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User-Oriented Piezoelectric Force Sensing and Artificial Neural Networks in Interactive Displays

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ABSTRACT Force touch based interactivity has been widely integrated into displays equipped in most of smart electronic systems such as smartphones and tablets. This paper reports on application of artificial neural networks to analyze data generated from piezoelectric based touch panels for providing customized force sensing operation. Based on the experimental results, high force sensing accuracy (93.3%) is achieved when three force levels are used. Two-dimensional sensing, also achieved with the proposed technique, with high detection accuracy (95.2%). The technique presented here not only achieves high accuracy, but also allows users to define the range of force levels through behavioral means thus enhancing interactivity experience.

INDEX TERMS Artificial neural network, customized force sensing, detection accuracy, interactive display.

I. INTRODUCTION

Touchscreens are an essential component for human-machine interactivity in mobile devices, which have become somewhat indispensable nowadays [1], [2]. Traditional touch panels support two-dimensional touch sensing by using capacitive and resistive architectures. Recently, three-dimensional force touch detection has been achieved by using capacitive and piezoelectric means [3], [4]. The former has been successfully commercialized by Apple Inc. since 2015. However, capacitive based force sensing adds additional component cost, circuitry complexity and power consumption and can only provide two force levels without the ability to support multiple force touch events [5]. In contrast, the piezoelectric based force sensing holds advantages of simple panel structure, convenient readout circuitry, passive amplitude detection, and more importantly, at low cost and low power [4]–[6]. The piezoelectric architecture provides higher force sensing sensitivity compared to the capacitive counterpart [5], potentially offering users enhanced user experience. Here, force detection is obtained by collecting force-induced charges generated by the piezoelectric material due to the change of polarization caused under stress [5], [7]. Since the magnitude of the force applied is directly related to the amount of the generated charges, the force magnitude can be quantified by integrating the generated charge [5], [6].

A variety of piezoelectric materials have been reported in [6] and [8]–[12] ranging from inorganic materials such as zinc oxide to organic counterparts with piezoelectric coefficient values in the range 20-40 nC/N [13], achieving state-of-the-art force detection sensitivity of 0.1 N [6].

However, successful use of piezoelectric force sensing in commercial interactive displays has not been reported yet. One reason is that current piezoelectric touch panels try to provide users with a one-size-fit-all solution, by setting up unified force thresholds to classify force levels [4], [14]. However, this brings up two issues. First, the piezoelectric touch panel requires users to adapt their original force touch gestures to the machine's standards, thus degrading user experience. Second, the nature of piezoelectric material does not satisfy the one-size-fit-all solution, because the physical characteristics of the human fingers vary substantially among

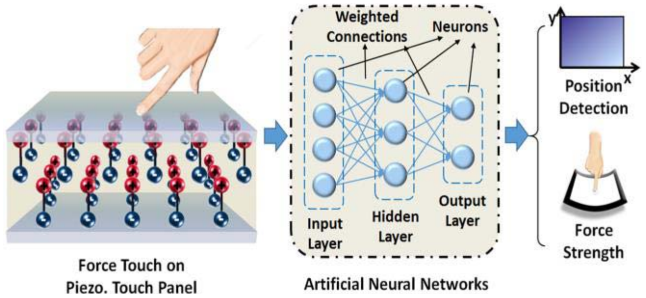


FIGURE 1. Conceptual description of piezoelectric and ANN based technique for force and position sensing.

people, giving rise to unstable force-voltage responsivity of the system [7], [15]. For example, when users with different finger size apply the same force amplitude, the force-induced stress is different. Hence the degree of generated charge is not equal [15]. Therefore, a different force amplitude may be interpreted by the system lowering the detection accuracy.

In this paper, an artificial neural network (ANN) based technique is proposed and implemented to address the issues above so as to provide a customized service to users. Here, a nested structure of supervised neural ANN is used to study the connections between touch panel factors and personal touch behavior to interpret both position and force amplitude. In this way, three-dimensional touch information is retrieved by solely utilizing a piezoelectric based architecture without the need to integrate an additional force sensing arrangement as deployed in [3]. The overall flowchart is conceptually illustrated in Fig. 1.

This paper is organized as follows: Section II studies the personal behavioral patterns in force recognition. Section III explains how machine learning can help a piezoelectric touch panel to provide customized function. Section IV describes the experimental test-bed deploying an ANN-based algorithm. Experimental results and discussion are provided in Section V.

II. PERSONAL BEHAVIOR ON FORCE RECOGNITION

It is difficult, if not impossible, for users without special training to quantify the exact force they apply [16], [17]. To detect touch events' an absolute force magnitude is not meaningful. In contrast, most people can distinguish different force levels (i.e., strong, light, etc.) based on their personal feeling and experience [17]–[19]. The objective of this study is to accurately interpret and distinguish among the different force levels of an individual.

