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RESEARCH ARTICLE



Combining force and kinematic signals for human-computer interface: insights from cursor control by flexible pressure sensors

Mingjie Qu^a and Kunlin Wei^{b,c,d} 

^aSchool of YuanPei, Peking University, Beijing, China; ^bSchool of Psychological and Cognitive Sciences, Peking University, Beijing, China; ^cBeijing Key Laboratory of Behavior and Mental Health, Peking University, Beijing, China; ^dNational Key Laboratory of General Artificial Intelligence, Beijing, China

ABSTRACT

Cursor control becomes difficult in space-constrained environments, such as operating portable computers while wearing pressurised gloves. Flexible pressure sensors can capture fingertip kinematic (centre of pressure, CoP) and force signals within confined spaces, offering a potential control method. In two experiments, we evaluated mappings that transformed kinematic and/or force signals into cursor movements. A hybrid mapping using CoP displacement and peak force to control cursor velocity achieved the highest throughput. Compared with a commercial TrackPoint, the hybrid mapping achieved 63% of its throughput but yielded smoother trajectories, indicating a speed–stability trade-off. These findings demonstrate the potential of fingertip pressure for cursor control in constrained environments and the benefits of combining kinematic and force information in human-machine interaction when hand motion is limited.

PRACTITIONER SUMMARY: This study introduces the design of a system based on flexible pressure sensors that supports precise cursor control with minimal fingertip movement. Fitts' task and subjective ratings showed that combining force and kinematic signals outperformed mappings using either signal alone, achieving 63% of TrackPoint throughput.

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KEYWORDS

Human-computer interaction; cursor control; flexible pressure sensor; finger-pressure input

1. Introduction

Effective human–computer interaction (HCI) in extreme or physically constrained environments remains a long-standing ergonomic challenge. A central concern is the selection and design of pointing devices that allow users to control the cursor accurately without large effector movements (Jacko 2012). For example, astronauts wear pressurised suits and gloves during extravehicular activity (Bishu and Klute 1995; Thompson et al. 2011; Welsh and Akin 2001), and firefighters, deep-sea divers, and surgeons wear protective gloves during their operations (Dianat, Haslegrave, and Stedmon 2010; Geng, Chen, and Holmér 1997; Herring, Trejo, and Hallbeck 2010; Khanlari, Ghasemi, and Heidarimoghadam 2023; Krausman and Nussbaum 2007; Zander and Morrison 2008). They all face the same challenge: how to interact with their portable computing devices when their hand and finger movements are restricted.

Flexible pressure-sensor technology offers a promising basis for cursor control in extreme settings where users must minimise hand motion. Previously, people have placed such ultrathin sensors in gloves, electronic skins, and wearables as measurement devices (Dos Santos et al. 2020; Kim et al., 2017; Nie et al. 2015; Xu et al. 2017; Yin et al. 2024). For instance, Layard Horsfall et al. (2023) developed a surgical glove lined with flexible pressure sensors to measure surgeons' grip forces in real time. However, the application of such technology in human-computer interaction remains limited, as previous studies have only used pressure distribution to categorise discrete postural states (Fukahori, Sakamoto, and Igarashi 2015; Tan, Slivovsky, and Pentland 2001). To the best of our knowledge, there has been no previous attempt to use pressure distribution for real-time continuous cursor control. Flexible pressure sensors can be fabricated as ultrathin multilayer films and attached to various

surfaces, tolerating substantial bending, stretching, or twisting without signal drift. These features make flexible pressure sensors a viable solution for the challenging scenarios described above, since these ultrathin layers can be mounted on the inner fingertip lining of a protective glove (Li et al. 2025; Tai et al. 2022; Xu et al. 2024). When a fingertip presses on the flexible pressure sensor, the resulting pressure distribution contains both kinematic information (e.g., movement of the centre-of-pressure, CoP) and force information. We argue that force information may be critical for cursor control based on flexible pressure sensors. Because the sensor is mounted between the finger and its supporting surface, the available finger workspace is relatively small, and additional force information may therefore help to support efficient cursor control. However, previous studies have not systematically investigated how to incorporate force information into cursor control. A conventional touchpad senses both kinematic and force information from the finger, but finger force magnitude is rarely used for cursor control; instead, it is typically exploited for secondary functions such as adjusting line thickness during drawing or modifying scrolling speed (Dempsey, Szablewski, and Atkinson 2015). Apparently, comparative analyses of various control modes, which combine kinematic and force signals differently, are essential for cursor control with pressure distribution, since the most suitable control mode depends critically on the available input signals (Card, English, and Burr 1978; Zhai 1996).

We hypothesised that incorporating force information can significantly improve our system's cursor control efficiency. Human motor control studies have consistently reported that control signals (e.g., muscle activity) scale positively with movement speed (Brown and Cooke 1981; Buneo, Soechting, and Flanders 1994). Thus, the magnitude of finger force should convey information about the user's intended movement speed. We therefore compared cursor control schemes with and without force information. We further hypothesised that users would be able to rapidly master a combined control scheme that integrates both kinematic and force information, without extensive practice, because previous work has shown that people can acquire complex mappings and exploit redundant information to enhance performance (Mosier et al. 2005; Radhakrishnan, Baker, and Jackson 2008; Ranganathan, Adewuyi, and Mussa-Ivaldi 2013; Ranganathan et al. 2014). To provide an intuitive performance reference, we benchmarked our device against the TrackPoint, a commercially available finger-operated pointing device. Because the TrackPoint

maps the applied force vector directly to cursor velocity, it may support faster cursor movement but is also associated with greater jitter and more submovements (Sutter and Ziefle 2005). By contrast, our pressure-sensor approach derives cursor control from the spatially distributed force readings across the sensor array. We therefore hypothesised that, relative to the TrackPoint, our device would yield lower speed but greater smoothness of cursor movement.

In this research, we developed an efficient cursor control system using flexible pressure sensors and conducted two experiments to verify the hypotheses above. To explore suitable control modes, we first devised three mapping schemes that translated either kinematic information or force information from the pressure distribution into cursor movements, and evaluated both pointing performance and user satisfaction (Experiment 1). We then combined the kinematic and force information in a hybrid mapping scheme, examined whether it improved performance, and benchmarked it against a classic TrackPoint pointing device (Experiment 2). Our results show that pressing a fingertip against a flexible pressure sensor enables rapid and precise pointing, and that combining the kinematic and force information improves cursor control efficiency.

2. Methods

Our system requires people to press their index finger against a flexible pressure transducer to drive cursor movement (Figure 1). The resulting pressure distribution is recorded as a two-dimensional matrix, and its centre-of-pressure (CoP) shifts with minute finger motions. In real-time, CoP movement drives the cursor. The complete hardware setup and signal-processing workflow, from pressure-matrix acquisition to cursor-command generation, is summarised in Figure 1(b). We evaluated several mapping functions in two separate experiments and found that a hybrid mapping, which combines peak force and CoP displacement, performed the best.

2.1. Hardware, software, and preprocessing of finger pressure data

Our system employs a commercially available flexible pressure distribution sensor (model RPPS-1600, Ligan Technology, Shenzhen, China; Figure 1(a)). The sensor has an active sensing area of 85×85 mm and a thickness of 0.2 mm. The active area comprises a 40×40 array (1600) of sensing units (taxels). Each taxel occupies a 2.1×2.1 mm cell (1.8×1.8 mm sensing pad with

a 0.3-mm inter-taxel gap), yielding a nominal spatial sampling pitch of 2.1 mm. The data-acquisition board streams the pressure data at approximately 60 frames/s. The pointing task was conducted on a Lenovo ThinkPad E590 notebook computer with a 15.6-inch display; the pressure sensor was placed flush on the tabletop beside the computer. TrackPoint, a miniature isometric joystick embedded in ThinkPad laptops and likewise operated with the index finger, served as the benchmark device, and both the pressure sensor and

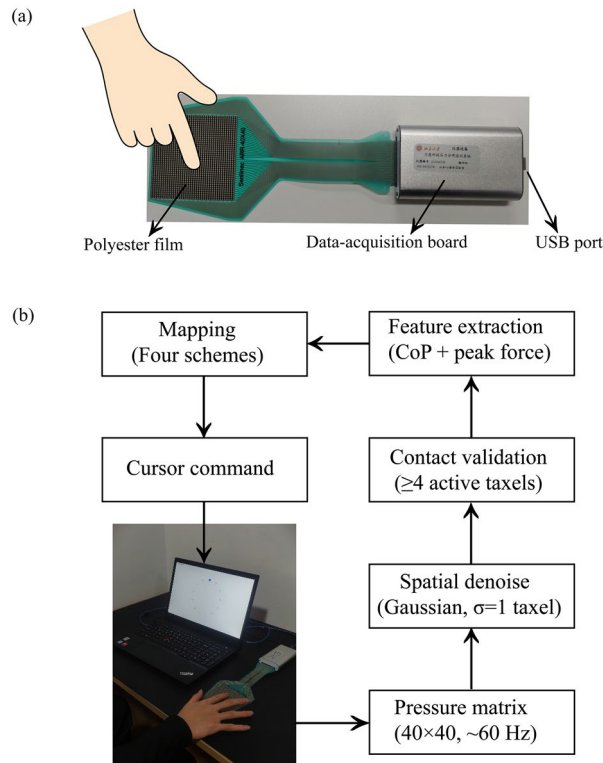


Figure 1. The hardware setup and signal processing. (a) The RPPS-1600 flexible pressure sensor. The picture of the pressure sensor was photographed by the authors. (b) Overview of the hardware setup and signal processing workflow.

