

"Who's Minding the Store?" starring Jerry Lewis



Investigating the Dexterity of Multi-Finger Input for Mid-Air Text Entry

Srinath Sridhar¹

Anna Maria Feit²

Christian Theobalt¹

Antti Oulasvirta²

¹  ²
max planck institut
informatik

A!

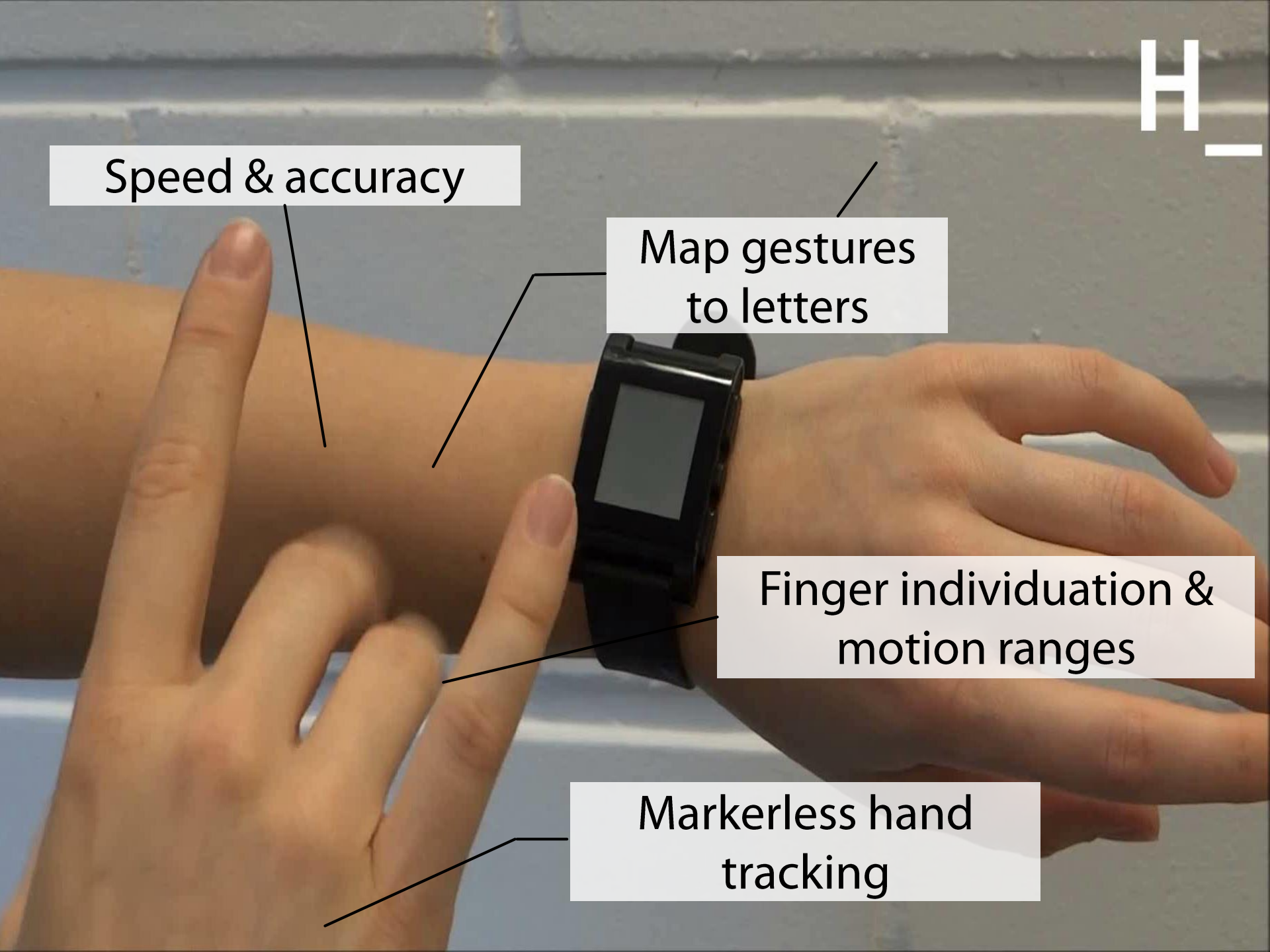


Speed & accuracy

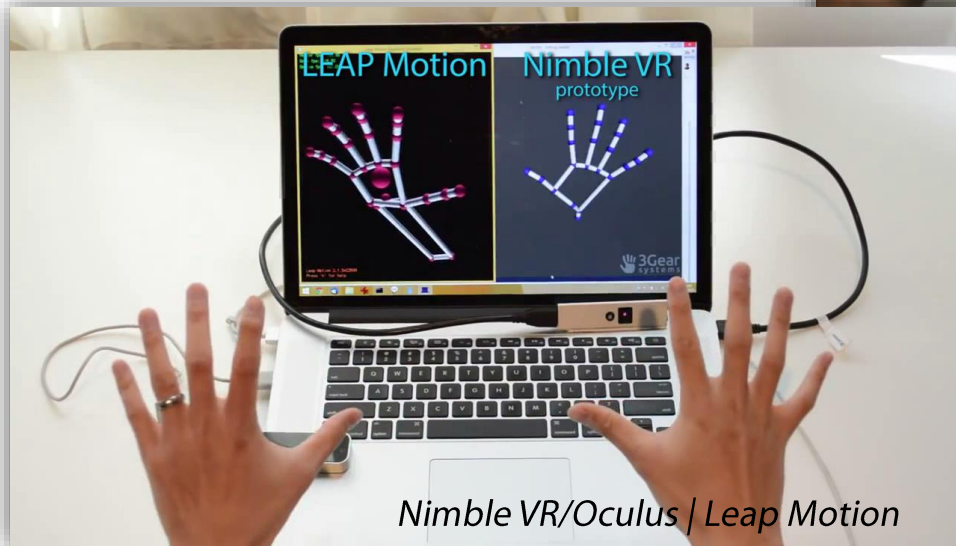
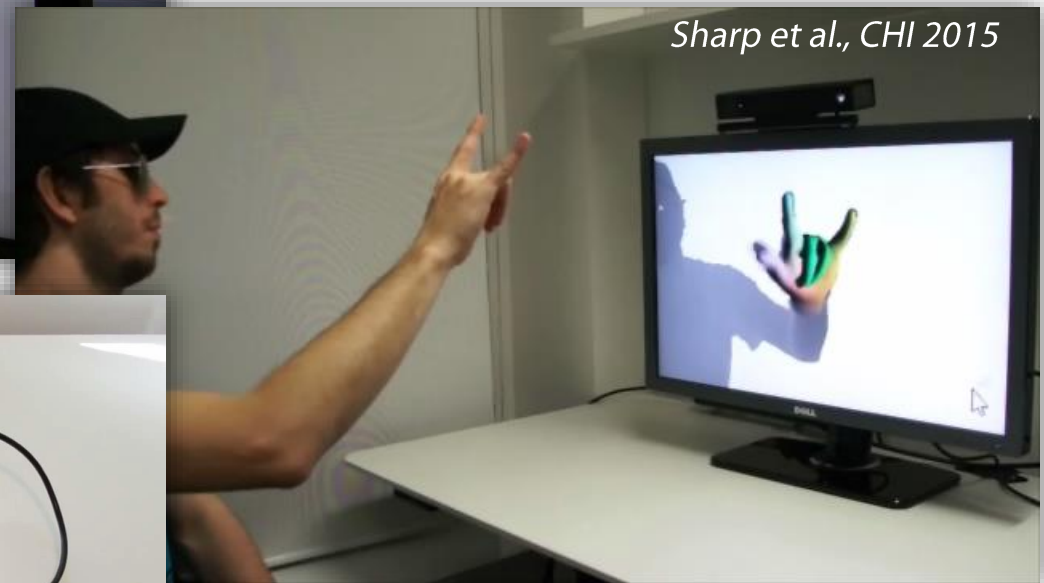
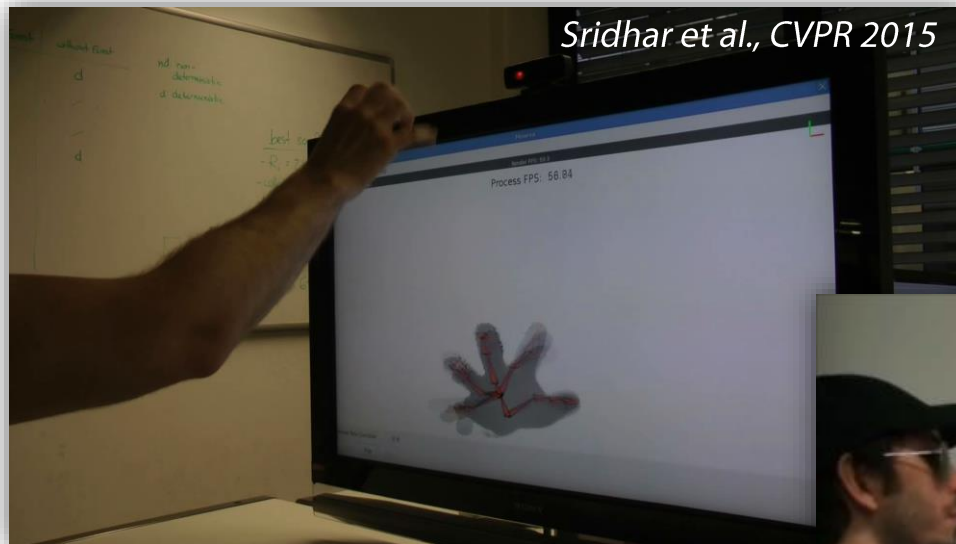
Map gestures
to letters