A biophysical experiment has been designed to study the user's force touch behavior for a range of different force levels. In the experiment, ten subjects are required to conduct force touches at different levels (2, 3, 4 and 5), according to their personal definitions. At each force level, 30 touches are performed on a commercial force sensor (PCB, 208C01). According to the experimental results, two observations are noted. First, most people cannot truly control their force level when the number of different levels is more than three. When subjects carry out a five-force-level test (force levels are categorized into: light, light-middle, middle, middle-strong and strong), none of the subjects could stabilize his/her strength to manage the associated force magnitudes within a specific category. To illustrate this, some experimental results are depicted in Fig. 2 (a).

Second, different subjects, according to their personal experience and physical conditions, have various interpretation of each force level, indicating that the same force amplitude can be categorized into different forces by different subjects. This is shown in Fig. 2(b) by comparing experimental data from three subjects.

Based on our experimental results and analysis, we can conclude that the definition of force levels is highly dependent on the individual in question. To provide enhanced user experience, force sensing in a piezoelectric touch panel should not be designed as a one-size-fit-all approach, but more as a human-centered system.

III. ARTIFICIAL NEURAL NETWORKS FOR CUSTOMIZED SMART SYSTEM DESIGN

Artificial Neural Networks (ANNs) are an information processing paradigm that were introduced for simulating the way human brain learns and processes information. The nature of an ANN enables it to learn features by itself and design specific models to adapt to different users according to personalized data provided [20].

The three major learning paradigms of ANNs are supervised learning [21], unsupervised learning [22] and reinforcement learning [23]. Among them, supervised learning uses labelled data to train the network. Parameters (weights and bias) of the network are adjusted constantly until the output yields a desired value. The supervised learning paradigm is mainly used for dealing with classification and regression problems. Related techniques have already been applied in other systems, such as smart home environment [24]–[26], smart security system [27], [28], and smart self-driving system [29], [30]. Our task aims to establish a user-oriented touch panel system, which enables smartphones to adjust touch sensing systems according to the customs of the user. Influenced by the nature of the piezoelectric based material itself, touch panel's mechanical property [5] and the individual difference of the user that is discussed in previous section, it is challenging to establish personalized models to find the potential connections between force touch factors and observed data using conventional statistical methods [15], and to threshold force levels (even for an individual user). But based on the nature of ANNs and the difficulty and complexity of the task mentioned above, supervised ANNs are found suitable to solve the problem proposed.

IV. EXPERIMENTAL SETUP

A sandwich structured force touch panel (as conceptually shown in Fig. 3 (a)) is assembled for our experiment. The width and length of the touch panel are both 27 mm. Here,

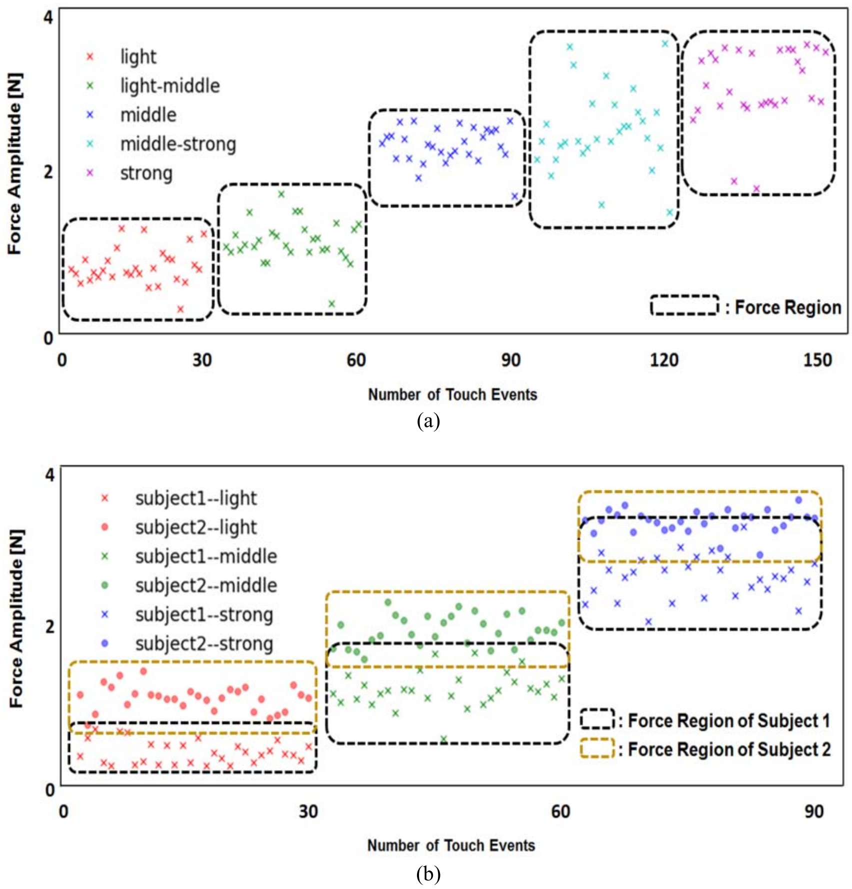


FIGURE 2. **(a) Five force levels extracted from the same subject. (b) Three force levels extracted from two different subjects.**

nine top copper electrodes in square shape are evenly distributed with a spacing distance at 2.5 mm. Details of the touch panel are provided in the Fig. 3 (b).

