# Piezoelectric and Machine Learning-Based Technique for Classifying Force Levels and Locations of Multiple Force Touch Events

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***Abstract*—Current commercial force touch panels can merely detect a single force touch's location and amplitude. However, in many applications, multiple force touch events can occur at the same time among different locations of the touch panel. To satisfy this need, in this article, a piezoelectric and machine learning-based technique is proposed. Here, the piezoelectric film-based touch panel is used to detect different force levels, while the machine learning algorithm is developed to interpret the locations and strengths of user applied multiple force touch events. High detection accuracy of 92.3% for location determination and 88.2% for force level recognition is achieved.**

***Keywords—Piezoelectric-based touch panel, multiple touch events, force sensing, machine learning***

## I. INTRODUCTION

Force touch panels are welcomed in commercial interactive electronic products, e.g. interactive display, due to their ability to provide high human-machine interactive efficiency. Current products, such as iPhone X, Huawei Mate S and ZET AXON Mini, can support single force touch event detection and classify the force amplitudes into 2 or 3 discrete levels. Nevertheless, in many application scenarios, multiple force touch events are required to be detected simultaneously with a high force resolution. For example, in a playing piano application, multiple keys may be stroked at the same time, and the sound amplitude is expected to have good resolution. Nevertheless, no solution is found in the literature now.

To satisfy this urgent need, in this paper, the piezoelectric touch panel developed in [1] is used for detecting force touch events. The choice of employing the piezoelectric touch panel is due to its high force detection sensitivity compared to piezoresistive and capacitive based architectures [2,4,5]. However, products using piezoelectric materials have faulty detection accuracy because of the unstable force voltage responsivity and unavoidable interference (propagated stress resulting from adjacent force touches) [3]. The issues above will become more complicated when two force-touch events occur simultaneously. To sum up, it is difficult to establish a physical model and apply formulas to solve the problems. In this article, three typical machine learning algorithms are used to interpret the touch locations and force levels.

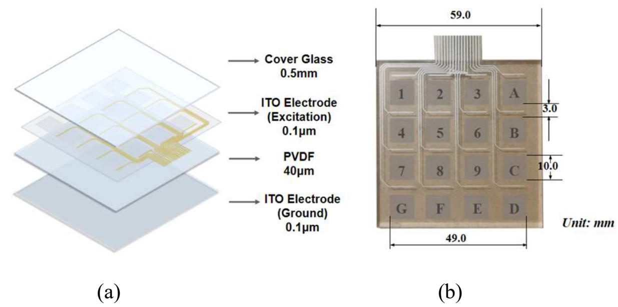


Fig. 1. (a) Structure of the touch panel. (b) Geometry of the piezoelectric touch panels.

## II. METHODOLOGY

### A. Hardware Description

In this paper, the piezoelectric touch panel developed in our previous work [1] is utilized. The structure, photograph and geometry are given in Fig. 1. The system experimentally showed an average force detection sensitivity of 0.028 N and an average responsivity of 0.412 V/N.

The whole data acquisition and processing procedure are shown in Fig. 2 (a). When fingers touch the piezoelectric panel, the charge generated by the PVDF membrane is amplified by the charge amplifier and becomes a voltage signal. Then the signal is sent to the MCU (STM32) after a 16-bit ADC. Finally, the digital signal is transmitted to a PC to do data pre-processing and classification.

### B. Experimental Protocol

As explained in [6]-[8], most people can easily distinguish three force levels (light, middle, strong). Therefore, we design the experimental protocol as follow. First, we perform the fundamental single-touch force detection by the piezoelectric panel. In the experiment, three volunteers were invited to touch the 16 locations, labelled from 1 to D as shown in Fig. 1 b, of the panel at three different force levels according to their personal feeling and experience.

Second, they were asked to carry out multiple touch events by using two fingers simultaneously. We found that it is hard

