HTPad: Hexagon-fractal TENG Pad for Scalable Touch Control

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ABSTRACT

The development of the human-machine interface (HMI) is endeavored to find effective approaches to interact with machines by applying emerging technologies. Triboelectric nanogenerator (TENG) can convert mechanical stimuli to electricity, which not only shows great potential in sensing but also is widely used in various HMI applications. This paper proposed a TENG-based hexagon-fractal touchpad (**HTPad**) system using two channels to realize 18 sliding patterns from 3 different modes and a signal recognition module. A one-dimensional convolution neural network (1D CNN) model is proposed for the recognition of the sliding direction signal with 96.5% accuracy, and handwriting digit signals collected by the touchpad can be recognized with a modified model with 99% accuracy. The proposed TENG-based hexagon-fractal touchpad is easy to fabricate, scalable, and with high sensitivity. Furthermore, the recognition model can serve as a unified platform for different recog.nition tasks with little computational cost, which reveals great potential in HMI applications.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; • **Computing methodologies** → *Machine learning*; • **Computer systems organization** → *Embedded and cyber-physical systems.*

KEYWORDS

Triboelectric sensor, deep learning, human machine interface

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1 INTRODUCTION

As an essential part of the fast development Internet of Things (IoT), efficient and intuitive human machine interface (HMI) is becoming more and more significant [2] [1] [5] [15]. Among many approaches for users to send instructions to the machine, handwriting or touch-control is the most intuitive one for human's dexterous hands. This leads to a specific need for touchpad. Traditional touchpads have two categories, resistive and capacitive. For the resistive touchpad, the contact finger position is tracked through the change of the resistance on different positions of indium tin oxide (ITO) film. The capacitive touchpad relies on monitoring the change of the charge distributions on the electrodes caused by the induced charge on human's fingers [6]. However, the resistive touchpad needs pressure to respond to the sliding movement, leading to a lower sensitivity. The capacitive touchpad requires multiple channels to track the contact point and it is susceptible to temperature, mechanical wear, and tear. In conclusion, these kinds of touchpads both have a shortage of high-power consumption, low resolution and restricted extensibility [3]. Besides, devices with low cost and high flexibility are also needed in the handwriting touchpad system.

The first triboelectric nanogenerator (TENG) was invented by Wang's group in 2012 [4]. It can be applied as a self-powered sensor because it is sensitive to mechanical changes [17]. There are four basic modes of TENG: vertical contact-separation mode [11], lateral sliding mode [9], single-electrode mode [10] and freestanding tribo-electric-layer mode [8]. Recently, there are many TENG-based HMI

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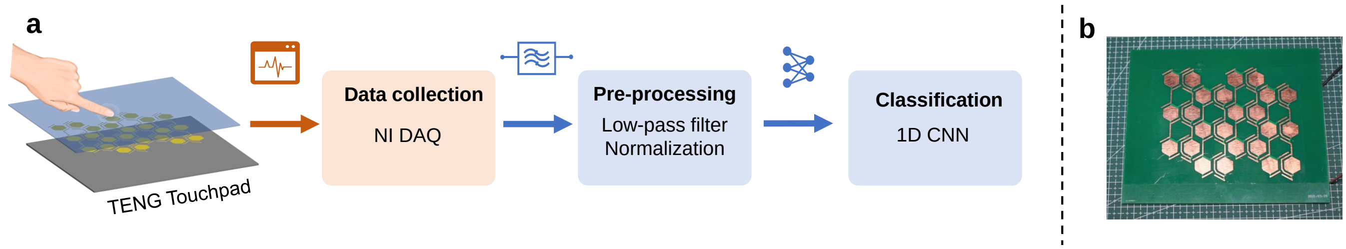

Figure 1: System architecture, a. signal flow of HTPad, b. arrangement picture of HTPad.

devices were designed. Yun *et al.* proposed a transparent touchpad with a 7×7 electrodes array that can track the position of the movement and recognize the digit sliding [16]. This work could locate the position of the finger with high precision and recognize complex handwriting. However, it required a large number of channels. Shi *et al.* designed a triboelectric interacting patch with only four sensing electrodes arranged around splitting ring structure which could recognize the different mechanical movement e.g., tapping, sliding, and identify different users [14]. Qiu *et al.* designed a self-powered remote-control disk based on Gray code for smart home control and authentication [12]. This work proposed a Gray code inspired encryption method with only two channels. However, it could not recognize complex handwriting. Shi *et al.* proposed a bio-inspired spider-net-coding interface which could detect multi-directional sliding signals with only one electrode, independent of different sliding force and speed [13]. They utilized a net structure to successfully reduce the number of channels. However, it lacked the ability of complicated handwriting tracking. Therefore, its application situations were limited. Lee *et al.* proposed a self-cleanable, transparent, and attachable ionic communicator which can be embedded in thimble-type and put in five fingers to achieve real-time communication [7]. However, a complex layout was required to accomplish handwriting recognition. Also, there remains a critical need for a touchpad system that combines sliding tracking and sliding gesture recognition.