The force-induced electrical signal is picked up and digitalized by a single-board microcontroller (as shown in Fig. 3 (c)) and then sent to a laptop for further processing.

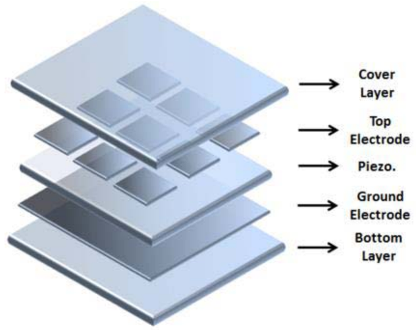
V. DATA PROCESSING AND ALGORITHM DESCRIPTION

The algorithm mainly contains the following two parts, data pre-processing and user behavior classification. The pre-processing process extracts useful information from raw data and feed them to a nested ANN for both position estimation and force level classification.

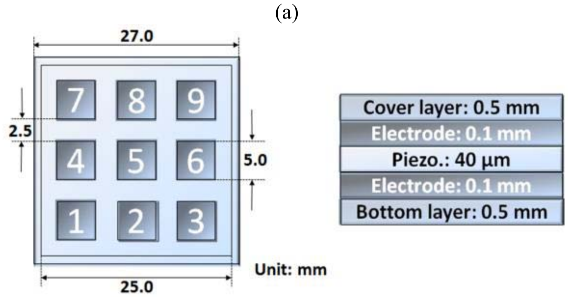
A. PRE-PROCESSING

The data we obtained from the touch panel is a series of continuous signals, distributed in nine channels representing the nine touch sensors respectively (Fig. 4 (a)). First, an initial noise filtering process is carried out to remove the power supply noise (Fig. 4 (b)). More specifically, the noise that is removed in the first place is the initial system noise produced when the single-board microcontroller is electrified. This kind of noise is always presented in pulse form appearing at the very beginning of the signal. We remove it by disregarding the data within one second after electrifying the system. Then, the dominant sensor is determined by finding the channel that has the strongest signal intensity (Fig. 4 (c)). Here, it is worth pointing out that the location of dominant sensor cannot represent the location of the touch event, due to the nun-uniform of the stress propagation and boundary conditions [15]. The peaks of the signal received from the dominant sensor is detected and the highest 10% and the lowest 10% of the data is filtered out to boost the training efficiency (Fig. 4 (d) and (e)). The touch event is assumed to be carried out at the time point of each selected peak on dominant channel. This helps the system to find corresponding information of the eight non-dominant channels (Fig. 4 (f)), which is used to consist a nine-element array along with the information from dominant channel (Fig. 4 (g)). Hence, raw data are converted into a $9\times n$ matrix (n denotes the number of touch events) for further processing.

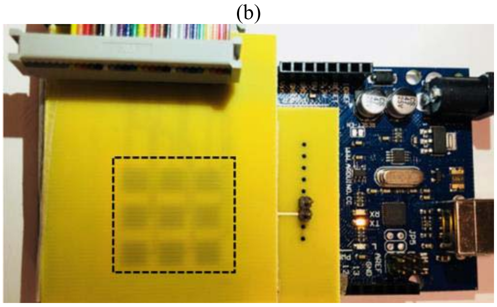
The software we used for pre-processing of data is Python. We installed pySerial, a Python serial port access module that enables us to import real-time force-induced electrical signal (digitalized by microcontroller) to software for analysing and processing. Apart from pre-processing, the nested ANN model described in the following section is



(a)



(b)



(c)

FIGURE 3. (a) Structure of the assembled touch panel. (b) Top view and cross section view of the touch panel. (c) PCB based touch panel prototype, dashed square (27×27 mm2) indicates the touch effective area. The cover layer and bottom layer for an interactive display used touch panel should not be PCB based, for the reason of non-transparency. Here PCB is used for concept validation only.

also established, trained and tested in Python deep learning library named Keras.

B. NESTED NEURAL NETWORKS

A standard ANN is composed of a series of interconnected processing units (neurons) that can compute values from inputs by feeding information through the network. Neurons are organized in layers. Each layer computes a non-linear transformation of the previous layer to transform the data into a more abstract representation and to learn features with multiple levels of abstraction [31].

