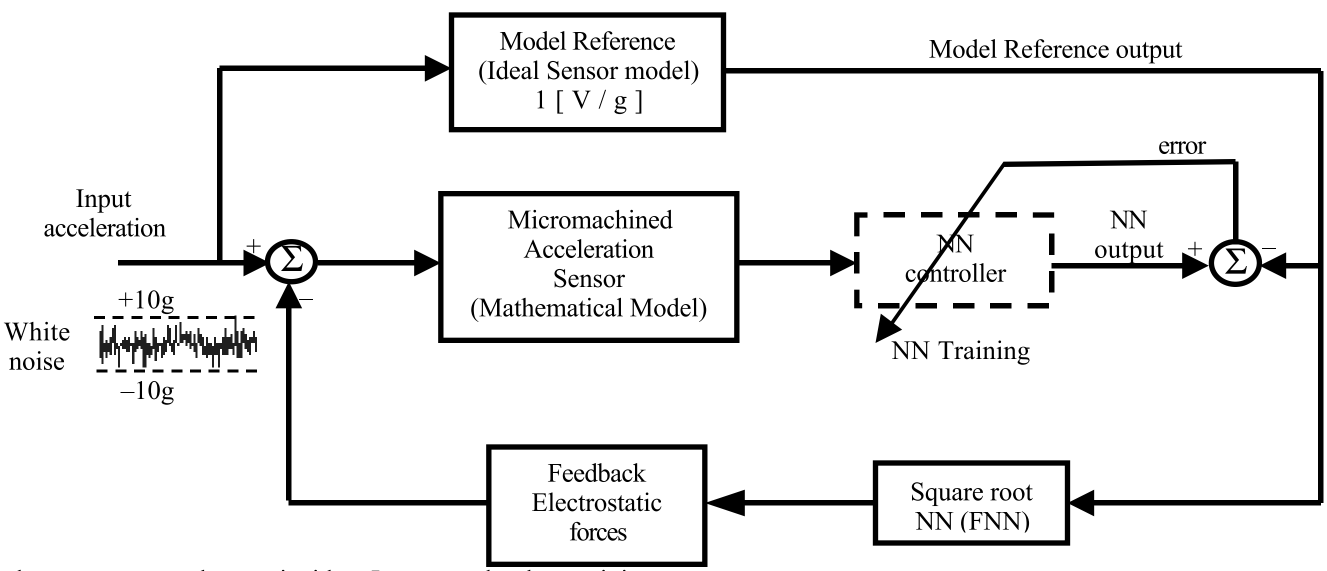

Figure 2. Closed-loop training scheme for the neural network controller with white noise acceleration input

Moreover, the FNN acts as a demodulator for the feedback signal, by applying it in a discontinuous manner, to only one electrode at a time.

This novel reset concept ensures that the feedback is always negative and therefore, even under adverse operating conditions, the seismic mass cannot lock-up.

The network used for this purpose has one input (the output voltage of the transducer), one hidden layer and two outputs, connected to the outer electrodes of the sensing element. Both the hidden and the output neurons are governed by a sigmoid-type transfer function, with bias.

The network has been trained to approximate the following input - output function:

$$output_1 = \begin{cases} \sqrt{input}\ \textit{if input}\ ?\,0 \\ 0\ \ \textit{if input} \le 0 \end{cases} \tag{1}$$

$$output_2 = \begin{cases} \sqrt{-input}\ \textit{if input} \le 0 \\ 0\ \ \textit{if input}\,?\,0 \end{cases}$$

The training set contained 200 examples, with the input samples evenly distributed in the range [-1 ; +1]. A dynamic version of the back-error propagation algorithm was used for the network training [5]. This included both a variable learning rate and a momentum term. The input and desired outputs of the network are presented in Figure 3. 20000 epochs of training (using MATLAB) were necessary for a 1x6x2 network to reach a preset sum-square error of 0.05 over 200 samples. Some scaling was necessary in order to integrate the trained network into the closed-loop transducer structure: the output of the transducer (which is the input to the feedback network) was divided by 100 and the outputs of the net were multiplied by 10 (in view of the required square root law). The testing and validation of the trained net was performed by subjecting it to previously unseen input stimuli and assessing its performance in terms of the sum-square error [5].

Signal Level

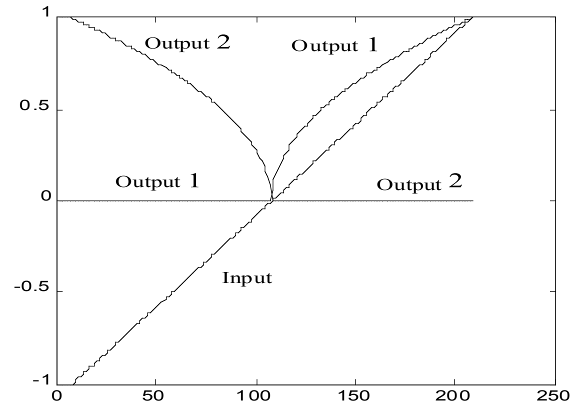

Figure 3: Scaled input and desired outputs of the FNN

3.2 The neural network controller

The controller neural network performs a dynamic mapping. A modified MLP architecture, which included tap delayed lines (TDL) was used for the controller design. The structure of the controller is presented in Figure 4. The history of the sensor output is incorporated into the network structure by means of two additional network input signals: one step and two steps delayed sensor outputs respectively. A 1kHz sampling frequency was chosen. The training set was formed by subjecting the structure in Figure 2 (which included the trained FNN) to a noise signal, covering an acceleration range of ±10g and with frequency components up to 100Hz.