Finger individuation &
motion ranges

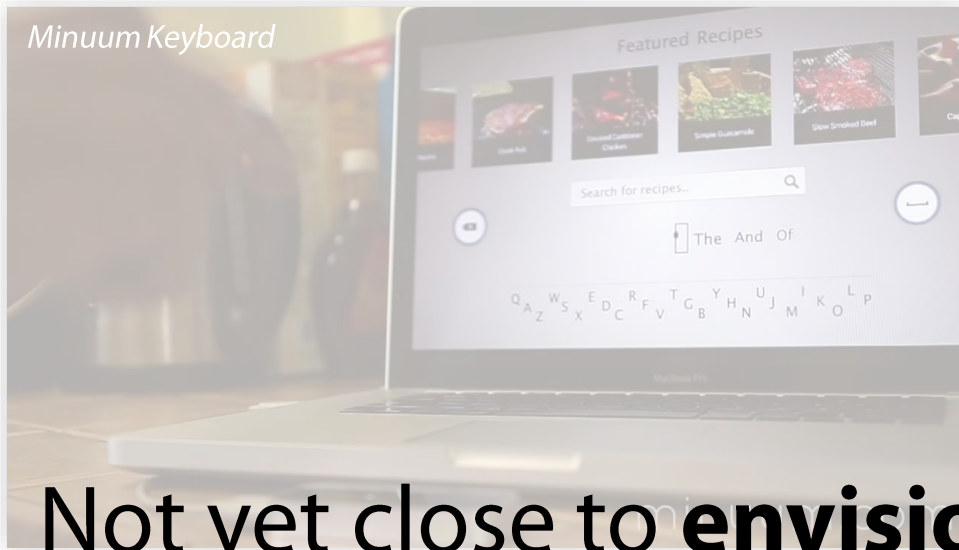
Markerless hand
tracking



Hand Tracking: State of the art



Current State of Mid-Air Gestural Input



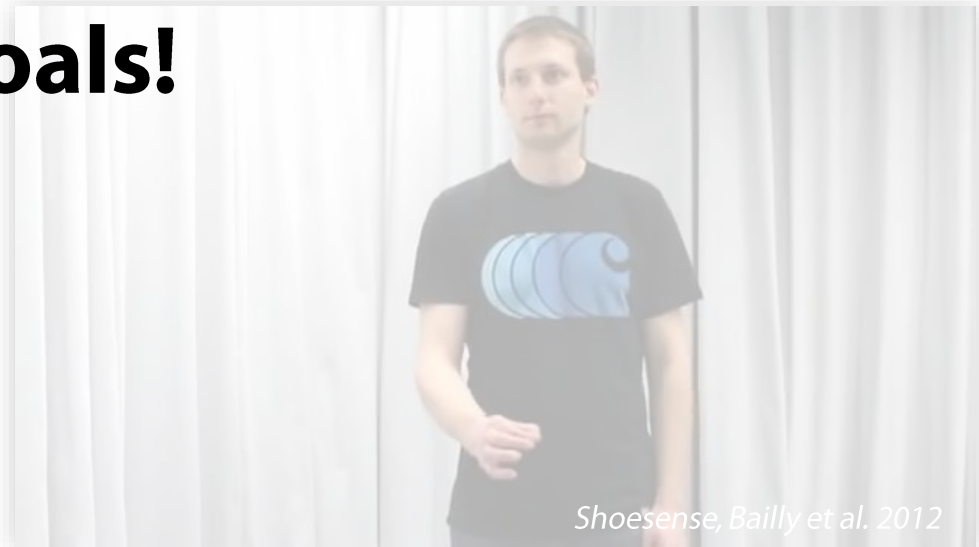
Limited use of **dexterity of fingers**.