We expect to study the inner connections between force touch factors and personalized data obtained from the sensing device by estimating the touch position according to data acquired, and then use both position information and touch panel data for force level classification. In this way, the position information can assist in improving classification accuracy of force levels. Therefore, a nested ANN structure is established to suit the experiment's needs.

The nested structure, shown in Fig. 5, mainly contains two five-layer networks. Each network is composed of three multi-layer perceptions for feature extraction and one Softmax classifier for classification. Data collected from touch sensors by pressing the nine positions on touch panel (around 90 times each position, in 3 different force levels) are pre-processed, and then separated into proportions of 80% for training and 20% for validation. Apart from these data, other groups of data are also collected (around 100 data per subject) for various touch positions and force amplitudes to test the performance of our network. The inner network is for position estimation. Input data are classified into nine classes (the nine positions on touch panel) corresponding to their desired output. The outer network inputs both pre-processed sensor data and position information predicted by the inner network for force amplitude estimation. They are expected to be classified into three force levels, light, middle and strong, according to the different degree of user's touch.

VI. RESULTS AND DISCUSSION

The results mainly consist of the following three parts, results from the training process, results of the touch position and force level classification, and a comparison of results with the conventional thresholding method.

A. DATA TRAINING AND VALIDATION

In the training process, Adam, a stochastic gradient-based optimizer [32] is used to optimize the values of weights and bias of the network for the minimization of the loss function [33] (Mean Squared Error function). This optimizer is proved to be computationally efficient and well-suited for problems of large data/parameters [34]. The activation function used in hidden layers is 'ReLU'. The two major benefits for choosing 'ReLU' activation are the reduced likelihood of the gradient to vanish and the much less time consuming comparing to using other activation functions such as sigmoid exponential [35]. The two graphs in Fig. 6 (a) and (b) reflect the changing trends of loss and classification accuracy for both training and validation data in the training process of the position estimation network. The criteria for terminating the training is whether the loss reaches a preset threshold value (0.3) or if the number of validation checks reaches 10 (indicating that the performance on the validation set is becoming worse on 10 successive epochs although the performance on the training set is getting better). The training process stops at around 500 epochs where loss is below threshold value. It takes about 5 minutes for the ANN to converge while using 2.80 GHz Intel Core i7-7700HQ CPU.

B. RESULTS ON POSITION AND FORCE AMPLITUDE INTERPRETATION

Since the nested ANN is well-trained, test data are put to the network for touch behavior classification. Experimental

