A Force–Voltage Responsivity Stabilization Method for Piezoelectric Touch Panels in the Internet of Things

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Abstract

Piezoelectric force touch panels are extensively utilized as human-machine interfaces for 3-dimensional touch sensing in internet of things (IoT) applications. However, the unstable force voltage responsivity issue induced by different touch orientations limits the successful use of piezoelectric touch panels. In this article, a piezoelectric touch panel, which is sensitive to both capacitive and force stimulation, is assembled; and a touch orientation classification technique is developed to calibrate the detected force amplitude by training a machine learning model with finger induced capacitive information. Finally, a high stable force voltage responsivity of 87.5% is achieved experimentally.

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***Abstract*—Piezoelectric force touch panels are attractive as human-machine interfaces and 3-dimensional touch sensing in internet of things (IoT) applications. The piezoelectric material has the intrinsic ability to convert mechanical to electrical signals. But the force responsivity issue induced by different touch orientations can be unstable. This paper presents a piezoelectric touch panel that is sensitive to both capacitive and force stimulation. A touch orientation classification technique is developed to calibrate the detected force amplitude by training a machine learning model with finger induced capacitive information. A high and stable force voltage responsivity of 87.5% is achieved experimentally, demonstrating its potential significance in force touch based human-machine interactivity.**

Keywords—Piezoelectric touch panel; touch orientation; force–voltage responsivity; internet of things.

I. Introduction

With the fast development of electronic and information technologies, the internet of things (IoT) is entering into our daily lives [1-2]. In an IoT architecture, the human machine interface (HMI) is a fundamental element. Among various HMI techniques that have been developed, the force touch based three-dimensional interactivity has gained interest, in view of high force detection sensitivity, passive mechanical-to-electrical conversion ability and simple readout circuitry [3-6]. However, the successful use of force touch in commercial products has rarely been reported. One of the main reasons is the inconsistent force-voltage responsivity induced by the user's distinct touch orientations [5]. When a user applies a force touch on the touch panel's surface, only the perpendicular component is detected by the piezoelectric d_{33} coefficient. This same force can give rise to different amplitude response for different touch orientations.

To address this issue, a piezoelectric material-based touch panel capable of detecting both the force and capacitive signal by utilizing the piezoelectric and dielectric properties of the piezoelectric layer was reported [7]. Touch orientation was estimated by using finger induced capacitance distribution. When the finger contacts the touch panel with different orientations, the capacitance value at each electrode changes, thereby modifying the whole capacitance matrix. The relationship between the capacitance matrix and touch orientation was modeled, and an averaged orientation detection accuracy of 85% was experimentally obtained. Although the stability of force voltage responsivity was boosted, it is still expected to be higher where precise force interpretations are required, such as in piano-type apps.

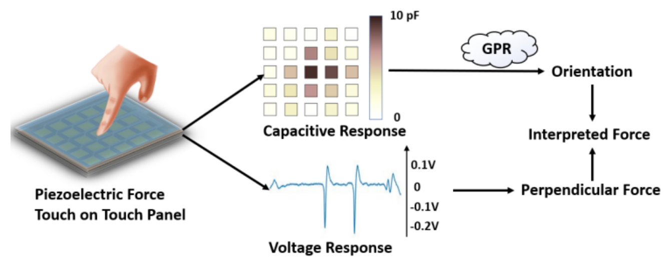


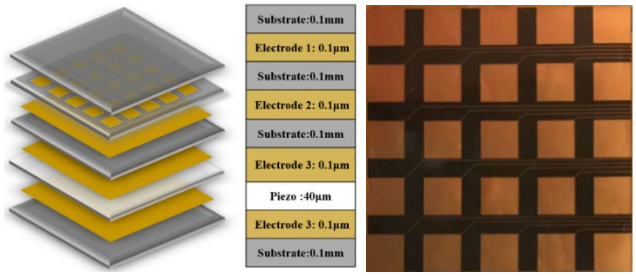
Fig. 1. Conceptual depiction of force–voltage responsivity stabilization technique for piezoelectric touch panels.

