# A Neural Network Approach for the Identification of Micromachined Accelerometers

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## ABSTRACT

The paper presents the identification procedure for a nonlinear accelerometer using a neural network. Simulation results obtained in SPICE and Matlab show good agreement between the behaviour of the sensor over its entire working range and the identification neural network (INN) model.

***Keywords***: accelerometer, micromachined, neural network, identification.

## INTRODUCTION

Transducers employing micromachined sensors are suited to a large variety of applications. A transducer which is the subject of considerable research and development at Coventry is the micromachined accelerometer. It is already known that micromachined devices, suitable for servo accelerometers, are non-linear dynamical systems, which need to be compensated [1,2].

In the development of a non-linear, model-based control strategy the choice of the process/sensor model is of paramount importance. A possible approach is to use the self-learning capabilities of neural networks (NN) for sensor identification. However, NNs merely perform a static non-linear mapping between inputs and outputs. Dynamics are not inherently included in their structures, whilst in many practical situations, such as servo-accelerometers, dynamic relationships do exist between inputs and outputs. In order to develop a dynamic model, use is made here of the time histories and/or feedback of the data as network inputs [3].

Two types of networks have been considered for solving the sensor identification problem: a multilayer perceptron and a radial basis function network, both having tapped delay lines at the input (TDL-MLP/TDL-RBF). Preliminary work revealed that of the two, the TDL-MLP was more suitable for this application.

## MATHEMATICAL MODEL OF THE MICROMACHINED SENSING ELEMENT

Figure 1 presents the mathematical model of a micromachined accelerometer, with capacitive-type pick-off [2].

The sensing element is basically a second-order system with a proof mass, a spring and a form of nonlinear damping caused by the motion of this mass in a gaseous medium. The saturation block represents the physical restraint in the movement of the mass, due to the fixed position of the top and bottom electrodes. The input to the system is the acceleration force acting on the mass, causing it to deflect from the rest position. The output signal is a measure of the position of the mass. The pick-off circuit can be modelled as a proportional gain factor which converts the displacement of the proof mass into a voltage.

This model has been shown [1,2] to accurately represent an actual accelerometer and has been used here as the basis for identification.

## THE IDENTIFICATION PROBLEM

The problem of identification consists of setting up a suitably parameterized identification model and adjusting the parameters of the model to optimise a performance function based on the error between the real system and the identification model outputs. In this context, the neural network approach represents a potentially valuable generic modelling technique which provides for rapid non-linear model formulation, whilst also allowing the capture of essential process/system characteristics. Additionally, through the enhanced models generated, neural networks provide a means by which to achieve control system improvements.

For engineering applications, the choice of the identification model structure as well as the specific method used to determine the system model depend upon a variety of factors:

- the accuracy desired and analytical tractability;
- the adequacy of the model to represent the real system;
- the simplicity of the model and the ease with which it can be identified;
- how readily the model can be extended if it does not satisfy specifications;
- whether the model chosen is to be used off-line or on-line.

Many of these decisions naturally depend upon the prior information that is available concerning the system to be identified.

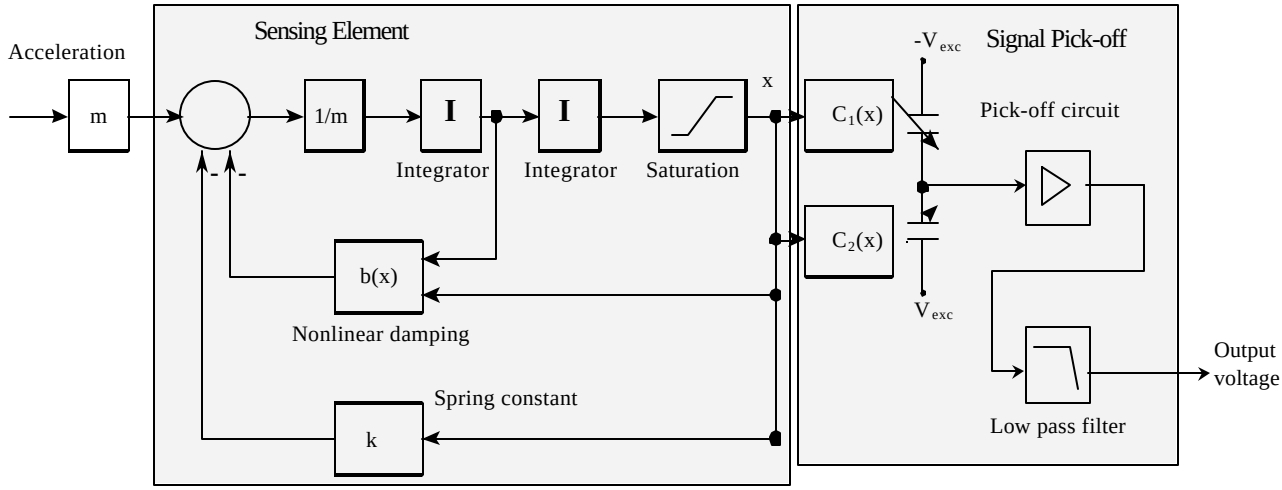


Figure 1 Mathematical model of the sensing element

## Choice of the identification model

Based on the mathematical model of the sensor [1], a good approximation of the sensor behaviour is given by:

