Localization performance of hum-noise-based touch sensor (HumTouch) with unknown participants

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***Abstract*—HumTouch is a touch sensing method that can turn object surfaces into touch sensors. The sensing method utilizes the current leak from the human body; therefore, the localization performance exhibits individual differences. In this paper, we research the localization performance of HumTouch involving multiple participants. A semi-conductive paper marked with 49 points was used for the experiment. Five participants participated in the experiments and the localization results were evaluated via leave-one-out cross validation, in which an estimation model was established by using the samples collected from four participants to localize the touch of the last participant. For four out of the five participants, there were mean estimation errors smaller than or equal to 1 cm, which is comparable to the size of a fingertip. This indicates that HumTouch has the potential to be applied to multiple participants without prior calibration conducted for a specific person.**

***Index Terms*—human antenna, human touch sensing, flexible touch sensor**

I. Introduction

Nowadays, touch sensors are widely used in consumer electronics. The usage of touch sensors allows people to operate electronic devices in a more intuitive manner. Although some types of touch sensors are commercially available, HumTouch [1]–[5] provides a different approach by converting day-to-day objects into touch sensors. The human body contains conductive elements that react to electromagnetic waves, such as in the case of AC hum [6]. When a human touches a conductive object, the current leaks from the finger to the surface of the object. By attaching electrodes to the object surface, the voltage of the current can be detected and used for localization or gesture recognition. Therefore, surface activation is not needed in HumTouch.

In our previous studies, we proposed a few different types of localization methods involving the use of kernel regression analysis [3]–[5]. In these studies, we constructed a regression model using different datasets, and each dataset comprised data recorded from a single participant. Owing to the differences in the electric properties of one human body and those of another, the leaked currents can also very from one individual to the other; this makes it difficult to realize an accurate model for the localization of touch for multiple unknown participants.

In this study, we investigated the localization performance of HumTouch by applying it to five participants. The localization method we used is based on the one proposed in [5], in which a nonlinear kernel regression analysis is performed using the voltages detected at the electrodes on the object surface as the explanatory values. To evaluate the localization accuracy, we applied leave-one-out cross-validation, where a dataset constructed using the data of one person was tested by the model constructed based on the datasets constructed using the data collected from different persons. The results suggest the potential of touch localization for unknown users, for which the HumTouch sensor is not calibrated.

This study was in part supported by MEXT Kakenhi #20H04263.

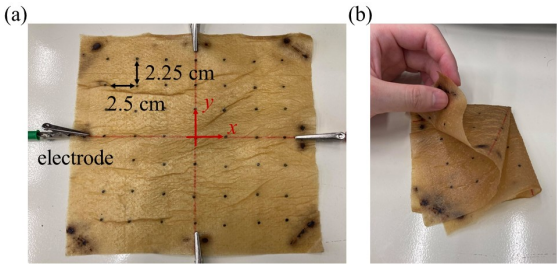

Fig. 1. (a) Semi-conductive paper marked with 49 points Their intervals were 2.5 and 2.25 cm. Four electrodes were attached to the center of each edge. (b) The paper is dry and flexible.

II. Material, apparatus and Experiment

We used a 20×18 cm^2 wiping paper (Kimtowel, Nippon Paper Crecia, Japan) painted with a semi-conductive ink [2]. The ink contains polyvinyl alcohol, polyethylene glycol and glutaraldehyde. The paper was dry and flexible after it was painted with the ink. Forty-nine grid points were marked on the paper at 2.5 cm and 2.25 cm intervals, as shown in Fig. 1. Four electrodes were located at each edge of the paper and connected to an oscilloscope (HS6 DIFF, TiePie Engineering, Netherlands; sampling frequency: 500kHz) to record the signals.

Five participants were asked to touch each of the 49 marked points with their index finger for approximately 1 s inside a normal office room. This procedure was repeated five times to collect five sample sets for every participant.

III. Localization Method

A. Data Preprocessing

To remove the high-frequency noise in the signals recorded by the electrodes, we applied a moving average filter with a window size of 0.01. After the smoothing process, the maximum voltages at the electrode were recorded as $\boldsymbol{v_{ij}} = \{v_{ij,e}\}$, where i, j, and e specify a trial, participant ($j = 1, ..., 5$), and

electrode ($e = 1, ..., 4$), respectively. The recorded voltage can then be normalized by

$$z_{ij,e} = \frac{v_{ij,e} - \mu_j}{\sigma_j}, \tag{1}$$

where $z_{ij,e}$ is the normalized maximum voltage for each electrode, and μ_j and σ_j are the mean value and standard deviation of the recorded maximum voltages for the jth participant, respectively.