To improve the detection accuracy of the touch orientation, this article presents a gaussian process regression (GPR)-based technique, in which touch-generated capacitive patterns are used to train the GPR to predict touch orientations, increasing the average stability of the force–voltage responsivity is by 2.5%. A conceptual description of the proposed technique is described in Fig. 1.

II. Methodology

A. Touch Panel Fabrication

In order to detect finger induced capacitance information, a multi-layered piezoelectric touch panel is constructed as follows: Polyethylene terephthalate (PET) / Cu / PET / Cu / PET / Cu / Polyvinylidene fluoride (PVDF) / Cu / PET. A conceptual description and corresponding photograph of the touch panel are given in Fig.2. Electrode 1 is used for self-capacitive sensing. Electrode 2 is used to shield the crosstalk between the capacitive and force sensing layers. Electrode 3 is the force sensing layers. The parameters of the experimental testbed are listed in Table I.



(a) (b)

Fig. 2. (a) Structure of the touch panel. (b)Prototype of the touch panels.

TABLE I. PARAMETERS OF EXPERIMENTAL TESTBED

Parameters of Experimental Testbed	
Diagonal	2.23 in
Sensing Array Size	40×40 mm^2
Substrate Array Size	40×40 mm^2
Electrode 1 Size	5×5 mm^2
Electrode 1 Array Spacing	3 mm
Electrode 2 Size	34×34 mm^2
Electrode 3 Size	34×34 mm^2

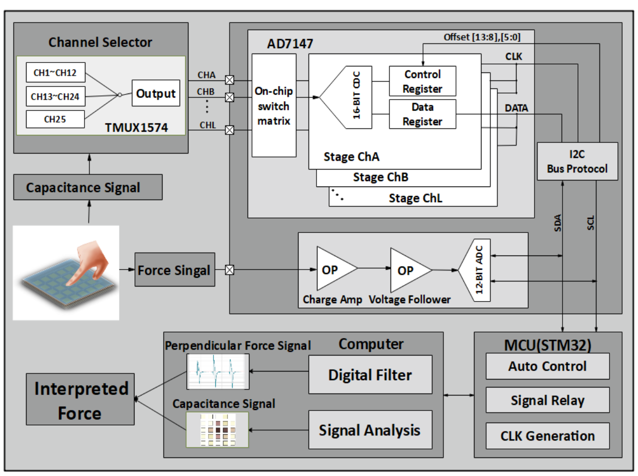


Fig. 3. Diagram of the readout circuitry for obtaining capacitive and force information.

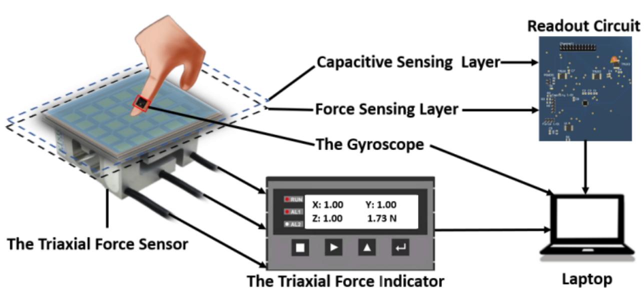


Fig. 4. The arrangement of the experiment devices.

B. Readout Circuitry

The capacitance readout circuit is based on the capacitance-to-digital converter (AD7147). For piezoelectric force sensing, a charge amplifier-based circuit is established, which converts force-induced charges into voltage outputs. The diagram of the readout circuitry for obtaining capacitive and force information is shown in Fig.3.