Extensions of **2D** gestures to **3D**.

Not yet close to **envisioned performance goals!**

Limited **vocabulary** of gesture sets.

No guarantees on **usability, performance, or accuracy**.



Objectives and Approach

Goal: *Inform the design of high throughput mid-air gestures.*

1 Dexterity

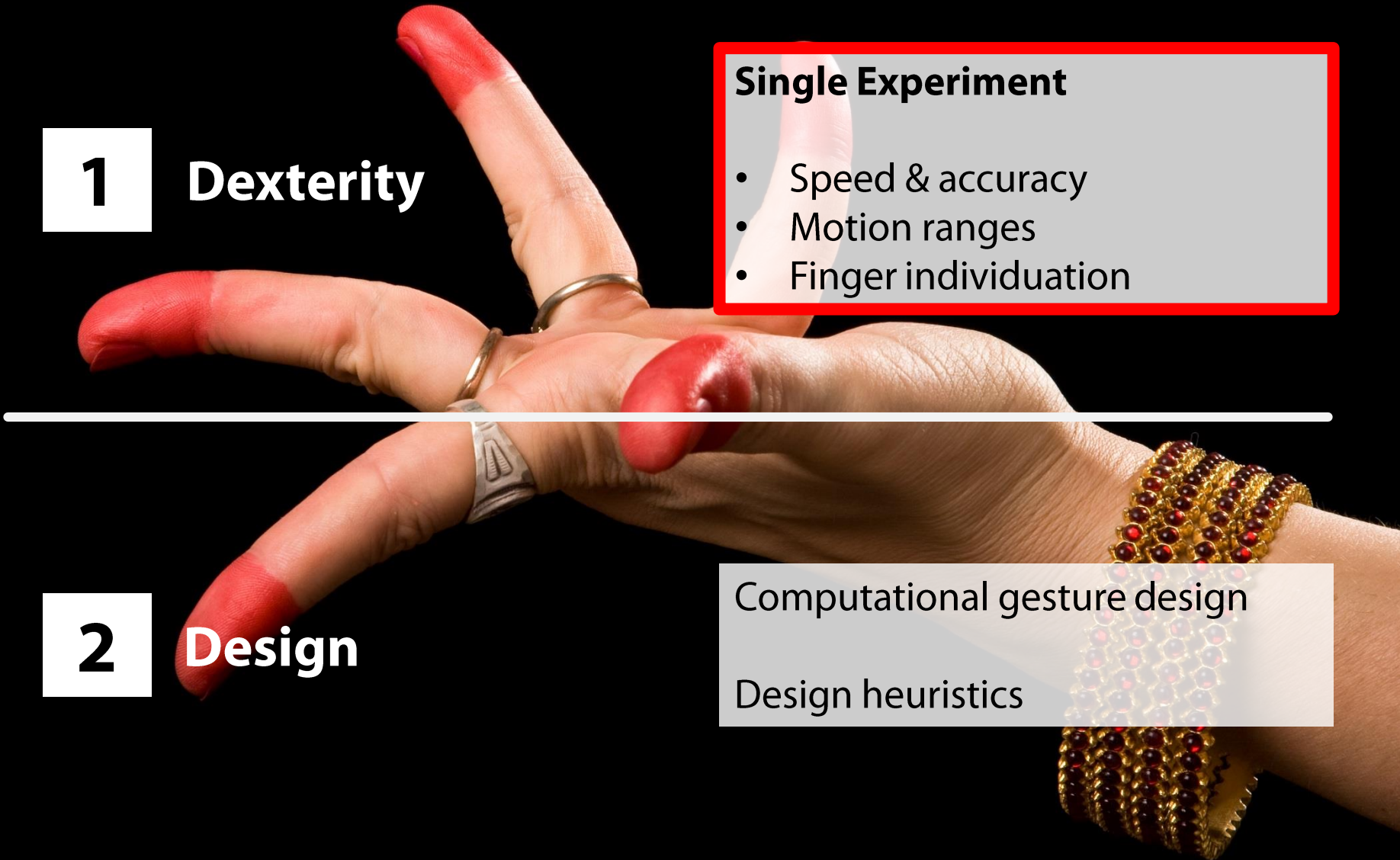
Single Experiment

- Speed & accuracy
- Motion ranges
- Finger individuation

2 Design

Computational gesture design

Design heuristics

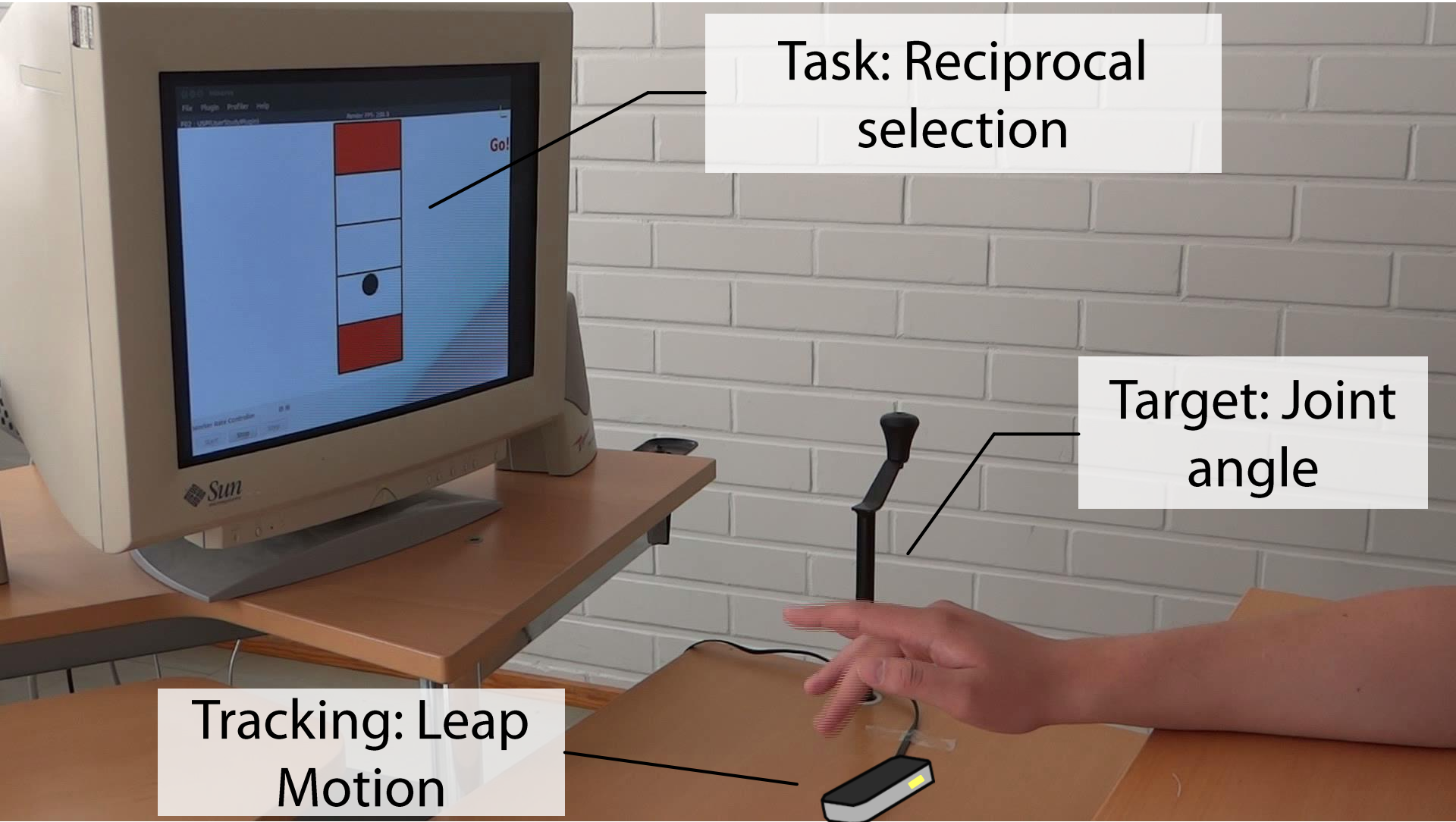


Experiment

Task: Reciprocal
selection