Herein, we propose a TENG-based hexagon-fractal touchpad with only two kinds of electrodes arranged alternately for multi-directional sliding recognition and handwriting digit recognition. Compared with other works, our **HTPad** adopts a commercially printed circuit board (PCB) which is suitable for massive production. Besides, the innovative hexagonal structure not only enables high resolution but also supports scalable design for customized applications. Also, a one-dimensional convolution neural network (1D CNN) is proposed to recognize signals from different sliding motions and the experimental results show that the accuracy of the sliding directions recognition reaches over 96% and the accuracy of handwriting digit recognition reaches 99%. The **HTPad** only has two sensing channels which can reduce the computational complexity and front-end circuit electronic hardware cost significantly. This work addresses the existing problem that the number of the sensing channels limits the resolution of the touchpad by a novel hexagon-fractal design. Also, the proposed 1D CNN network can not only be used to recognize the sliding direction signals and handwriting signals of our **HTPad** but also be considered to be applied to other similar tasks. Moreover, the TENG-based hexagon-fractal touchpad is suitable for massive fabrication and the proposed recognition model has high accuracy with a high level of robustness and cost-efficiency. The whole system is expect to play an important role in HMI in IoT and other applications.

2 SYSTEM DESIGN AND OPERATION PRINCIPLE

In this section, the designed TENG-based hexagon-fractal touchpad with a triple-layer structure is demonstrated. Basic working principles and experimental situations are therefore illustrated to introduce the first component of the whole **HTPad** system.

2.1 System Design

The **HTPad** structure is illustrated in Figure 1(a). The TENG-based hexagon-fractal touchpad consists of three layers: the bottom layer is made of FR-4 baseboard, the middle layer using copper as electrode and conductor trace, the top layer is transparent fluorinated ethylene propylene (FEP) film. The thickness of the baseboard, copper electrode and FEP film is 1.6mm, 35um, and 40um respectively.

There are two kinds of electrodes with different patterns as the basic units are arranged alternately on the board. Different electrodes of the same channel are connected by the copper trace. The size of each electrode is approximately 10mm ×10mm and the units can be scaled up and down collaboratively to adapt to different requirements. The **HTPad** illustrate in Figure 1(b) contains 24 electrodes within 15.80cm × 13.39cm.

2.2 Operation Principle

The working principle of the **HTPad** is based on the single-electrode mode of TENG. Because of triboelectrification and the different tendancies to gain or lose electrons between the hand and FEP film, the electrostatic charges will be produced on the surface of the electrode during contact. The charge distribution on the FEP film will change and the current will be generated between the electrode and the ground when the finger slides over the surface of the electrode. A load resistor is connected in series between the electrode and the ground to obtain a larger amplitude and more stable output signals. The voltage on the load serves as the output signal.

Fractal design is adopted for electrodes to achieve a scalable touchpad with only two signal channels. The outputs of the three modes are shown in Figure 2. The blue geometric shapes are electrode1 (E1) and the red ones are electrode2 (E2). Both E1 and E2 are composed of a large hexagonal electrode area in the center and