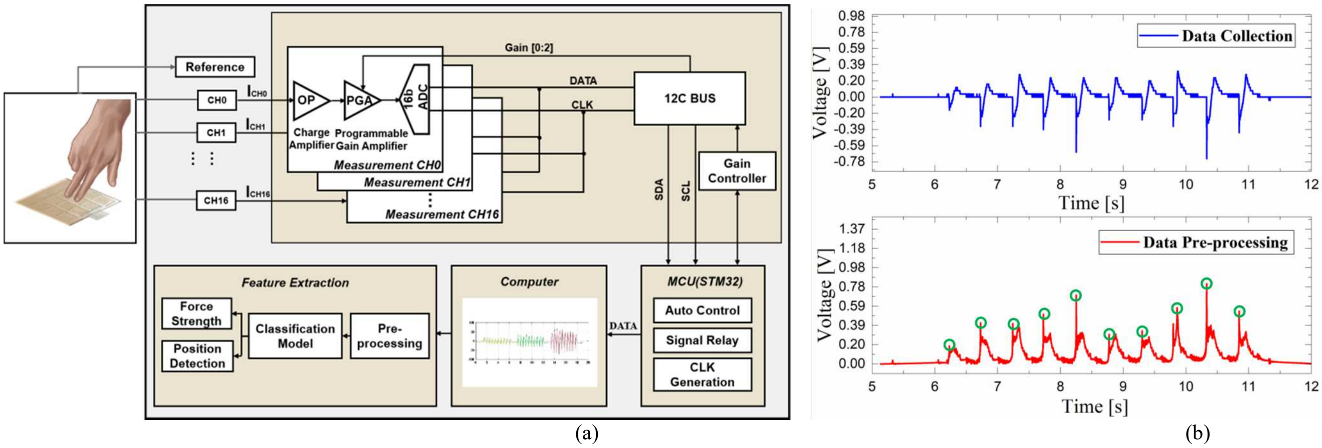


Fig. 2. (a) Block diagram of touch signal reading and data processing. (b) Raw signal and processed signal.

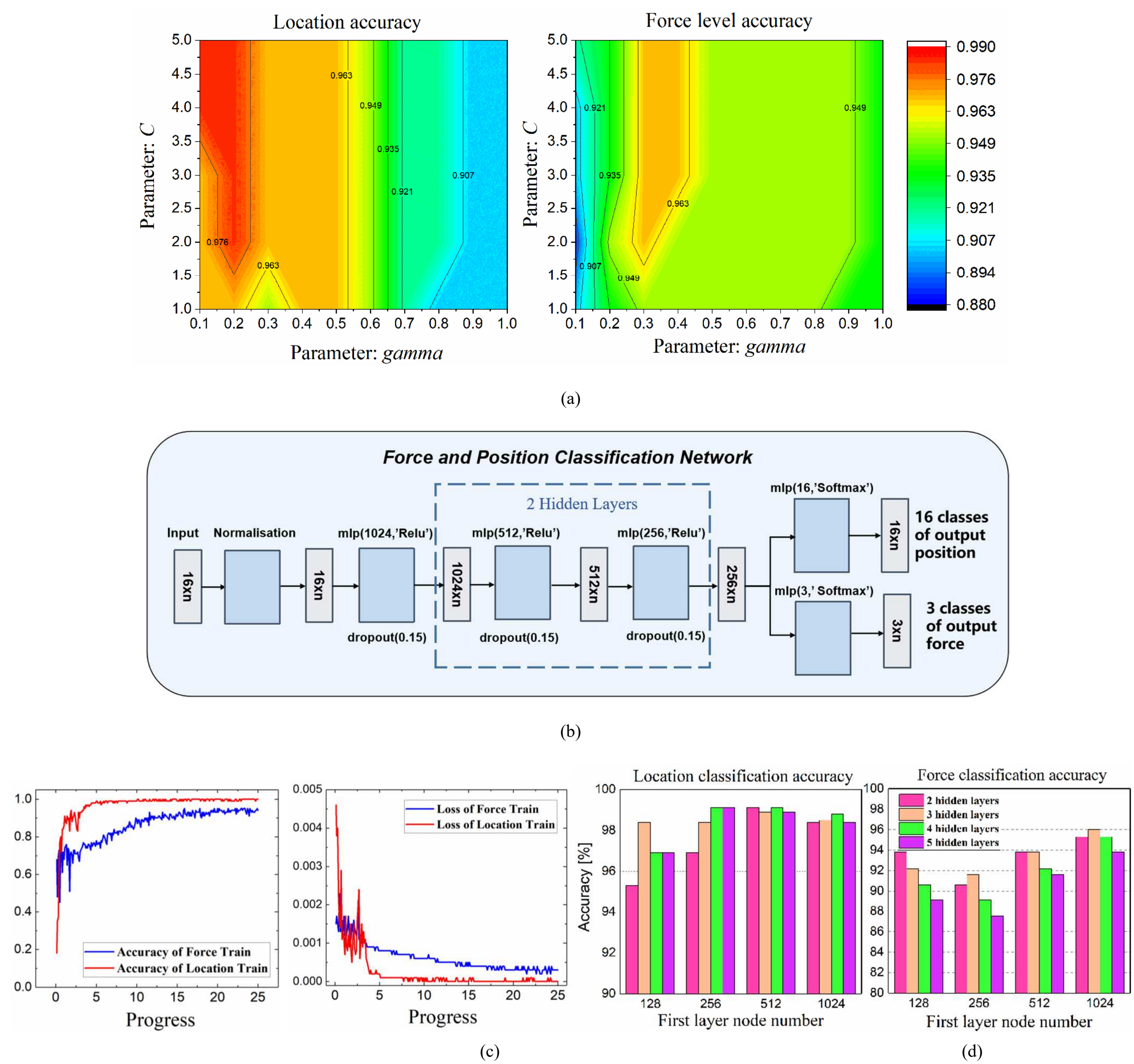


Fig. 3 (a) Classification accuracy of SVM using different parameters: *gamma* and *C*. (b) The nested structure of the neural networks (c) Training history for location detection and force level detection of ANN.(d) Classification accuracy of ANNs using different layer numbers and node numbers.

precisely control the strengths of two fingers at the same time. Hence, we consider three cases: light-light, middle-middle, strong-strong.

