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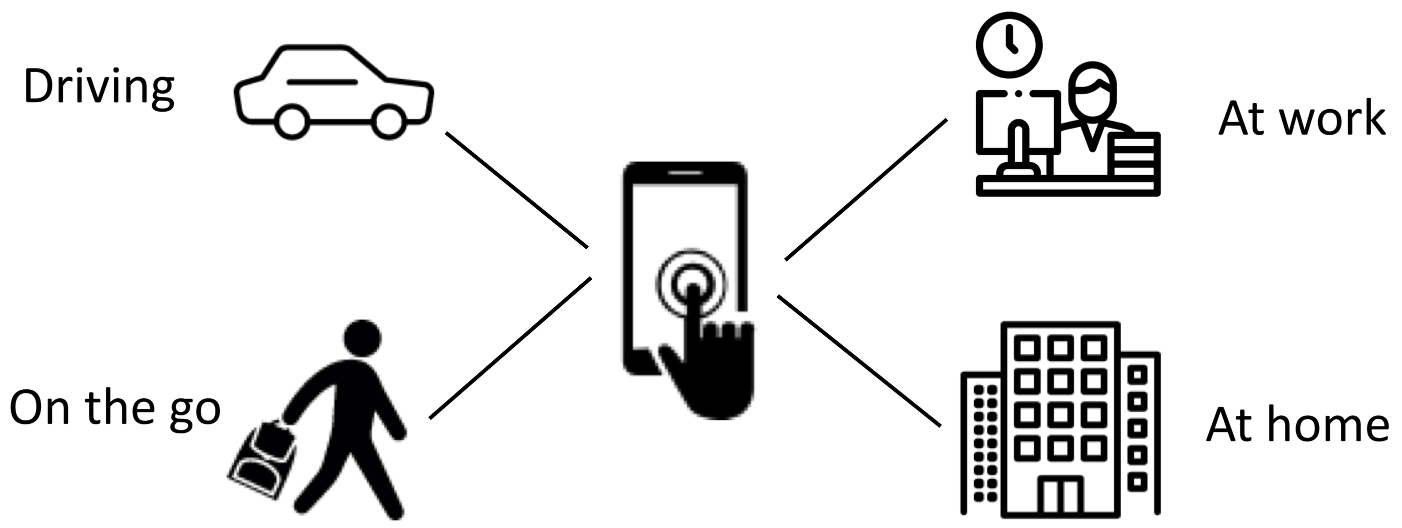
Leveraging Self-sourcing as a Model-free Approach to Improve Touch Accuracy

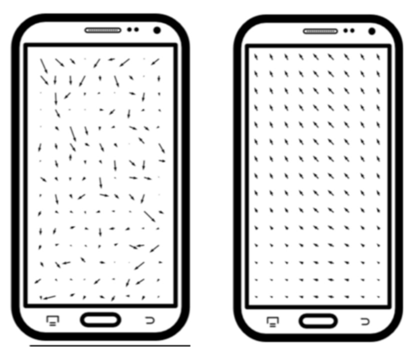
Raymond Fok (Honors Capstone), Martez Mott, Walter Lasecki

Motivation

Touch input has become one of the most prevalent forms of interaction with tech.



However, touch-enabled technologies may be less reliable or even inaccessible for individuals with **motor impairments** such as Cerebral palsy or Parkinson's disease, or those with **situational impairments** such as walking or driving.



Prior work has developed models to predict touch offset and offset magnitude.

These model-based systems have several **disadvantages**:

- They require large amounts of **training data**, which can be difficult to collect for specific users.
- They are highly sensitive to the data on which they were training. For example, their **performance varies** greatly across different users, with different devices, or with a different hand position or posture.

Smart-surfaces

Tablets

Smartphones

Public Kiosks

We want to explore new intuitive, model-free approaches to enable improved touch accuracy for people of any ability.

Approaches

Drawing on prior work in touch screen accessibility, ensemble methods from machine learning, and aggregation techniques from crowdsourcing, we introduce **self-sourced aggregation** as a training-less method to improve touch accuracy.

Methods

1. The (unweighted) **centroid** aggregation method returns the mean position of all touches.

$$C = \frac{x_1 + x_2 \cdots + x_k}{k}$$

2. The **weighted centroid** aggregation method returns the iterative pairwise mean position of all touches.

$$WC = \frac{x_1 + x_2 + 2x_3 + \cdots + 2^{k-2}x_k}{2^{k-1}}$$

3. The **geometric median** aggregation method returns a point that minimizes the sum of the Euclidean distances between each touch and itself.