The resultant mapping (after suitable scaling) required to be performed by the controller network is presented in Figure 5. A 3x17x9x1 tap delayed lines MLP was successfully trained to perform this mapping, reaching in roughly 100000 epochs a sum-square error of 0.2 over 1000 samples. Once trained, the neural controller was incorporated into the structure shown in Figure 1 and the performance of the closed loop transducer was assessed.

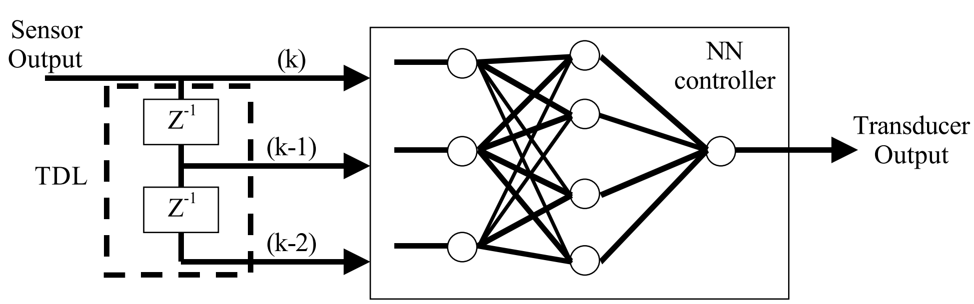

Figure 4. Structure of the neural network controller

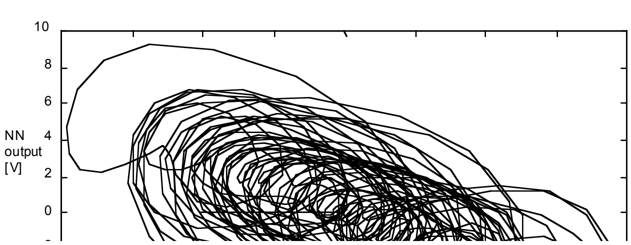

Figure 5: Dynamic mapping desired to be performed by the neural controller

4 THE PERFORMANCE OF THE CLOSED-LOOP TRANSDUCER

The performance of the closed-loop transducer was assessed by comparing its behaviour to that of the open-loop accelerometer. By subjecting both transducers to noise type signals, their transfer characteristics were built (Figures 6 and 7, respectively). It can be noted that the closed loop transducer has a dynamic range of ±10g, which is twice that of its open-loop counterpart. Moreover, although not fully linear, the characteristic of the closed-loop transducer shows approximately an order of magnitude improvement in measurement accuracy.

Further tests were run to determine the stability range of the neural transducer. It was found that accelerations in the range ±100g could be withstood by the transducer without locking up, if the frequency of such signals falls in the 0-100 Hz range. The drawback of the design consisted in the inability of the closed-loop transducer to maintain its stability for shocks in acceleration.

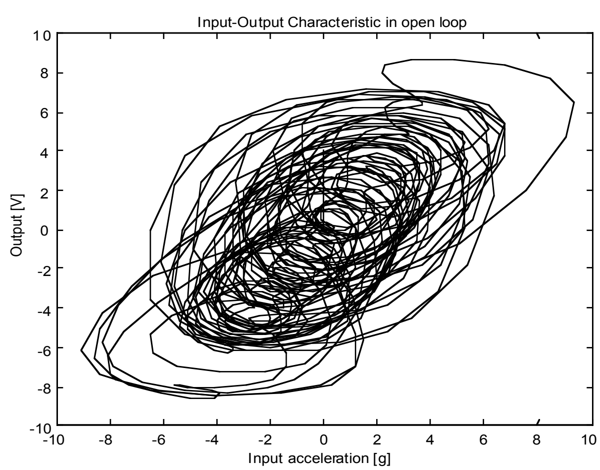

Figure 6: Dynamic transfer characteristic of the open-loop accelerometer for noise

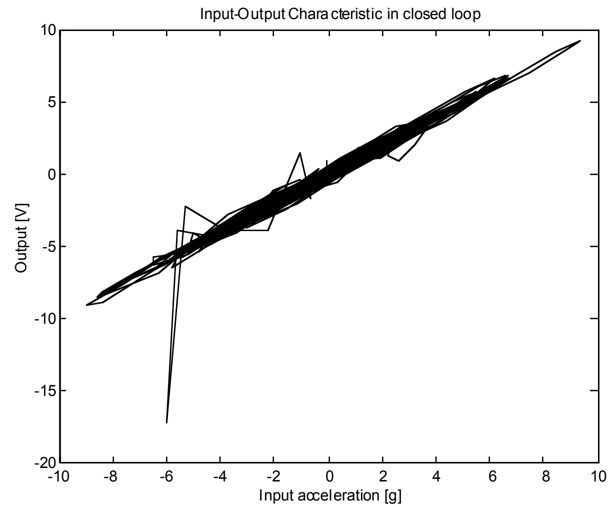

Figure 7: Dynamic transfer characteristic of the closed-loop transducer for noise

CONCLUSIONS

A model reference based closed-loop transducer design was presented in this paper. The mathematical model of a capacitive micromachined accelerometer was used as a basis for the design. Neural network techniques were used for implementing the control strategy. The performance of the transducer was assessed in simulation. It was found that the transducer exhibited improved performance compared to its open-loop version, in terms of measurement accuracy (improved by an order of magnitude over the 0-100Hz range), dynamic range (extended to ±10g) and stability range (extended to ±100g for slow varying signals). The drawback of the design consists in its lock up behaviour for shocks. Further design work is necessary to eliminate this condition.

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