Comparison of Two Novel Control Strategies for A Closed Loop Micromachined Tunnelling Accelerometer

E. Gaura *, M. Kraft **

* Coventry University, School of Engineering, Priory St,
Coventry CV1 5FB, UK, e.gaura@coventry.ac.uk
** University of Southampton, Microelectronics Centre, mk1@ecs.soton.ac.uk, UK

ABSTRACT

This paper presents system level modelling and simulations results of two closed loop, force-feedback control strategies for micromachined tunnelling accelerometers. The first approach is based on the incorporation of the sensing element in a sigma-delta modulator loop. The second strategy relies on two artificial neural networks (ANN) for both controlling the sensor and linearising the feedback loop.

Both approaches have their merits and disadvantages. The former results in a direct digital sensor but it may prove problematic to achieve sufficiently high signal to quantisation noise ratios. The latter requires the use of an analogue to digital converter (at the output of the pick-off circuit) but has the advantage of achieving better measurement linearity.

Keywords: tunnelling accelerometers, sigma-delta modulator, artificial neural networks

1 INTRODUCTION

Using tunnelling current as a detection method for the position of the seismic mass of a micromachined accelerometer is the most accurate pick-off mechanism reported to date [1]. Researchers have demonstrated resolutions down to 10^{-5} g. However, the tunnelling tip has to be maintained within a few nanometers from an electrode to attain a measurable tunnelling current, consequently these sensors require closed loop control. This is usually achieved by applying an electrostatic feedback force cancelling the inertial force deflecting the seismic mass; the voltage required to generate this force provides the output signal of the sensor. So far, analogue feedback strategies have been reported for tunnelling accelerometers which have disadvantages concerning system stability since under certain conditions electrostatic pull-in may occur [2].

The sensing element which is under development for this work uses a proof mass with a lateral tunnelling edge which is brought into close proximity to an electrode. This has the advantage that the position of the mass can be controlled differentially by two actuation electrodes using electrostatic forces.

In this paper two new control strategies for this sensor type are discussed. The first is based upon the incorporation of the micromachined sensing element in a ΣΔ-Modulator (ΣΔM) which has been used successfully for capacitive accelerometers and gyroscopes [3,4]. A major advantage over analogue force feedback control strategies is that the sensor produces a direct digital output signal in form of a pulse density modulated bitstream which is suitable to be processed by a standard DSP. Furthermore, since electrostatic forces are always attractive, in analogue force feedback systems it is necessary to superimpose two forces to realize a negative feedback relationship. For this a bias voltage is required which also linearises the quadratic force–voltage relationship but introduces an electrostatic pull-in problem if the proof mass is displaced appreciably away from its rest position. In a ΣΔM control system only the electrode further away from the proof mass is energized, the other being grounded; consequently only an electrostatic force pulling the mass to the mid position between the electrodes is produced, thus the system stability is improved.

The second strategy relies on two artificial neural networks (ANN) for both controlling the sensor and linearising the feedback loop. The ANN approach for sensor control has also been previously successfully applied to capacitive accelerometers [5]. It has been shown that ANN techniques can be used as a representation framework for modelling and controlling nonlinear dynamical systems [5]. Amongst the features which make neural networks suitable for control tasks the main ones are:

- they can be trained to learn any function, provided that enough information is given during the training process, coupled with judiciously selected neural models.
- due to their self-learning capability, neuro-controllers do not require extensive a-priori information about the system under control.

2 ΣΔ-MODULATOR BASED CONTROL

2.1 Sensing Element Model

The mechanical sensing element can be modelled by a mass-spring-damper system, thus a second order transfer