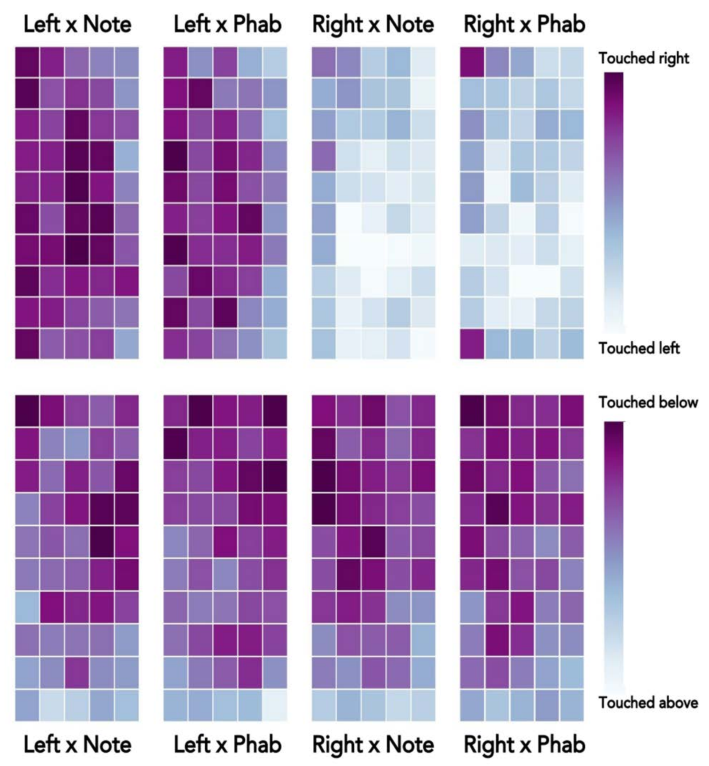
$$GM = \arg\min_{y \in \mathbb{R}^2} \sum_{i=1}^{k} ||x_i - y||_2$$

Experimental Conditions

8 Participants with Motor Impairments	Dominant/Off hand	Lenovo Phab 2 Pro (16.3cm diagonal)
15 Participants under Situational Impairment	Left/Right hand	Samsung Note 4 (14.5cm diagonal)

A visualization of touch points for three different participants without motor impairments

Results

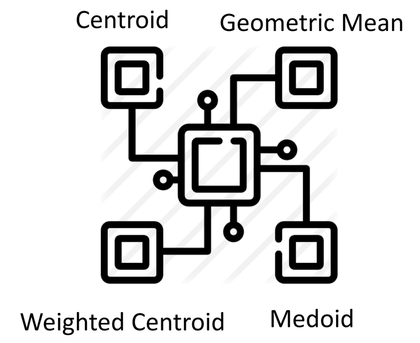


A heatmap visualization of offset direction for participants without motor impairments. Variations in touching hand created significant offset variation, but variations in device size did not have significant effect. Offset direction was distinctly mirrored between hands in the x-direction, but was similar in the y-direction.

Condition	Centroid	Weighted Centroid	Geometric Median	1st	2nd	3rd	4th	Average
MI	**1.94 (0.28)**	1.96 (0.27)	2.03 (0.28)	2.23 (0.34)	2.20 (0.37)	2.30 (0.33)	2.40 (0.32)	2.28 (0.30)
SI - Left, Phab	2.50 (0.58)	**2.45 (0.58)**	2.58 (0.56)	3.80 (1.41)	3.34 (1.18)	2.97 (0.72)	2.73 (0.64)	3.06 (0.76)
SI - Right, Phab	**2.38 (0.45)**	**2.38 (0.47)**	2.45 (0.45)	3.81 (1.34)	3.22 (0.74)	2.89 (0.68)	2.77 (0.71)	3.08 (0.71)
SI - Left, Note	2.29 (0.55)	**2.20 (0.55)**	2.29 (0.54)	3.74 (0.94)	3.03 (0.97)	2.50 (0.58)	2.35 (0.58)	2.79 (0.66)
SI - Right, Note	2.34 (0.0.67)	**2.31 (0.68)**	2.36 (0.66)	3.57 (1.12)	3.01 (0.0.82)	2.66 (0.63)	2.57 (0.71)	2.88 (0.70)

Takeaways

- Overall, **weighted centroid** performed best for participants *without* motor impairments but under situational impairment. **Centroid** performed best for participants *with* motor impairments.
- Participants *with* motor impairments tended to touch **less** accurately with successive touches, while participants *without* motor impairments were **more** accurate with successive touches.
- Model-free aggregation improved overall touch accuracy for both groups by approximately 18-25%, varying by individual based on their touch offset distribution.



We found that different aggregation methods performed best in different conditions across participants.

Our ongoing work is looking into hybrid aggregation strategies that intelligently combine the model-free approaches presented here.