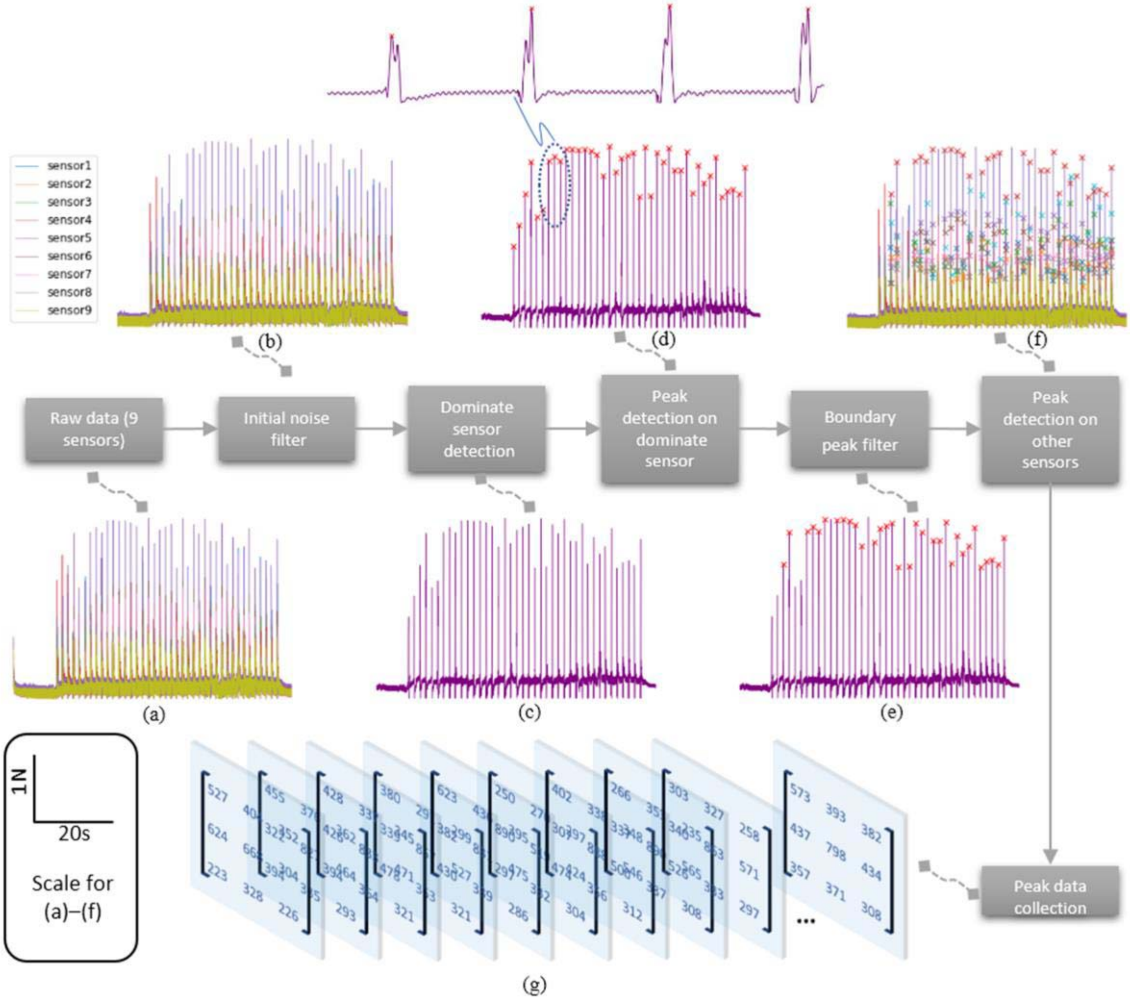


FIGURE 4. Flowchart of data pre-processing. In (d), the peaks of the signal waveform are detected using continuous wavelet transform which performs a convolution with data along a predefined width using the wavelet function.

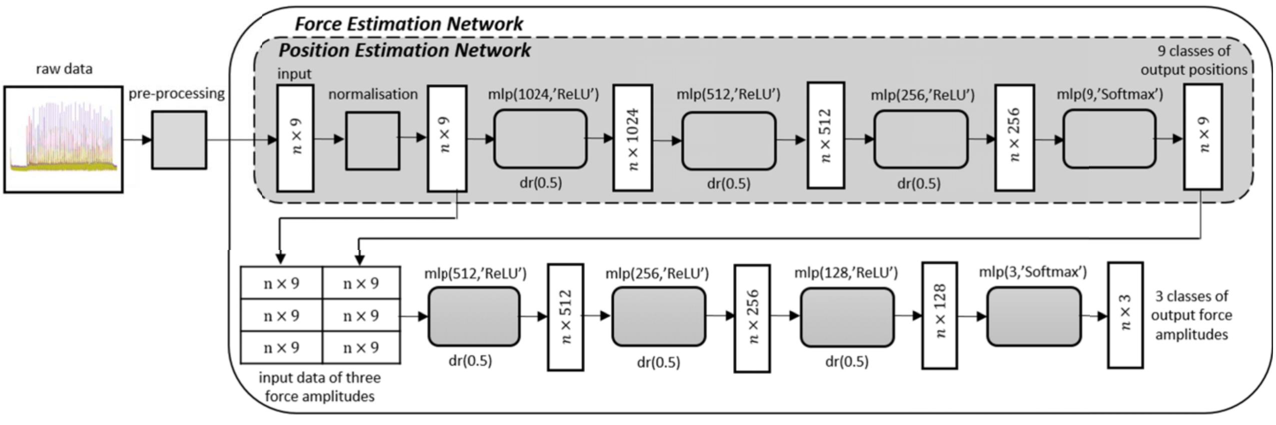


FIGURE 5. Flowchart of data processing in piezoelectric based interactive displays by Nested ANNs. Here, "mpl(X,'Y')" stands for multi-layer perceptron with hidden size X and activation function Y and "dr(0.5)" refers to that the dropout rate of the layer which is 50%.

results illustrate that the test accuracy among 10 experimenters of touch position classification is between 90.1% and 97.8%, with an overall accuracy of 95.2% (as is shown in Fig. 7 (a)). It is noticed that all the errors are generated in the immediate neighborhood of the target location (see Fig. 3 (b) for detailed position numbering). It can be