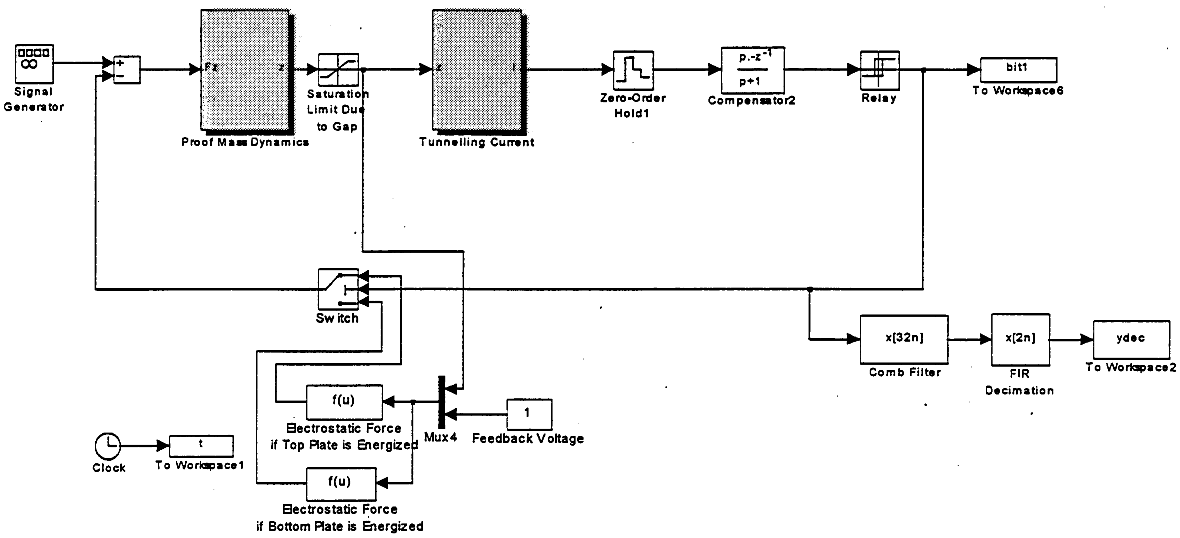

Fig. 1:. Simulink model of the tunneling accelerometer incorporated in a ΣΔ-modulator.

function. The damping force is due to squeeze film damping which is usually highly nonlinear. However, since the mass movement is kept very small by the closed loop feedback control, it is assumed here that the damping coefficient is constant. Values typical for a bulk-micromachined sensing element fabricated in SOI technology were chosen for the simulation: mass $m=10^{-5}$ kg, damping coefficient b=0.01Ns/m and spring constant k=10N/m. These value result in a critically damped behaviour with a resonant frequency of ω_0=1000rad/s.

2.2 Signal Pick-Off

The tunnelling current can be described by the following equation:

$I=I_0 \exp(-\beta \sqrt{\phi}\, z)$ (1)

where I_0 is a scaling current dependent on material, tip shape, etc. and was assumed here as 1.4×10^{-6}A, β is a conversion factor with a typical value of 10.25 $eV^{-1/2}$/nm, φ the tunnel barrier height with a typical value of 0.5 eV and z the tip/surface separation which was assumed to be 1nm for no input acceleration. The current is then converted into a voltage by feeding it into a transimpedance amplifier whose effective resistance was assumed to be 1GΩ.

2.3 ΣΔM and Feedback Arrangement

The voltage from the signal pick-off is passed to a compensator which adds a zero at a frequency well above the resonant frequency of the sensing element to provide some phase lead. Without this compensator the ΣΔM loop would become unstable. The signal from the compensator is subjected to a clocked comparator. The clock frequency is chosen much higher than the bandwidth of the accelerometer, an oversampling ratio of 256 was chosen assuming a bandwidth of 1kHz. The output of the comparator provides the output signal which is in the form of a pulse density modulated bitstream. This signal also controls a switch which determines which feedback electrode is energized. The mass consequently experiences a feedback force of:

$$F_{el} = \mathrm{sgn}(D)\frac{1}{2}\frac{\varepsilon_o A_{fb} V_{fb}^{\;2}}{\left(d_0 + \mathrm{sgn}(D)z\right)^2} \qquad (2)$$

where ε_0 is the dielectric constant, A_{fb} the area of the feedback electrode, V_{fb} the feedback voltage, d_0 the nominal gap between proof mass and the electrodes to either side, z the proof mass deflection from its rest position and D the comparator output assumed to be +1 or −1.

2.4 Simulation Results

The building blocks described above were implemented as a system level model in Matlab/Simulink as shown in fig.1. A simulation run was carried in the unforced condition. The bitstream shows a typical (2,2) mode as expected for a second order system.

In a second simulation a sinusoidal input acceleration of 0.9g was applied. The proof mass deflection and hence the tunnelling edge distance to the electrode is controlled well below 1nm accuracy hence it is ensured that the tip does not touch the substrate. The simulation results are illustrated in fig. 2. An important performance criteria in ΣΔM control systems is the quantisation noise. In this application the noise shaping is mainly determined by the dynamics of the sensing element. A simulation was carried out which calculated the signal to quantisation noise ratio (SQNR) for different input acceleration amplitudes. The result is shown in fig. 3. The full scale SQNR may not be sufficient for high-precision applications. The problem can be alleviated by choosing a higher oversampling ratio or using a higher order ΣΔM architecture. A further example of the system response for a ramp type input acceleration is presented in fig.4.