C. Touch Orientation Detection and Classification

In order to establish the correlation between capacitive information and the touch orientation, a gyroscope (MPU9250) is used to precisely recognize the touch orientation. This gyroscope is aligned to the finger, and, when a touch is performed, the real touch orientation of the finger is measured by the gyroscope. The capacitance values and gyroscope angles are collected as the dataset to train several widely used machine learning models. After comparing the outputs, the optimized machine learning model is determined and the relationship between capacitive information and touch orientation is established.

D. Force Measurement Testbed and Experiment Setup

A triaxial force sensor (VC40D), capable of measuring force components in the x-y-z directions, is used to recognize the force information. The assembled force touch panel is placed above the force sensor.

The arrangement of experimental devices is illustrated in Fig.4. When touch events are applied to the touch panel, the readout circuitry obtains the capacitive and force signals. The former is sent to a trained GPR model to predict the touch orientation. Then the interpreted touch orientation is employed to calibrate the perpendicular force amplitude as per Eq.1:

$$F_{interpreted} = \frac{F}{sin\alpha} \tag{1}$$

where α is the interpreted touch orientation, F is the detected perpendicular force amplitude, and $F_{interpreted}$ is the interpreted force amplitude.

Finally, the calibrated force is compared to the force obtained from the triaxial force sensor to evaluate the accuracy of the proposed method. The procedure for calibrating the touch force is shown in Fig.5.

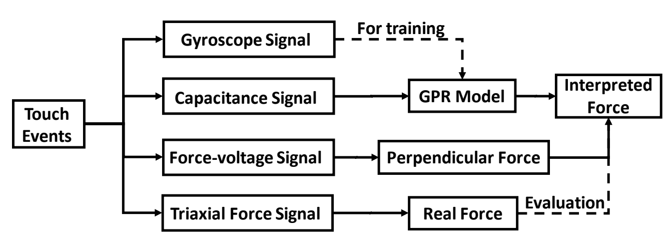


Fig. 5. The procedure for calibrating the touch force.