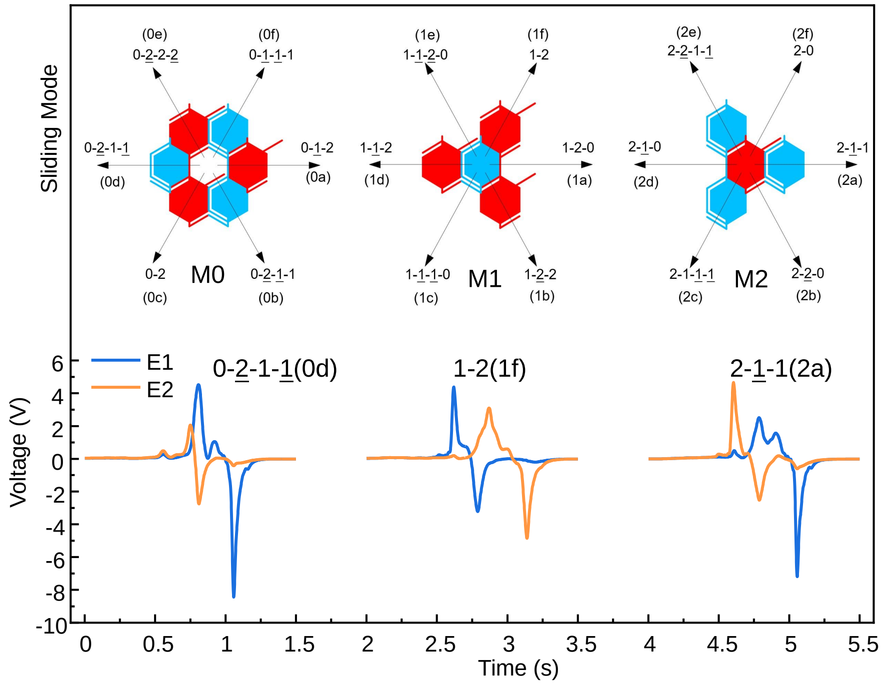

Figure 2: Three basic sliding patterns and the sample measured data

some narrow strips around the center. The size of the center area of E1 and E2 are the same and the width of the narrow strips is also the same. The ratio of the width of the narrow strip to the diameter of the hexagon is almost 1:12 to make a significant distinction between the two signals. Therefore, when the finger with glove slides over the narrow electrodes and hexagon electrodes, the different amplitude and pulse width on the load resistor will be generated accordingly.

Different sliding modes are proposed to recognize the different signals generated from the **HTPad**. There are three types of basic modes on the **HTPad** design, mode0 (M0), mode1 (M1) and mode2 (M2), as shown in Figure 2. Each mode consists of a central block, surrounded by six blocks, which enables totally 18 sliding directions. As shown in Figure 2, the numerical mark "0" means the sliding action does not pass between the electrode areas, "1" and "2" represent the signals generated by sliding over the large hexagon electrode, while the underlined "1" and "2" represent the signals generated by sliding over the narrow strip.

3 DATA ACQUISITION, PROCESSING, AND RECOGNITION

In this section, we introduced a systematic signal acquisition, preprocessing, and recognition pipeline of the proposed **HTPad** system and evaluate the performance of our system on direction recognition.

3.1 Data Collection and Pre-processing

Each of the two channels of the HTPad is grounded through a 100MΩ resistor, and the corresponding voltage is measured by the NI9223 DAQ module and LabVIEW system at the sampling rate of 1 kHz.

To eliminate the influence of high-frequency environmental noises to the signal, we adopt the finite impulse response (FIR) equiripple low-pass filter with 50Hz stopband setting. However, the signal amplitude from different users' sliding could be diverse. To increase the robustness meanwhile reduce the computational cost of the recognition model, normalization is utilized to map the data into the same interval (0,1).

The original data has two channels. Since the sampling frequency of ADC is 1 kHz and the sampling time interval is standardized to be 1.5 seconds, the number of original data points in the time domain is 1500. Further data augmentation methods of shifting the pre-processed data in temporal dimension for various time intervals forward and backward are used for better recognition performance.

3.2 1D CNN Algorithm

For time series classification tasks, one-dimensional convolution neural network (1DCNN) have attracted great interest because of its ability to capture local patterns and combines feature extraction and classification and the recognition performance is improved compared with traditional feature extraction methods. Also, the one dimensional CNN (1D CNN) is very efficient for extracting features from fixed-length segments, where the location of the feature within the segment does not affect the classification result.

Here, a 1D CNN model is proposed for two-channel direction recognition based on **HTPad** signals. The program is developed in Python using Keras library. The proposed network structure is shown in Figure 3, along with a sample flow of input and output shape marked below each block. The proposed neural network

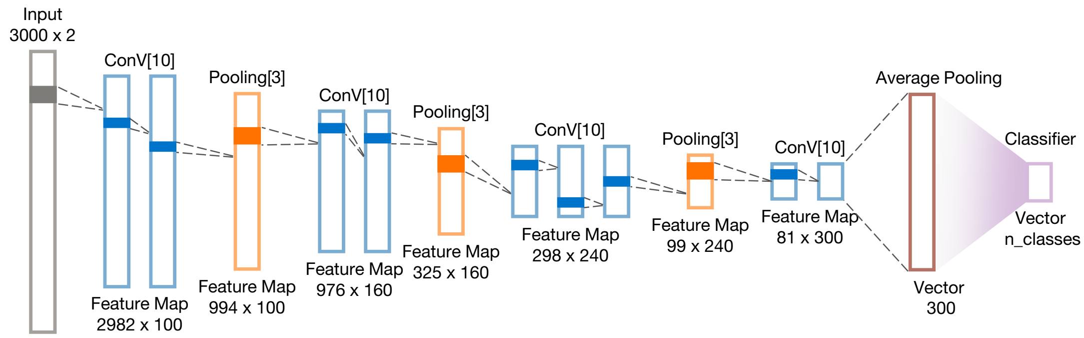

Figure 3: Sample of the proposed 1D CNN architecture.