$$ma = m\frac{d^2x}{dt^2} + \frac{\mu A}{2}\left(\frac{1}{(d_0 - x)^3} + \frac{1}{(d_0 + x)^3}\right)\frac{dx}{dt} + \mathrm{K}x \quad (1)$$

where $a$ is the input acceleration; $m$ is the mass of the proof mass; $x$ is the movement of the proof mass relative to casing; $A$ is the area of the proof mass; $d_0$ is the distance between the seismic mass and either of the outer plates at rest; K is the spring constant and $\mu$ is the viscosity of air.

As the process of forward identification is of interest here, the output of the system has to be written as a function of input and previous outputs. Equation (1) is discretised as:

$$x_{k+1} = \frac{(d_0 - x_k)^3 (d_0 + x_k)^3 \left[2mT^2 a_k - \frac{m}{2} x_{k-1} + (m + 2T^2\mathrm{K}) x_k\right]}{\mu AT[(d_0 - x_k)^3 + (d_0 + x_k)^3] + 2m(d_0 - x_k)^3 (d_0 + x_k)^3} -$$

$$- \frac{\mu ATx_k[(d_0 - x_k)^3 + (d_0 + x_k)^3]}{\mu AT[(d_0 - x_k)^3 + (d_0 + x_k)^3] + 2m(d_0 - x_k)^3 (d_0 + x_k)^3}$$

where $T$ is the sampling interval (here $T$ = 1ms is an appropriate choice, given the bandwidth of the sensor).

It can be seen that this equation is fully nonlinear in the input as well as the output signal history. The structure of the identification model should be chosen to be identical to that of the system, as far as the system order is concerned [3]. Consequently, the identification neural network (INN) has three inputs (the sensor input and the sensor outputs at the instants (k-1) and k) and one output (the sensor output at instant (k+1)).

A structure for achieving the forward modelling task is shown schematically in Figure 2. The neural network model is placed in parallel with the system and the error between the system and network outputs (the prediction error) is used as the network training signal. This learning structure is a classical supervised learning problem where the teacher (i.e. the system) provides target values (i.e. its outputs) directly in the output co-ordinate system of the learner (i.e. the network model).

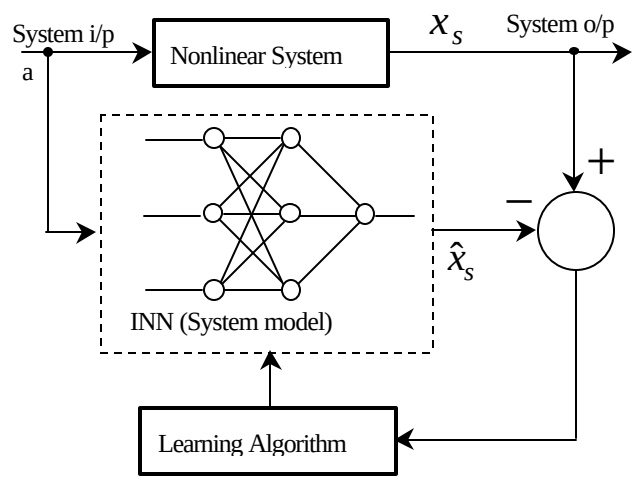


Fig. 2: Forward modelling of nonlinear systems using neural networks

A series-parallel model procedure has been adopted here for the sensor identification, due to the advantages this method offers over the parallel model procedure. The output of the sensor, (rather than the identification model) is fed back into the identification model. This implies that the identification model has the form:

$$\hat{x}_s(k) = N[a(k-1), \hat{x}_s(k-1), \hat{x}_s(k-2)] \quad (2)$$

The series-parallel identification model corresponding to the system described by (2) has the form shown in Figure 3. 'TDL' in Fig. 3 denotes a tapped delay line whose output vector has as its elements the delayed values of its input signal. Hence the past values of the input and output of the system form the input vector to a neural network whose output $\hat{x}_s(k)$ corresponds to the estimate of the system output at any instant $k$.