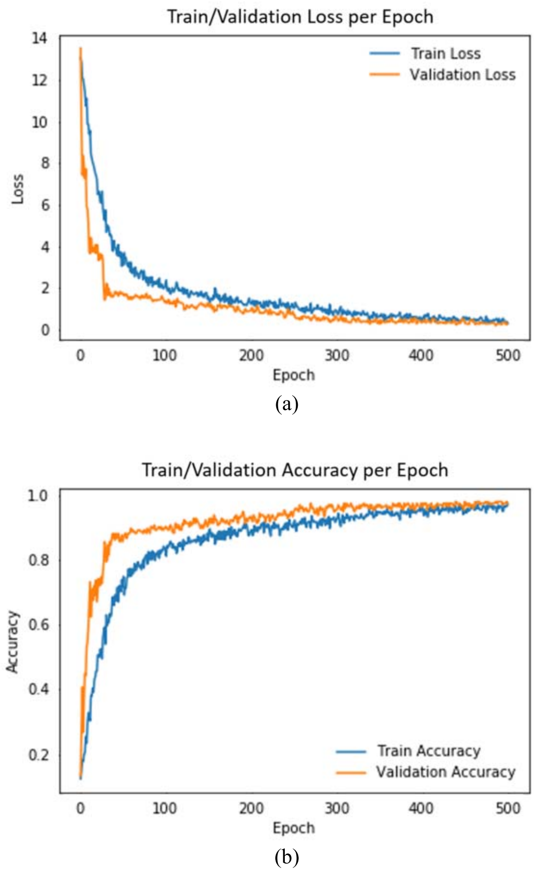


FIGURE 6. **Touch position classification network training process.**

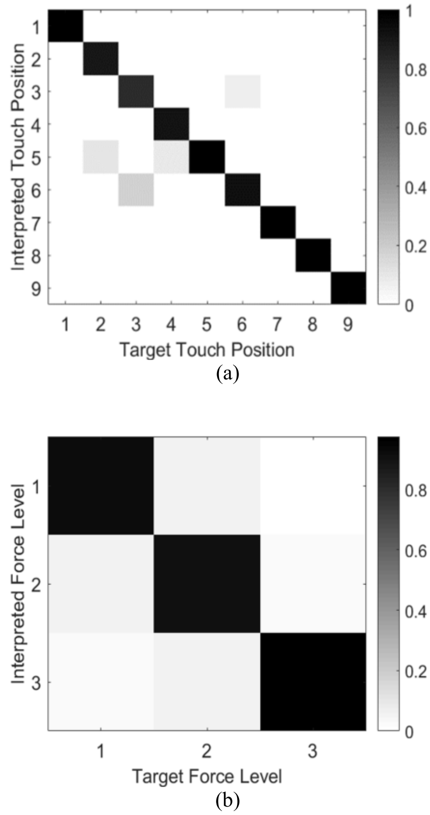


FIGURE 7. **Correlation maps of touch position and force amplitude level.**

presumed that these errors occur due to human error of non-ideal control over touch position (the real touch position is slightly shifted compared to the intended test position). Fig. 7 (b) shows the correlation map of force level classification on test dataset. An overall classification accuracy of 93.3% is achieved when force amplitudes are classified into three levels. It can be observed from the figure that the main error exists between the two adjacent force levels, which is mainly result from the inconsistency of subjects' strength.

C. COMPARISON WITH CONVENTIONAL THRESHOLDING METHOD

As explained in Section II, different subjects have different understanding to the grade of strength. To further demonstrate this, Fig. 8 shows the data obtained from the dominant channel of three experimenters applying three different grades of force on the touch panel. It can be observed from the figure that the same force amplitude may be categorized into different force levels by different experimenters. The two horizontal dotted lines in orange are the dividing lines of the strength grade specifically optimized for these three subjects (using least squares regression), which gives the highest possible overall classification accuracy of 82.7%. For the 10 subjects that participated in our experiment, the highest possible classification accuracy using the thresholding method mentioned above drops to 65.8%. This result is much lower than the classification accuracy of 93.3% that we achieved while using customized ANN, showing that the one-size-fit-all method is not generally applicable in solving user-oriented touch interactive problems.

Furthermore, due to the mechanical property and boundary conditions of the touch panel, the force-voltage responsivity among the touch panel is non-uniform, which may result in considerable difference for the same force-induced amplitude voltage level when touch position shifts [7]. To compensate for this, conventional thresholding method needs to record user-performed force touches of different levels for all locations (or as many as possible) of the touch panel to maintain an acceptable detection accuracy, putting burdens on both user and system's sides. The technique reported in this paper is able to generate a reliable network to accurately recognize customer's touch panel patterns by using limited input from the user. In view of saving material resources and manpower costs, the proposed method provides a feasible and promising application that can be widely used by the touch panel industry.

D. ALGORITHM ENERGY BUDGET

Based on the neural network architecture shown in Fig. 5 with specified number of hidden layers and neurons,