TrackPoint were sampled at 60 frames s^{-1} . The experimental pipeline used three software components. A custom Python application continuously read the pressure matrix from the RPPS-1600 board, extracted CoP and peak-force features, and updated the operating-system cursor according to the selected mapping. The ISO 9241-411 pointing task was implemented in MATLAB R2022b with Psychtoolbox. The MATLAB application presented the targets, sampled the resulting cursor position, and stored cursor trajectories and keyboard responses for offline performance analysis. All offline statistical analyses and figure generation were conducted in R 4.2.2.

CoP was estimated for every frame using the weighted centroid of the pressure matrix (Bincalar, Freeman, and Schraefel 2025; Figure 2). The incoming 40×40 matrix was first convolved with a small Gaussian kernel ($\sigma = 1$ taxel) to suppress single-element spikes while preserving pressure gradients. This choice follows common practice in pressure-map preprocessing, which uses small-kernel Gaussian filtering for denoising (Stecher et al. 2024). Values below the noise floor were then masked, and contact was accepted only if at least four contiguous taxels remained active. All preprocessing steps are performed within a frame time and do not add extra latency for cursor control. We selected four contiguous taxels as the minimum-area criterion based on practical observations: the sensor's residual noise after preprocessing typically appears as isolated single-taxel spikes or very small clusters, which are eliminated by requiring a contiguous patch of this size. In contrast, genuine fingertip contact consistently produces an activated region substantially larger than four taxels. Thus, choosing four contiguous taxels as the threshold effectively suppresses noise-induced false contacts while preserving true contacts, without reducing the sensitivity of contact detection. For valid frames,

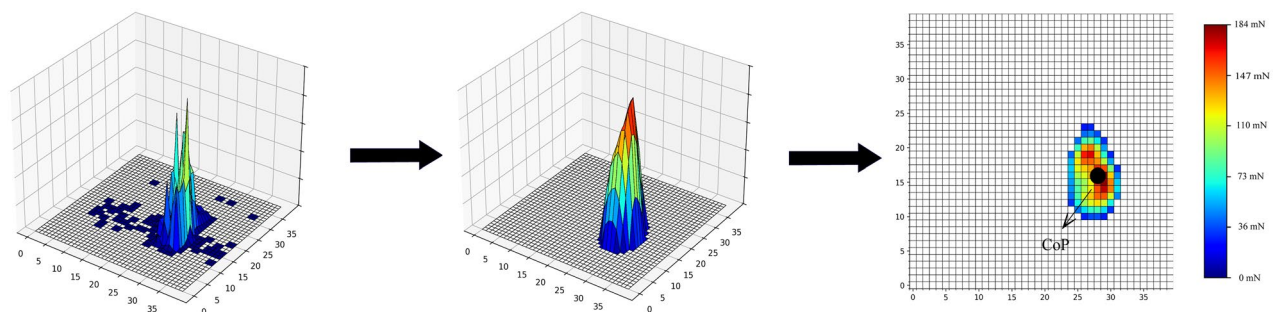


Figure 2. The illustration of data preprocessing to compute the CoP. The numerical colour scale represents the normal force (mN) acting on each taxel. The raw 3-D pressure matrix from the sensor is convolved with a Gaussian kernel, and values below the noise floor are masked. Subsequently, the weighted centroid of the remaining pressure values is computed, yielding the fingertip's instantaneous CoP.

CoP coordinates were calculated as the taxel-weighted sum of Cartesian positions divided by total force:

$$\begin{aligned} COP_x(t) &= \frac{\sum_{i=1}^{40} \sum_{j=1}^{40} x_{i,j} F_{i,j}(t)}{\sum_{i=1}^{40} \sum_{j=1}^{40} F_{i,j}(t)}, \\ COP_y(t) &= \frac{\sum_{i=1}^{40} \sum_{j=1}^{40} y_{i,j} F_{i,j}(t)}{\sum_{i=1}^{40} \sum_{j=1}^{40} F_{i,j}(t)} \end{aligned} \quad (1)$$

2.2. Cursor control design

When users press their index finger against the film, the sensor yields a pressure matrix in each frame, and we extract two signals from it: the peak force vector and the two-dimensional displacement of the CoP. For using a single signal, we designed three mapping schemes to map these two signals to cursor motion, namely Displacement to Displacement (D2D) Mapping, Displacement to Velocity (D2V) Mapping, and Force to Velocity (F2V) Mapping. To explore whether combining kinematic signals and force signals can improve cursor control efficiency, Experiment 2 evaluated a hybrid mapping that combined these two signals. Using a separate group of participants, we compared their

performance to TrackPoint. The details of these mappings are shown below.

2.2.1. Displacement to displacement (D2D) mapping
D2D translates each frame's instantaneous CoP displacement directly into the cursor displacement (Figure 3(a)), without a fixed reference point (Figure 3(b)).

At every frame t , the CoP displacement from the previous frame is computed as Δp_t , a vector $(\Delta x_t, \Delta y_t)$. This vector is multiplied by a gain G_{D2D} to obtain the cursor displacement for this frame, namely $\Delta c_t = G_{D2D} \Delta p_t$.

G_{D2D} nonlinearly depends on the instantaneous cursor speed of the current frame $\|v\|$ (Figure 4(a)). G_{D2D} is a sigmoid function of $\|v\|$: $G_{D2D} = 0.7 + \frac{1}{1 + e^{-k(\|v\| - m)}}$, where k is the slope factor and m is the inflection point (Casiez et al., 2008). In our setup, $k = 4.5$ and $m = 0.5$. Because the fingertip's force envelope against a hard surface is anisotropic (Yokogawa and Hara 2002; their Figure 4), we further scale G_{D2D} by a directional gain factor to compensate for the smaller force envelope in certain directions (Figure 4(b)). The directional gain factor is set at [1.4 1.3 1.2 1.0 0.9 1.0 1.2 1.0] for the directions of [0° 45° 90° 135° 180° 225° 270° 315°], respectively. Periodic cubic spline

