Improving Touch Accuracy in Surface Capacitive Touch Panel using Deep-Learning

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Conventional surface capacitive touch panel (SCAP TP) recognizes touch by sensing currents at corners. In this paper, we propose a novel method to identify touch positions on SCAP TP by using a convolutional neural network (CNN) model applied to measured corner voltages rather than currents.

We applied a triangular wave to one corner. Then, we obtained three minimum voltages from the three remaining corners. In this way, we could get twelve minimum voltages by applying the triangular signal to remaining corners sequentially. 12 voltage data were reshaped in the form of 4×4 data set as shown in Fig. 1. We divided the SCAP TP into 19 rows and 34 columns as shown in Fig. 2. Each square is 0.8cm by 0.8cm. Data sets were obtained by touching squares on first eight rows . We obtained 12 data sets per square or per grid point from row 1 to 8 for 12 cycles, and totally got 4,464 data sets. CNN model was trained using obtained data set and the coordinates of touch point as a label.

The structure of the model is shown in Fig. 2. First, input layer is a convolution 2d layer. Each row of a data set has values obtained by the same voltage source applied to the same corner. We used 1 by 4 convolution 2d filter. Second, a hidden layer is dense layer. Finally, the x or y coordinate is obtained through the output dense layer.

Training and testing were conducted in three ways according to distance between training points (DTP) as shown in Fig. 3. The test results after learning were shown in Table 1. Table 1 shows the average difference between actual coordinates (label) and estimated ones by the model of test points. The average deviation was about 0.12cm on average when DTP=1.6cm. Although the ratio of the number of training points to that of testing ones was 1:3, it shows that our method can estimate where to touch very accurately. This supports that deep-learning can achieve highly accurate touch recognition without complicated mathematical or electrical analysis.

The source code and data set for the trained model are uploaded to https://github.com/ByeongHunAn/CNN-model-for-recognition-touch-point and can be checked.

Sourcing A	0	$V_{min,B}$	$V_{min,C}$	$V_{min,D}$
Sourcing B	$V_{min,A}$	0	$V_{min,C}$	$V_{min,D}$
Sourcing C	$V_{min,A}$	$V_{min,B}$	0	$V_{min,D}$
Sourcing D	$V_{min,A}$	$V_{min,B}$	$V_{min,C}$	0

Fig. 1. Shape of data set

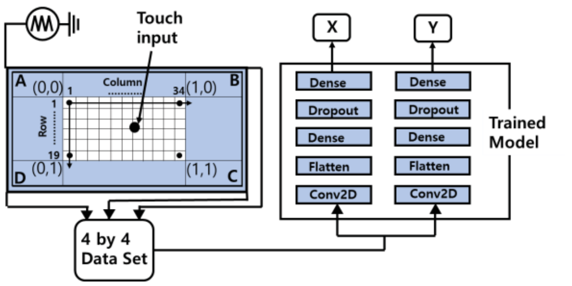

Fig. 2. Touch point recognition System with CNN model

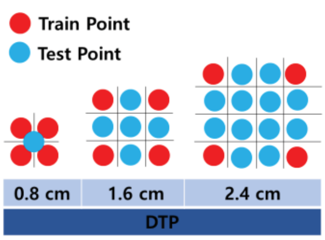

Fig. 3. Three types of training and testing

Table 1 Average deviation of test points

DTP (cm)	$\sqrt{\Delta x^2 + \Delta y^2}$ (cm)
0.8	0.21
1.6	0.12
2.4	6.60

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References