High Force Sensing Accuracy in Piezoelectric Based Interactive Displays by Artificial Neural Networks

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Abstract

Over panel stress non-uniformity strongly limits the detection accuracy of piezo based force sensing in interactive displays. In this work, nested artificial neural networks based technique is presented to address the issue of stress non-uniformity. High detection accuracy in terms of touch position and force amplitude is demonstrated by the proposed technique.

Author Keywords

interactive display; piezoelectric touch panel; force sensing; artificial neural networks.

1. Introduction

Force sensing in interactive displays based on thin film piezo has attracted broad interests due to its simple panel structure, high detection sensitivity and low power consumption [1]. However, stress non-uniformity [2], arising from the mechanical behaviour of the touch panel [3], can have adverse effects on sensitivity. In particular, the non-uniformity over the panel can lead to the same force amplitude resulting in different force induced voltage levels when the touch location changes [2], hence degrading the force touch detection accuracy in terms of both touch position and force amplitude.

In previous work [2-3], we reported theoretical analysis and simulation/experimental results of force detection along with the challenge of establishing mathematical models that are able to describe the inner connections between force touch factors and observed data using conventional statistical methods. This was due to the complex mechanical property and boundary conditions of the touch panel [3]. To solve the non-uniformity issue, this work reports supervised neural networks that are applied to learn from training data samples and to extract potential features automatically. A set of nested neural networks is applied to analyze potential connections among touch position, force amplitude, and data displayed as conceptually shown in Fig. 1. The inner layer network is for position estimation. The original sensing data along with the position coordinates estimated from the inner network are concatenated as input to train the outer layer network to classify force amplitude. Simulation results demonstrate that the estimated touch position only shifts 0.56 mm on average from the original touch position, and accuracies of force amplitude are 94.2% when the amplitude of force resolution is 1N.

2. Simulation Results of Force Induced Electrical Signal

To obtain the training data for the nested neural network, a touch panel (conceptually shown in Fig. 2 a) with 3×3 touch pads and 9×9 touch locations eventually distributed among the touch panel is simulated. The area of each touch pad is 5×5 mm2 with 2.5 mm spacing. The contact touch area is a circle with radius 5 mm, mimicking the geometry of a human finger. The touch panel's top view and cross section are described in Fig. 2 b. Mechanical properties such as Young's modulus and boundary conditions are the same as reported in our previous work [3].

After each force touch simulation, 9 voltage values are obtained through the 9 touch pads. These 9 voltage vales are treated as a set of training data for the neural networks. As we have 81 touch positions, and at each touch position 9 force amplitudes (1N to 5N, spacing at 0.5N) are simulated, hence we obtain 729 sets of training data in total (as shown in Fig. 2 d).

3. Neural Networks Process

Artificial neural networks are composed of multiple layers to learn feature representations of data with multiple levels of abstraction [4]. Each layer computes a non-linear transformation of the previous layer, which transforms the data into a more abstract representation. In our experiment, a nested neural network structure is established for both locating touch position and detecting force amplitude given the data displayed on the sensing device. This nested structure mainly contains two 4-layer networks. The inner network is for position estimation. It uses 729 sets of simulation data obtained from 9 as input, and considers a specific touch position set corresponding to each simulation process as desired output for training. The outer network inputs both sensor data displayed on touch panel and position information obtained from the inner network for force amplitude estimation. We simulate 125 sets of data that are different from training data with force amplitude varying from 1N to 5N to test the performance of our networks. The two graphs in Fig. 3 reflect the changing trends of loss and classification accuracy in the training process of the force estimation network. The training process stops at around 250 epochs to prevent over-fitting.

4. Results of Interpreted Touch Position and Force Amplitude

Fig. 4 shows the error distribution of touch position over the simulated touch panel. The overall estimated touch position shifts around 0.56 mm. Five groups of testing samples along with their corresponding estimated positions are presented as well. It can be observed from the figure that testing samples that are close to the position of training samples can be positioned more accurately. Therefore, the increase in number of training samples should have positive influence on touch position locating accuracy.

Simulation results shown in Fig. 5a illustrate that the accuracy of force amplitude classification is 94.2% when the network is trained to classify force amplitudes from 1N to 5N with a 1N resolution into 5 levels. When trying to classify force amplitude with finer resolution (0.5N) using the same network, as shown in Fig. 5b, the accuracy drops to 53.2%, and the neighbouring-3 accuracy is 93.6%. Fig. 5c shows the force correlation map with

0.5N resolution using a neural network trained with simulation data of the same resolution. The accuracy raises to 74.3%, and the neighbouring-3 accuracy also increases to 97.5%.

5. Summary

High force touch detection accuracy in piezoelectric based interactive displays involves both high detection sensitivity and stable force-voltage responsivity. While the former has been reported [1][3], the latter, due to the over panel stress non-uniformity, hasn't been addressed properly.

In this work, stable over panel force-voltage uniformity is obtained by utilizing artificial neural networks. A high force detection resolution (1N) with detection accuracy of 94.2% is achieved. Our results also demonstrate that with the increment of training data, the force detection resolution can be further improved. The presented work has significant implications in terms of advancing user experience in force touch interactivity.