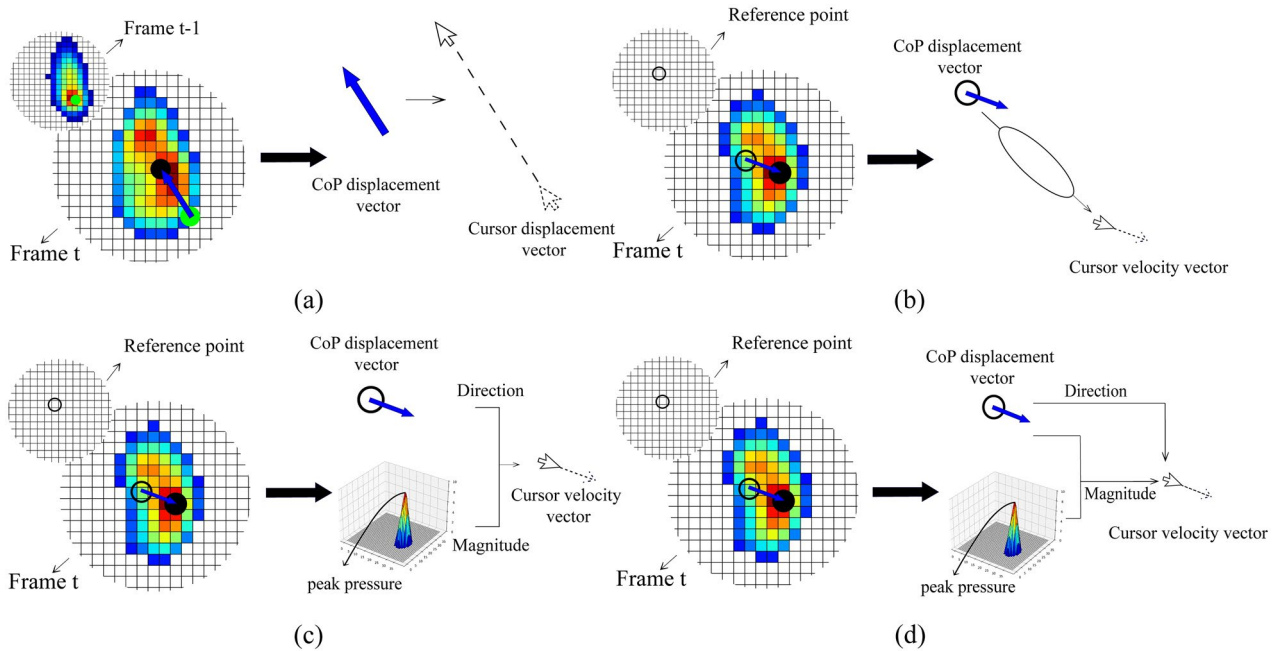


Figure 3. Schematic illustrations of the four mapping schemes. (a) The Displacement to Displacement (D2D) Mapping. The CoP displacement vector is obtained by subtracting the current CoP at frame t from the previous CoP at frame $t-1$. This displacement vector is directly mapped onto the cursor displacement vector by using the gain G_{D2D} . (b) The Displacement to Velocity (D2V) Mapping. The CoP displacement vector is obtained by subtracting the current CoP from the reference point, which is the average CoP during the first 0.5s of contact. This displacement vector is directly mapped onto the cursor velocity vector by using the gain G_{D2V} . (c) The Force to Velocity (F2V) Mapping. The displacement vector, defined the same as in D2V, only determines the cursor's direction; the fingertip's peak force determines the cursor's speed. (d) The Hybrid Mapping. The CoP displacement vector determines the cursor's direction, but the cursor speed is jointly determined by the CoP vector's magnitude and peak force.

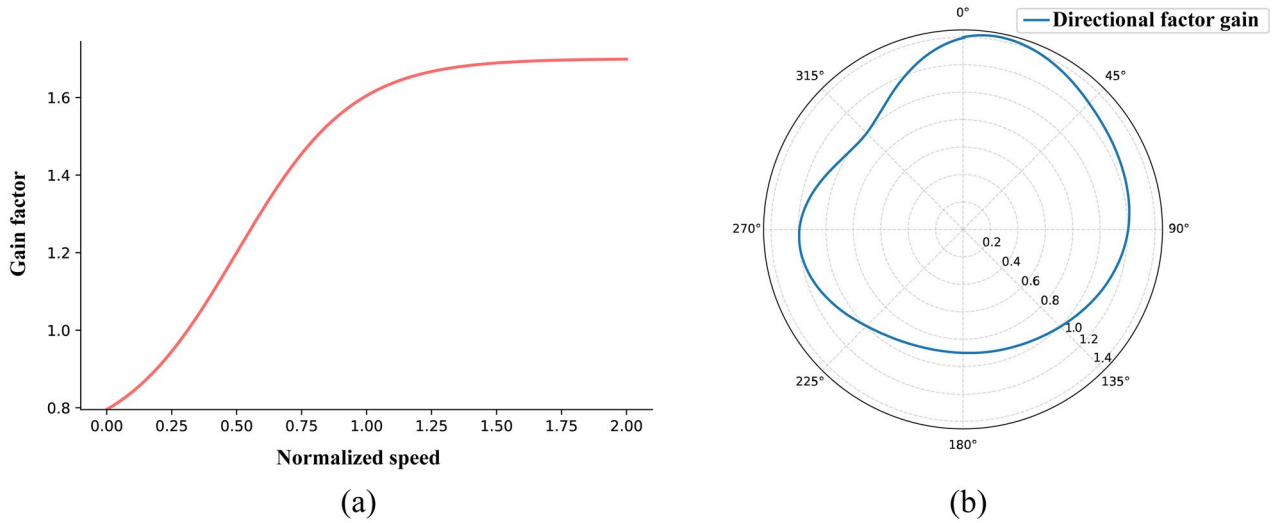


Figure 4. The illustrations of the dependency of the gain G_{D2D} in Displacement to Displacement Mapping. (a) G_{D2D} as a function of cursor speed. (b) The additional multiplicative gain for G_{D2D} as a function of cursor movement directions.

interpolation was used to obtain a smooth gain function in all directions (De Boor and De Boor 1978).

To ensure our system achieves the optimal balance between responsiveness and stability, we use two mechanisms to adjust cursor velocity. The first mechanism is to smooth out the velocity by using the adaptive exponential smoothing filter (Brown 2004) in the form of $v_t = -\alpha_t u_t + (1 - \alpha_t) v_{t-1}$ where v_t is the smoothed velocity of the current frame, u_t is the velocity before applying this filter, v_{t-1} is the smoothed velocity of the previous frame, and α_t is the smoothing coefficient. Instead of using a fixed α , we let it vary with instantaneous acceleration (Equation 2). Our inspiration comes from the 1€Filter (Casiez, Roussel, and Vogel 2012).

$$\alpha = \begin{cases} 0.80, & \|u_t\| < \|v_{t-1}\| \\ 0.52, & \|u_t\| \geq \|v_{t-1}\| \end{cases} \quad (2)$$

Thus, the smoothing is larger when the cursor is decelerating and smaller during acceleration or steady motion.

The second mechanism is to increase cursor velocity when the cursor changes direction (also known as negative inertia boost; Barrett et al. 1995). Essentially, this mechanism briefly adds a small and quickly-fading boost n_t to the current cursor velocity v_t whenever it changes its direction in the form of

$$n_t = \gamma n_{t-1} \left\{ +k \frac{\Delta p_t}{\|\Delta p_t\|} - \frac{\Delta p_{t-1}}{\|\Delta p_{t-1}\|} \right\}, \text{ where } \gamma = 0.75 \text{ and } k = 1.6. \text{ The final cursor velocity is modified as } v_t = v_t + n_t. \text{ This mechanism counteracts lag and helps}$$

the cursor 'pick up' speed when the cursor direction suddenly changes.

2.2.2. Displacement to velocity (D2V) mapping

D2V computes CoP displacement relative to a fixed reference point (Figure 3(b)). The reference point p_0 is defined as the average CoP coordinates recorded during the first 0.5 s of finger contact. For each subsequent frame, the displacement vector is $d_t = p_t - p_0$. The direction of the vector controls that of the cursor, whereas the speed $\|v_t\|$ is proportional to $\|d_t\|$, scaled by a gain G_{D2V} , namely $\|v_t\| = \|d_t\| G_{D2V}$.

G_{D2V} also depends on cursor speed and direction as G_{D2D} (Figure 4). Besides, we defined a dead zone around the p_0 to prevent jittering when the finger is idle: if the CoP's normalised displacement d_t from p_0 is below a threshold r , the system holds the cursor still by multiplying G_{D2V} with an on-and-off gain g_z :

$$g_z = \begin{cases} 0, & \|d_t\| < r \\ 1, & \|d_t\| \geq r \end{cases} \quad (3)$$

The adaptive exponential smoothing filter and the negative inertia boost are also applied identically as D2V.

2.2.3. Force to velocity (F2V) mapping

F2V scales cursor speed directly with the peak force P_t of the pressure matrix (Figure 3(c)). As in D2V, the cursor direction is also determined by the displacement of the CoP from p_0 , but its speed is determined by $\|v_t\| = P_t G_{F2V} \cdot G_{D2V}$ shares the same nonlinear gain

function, directional gain factors, and deadzone as G_{D2V} . The adaptive exponential smoothing and the negative inertia boost are again employed to condition cursor velocity.

2.2.4. Hybrid mapping

Hybrid Mapping combines force signals and kinematic signals to jointly control the cursor (Figure 3(d)).

The magnitude of the displacement vector $\|d_t\|$ from D2V and the peak force P_t from F2V now jointly determine cursor speed, as $\|v_t\| = \|d_t\| P_t G_{Hybrid}$. The gain G_{Hybrid} inherits the nonlinear function, the directional gain factor, and the dead zone used in D2V and F2V. As before, the cursor speed is modulated by the adaptive exponential smoothing filter and the negative inertia boost.

Conceptually, the four mappings imply different user strategies and control demands. D2D implements position control: small fingertip deflections produce immediate CoP shifts that translate directly into cursor displacement, similar in principle to a mouse or touchpad. However, because the finger cannot slide and the available deflection workspace is small, even minimal deflections can yield large cursor motions, placing high demands on precise postural control; movement can be fast but harder to stop accurately, often requiring iterative corrective adjustments. D2V is better viewed as joystick-like rate control: users first hold a stable press to establish a reference point, then steer by maintaining a CoP bias – direction follows the bias and speed increases with its magnitude – yielding higher stability but a limited speed range due to the constrained CoP excursion. F2V adopts the TrackPoint-like strategy of rate control with force-based speed modulation: direction is still set by CoP bias, but speed scales with peak force, which can vary over a wider range than CoP and thus supports higher speeds than D2V, albeit with reduced stability because fingertip force is less steady. Hybrid retains CoP-based steering after reference-point establishment while allowing speed to be increased via either greater force or larger CoP bias, expanding the controllable speed range while preserving the stability advantages of D2V.