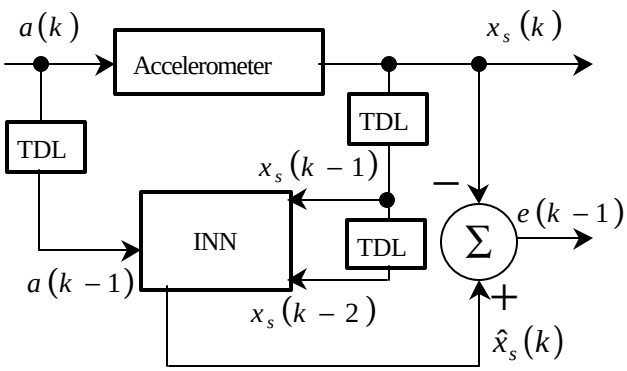


Fig. 3: Series-parallel identification structure

Since no feedback loop exists in the model, classic training procedures can be used to adjust the parameters of the TDL-MLP and the TDL-RBF.

## The training procedure

A common choice in building the network training set for the purpose of identification is to perturb the system/sensor with uniformly distributed white noise. The noise should cover the whole dynamic range of the system and should subsequently be scaled, to form the identification network inputs.

For the micromachined sensor, the training set was generated using the random number generator in Matlab. A random sequence of 200 numbers in the interval [-1;1], over a time interval of 0.8 s was generated. As the sensing element is simulated in SPICE, the random sequence of numbers will represent, in SPICE, the point-to-point description of a piecewise linear input signal for the sensing element.

The simulated sensor circuit is a sample-data system, with clock frequency of 1 kHz. The input and output of the sensor have been buffered in order to prevent changes in the sensor output due to the changes in the output load, in the process of network testing. Due to the excessively large data set obtained from SPICE, for a 0.85 s simulation, the results are filtered such that, only one sample is selected for every 1 ms interval. Consequently, the neural network training file will contain 850 examples. Thesensor input is presented in Figure 4. Figure 5 shows the highly nonlinear transfer characteristic of the sensor, for white noise input.

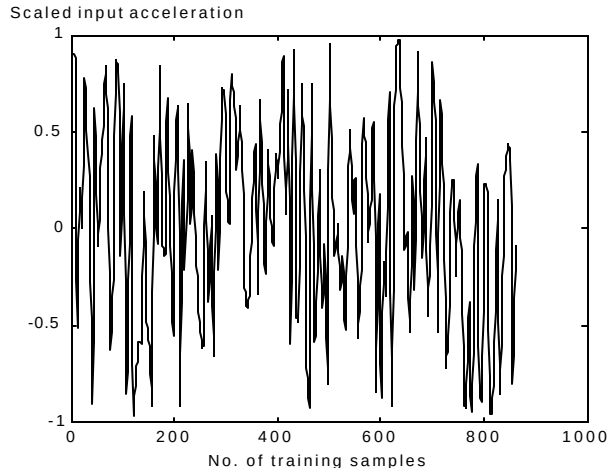


Fig. 4: Sensor input

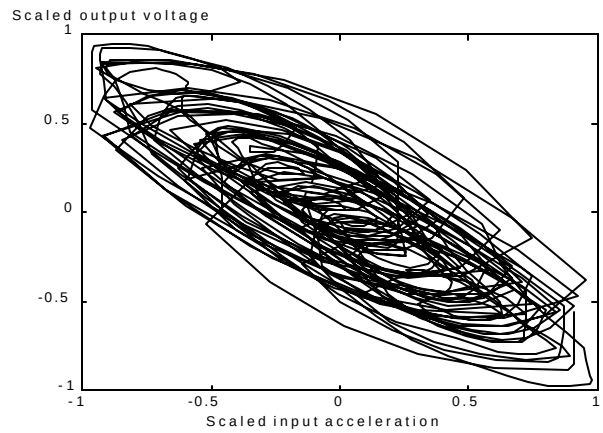


Fig. 5: Transfer characteristic of sensor for white noise

Several network architectures of TDL-MLP/TDL-RBF have been studied. It has been found that, in spite of learning very quickly, the optimal RBF structure was quite large (over 60 neurons). By comparison, the MLP structure was much smaller but took longer to produce the same output error. Thus, SPICE implementations and tests have only been run for the TDL-MLP network.

A TDL-MLP 3-9-5-1 architecture has been trained [4] up to a very small training error of 0.057/850 samples. The network needed about 50000 epochs to reach this error.

## Network performance testing

In order to test the performance of the INN, several test files have been generated, containing sine waves of amplitudes up to $\pm 5|g|$ and frequencies in the range [0.5 - 80 Hz] (this has been identified as the working range of the sensor [5]). The behaviour of the INN was found to be satisfactory over the entire range.