Target: Joint
angle

Tracking: Leap
Motion



Experiment

13 participants (8 m / f)
22–32 (avg 27) years
45500 movements

Comfortable
motion ranges

Finger
individuation

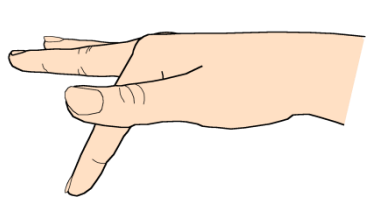
Speed &
accuracy



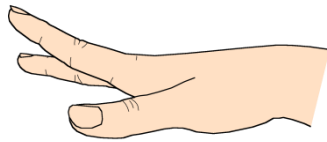
Performance Analysis

Joint-specific Fitts' Law models

Record movement ranges



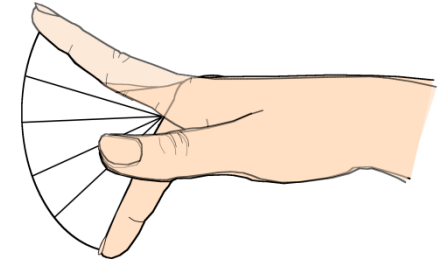
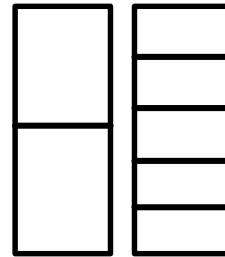
flexion



extension



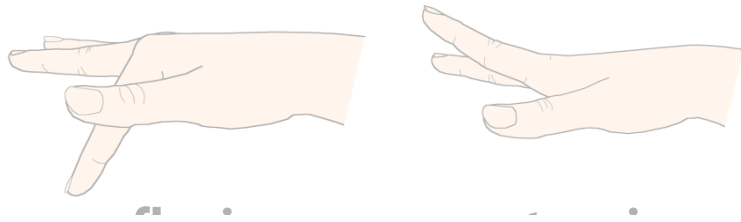
Divide movement range into
2–5 bins, 4 ID conditions