### C. Data Pre-processing

The pre-processing of data is conducted in MATLAB, and the specific steps are as follows. First, the DC offset is removed by subtracting the mean voltage of each channel. Second, envelope detection is conducted by the Hilbert Transform method. Third, a trap filter is designed to eliminate power frequency interference of 50Hz. Finally, the MATLAB function – findpeaks() was used to detect the peaks. The peaks of the sixteen channels may not appear at the same time. However, it is feasible to choose the time corresponding to the channel with the largest value as the reference time. Then we assume the peaks of different channels were extracted based on the reference time. As shown in Fig. 2 (b), we selected some data to show the pre-processing process.

### D. Algorithm Description

After the voltage peaks of each channel have been acquired, three typical machine learning algorithms are employed to classify locations and force levels: Light Gradient Boosting Machine (LightGBM) [9], Support vector machine (SVM) [1], and Artificial neural network (ANN) [10]. The three machine learning methods are selected due to their superior performance in classification of complex signals.

## III. Results and Discussion

The datasets were all split into 8:1:1 for training, validation, and testing. Three types of classifiers are constructed by Sklearn. LightGBM uses a leaf-wise strategy to grow trees. When training the SVM model, we choose Radial Basis Function Kernel (RBF) as the kernel function. The parameters of ANN are based on [10]. All of the graphs in Fig. 3 use dataset2 of single-touch. Fig.3 (a) shows the classification accuracy when adjusting SVM parameters. Fig.3 (b) shows the structure of the ANN. The two graphs in Fig. 3 (c) correspond to the accuracy and the loss of the training progress. And Fig. 3 (d) shows the accuracy of location detection and force level classification by changing the layers and node number.

Table I and Table II, respectively, show the single-touch and double-touch test samples' performance on each model. Comparing these three classifiers, we find that ANN performs better than its counterparts in both double-touch and single-touch detection. The detection accuracy of the single-touch force level and location is 99.1% and 98%. Double-touch force level detection accuracy reaches 88.2%; location detection accuracy reaches 92.3%. Our experimental results give the following facts. First, when the same classifier is extended from single-touch to multi-touch detection, the detection accuracy will decrease slightly. Second, the best algorithm for different users is distinct. Third, double force touches with three different force levels can be successfully obtained by the presented research.

TABLE I. Single-touch Accuracy for Different Datasets and Classifiers

| **Results of Different Datasets and Classifiers** | | | |
|---|---|---|---|
| ***Dataset*** | ***Classifier*** | ***Location detection accuracy*** | ***Force level detection accuracy*** |
| 1 | Lightgbm | 95.2% | 91.9% |
| | SVM | 96.8% | **96.8%** |
| | ANN | **98.4%** | 95.2% |
| 2 | LightGBM | **89.3%** | 85.7% |
| | SVM | 85.7% | **92.9%** |
| | ANN | **98.4%** | **95.3%** |
| 3 | LightGBM | 94% | 96% |
| | SVM | 92% | **98%** |
| | ANN | **99.1%** | **98%** |

TABLE II. Double-touch Accuracy for Different Datasets and Classifiers

| **Results of Different Datasets and Classifiers** | | | |
|---|---|---|---|
| ***Dataset*** | ***Classifier*** | ***Location detection accuracy*** | ***Force level detection accuracy*** |
| 1 | LightGBM | 82% | **86.0%** |
| | SVM | 75% | 58.0% |
| | ANN | **91%** | 76.0% |
| 2 | LightGBM | 84.4% | **78.1%** |
| | SVM | 84% | 78.0% |
| | ANN | **92.3%** | 76.9% |
| 3 | LightGBM | 74.5% | 82.4% |
| | SVM | **90.2%** | 84.3% |
| | ANN | **90.2%** | **88.2%** |

## IV. Conclusion

Multi-touch events' force levels and locations are successfully obtained in this paper by using a piezoelectric touch panel and machine learning algorithms. The work presented here showcases the ability to obtain force levels of multiple touches for the first time. The developed technique potentially enables more advanced and novel applications for users.

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