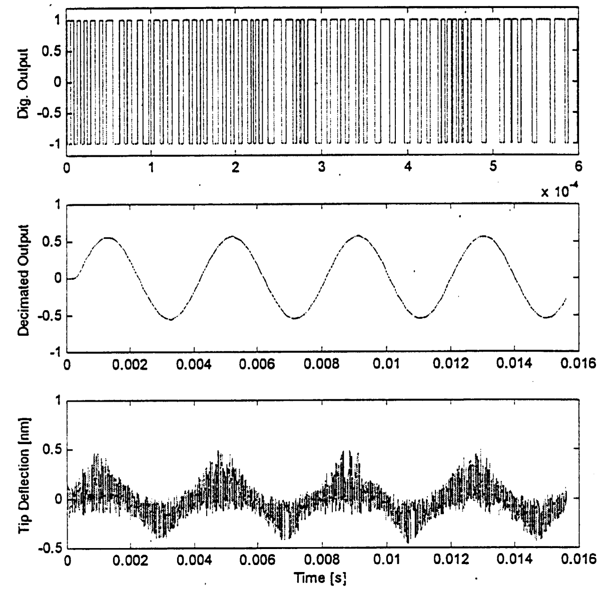

Fig. 2: Simulation results for an input sinusoidal acceleration of 0.9g, 250Hz. Top curve: output bitstream, middle curve: decimated output signal, bottom curve: residual movement of the proof mass.

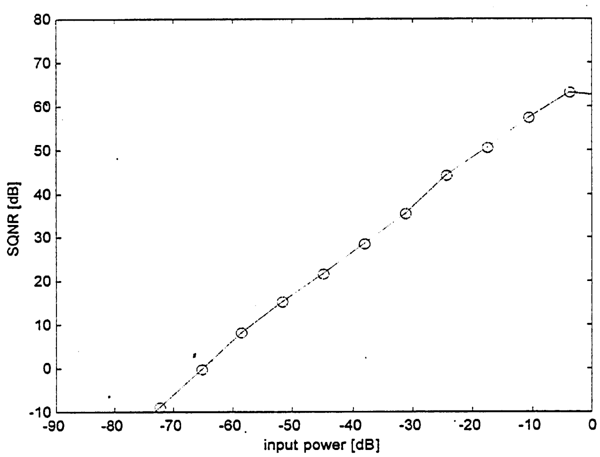

Fig. 3: SQNR for the ΣΔM based accelerometer system.

3 ANN CONTROL SYSTEM

3.1 The Neural Network Based Control Strategy

The second transducer design proposed by the authors uses the nonlinear mapping capabilities of neural networks for controlling the sensing element and linearising the electrostatic forces. At this stage of research, the system developed was tested in simulation only. A block diagram representation of the proposed system is given in fig. 5.

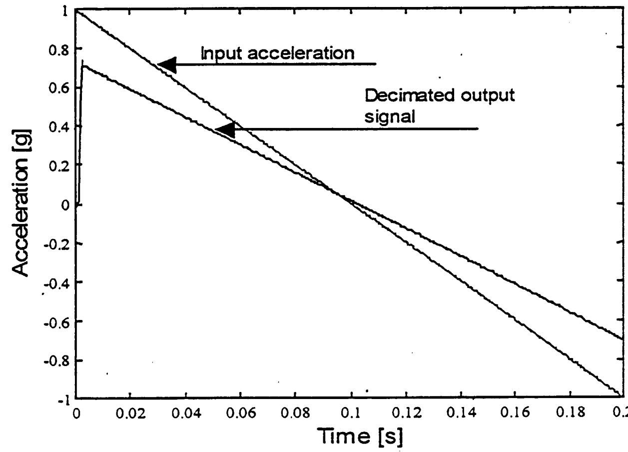

Fig. 4: System response for a ramp of input acceleration from +1g to -1g for the ΣΔM based accelerometer system.

The compensating neural network (CNN) performs a static mapping acting as a nonlinear gain controller. The feedback neural network (FNN) has two functions. Firstly, it calculates the square root of the output voltage, 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. Details of the FNN implementation, which is sensor type independent were presented in [5].

This design combines the advantages of linear feedback electrostatic forces and soft-limiting nonlinear gain control. The functionality of the system was studied by subjecting the transducer to a wide variety of stimuli and establishing both its advantages and limitations.

3.2 Simulation Results

The multilayer perceptron (MLP) has been selected for this study due to its simplicity, ease of training for small scale problems, and the profound knowledge and experience that the authors have with this architecture.

The same architecture and training algorithm have been used both for the FNN and CNN. The formation of the training set for the CNN design implied that initially, an inverse mathematical model of the tunneling current module (fig. 1) was determined and inserted in the closed loop structure, together with the sensor independent FNN module. The resulting transducer was then subjected to a ramp type of acceleration rising from –0.88g to +0.88g (which is the full dynamic range of the accelerometer) in 0.1 seconds. Having chosen a sampling frequency of 10KHz, a 1000 samples training set for the CNN resulted. A 1-11-9-1 MLP was successfully trained to perform the required static mapping, in roughly 150000 epochs.