2.3. Experiments

We assessed the performance of the mapping schemes with the ISO 9241-411 multi-directional pointing task and subjective questionnaires in two separate experiments. Experiment 1 compared three mapping schemes that use only one type of information to identify the best control mode. Experiment 2

evaluated whether the Hybrid mapping improves performance and benchmarked it against a commercially available TrackPoint.

2.3.1. Participants

Twelve healthy participants (5 females) took part in Experiment 1. Their ages ranged from 19 to 25 ($M=21.2$, $SD = 2.2$). All reported full (corrected) vision and no history of neuromuscular disorders. All participants self-identified as right-handed. When using our device, the mean and maximum forces across participants are 2.58 N (0.77 N²) and 3.76 N (0.54 N²), respectively. The numbers in the parentheses are the variance across participants. Before data collection, they received a brief demonstration of the task. Each participant took 70 to 80 minutes to complete all trials. Experiment 2 recruited a new group of 12 participants (8 females) with the same inclusion criteria. Their ages ranged from 18 to 23 ($M=21.4$, $SD = 1.3$). None of them had prior experience with our system and TrackPoint. Each participant took 50 to 60 minutes to complete all trials.

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board of the School of Psychological and Cognitive Sciences at Peking University. All participants provided written informed consent before participation and received 60 yuan for their time.

2.3.2. Experimental task

The multi-direction pointing task follows the ISO 9241-411 ergonomics standard for non-keyboard input devices (Fitts 1954; MacKenzie and Buxton, 1992; MacKenzie, Kauppinen, and Silfverberg 2001; Soukoreff and MacKenzie 2004) and is widely used to benchmark various pointing devices (Bækgaard et al. 2019; Burno et al. 2015; Douglas, Kirkpatrick, and MacKenzie 1999; Hansen et al. 2018; Roig-Maimó et al. 2018; Sanchez et al. 2021; Teather and Stuerzlinger 2011; Thomas 2018; Thushara, Adithya, and Sreekanth 2025; Van Zon et al. 2020; Weiss et al. 2024; Zhang et al. 2007). The task requires the participant to move the cursor as quickly and accurately as possible between 13 circular targets on an invisible ring and separately by an equal angular interval (movement amplitude $A=300$ or 700 px; target width $W=45$ or 80 px). Each new target appeared diametrically opposite to the last, creating 12 alternating movements per sequence (Figure 5(b)). One sequence only involves one target type, and we have four target types (W80A300, W80A700, W45A300, W45A700). Each target type corresponds to an index of difficulty ($ID = 2.07, 3.12, 3.17,$

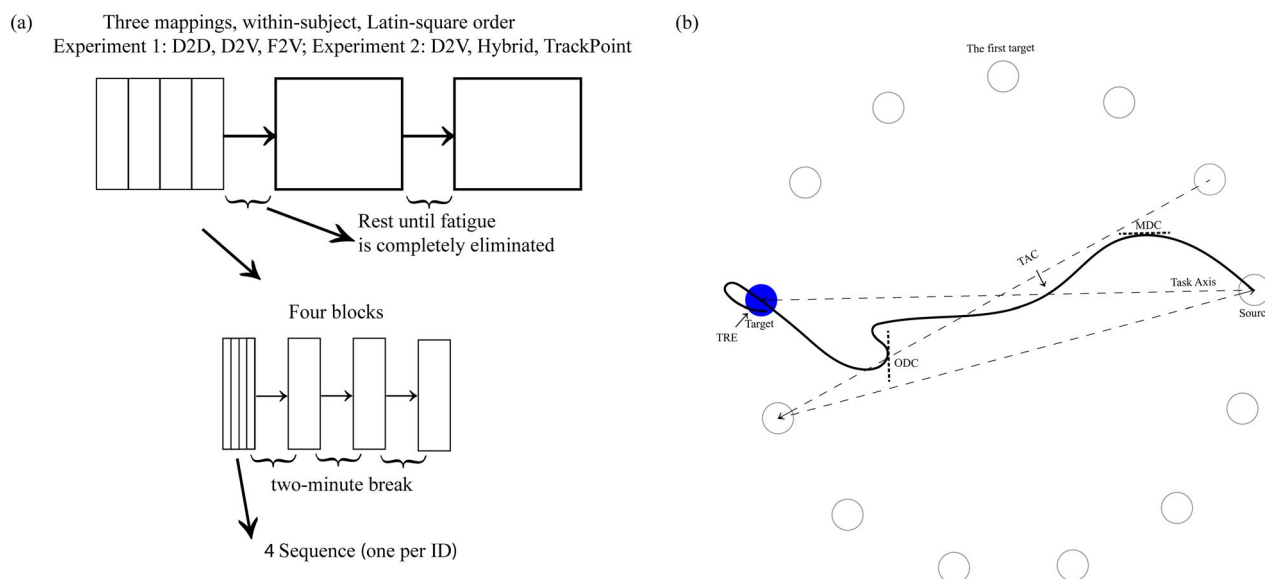


Figure 5. (a) Experiment design. (b) Schematic illustrations of the multi-direction pointing task used in Experiments 1 and 2. The solid black curve shows a representative cursor trajectory. Target re-entry (TRE) represents how many times, after the first entry, the cursor re-enters the target; movement direction change (MDC) represents the number of times the cursor path changes direction parallel to the task axis; orthogonal direction change (ODC) represents the number of times the cursor path changes direction perpendicular to the task axis; task axis crossing (TAC) represents the number of cursor crossing of the ideal movement trajectory. The lower the number of these four variables, the smoother and thus better the cursor movement.

and 4.13, respectively) according to Fitts' law. The four A-W combinations spanned low, intermediate, and high nominal difficulty levels. The two intermediate conditions, W80A700 and W45A300, had similar nominal IDs (3.12 and 3.17).

We also collected subjective comfort ratings. The questionnaire conformed to ISO 9241-411 and was similar to the instruments used in earlier device-evaluation studies (Douglas, Kirkpatrick, and MacKenzie 1999; Herring, Trejo, and Hallbeck 2010; Roig-Maimó et al. 2018; Thushara, Adithya, and Sreekanth 2025; Widodo et al. 2019). It comprised 12 statements, scored on a 7-point Likert scale (1 = 'very low satisfaction', 7 = 'very high satisfaction'). The items cover both performance-related and ergonomic dimensions. Performance-related items include the force required to engage the cursor, the perceived smoothness of pointer motion, and satisfaction with pointing speed. Ergonomic items are designed to reduce fatigue in the fingers, wrist, arm, shoulder, and neck after prolonged use.

Before formal data collection, the experimenter explained and demonstrated each mapping to ensure participants had a rudimentary understanding of the basic control rules. For example, the brief instruction for F2V was: 'press your index finger in the direction you want the cursor to move; pressing harder makes it move faster.' To ensure comparable familiarity and comfort across devices, before each

condition (including TrackPoint in Experiment 2), participants were given 1 min of practice and could freely adjust the control gain (cursor sensitivity) to their preferred setting; TrackPoint sensitivity was initialised from the ThinkPad factory default before this adjustment. The order of mappings was counterbalanced across participants with a Latin square to minimise practice and order effects. Each participant completed four blocks of trials for every mapping. Each block contained four pointing sequences, one per ID condition. The sequence order was randomised within the block.

At the start of a sequence, the screen displayed the sequence number together with the target width (W) and movement amplitude (A). Participants pressed the spacebar to initiate the sequence and again to indicate they reached the target as soon as possible. A successful hit turned the blue solid target grey and hollow. The next target appeared diametrically opposite to the previous one after 50 ms. The opposing target pairs rotated clockwise until all the targets were reached, yielding twelve pointing movements. If the spacebar was pressed while the cursor lay outside the target, the movement was logged as an error, and the circle flashed solid red for 30 ms, then grey for 20 ms to inform the participant. Participants did not need to correct errors but moved directly to the next target. When the thirteenth click was registered, a message on the screen indicated the end of the sequence, and

participants were free to press the spacebar to advance to the next sequence. A mandatory two-minute break was inserted between blocks to minimise fatigue. In addition, between mapping conditions, participants rested until they reported that any fatigue had fully dissipated, with a minimum rest duration of 5 min. Participants were explicitly encouraged to request extra rest whenever needed. Custom software recorded target parameters, timestamps of all events, and full cursor trajectories for offline analysis. After completing the pointing task, participants filled in the subjective questionnaire, which was exported to an Excel spreadsheet for processing. The pointing task was conducted on a Lenovo ThinkPad E590 notebook computer equipped with a 15.6-inch display. Both the pressure sensor and the TrackPoint were sampled at 60 frames s^{-1} . The pressure sensor lay flush on the tabletop beside the computer.