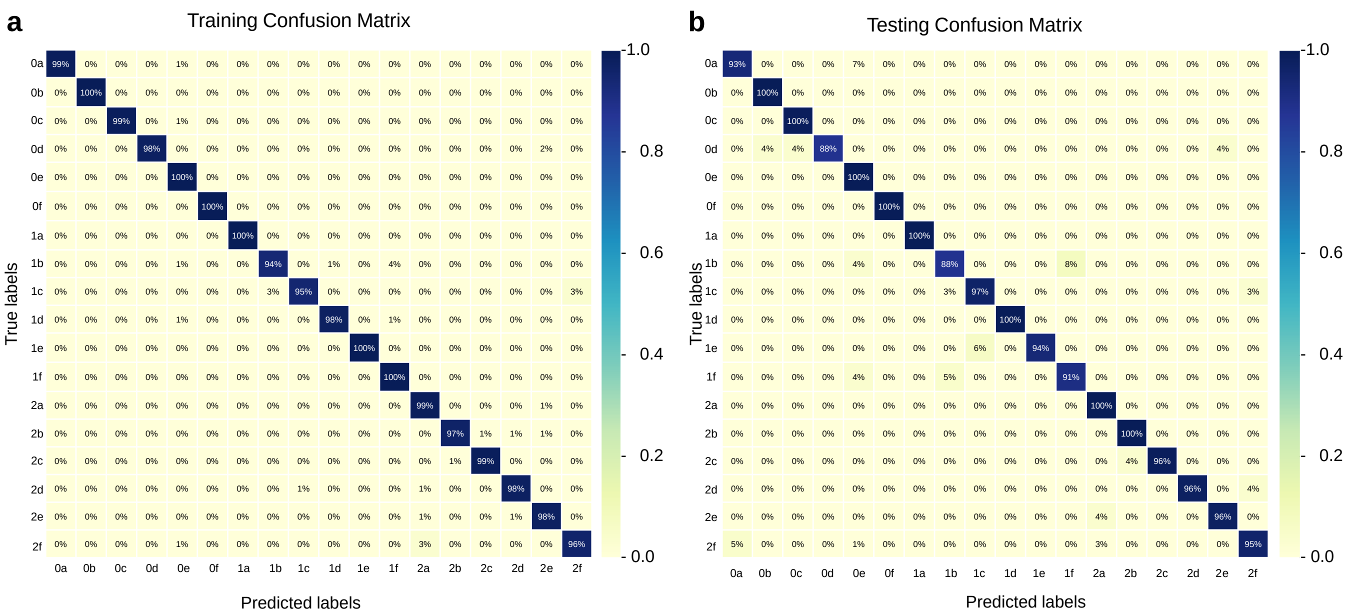

Figure 4: Confusion matrix of direction recognition, a. on the training set, b. on the testing set

consists of a sequential model of 1D convolution layers, 1D max-pooling layers, global average pooling layer, dropout layers, and fully connected layers. The working principle of these layers is as follows.

- 1D convolution layer: the 1D convolution layers in the proposed model have a uniform kernel size of 10 with a stride of 1 and none zero-padding, and the output channel number is determined by the number of the filters of each 1D convolution layers respectively.
- 1D max-pooling layer: the 1D convolution layers in the proposed model has a uniform kernel size of three. For each input feature map, 1D max-pooling layers selected the largest feature value within the given kernel size. The output of 1D max-pooling layer will have a reduced size of one-third of the input spatial size while keeping the channel number unchanged.
- Global average pooling layer: the global average pooling layer takes the average of each feature value in each channel of the input feature map and turns the feature map into a feature vector.
- Dropout layer: dropout layers are applied to prevent the network from overfitting. The feature vector extracted by 1D convolution layers and pooling layers are placed as the input to the fully-connected layers after a dropout probability of 0.5.
- Fully-connected layer: the fully-connected layer with the activation function of softmax acts as the classifier. It calculates the probability of each class, given the long input feature vector. The class with the highest probability is determined to be the classification result.

The forward path of the proposed 1D CNN model consists of four convolution blocks, each block followed by a pooling layer and a fully-connected layer as the classifier. Each of the first and second convolution blocks is composed of two convolution layers, and each of the third and fourth convolution blocks consists of three convolution layers. The 1D CNN model with the chosen structure ideally identifies the curve features, the frequency characteristics and the phase difference between the two channels, which act as the key features used for classification.