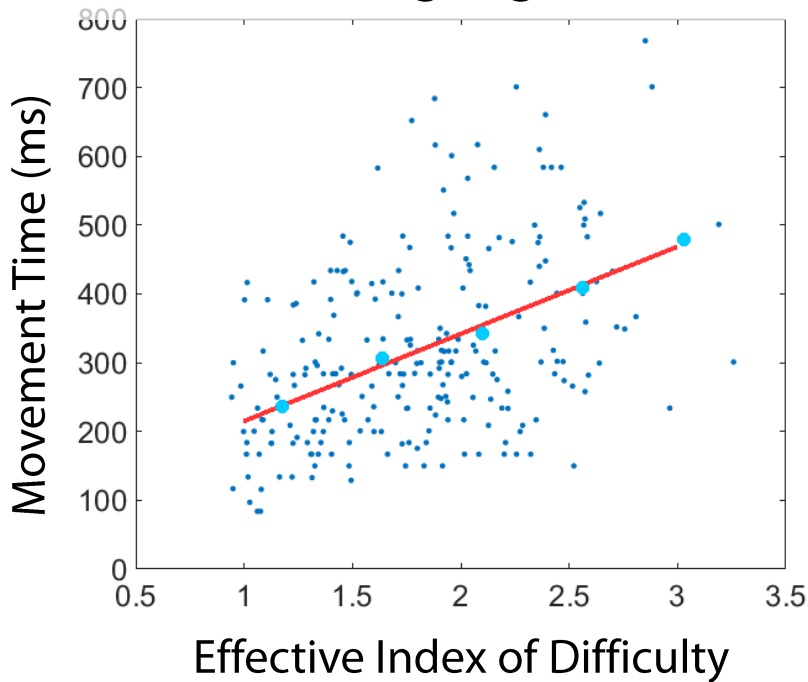
Performance Analysis

Joint-specific Fitts' Law models

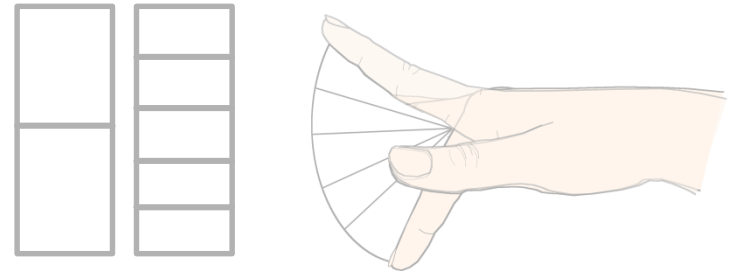
Record movement ranges



Ring finger



Divide movement range into 2 – 5 bins, 4 ID conditions



Angular model

$$MT = a + b \log_2 \left(\frac{\alpha_D}{\beta_W} + 1 \right)$$

Kondraske, 1994

*Soukoreff et al.,
2004*