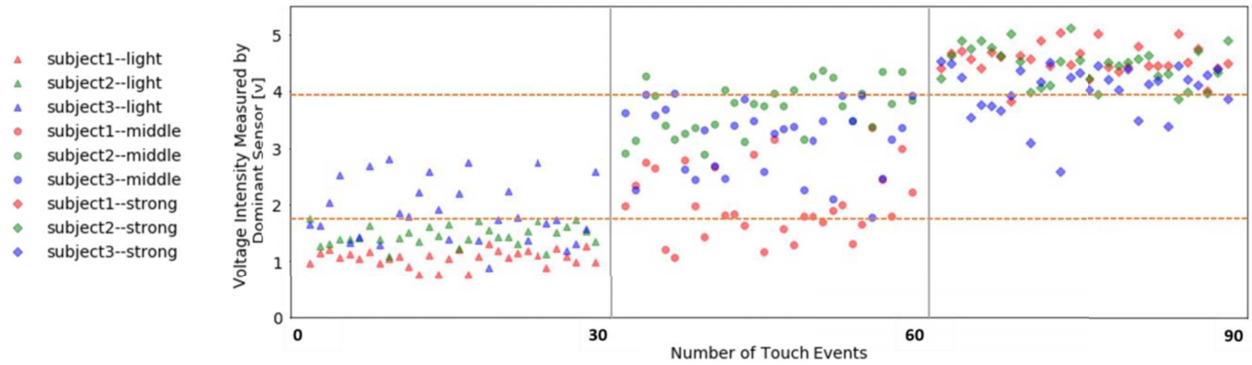


FIGURE 8. Conventional thresholding method for force level classification among three different subjects.

around 8×10^5 multiply-accumulate (MAC) operations are estimated to be taken on feedforward propagation for the processor to execute. The MAC operations account for over 99% of total operations in our network, therefore, dominating power consumption and processing time. Current machine learning processors for mobile devices have a power efficiency of 3TOPS/W [36], hence the power consumption for the technique developed in this paper is roughly 26.7nW.

The work in this article focuses on addressing the dynamic force touch events. The recognition of static force touch can be achieved by adopting the technique proposed in our previous work [6].

VII. CONCLUSION

The current one-size-fit-all solution provided by piezoelectric based touch panels is not broadly accepted by users, due to the unreliable force-voltage responsivity and highly individual-dependent touch behavior. To address these two issues, an ANN is employed to process the force touch signals. Experimental results show that good force detection accuracy of 93.3% is achieved, demonstrating that the customized service and stable force-voltage responsivity are both successfully obtained, enhancing the user's force interactivity experience.

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REFERENCES

[1] G. Walker, "A review of technologies for sensing contact location on the surface of a display," *J. Soc. Inf. Display*, vol. 20, no. 8, pp. 413–440, 2012.
[2] A. Nathan and S. Gao, "Interactive displays: The next omnipresent technology [point of view]," *Proc. IEEE*, vol. 104, no. 8, pp. 1503–1507, 2016.
[3] O. Raymudo, *IPhone 6S Display Teardown Reveals How 3D Touch Sensors Actually Work*, Macworld, San Francisco, CA, USA, Oct. 13, 2015.
[4] *CTT Shows Smartphone Demo at CES*, Cambridge Touch Technol. Inc., Cambridge, U.K., [Online]. Available: http://www.camtouch3d.com/news/2017/10/31/test
[5] S. Gao, V. Arcos, and A. Nathan, "Piezoelectric vs. capacitive based force sensing in capacitive touch panels," *IEEE Access*, vol. 4, pp. 3769–3774, 2016.
[6] S. Gao, X. Wu, H. Ma, J. Robertson, and A. Nathan, "Ultrathin multifunctional graphene-PVDF layers for multidimensional touch interactivity for flexible displays," *ACS Appl. Mater. Interfaces*, vol. 9, no. 22, pp. 18410–18416, 2017.
[7] S. Gao and A. Nathan, "P-209: Augmenting capacitive touch with piezoelectric force sensing," *SID Symp. Dig. Tech. Papers*, vol. 48, no. 1, pp. 2068–2071, 2017.
[8] T. Vuorinen *et al.*, "Printable, transparent, and flexible touch panels working in sunlight and moist environments," *Adv. Funct. Mater.*, vol. 24, no. 40, pp. 6340–6347, 2015.
[9] W. Park *et al.*, "Characteristics of a pressure sensitive touch sensor using a piezoelectric PVDF-TrFE/MoS_2 stack," *Nanotechnology*, vol. 24, no. 47, 2013, Art. no. 475501.
[10] J. H. Yang, H. J. Hwang, S. C. Kang, and B. H. Lee, "Sensitivity improvement of graphene/Al_2O_3/PVDF-TrFE stacked touch device through Al seed assisted dielectric scaling," *Microelectron. Eng.*, vol. 147, pp. 79–84, Nov. 2015.
[11] Z. Pi, J. Zhang, C. Wen, Z.-B. Zhang, and D. Wu, "Flexible piezoelectric nanogenerator made of poly(vinylidenefluoride-co-trifluoroethylene) (PVDF-TrFE) thin film," *Nano Energy*, vol. 7, no. 3, pp. 33–41, 2014.
[12] S.-H. Bae *et al.*, "Graphene-P (VDF-TrFE) multilayer film for flexible applications," *ACS Nano*, vol. 7, no. 4, pp. 3130–3138, 2013.
[13] L. Maiolo *et al.*, "A comparison among low temperature piezoelectric flexible sensors based on polysilicon TFTs for advanced tactile sensing on plastic," *J. Display Technol.*, vol. 12, no. 3, pp. 209–213, Mar. 2016.
[14] K. Reynolds, S. Petr, and G. Arnulf, "Invited paper: Touch and display integration with force," *SID Symp. Dig. Tech. Papers*, vol. 47, no. 1, pp. 617–620, 2016.
[15] S. Gao and L. Wu, "Why piezoelectric based force sensing is not successful in interactive displays?" *IEEE Consum. Electron. Mag.*, to be published.
[16] C. Patten and G. Kamen, "Adaptations in motor unit discharge activity with force control training in young and older human adults," *Eur. J. Appl. Physiol.*, vol. 83, nos. 2–3, pp. 128–143, 2000.
[17] L. A. Jones, "Perception and control of finger forces," in *Proc. ASME Dyn. Syst. Control Div.*, vol. 5, 1998, pp. 133–137.
[18] L. A. Jones, "The control and perception of finger forces," in *The Human Hand As an Inspiration for Robot Hand Development*. Cham, Switzerland: Springer Int., 2014.
[19] W. H. Park and C. T. Leonard, "The effect of intervening forces on finger force perception," *Neurosci. Lett.*, vol. 438, no. 3, pp. 286–289, 2008.
[20] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[21] S. B. Kotsiantis, "Supervised machine learning: A review of classification techniques," *Emerg. Artif. Intell. Appl. Comput. Eng.*, vol. 160, pp. 3–24, Jun. 2007.
[22] H. B. Barlow, "Unsupervised learning," *Neural Comput.*, vol. 1, no. 3, pp. 295–311, 1989.