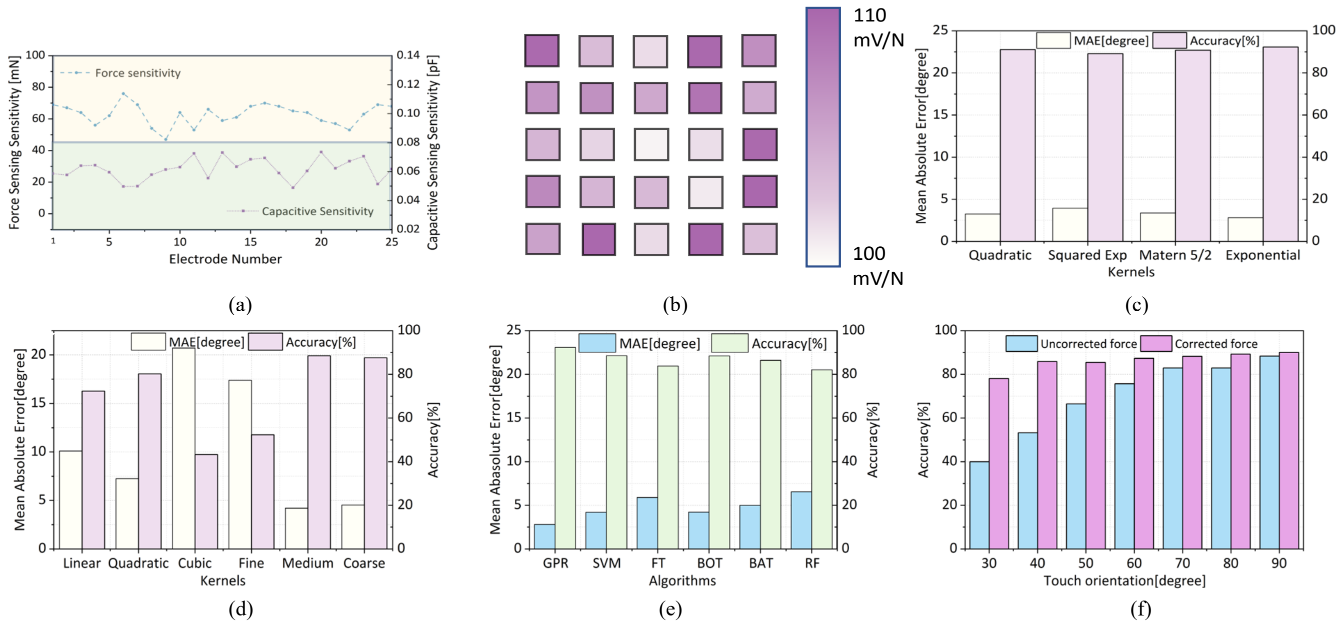


Fig. 6. (a) Sensitivities for force sensing and capacitive sensing. (b) The distribution of the force voltage responsivity of each electrode in the touch panel (c) Gaussian process regression with different kernels. (d) Support vector machine with different kernels (e) Performance for the different algorithms in estimating the touch orientation (f). Accuracy of uncorrected and corrected force at different touch orientations.

III. Results and Discussion

The force and capacitive sensing sensitivities are given in Fig6. a. Fig.6 b shows the distribution of the force voltage responsivity of each electrode in the touch panel. The experimental device yield an average of force sensing sensitivity of 63 mN, capacitive sensitivity of 0.06 pF and force-voltage responsivity of 106.4 mV/N. The performances of the device are listed in Table II.

A total of 192 samples of capacitive information and touch orientation were used to establish the relationship between them, and 80 percent of the samples were used for training, the rest were used for validation set. We compared common machine learning algorithms and used different kernel functions. The performance gaussian process regression [8-11] with kernels [12] of rational quadratic (Quadratic), squared exponential (Squared Exp), matern 5/2 and exponential is shown in Fig.6 (c). The error and accuracy of support vector machine [13,14] with different kernels [15] of linear, quadratic, cubic, fine gaussian (Fine), medium gaussian (Medium) and coarse gaussian (Coarse) is given in Fig.6 (d). And Fig.6 (e) shows the performance of different algorithms, including exponential gaussian process regression (GPR), medium gaussian support vector machine (SVM), fine tree (FT) [16], boosted trees (BOT) [17], bagged trees (BAT) [18] and random forest (RF) [19,20]. The exponential GPR model has the best performance with a mean absolute error of 2.81° and an average accuracy of 92.3% for the validation set. The accuracy is defined as follows:

$$Accuary = 1 - \frac{|predicted\ angle - gyroscope\ angle|}{gyroscope\ angle} \tag{2}$$

TABLE II. Performances of Experimental Device

Performances of Experimental Device	
Capacity Refreshing Rate	60 Hz
Force Refreshing Rate	60 Hz
Orientation Response Delay Time	2.28 ms
Force Response Delay Time	0.2 ms
Force-Voltage Responsivity	106.4 mV/N
Capacitive Sensing Sensitivity	0.06 pF
Force Sensing Sensitivity	63 mN

Fig. 6 f shows that the finger performs touch events from seven different angles. Among them, the accuracy is the highest at 90° (90.04%) and the lowest at 30° (78.12%). An average detection accuracy of 87.5% is achieved. In an interactive touch system, the value of perpendicular force is low, hence the importance of performing calibration is reflected.

IV. Conclusion

The issue of inconsistent force-voltage responsivity in piezoelectric touch panels induced by different touch orientations constrains the full scope of force touch sensing for the internet of things (IoT) applications. The technique reported here addresses this responsivity issue by estimating touch orientations using touch induced capacitive information. The experimentally obtained high detection accuracy of 87.5% validates the feasibility of the technique proposed here. The technique can be used by piezoelectric touch panels to precisely interpret different orientations of force touch, enhancing the user experience in piezoelectric-based human-machine interactivity.

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