Experiment 1 employed a 3 (mapping conditions) $\times$ 4 (ID conditions) within-subjects design to compare participants' pointing performance across the three mappings. Experiment 2 used the same 3 $\times$ 4 design, but the mappings included D2V (the best mapping scheme identified in Experiment 1), Hybrid, and TrackPoint. The full experimental design, including the mapping conditions, ID conditions, blocks, and counterbalancing procedure, is summarised in Figure 5(a). The TrackPoint is a miniature isometric joystick embedded in Lenovo ThinkPad laptops and is likewise operated with the index finger (Sutter and Ziefle 2005).

2.4. Data analysis

In the multi-direction pointing task, we used movement time (MT) to evaluate speed. For overall efficiency, we used throughput (TP), the effective information transmitted per unit time ($bits s^{-1}$) where $TP = \frac{ID_e}{MT}$ and $ID_e = \log_2 \left(1 + \frac{A_e}{w_e} \right)$. In practical terms, TP indicates that the device enables genuinely usable pointing performance (beyond proof of concept), with higher TP reflecting more efficient real-world target acquisition through the combined effects of speed and accuracy. ID_e reflects the effective difficulty the users experienced. The effective movement amplitude A_e is the average distance the cursor travels from the start point to the position at which selection occurs, computed for each ID condition separately. The effective target width follows $w_e = 4.133 * SD_x$ where SD_x is the standard deviation of the horizontal deviation of all the pointing movements, computed for each ID

separately. We computed the mean MT across all the correct trials within a sequence to calculate TP.

We used four metrics suggested by MacKenzie, Kauppinen, and Silfverberg (2001) to evaluate trajectory smoothness. Target re-entries (TRE) represents how many times, after first entry, the cursor re-enters the target; movement direction change (MDC) represents the number of times the cursor path changes direction parallel to the task axis; orthogonal direction change (ODC) represents the number of times the cursor path changes direction perpendicular to the task axis; task axis crossing (TAC) represents the number of cursor crossing of the ideal movement trajectory (Figure 5). The lower these metrics are, the smoother the trajectory is.

All analyses were conducted in R 4.2.2. One-way repeated-measures ANOVA was used to compare mappings. To explore the effect of ID, we performed separate one-way repeated-measures ANOVAs across the four ID conditions within each mapping. Tukey post-hoc tests were conducted if the main effect was significant. Besides, in order to evaluate the learning pattern during our experiment, we fitted a Wright Learning Curve (WLC) model to MT data for each mapping condition. In this model, $R_n = R_1 n^b$, where R_n is the mean time on the n -th block, R_1 is the mean time on the first block, and b is the learning rate. b ranges from 0 to -1 ; more negative exponents indicate faster learning (Jaber 2016). This learning analysis is exploratory and based on a limited number of blocks, so the overinterpretation of the fitted learning parameters should be avoided. The results of subjective questionnaires were descriptively summarised with a radar plot.

3. Results

3.1. Experiment 1

3.1.1. Movement time (MT) and throughput (TP)

Overall, MT and TP showed that D2V performed the best and D2D performed the worst. MT was 4645 ± 295 (SEM), 5862 ± 321 , and 6693 ± 480 ms for D2V, F2V, and D2D, respectively. A one-way repeated-measures ANOVA revealed a significant main effect of mapping (Figure 6(a); $F(2, 22) = 9.573$, $p = .001$). Tukey post-hoc comparisons showed that D2V had lower MT than both D2D and F2V ($ps < .05$), whereas the difference between D2D and F2V was not significant ($p = .204$). TP exhibited the same effects as MT: it was 0.546 ± 0.036 (SEM), 0.580 ± 0.033 , and 0.714 ± 0.030 for D2D, F2V, and D2V, respectively. A one-way repeated-measures ANOVA revealed a significant main effect of mapping on TP (Figure 6(b); $F(2, 22) = 8.347$, $p = .002$). Tukey post-hoc

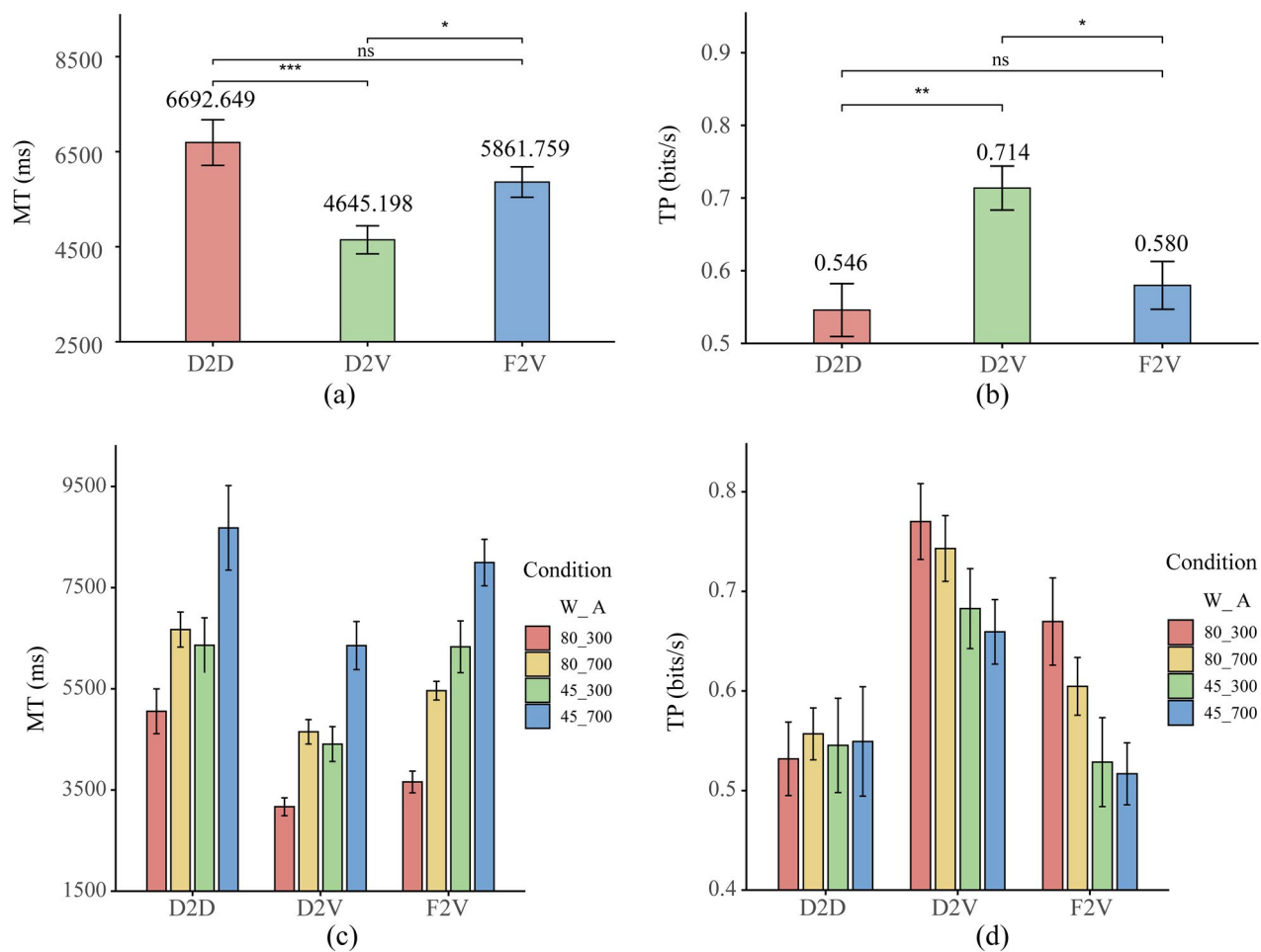


Figure 6. Movement time and throughput for the three mapping conditions. Error bars represent ± 1 standard error of the mean (SEM) across participants; numbers above the bars give the corresponding condition averages. Horizontal brackets indicate Tukey post-hoc pairwise comparisons ($***p < .001$, $**p < .01$, $*p < .05$, ns = not significant). (a) Movement time (MT) as a function of mapping. (b) Throughput (TP) as a function of mapping. (c) MT as a function of ID, plotted separately for each mapping. (d) TP as a function of ID, plotted separately for each mapping.

comparisons showed that D2V had higher TP than both D2D and F2V ($ps < .05$), whereas the difference between D2D and F2V was not significant ($p = .716$).