B. Kernel Regression Analysis

Kernel regression analysis was applied to estimate the touched location because the relationship between the touched locations and the recorded voltages was nonlinear. We used the Cartesian coordinate system to define the location for each marked point. The estimated location $(\tilde{x}, \tilde{y})$ was computed using the observed values $\boldsymbol{z} = (z_{ij,e})$ as follows:

$$\begin{bmatrix} \tilde{x} \\ \tilde{y} \end{bmatrix} = \begin{bmatrix} \sum_{s=1}^{m} \alpha_{x,s} k(\boldsymbol{z_s}, \boldsymbol{z}) \\ \sum_{s=1}^{m} \alpha_{y,s} k(\boldsymbol{z_s}, \boldsymbol{z}) \end{bmatrix} \tag{2}$$

where m is the number of samples (four participants $\times$ five trials $\times$ 49 points = 980) and $k(\boldsymbol{z_s}, \boldsymbol{z})$ is a Gaussian kernel:

$$k(\boldsymbol{z_s}, \boldsymbol{z}) = \exp(-|\boldsymbol{z_s} - \boldsymbol{z}|^2), \tag{3}$$

which $|.|$ is the L2 norm. The coefficients α_{xs} and α_{ys} are the sth elements of $\boldsymbol{\alpha_x}$ and $\boldsymbol{\alpha_y}$, respectively. They are computed as follows:

$$\boldsymbol{\alpha_x} = (\boldsymbol{K} + \lambda \boldsymbol{I})^{-1} \boldsymbol{x} \tag{4}$$

$$\boldsymbol{\alpha_y} = (\boldsymbol{K} + \lambda \boldsymbol{I})^{-1} \boldsymbol{y}, \tag{5}$$

where $\boldsymbol{x} = (x_1, ..., x_m)^{\mathrm{T}}$ and $\boldsymbol{y} = (y_1, ..., y_m)^{\mathrm{T}}$ are the actual x and y locations for the learning samples, respectively. Matrix $\boldsymbol{K} \in \mathbb{R}^{m \times m}$ is formed by the Gaussian kernel:

$$\boldsymbol{K} = \begin{bmatrix} k(\boldsymbol{z_1}, \boldsymbol{z_1}) & \dots & k(\boldsymbol{z_1}, \boldsymbol{z_m}) \\ \vdots & \ddots & \\ k(\boldsymbol{z_m}, \boldsymbol{z_1}) & & k(\boldsymbol{z_m}, \boldsymbol{z_m}) \end{bmatrix}. \tag{6}$$

The regularization values λ and $\boldsymbol{I}$ were 0.001 and $m \times m$, respectively. To estimate the locations of the jth participant, the learning samples were obtained from the other four participants.

IV. Results

The points presented in Fig. 2 show the mean values of the estimated locations and the standard deviations. The points near the center of the paper appeared to have smaller estimation errors and the smallest value was 0.15. On the other hand, expect for P5, the points near edges have large estimation errors and the largest value was 4.4 cm. For four (P1–P4) out of the five participants, the mean errors were equal to or smaller than 1 cm. These errors are comparable to those presented in our previous study, which involved only one participant, and the mean error was 0.48 ± 0.10 cm on a 20×16 cm^2 paper [5]. For one participant (P5), the mean localization error was 2.68 cm, and the other errors, overall, were significant.

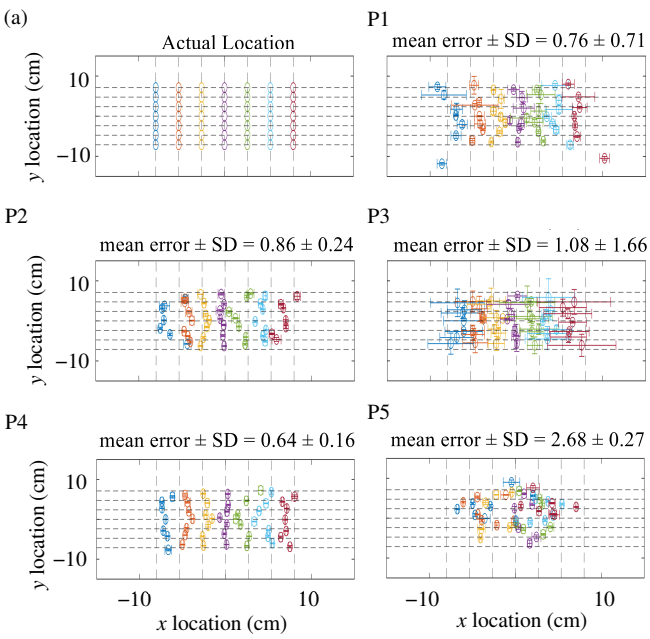

Fig. 2. (a) Actual locations for the 49 marked points. P1–P5 specify the five participants. The dots represent the mean estimated locations for the five tested trials with the corresponding standard deviations.

V. Conclusions

We investigated the localization performance of the HumTouch sensor for unknown participants. The localization for each participant was realized via a regression model constructed using the data recorded the other participants. Over all, the estimation errors for the points near the center of paper were small but large for the points near the edges. For four out of the five participants, the model showed mean errors close to or smaller than 1 cm, whereas that of one participant was significant. The results showed that the HumTouch sensor can be potentially used for unknown users whose data are not used for training the localization model of the sensor.

References

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