6. Acknowledgement

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7. References

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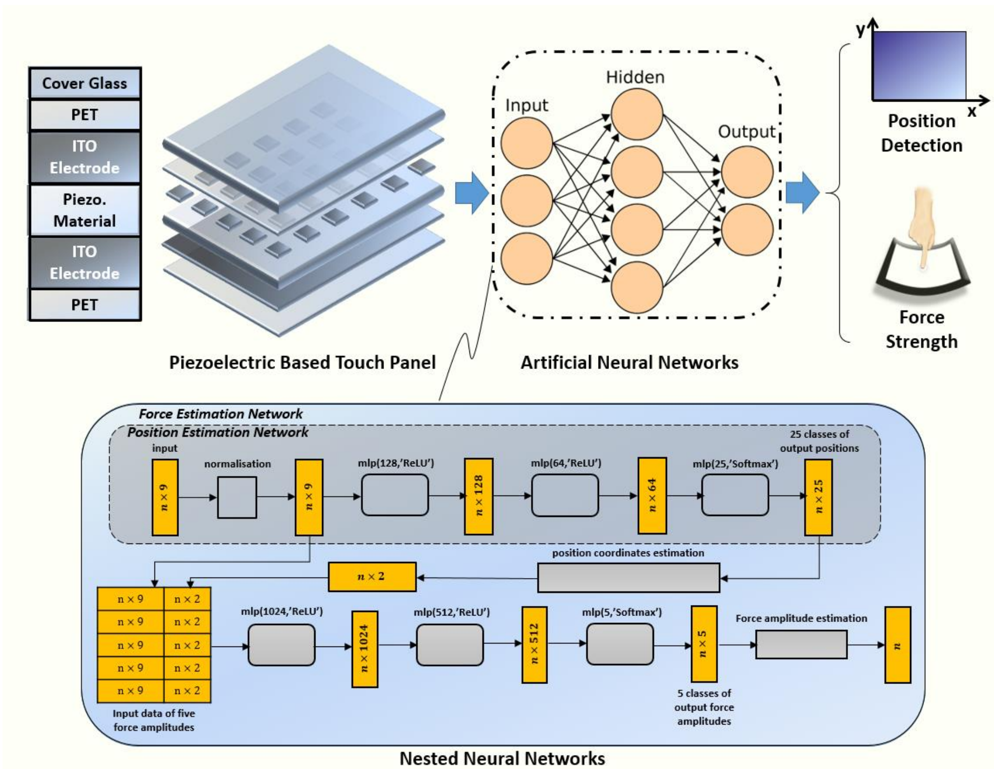


Figure 1. Conceptual description of force touch detection in piezoelectric based interactive displays by Nested Neural Networks. "mpl(x,'Y')" stands for multi-layer perceptron with hidden size x and activation function Y.

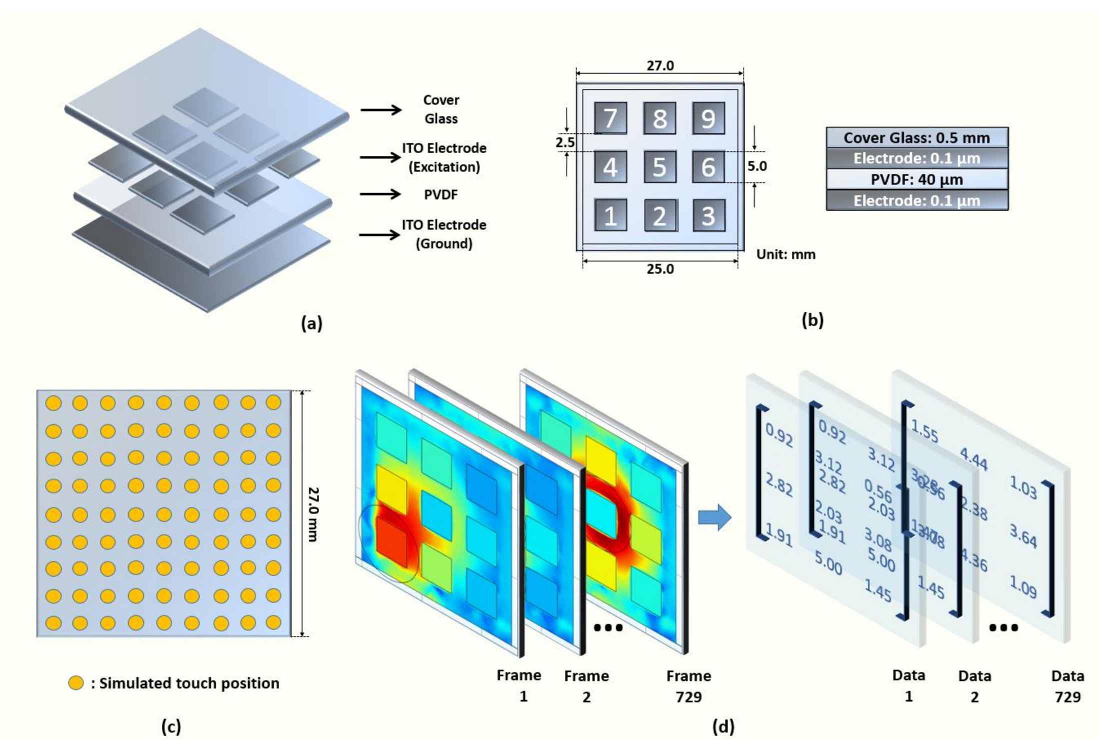
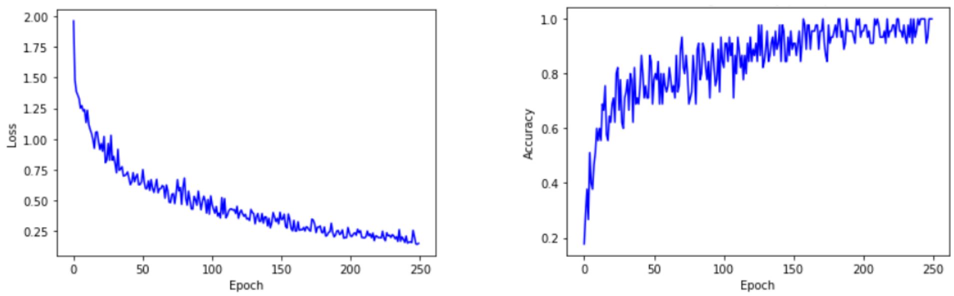