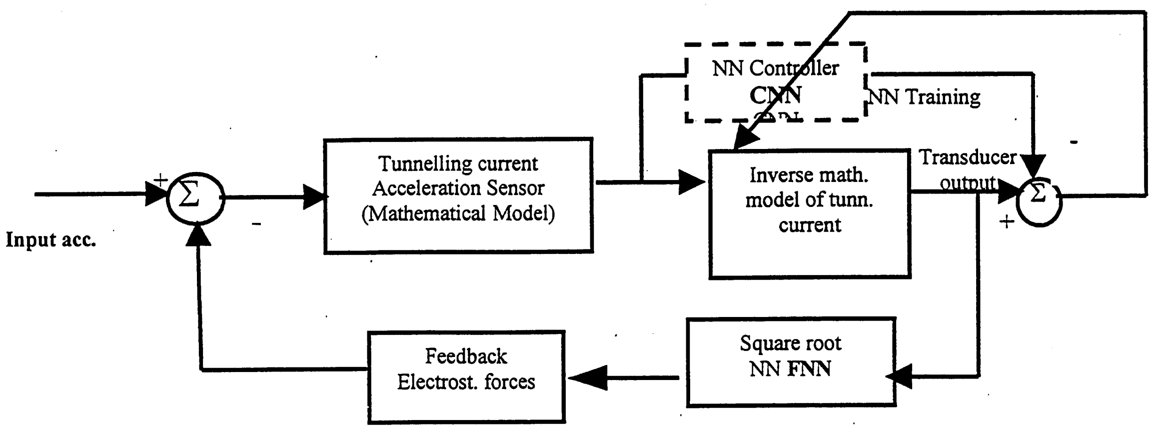

Fig. 5: Block diagram of the tunneling accelerometer incorporated in an ANN based control system.

The trained network, with fixed weights, has then been integrated into the transducer structure, replacing the inverse mathematical model of the tunneling current (using adequate scaling factors). An example of the system response for a ramp type input acceleration is presented in fig. 6. The system exhibits a linear behaviour, with a linearity error of 0.1% for the restricted range ±0.1g and 0.7% for the overall range ±0.88g. The transducer sensitivity is 1.1094v/g. According to the application requirements for the acceleration sensor, the design can be easily altered. By modifying the CNN scaling factors, improved linearity can be obtained for a restricted range (precision applications), or the whole dynamic range extended, with a reduced linearity.

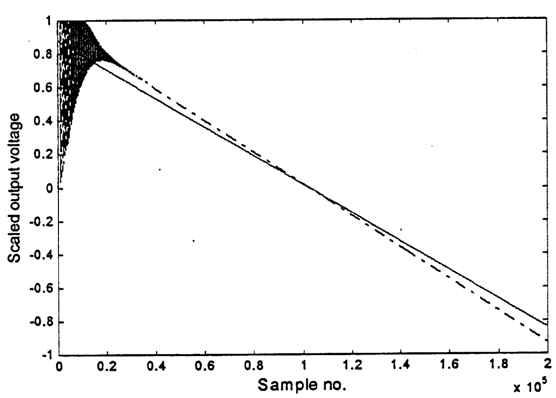

Fig. 6: NN transducer response to a ramp in acceleration (±0.88g, 0.2s duration). Input acceleration – full line; Output voltage – dotted line; sampling rate – 100KHz.

4 CONCLUSIONS

Two control approaches for the design of closed-loop tunnelling accelerometers have been presented, both based on the mathematical model of a micromachined sensing element. The first design uses digital control, and involves incorporating the sensing element into a sigma-delta modulator loop, whilst the second design uses a nonlinear control strategy based on neural networks. A comparative study has been made of the two resulting transducers, with a variety of stimuli being applied to their simulated implementations. It was found that the behaviour of the two transducers was similar in terms of linearity and signal to noise ratios. From the hardware implementation viewpoint, the neural based methods of feedback and control significantly reduced the complexity of the electronics associated with the sensing element and pick-off compared to the digital case.

5 REFERENCES

[1] Rockstad, H. K., et.al. A miniature, high-sensitivity, electron tunnelling accelerometer. Sensors and Actuators, A 53, pp. 227-231, 1996.

[2] Kraft, M., et.al. Closed loop silicon accelerometers. IEE Proceedings - Circuits, Devices and Systems, Vol. 145, No. 5, pp. 325 – 331, 1998.

[3] Lemkin, M.A. and Boser, B.E. A 3-axis micromachined accelerometer with a CMOS position-sense interface and digital offset-trim electrodes. IEEE J. of Solid-State Circuits, Vol. 34, No. 4, pp. 456-468, 1999.

[4] Xuesong, J., et.al. A Monolithic surface micromachined Z-axis gyroscope with digital output. *Proc. Symposium on VLSI Circuits*, Hawaii, pp. 16-19, USA, June 2000.

[5] Gaura, E. et.al. Closed-loop neural network controlled accelerometer, Proceedings of the I. Mech. E, Part I, Journal of Systems and Control Engineering, vol. 214, no.I2, pp.129-138, 2000.