[23] J. Kober, J. A. Bagnell, and J. Peters, "Reinforcement learning in robotics: A survey," *Int. J. Robot. Res.*, vol. 32, no. 11, pp. 1238–1274, 2013.

[24] P. N. Dawadi, D. J. Cook, and M. S. Edgecombe, "Automated cognitive health assessment from smart home-based behavior data," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 4, pp. 1188–1194, Jul. 2015.

[25] M. H. Kabir, M. R. Hoque, H. Seo, and S. H. Yang, "Machine learning based adaptive context-aware system for smart home environment," *Int. J. Smart Home*, vol. 9, no. 11, pp. 55–62, 2015.

[26] J. Wan, M. J. O'Grady, and G. M. P. O'Hare, "Dynamic sensor event segmentation for real-time activity recognition in a smart home context," *Pers. Ubiquitous Comput.*, vol. 19, no. 2, pp. 287–301, 2015.

[27] A. Ritter, E. Wright, W. Casey, and T. Mitchell, "Weakly supervised extraction of computer security events from Twitter," in *Proc. 24th Int. Conf. World Wide Web*, 2015, pp. 896–905.

[28] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1153–1176, 2nd Quart., 2016.

[29] L. M. A. Alheeti and K. McDonald-Maier, "Hybrid intrusion detection in connected self-driving vehicles," in *Proc. 22nd Int. Conf. Autom. Comput. (ICAC)*, 2016, pp. 456–461.

[30] Y. Pan *et al.*, "Agile off-road autonomous driving using end-to-end deep imitation learning," *Robotics*, 2017.

[31] Y. Bengio, "Learning deep architectures for AI," *Found. Trends Mach. Learn.*, vol. 2, no. 1, pp. 1–127, 2009.

[32] V. K. Ojha, A. Abraham, and V. Snasel, "Metaheuristic design of feedforward neural networks: A review of two decades of research," *Eng. Appl. Artif. Intell.*, vol. 60, pp. 97–116, Apr. 2017.

[33] G. M. James, "Variance and bias for general loss functions," *Mach. Learn.*, vol. 51, no. 2, pp. 115–135, 2003.

[34] D. Kinga and J. B. Adam, "Adam: A method for stochastic optimization," in *Proc. Int. Conf. Learn. Represent.*, 2015.

[35] A. L. Maas, A. Y. Hannun, and A. Y. Ng, "Rectifier nonlinearities improve neural network acoustic models," in *Proc. Int. Conf. Mach. Learn.*, 2013, pp. 3–8.

[36] (Jun. 2018). *Arm ML Processor*. [Online]. Available: https://developer.arm.com/products/processors/machine-learning/arm-ml-processor

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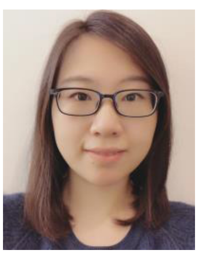

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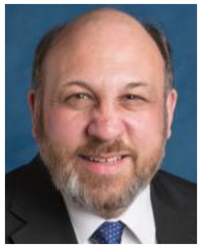

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