Figure 2. (a) Structure of simulated touch panel with 9 touch pads; (b) top view of the simulated touch panel and geometries (numbers indicate locations of touch pads) and thickness of layers of the touch panel. (c) Simulated touch positions. (d) Force touch-generated training data.



(a) (b)

Figure 3. Force estimation network training process. (a) Training loss per epoch (b) Training accuracy per epoch.

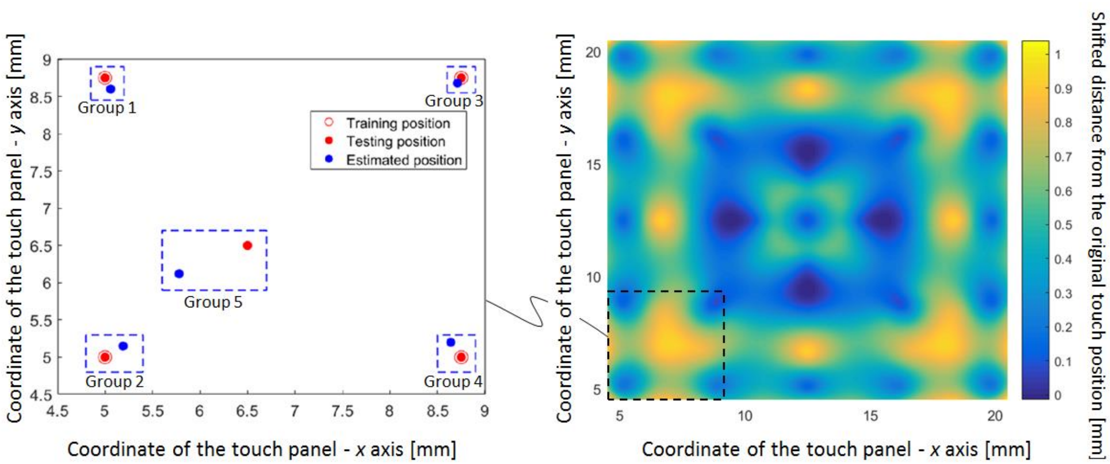
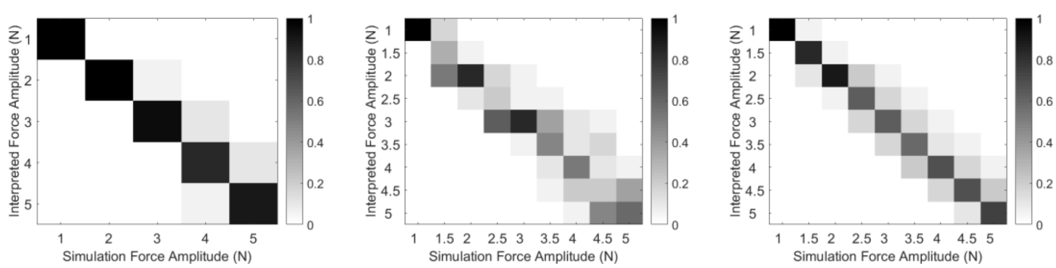


Figure 4. Touch position error distribution map.



(a) (b) (c)

Figure 5. Correlation maps of force amplitude level. (a) Input force classified into five force amplitude levels using neural network trained with 5 force amplitude levels (b) Input force classified into 9 force amplitude levels using neural network trained with 5 force amplitude levels (c) Input force classified into 9 force amplitude levels using neural network trained with 9 force amplitude levels.