We ran separate one-way repeated-measures ANOVAs to compare ID conditions within each mapping condition. For all mappings, ID had a similar influence on MT. All three separate one-way ANOVAs yielded a significant main effect of ID ($ps < .01$), and Tukey post-hoc tests confirmed the overall trend that as the ID increased, their MT significantly increased (Figure 6(c)). The corresponding TP-by-ID results are shown in Figure 6(d); TP tended to decrease with increasing ID for D2V and F2V, whereas D2D showed little change across ID levels.

3.1.2. Trajectory smoothness metrics

Overall, D2V had the smoothest trajectory with the smallest TRE, TAC, MDC, and ODC. F2V had the highest TRE while D2D had the highest TAC, MDC, and ODC. TRE counts, indicating movement corrections near the target,

varied significantly across the three mappings (Figure 7; $F(2, 22) = 4.245$, $p = .028$). Tukey post-hoc comparisons showed that F2V had higher TRE than D2V ($p = .021$), whereas the differences between the other pairs were not significant. MDC, ODC, and TAC collectively indicate the number of corrections during the overall pointing movements. For all three measures, D2V performed the best, and D2D performed the worst (Figure 7).

3.1.3. Learning rate and subjective evaluation

We found that our naive participants improved their performance over the four consecutive blocks of trials (Figure 8(a)). We fitted a Wright Learning Curve (WLC) model to MT data for each mapping condition. The fitted exponents were: $b = -0.354 \pm 0.064$ (95% CI), -0.164 ± 0.103 , and -0.155 ± 0.026 for D2D, F2V, and D2V, respectively. Our data showed that people improved 39.1%, 20.7%, and 20.2% for D2D, F2V, and D2V, respectively, in merely four blocks of trials.

The results of the subjective questionnaire are shown in Figure 8(b). D2V received the highest scores on every dimension and the highest overall preference, followed by F2V; D2D was rated lowest across the board. The ranking of these subjective ratings

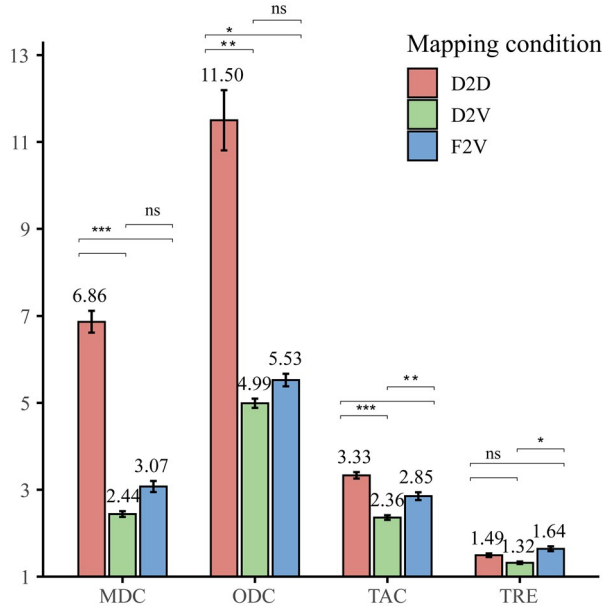


Figure 7. Trajectory smoothness metrics for the three mappings. Higher values indicate less smooth cursor paths. Error bars indicate ± 1 standard error of the mean (SEM) across participants; numbers above the bars give the corresponding condition means. Horizontal brackets show Tukey post-hoc pairwise comparisons (** $p < .001$, ** $p < .01$, * $p < .05$, ns=not significant).

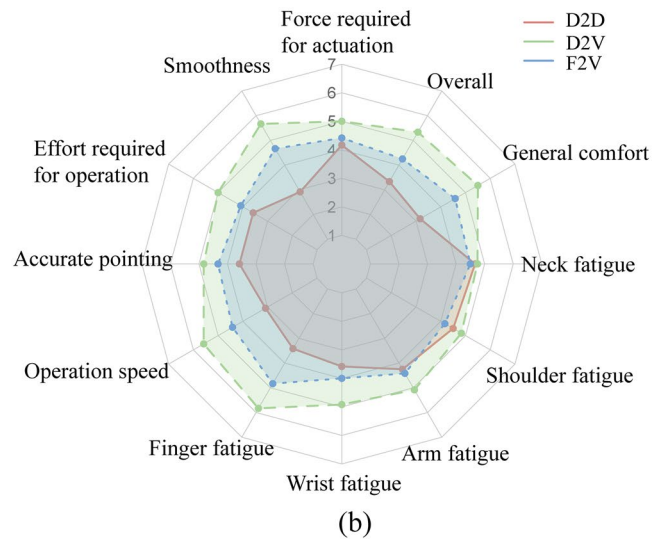
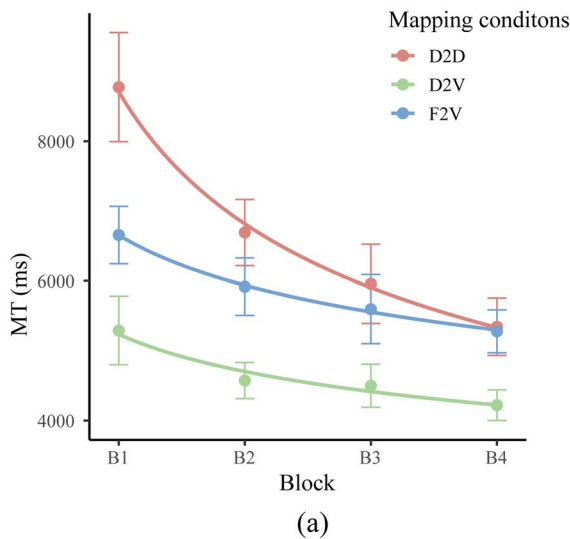


Figure 8. Learning rate and subjective evaluation of the three mappings. (a) Learning curves based on movement time across the four experimental blocks (B1 – B4). Error bars show block means and their standard error (SEM) across participants. Solid lines depict the fitted power-law functions. (b) Radar chart of average Likert ratings for the twelve usability and fatigue items. Higher scores indicate more favourable judgments.

across mappings matched their rankings based on objective performance.

3.2. Experiment 2

3.2.1. Movement time (MT) and throughput (TP)

Overall, MT and TP showed that Hybrid outperformed D2V, but did not match TrackPoint's performance. MT was 2633 ± 119 , 4065 ± 283 , and 4811 ± 334 ms for TrackPoint, Hybrid, and D2V, respectively (Figure 9(a)). A one-way repeated-measures ANOVA confirmed the main effect of mapping on MT ($F(2, 22) = 30.51$, $p < .001$). Tukey post-hoc tests showed that Hybrid had significantly smaller MT than D2V, but both Hybrid and D2V had longer MT than TrackPoint ($ps < .05$). TP showed the same effect of mapping: it was 0.703 ± 0.050 , 0.840 ± 0.053 , and 1.336 ± 0.057 bit s^{-1} for D2V, Hybrid, and TrackPoint, respectively (Figure 9(b)). A one-way repeated-measures ANOVA revealed a significant main effect of mapping ($F(2, 22) = 81.12$, $p < .001$). Tukey post-hoc comparisons showed that the Hybrid had significantly larger TP than D2V, but both Hybrid and D2V had significantly smaller TP than TrackPoint ($ps < .05$).

We ran separate one-way repeated-measures ANOVAs for comparing ID conditions within each mapping. We found significant main effects of ID in all three cases ($ps < .01$). Tukey post-hoc tests confirmed the overall trend that MT increased with higher ID values in most cases (Figure 9(c); all $ps < .05$). The corresponding TP-by-ID results are shown in Figure 9(d); TP