The next step in the identification process involved eliminating the sensor and designing the stand-alone INN (parallel model of the sensor for off-line use). This was achieved by replacing the delayed outputs of the sensor as network inputs with delayed

versions of the network outputs. As expected, the identification error has increased due to an 'avalanche' process of error propagation. However, the results are still acceptable for the range [15 - 80 Hz] and accelerations up to 4g. An example of the sensor-net performance versus stand-alone net performance is shown in Figure 6, for a sine wave input acceleration of 2g and frequency 50Hz. The squared sum error has increased by about 60%, for the stand-alone configuration.

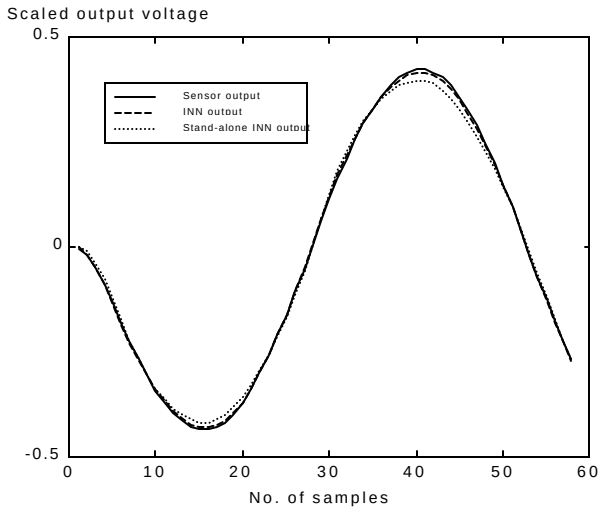


Fig. 6: Sensor output, INN output and stand-alone NN output (Matlab simulation results)

Once satisfactory results have been obtained in Matlab, both sensor-network and stand alone net were implemented in SPICE, and new tests have been run. An example of the worst behaviour of the stand-alone INN is shown in Figure 7. The maximum error for the working range of the accelerometer was 2%, thus the NN identification has a resolution of 0.1g for the whole range. A resolution of 0.05g was achieved for the range [15 - 80 Hz]

## CONCLUSIONS

In the context of nonlinear system identification, the aim of this work was to build a neural network identification model for a micromachined acceleration sensor. Simulation results obtained show good agreement between the behaviour of the sensor over its entire working range and the identified neural network model. However, for high accuracy applications, the training set for the INN must be selected with particular care. As the sensor is highly nonlinear, on-line identification is likely to lead to better results (i.e. the INN will always work in a series-parallel configuration.). The feasibility of the neural network approach to sensor identification based on a mathematical model has been established and the software developed is now fully structured for processing device-based measurements.

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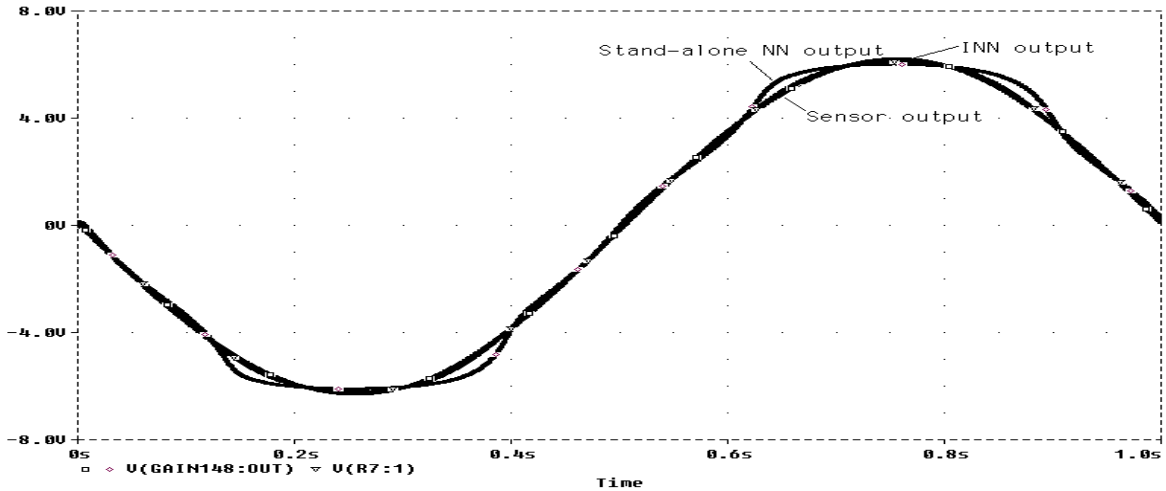


Fig. 7: Output voltages of sensor, INN and stand-alone NN (SPICE simulation results)