During the training progress, 80% of the total data is used as the training set and 20% of the total data are used as the testing set. To prevent overfitting, one batch normalization layer is implanted after each 1D convolution layer. The cross-validation strategy is also used. During each training epoch, 20% of the training data are used for cross-validation. The validation accuracy is monitored during training and early stopping of 5 epochs of non-increasing validation accuracy is utilized. The model was trained offline using an Adam optimizer configured with a manually-adaptive learning rate, running with a GeForce RTX 3090 GPU.

3.3 Performance Evaluation

The acquired and pre-processed data has a shape of 1500 by 2. The total number of the input training set is 2359, consists of all 18 directions. The directions are encoded for the convenience of recognition, and the encoded marks are shown in Figure 2. The training and testing results are shown in Figure 4(a) and Figure 4(b). After manual adjustments of the learning rate, the testing accuracy reaches 96.5%, indicating that the proposed model can achieve high classification accuracy and reliable direction recognition results.

4 APPLICATION: HANDWRITING DIGIT SIGNAL RECOGNITION

In this section, a handwriting digit signal recognition system is introduced based on the identical data acquisition and signal recognition pipeline. Handwriting digit signals based on the **HTPad** can be considered as a series of direction signals. Therefore, handwriting digit signals can be collected by the **HTPad** and be recognized by adjusting the recognition model for this specified task theoretically.

4.1 Experiment Settings

The data acquisition progress is similar to the data acquisition of direction signals, and the only difference is that the sampling time window interval is extended to 3 seconds. The sample measured handwriting signals are shown in Figure 5. Then, the collected data are filtered, normalized, and augmented with the same preprocessing strategy as the input to the proposed 1D CNN model. The input shape is uniformly set to be 3000 by 2 and the batch size is set to be 100 samples. Compared to the direction recognition system, the number of classes of the final classifier of the 1D CNN model is changed from 18 to 10. And other training processes follow the settings of the direction recognition system.

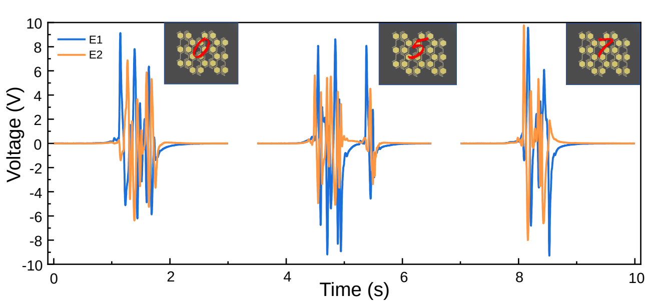

Figure 5: The sample measured handwriting data.

4.2 Performance Evaluation

Each class of the 10-class (0-9) handwriting digit data has 2391 samples. The training and testing confusion matrices are shown in Figure 6(a) and Figure 6(b) respectively. The testing recognition accuracy raises quickly to 99% within 100 training epochs. These results not only show the model's precision in classifying handwriting digits but also shows robustness on various handwriting styles of different people and a great potential to be a uniform handwriting signal recognition processing model.

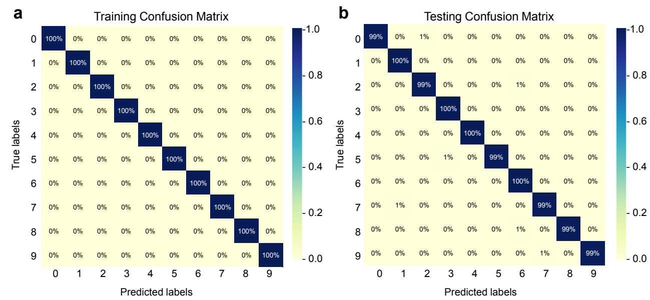

Figure 6: Confusion matrix of handwriting digit recognition, a. on the training set, b. on the testing set

5 CONCLUSION

In summary, a TENG-based hexagon-fractal structure touchpad is proposed to recognize multi-directional sliding signals from three basic modes and handwriting digit signals. The special structure of the **HTPad** consists of two sensing electrodes which are composed of a large hexagonal electrode area in the center and narrow strips around the center. The **HTPad** can be extended by adding electrode units repeatedly and enlarging or shrinking the electrodes collaboratively. We also designed a 1D CNN model to distinguish different sliding directions and it can achieve reliable recognition results with low computational complexity, which shows a huge potential in trajectory tracking, gesture interface, instruction collection, and can be widely applied in HMI and other applications of the IoT.

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