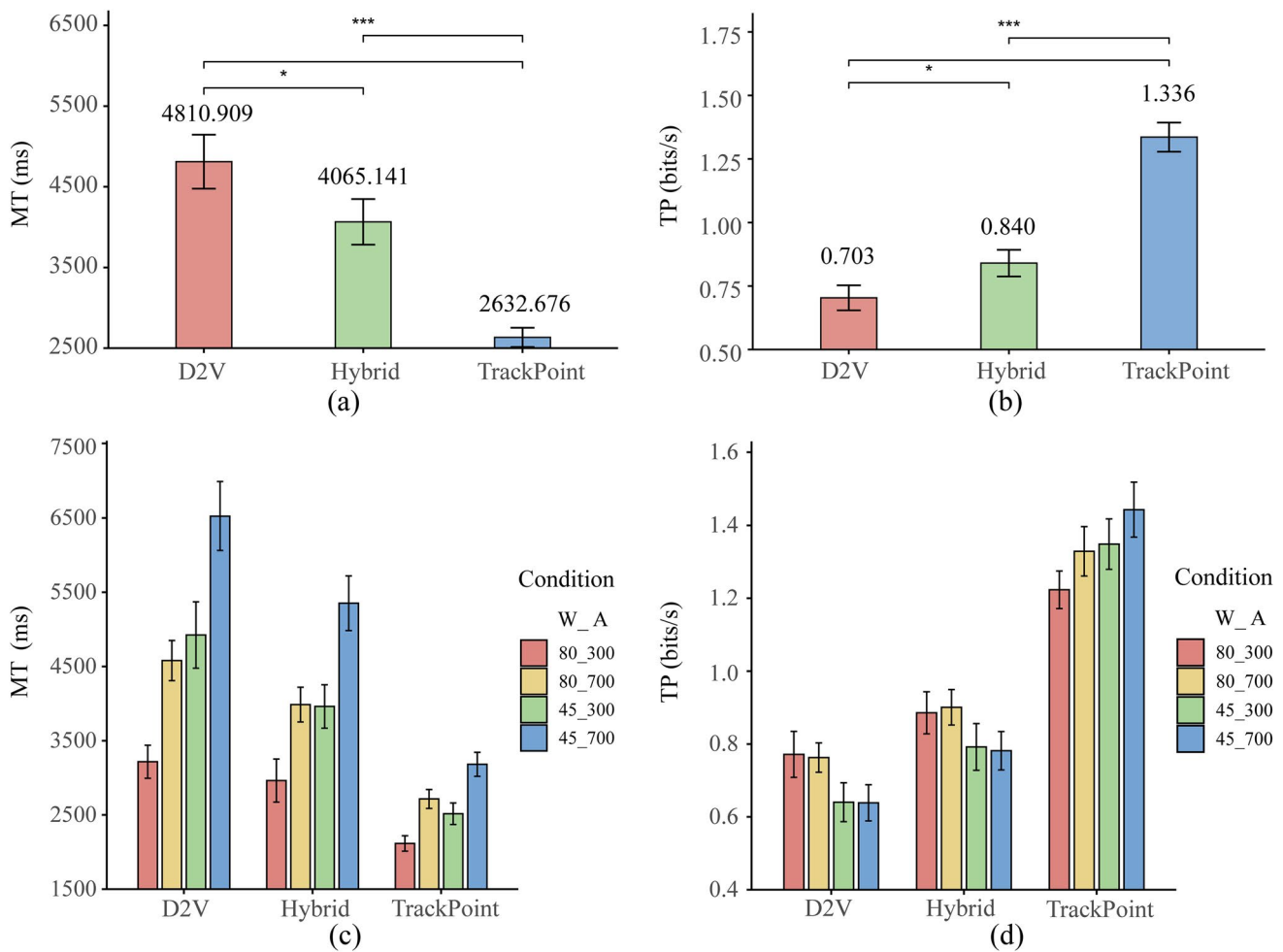


Figure 9. Movement time and throughput for the three mapping conditions. Error bars represent ± 1 standard error of the mean (SEM) across participants; numbers above the bars give the corresponding condition average. Horizontal brackets indicate Tukey post-hoc pairwise comparisons (*** $p < .001$, ** $p < .01$, * $p < .05$, ns = not significant). (a) Movement time (MT) as a function of mapping. (b) Throughput (TP) as a function of mapping. (c) MT as a function of ID, plotted separately for each mapping. (d) TP as a function of ID, plotted separately for each mapping.

decreased with increasing ID for D2V and Hybrid, whereas TrackPoint showed the opposite pattern.

3.2.2. Trajectory smoothness

Overall, TrackPoint had larger TRE, TAC, MDC, and ODC than both D2V and Hybrid, indicating a less smooth trajectory (Figure 10; $ps < .05$). Hybrid and D2V did not differ from each other on any of these metrics. Thus, Hybrid mapping improved its movement time and throughput over D2V, but not for trajectory smoothness.

3.2.3. Learning rate and subjective evaluation

Similar to Experiment 1, we found that our naive participants improved their performance across the four consecutive blocks of trials (Figure 11(a)) and fitted Wright's Learning Curve (WLC) model to the MT data for each mapping condition. The fitted exponents were: $b = -0.205 \pm 0.049$ (95% CI), -0.100 ± 0.200 , and

-0.155 ± 0.061 for TrackPoint, Hybrid, and D2V, respectively. Thus, the learning rate did not differ between maps. Our data showed that people improved 24.2%, 14.6%, and 12.2% for TrackPoint, Hybrid, and D2V, respectively, in merely four blocks of trials.

The results of the subjective questionnaire are shown in Figure 11(b). Hybrid was judged marginally better than D2V on most items, and TrackPoint received the most favourable scores on nearly every dimension. The ranking of these subjective ratings across mappings matched their rankings based on objective performance.

4. Discussion

In this study, we developed an efficient cursor control system based on fingertip pressure distributions and showed that combining kinematic and force

information can enhance cursor control performance. Across several mapping schemes, the hybrid mapping that used both the CoP displacement vector and peak force to drive cursor velocity yielded the best performance on the standard Fitts' task as well as on subjective ratings. This hybrid mapping achieved approximately 63% ($0.840 \text{ bit s}^{-1}/1.336 \text{ bit s}^{-1}$) of the

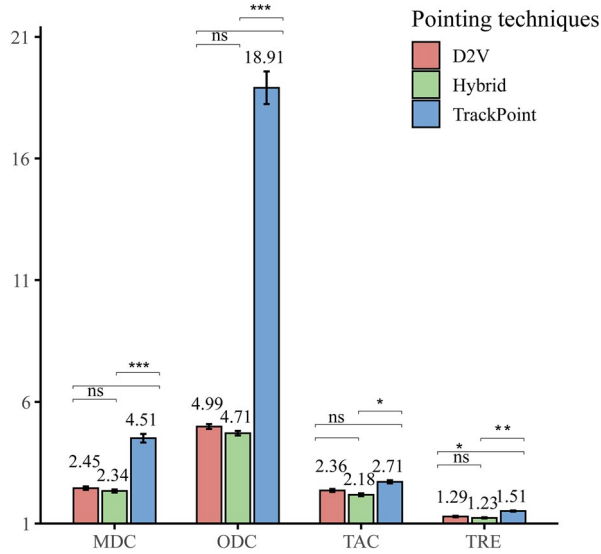


Figure 10. Trajectory smoothness metrics for the three mappings. Higher values indicate less smooth cursor paths. Error bars indicate ± 1 standard error of the mean (SEM) across participants; numbers above the bars represent the corresponding condition means. Horizontal brackets represent Tukey post-hoc pairwise comparisons (** $p < .001$, * $p < .01$, * $p < .05$, ns = not significant).

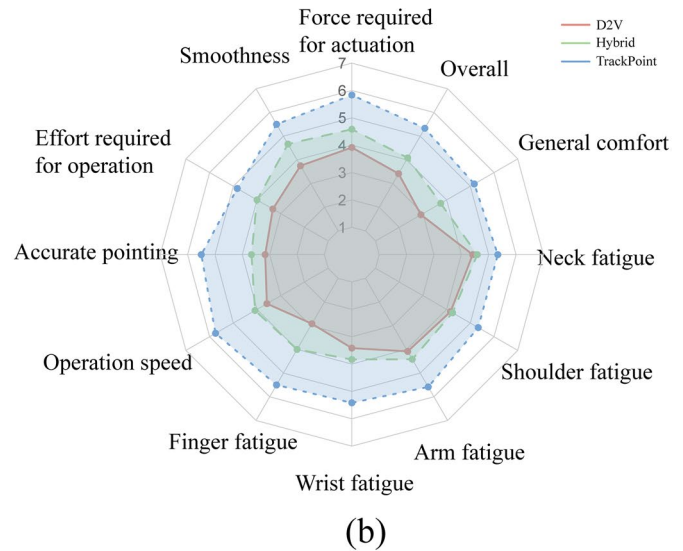
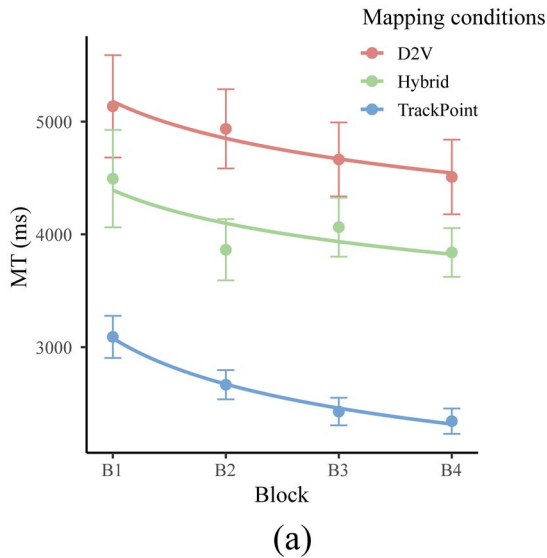


Figure 11. Learning rate and subjective evaluation for the three mappings. (a) Learning curves based on movement time across the four experimental blocks (B1 – B4). Error bars show block means and their standard error (SEM) across participants. Solid lines depict the fitted power-law functions. (b) Radar chart of average Likert ratings for the twelve usability and fatigue items. Higher scores indicate more favourable judgments.

throughput of TrackPoint, a commercial cursor control device that similarly relies on finger force input, while outperforming it for trajectory smoothness.

Our comparative analysis of mappings based on a single signal type indicated that cursor control efficiency, from highest to lowest, was D2V, F2V, and D2D. The D2D mapping, which translated CoP displacement directly into cursor displacement, produced the poorest performance. This likely reflects the limited CoP movement range that can be registered at the fingertip: D2D must map a relatively small area onto the entire display, which constrains efficiency. The D2V mapping, which translated the CoP displacement vector into velocity, was more efficient than the F2V mapping, which mapped the force vector to velocity. We suggest that this advantage arises because precisely controlling force magnitude and direction is challenging, whereas people may have ample experience with cursor velocity control from using a regular mouse.

In line with our initial hypothesis, we found that combining kinematic and force information enhanced the throughput of our finger pressure-based cursor control system compared with mappings that relied on either kinematic or force signals alone. Previous work has extensively explored the use of force and haptic feedback to improve joystick performance (Giri, Bloom, and Morimoto 2023; Meera et al., 2020; Oh, Kim, and Hong 2014; Weber et al. 2020), but attempts to integrate force signals as a continuous cursor-control input remain rare. In our system, force information proved essential because participants were unable to

slide their fingers across the sensor surface. When participants pressed the flexible film to move the cursor, the CoP exhibited a very limited range of motion: across all participants, the maximum CoP displacement relative to the reference point during the task did not exceed 1 cm. As shown in Experiment 1, this restricted kinematic workspace hindered fast and accurate cursor control across the screen. This limitation was substantially mitigated in Experiment 2 when we added peak force as an additional input: peak force scaled cursor speed, and this velocity-based control increased throughput by approximately 20% (Figure 9(b)). Moreover, participants learned this seemingly complex mapping rapidly (Figure 11(a)), possibly because human motor control is often characterised by a strong scaling effect between control signals (e.g., muscle activity) and movement speed (Brown and Cooke 1981; Buneo, Soechting, and Flanders 1994). This natural scaling likely made the integration of force with kinematic information intuitive for our novice users.

Participants quickly reached the plateau stage of the learning curve when using the hybrid mapping, indicating that they mastered this complex mapping without extensive practice. Interestingly, the perception of force beneath the fingertip is limited in accuracy because tactile and proprioceptive feedback are imprecise for the actor (Birznieks et al. 2001; Fuentes and Bastian 2010; Tong, Mao, and Goldreich 2013). Why, then, did our naive users achieve decent performance in a precise pointing task by using fingertip pressure distribution? We postulate that visual augmentation of pressure signals underlies help overcomes the sensory limitations: in tasks such as Fitts' task tested here, the large visual display magnifies any motor error during cursor manoeuvre, and researchers have consistently demonstrated that the motor system can achieve superior movement precision with visual amplification (Bohan et al. 2010; Ma and Fei 2021; Sharp, Huang, and Patton 2011; Sung and O'Malley 2011; Yan et al. 2023; Yejun Wei et al., 2005). For example, when using the Hybrid Mapping, a mere 1 mm extra CoP shift can result in an additional cursor motion up to 13 cm per second, providing users with amplified visual feedback for minimal fingertip motion. Furthermore, we introduced two novel control algorithms to facilitate cursor control: a variable directional gain factor to compensate for the anisotropy of fingertip motion, and an adaptive exponential smoothing filter to balance jitter suppression and control latency. Together with visual amplification, these algorithmic improvements enable our system to function efficiently without extensive training.

The aim of using fingertip pressure distribution for pointing is to enable human-computer interaction in extreme or physically restricted settings, such as extra-vehicular activity performed by astronauts wearing pressurised suits and gloves, or surgery performed by surgeons operating in sterile clothing. Conventional pointing devices, such as mice and trackpads, perform well in ideal conditions but are impractical when the user's range of motion is constrained (Welsh and Akin 2001). TrackPoint, although compact, is a rigid protrusion that cannot be comfortably embedded in a limited space such as a glove. Unconventional means of cursor control, including BCIs, gaze-based cursor control, head-movement tracking, and hand gesture recognition, are excellent solutions for certain specific environments or populations, but not for extreme environments with spatial limitations for device mounting (Edelman et al. 2025; Fu and Huang 2007; Grif and Farcas 2016; Kreiling et al. 2011; Majaranta and Bulling 2014; Thushara, Adithya, and Sreekanth 2025; Widodo et al. 2019; Wolpaw et al. 1991; Zhang et al. 2020; Zhang et al. 2007). Our system offers a viable solution for cursor control in the aforementioned extreme situations: it requires users to press their index finger against a thin pressure film that can be flexibly installed in a limited space. Potentially, the film can be bent and cut into various shapes without compromising performance (Layard Horsfall et al. 2023; Li et al. 2025; Tai et al. 2022; Xu et al. 2024), making it versatile for many situations beyond the test conditions evaluated here. For example, in a fast-moving vehicle with unpredictable mechanical perturbations, our system may still function as the pressure signals collected from a non-moving finger (pressing against its contact surface mounted with a sensing film) are relatively immune to external disturbances. Moreover, although our device did not match the TrackPoint's efficiency, it produced smoother trajectories. We attribute this difference to two factors. First, the TrackPoint operates on a force-vector input and maps it directly to cursor velocity; because fingertip force output is inherently more variable, this control mode is prone to increased submovements and jitter, which can degrade trajectory smoothness. This interpretation is consistent with our findings that although both D2V and F2V employ rate control, the force-driven mapping (F2V) exhibited poorer stability (Figure 7). Second, these results underscore a fundamental speed-stability trade-off rather than a simple ranking of devices: while force-based velocity control can enable higher cursor speeds, it may do so at the expense of smoothness and steadiness, and in application contexts where precise and stable control is critical, stability may be preferred over maximum efficiency.

Despite encouraging results, our study has several limitations that require further investigation. First, although our system achieved smoother trajectories than TrackPoint, its movement time was longer. One route to improve is to increase the gain (e.g., the gain mapping from peak force to cursor velocity), which can effectively reduce MT and increase overall throughput. However, such an adjustment would require simultaneous adjustments of jitter control and end-of-movement braking. These algorithmic fine-tunings should be systematically investigated in future studies following our initial endeavours here. Second, previous studies indicate that the effector size, such as hand size, can influence pointing performance (Umami, Zannah, and Lumintu 2019). Finger size, undoubtedly, would also affect the efficiency of using our system, and our current algorithms do not yet account for differences in finger size among individuals. A further limitation is that both experiments tested young adults only; therefore, the present data do not establish how the system would perform across broader and more diverse age groups. The optimised parameters reported here may not be directly applicable to children, older adults, or users with reduced tactile sensitivity, hand strength, or fine motor control. Although the hybrid mapping may remain advantageous because it combines CoP displacement with peak force rather than relying on a single input signal, this possibility requires direct empirical testing. Future work should therefore test age-diverse samples and examine whether gain calibration, dead-zone thresholds, or force-scaling parameters need to be adapted for different user groups. Lastly, as a proof of concept, the present evaluation used a flexible film mounted flush on a tabletop and was laboratory-based. The real-world deployments may introduce additional constraints not captured here. We need to demonstrate its usability, robustness, and performance in its intended extreme environments, e.g., fitting the film into tight gloves or clothing, and in dynamic, vibrating environments such as fast-moving vehicles.

5. Conclusion

This study proposed a flexible pressure-sensor-based cursor control system for space-constrained interaction where hand motion is limited. In contrast to most pressure-based HCI approaches that use pressure distributions primarily for discrete inputs or gesture classification, it demonstrates that fingertip pressure distributions can support continuous control (e.g.,

cursor pointing) and that combining the distributions' force and kinematic signals yields a substantial performance benefit when used as a pointing-device input. Across two multi-directional pointing experiments, the combination of force and kinematic signals yielded better performance than using either signal alone. Although the combined approach did not reach the throughput of the commercial benchmark TrackPoint, it produced smoother cursor trajectories, suggesting a speed–stability trade-off in which stability may be prioritised over speed. Overall, these findings establish flexible pressure films as a viable pointing modality in constrained settings and highlight the practical advantage of combining force and kinematic signals for continuous cursor control. Further studies of implementing our pressure cursor methodology in space-constrained environments are warranted.

Author contributions

CRediT: **Mingjie Qu:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Kunlin Wei:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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ORCID

Kunlin Wei  <http://orcid.org/0000-0001-5098-3808>

Data availability statement

Data will be made available on request.

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