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1 Dexterity

Single Experiment

- Speed & accuracy
- Motion ranges
- Finger individuation

2 Design

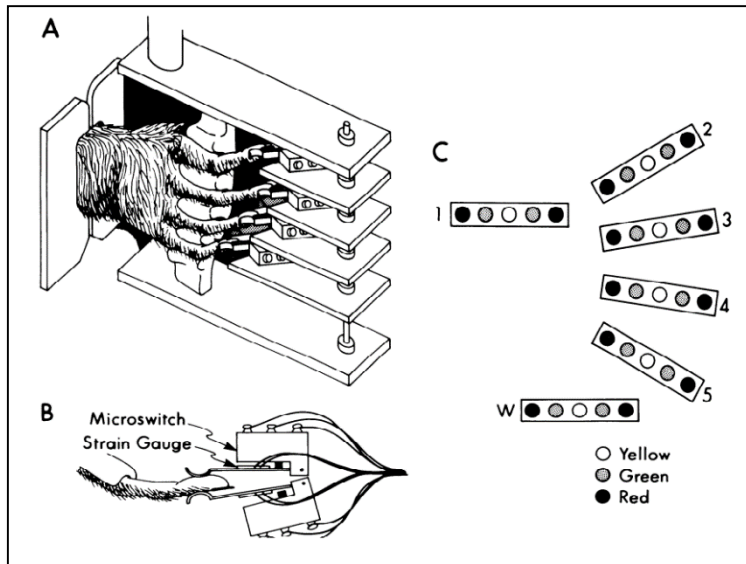
Computational gesture design

Design heuristics

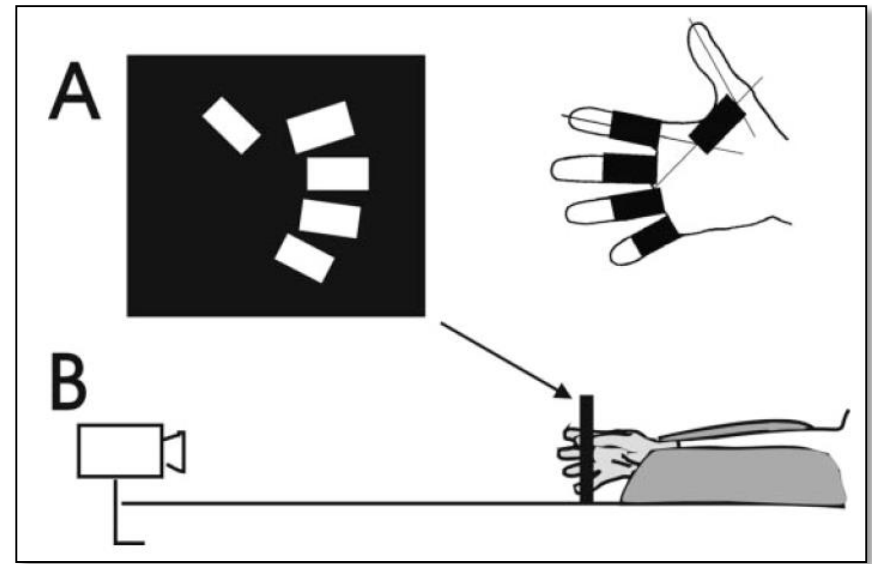
Individuation Analysis

Schieber Index

Quantify independence of uninstructed joints



Schieber, Journal of Neurophysiology, 1991

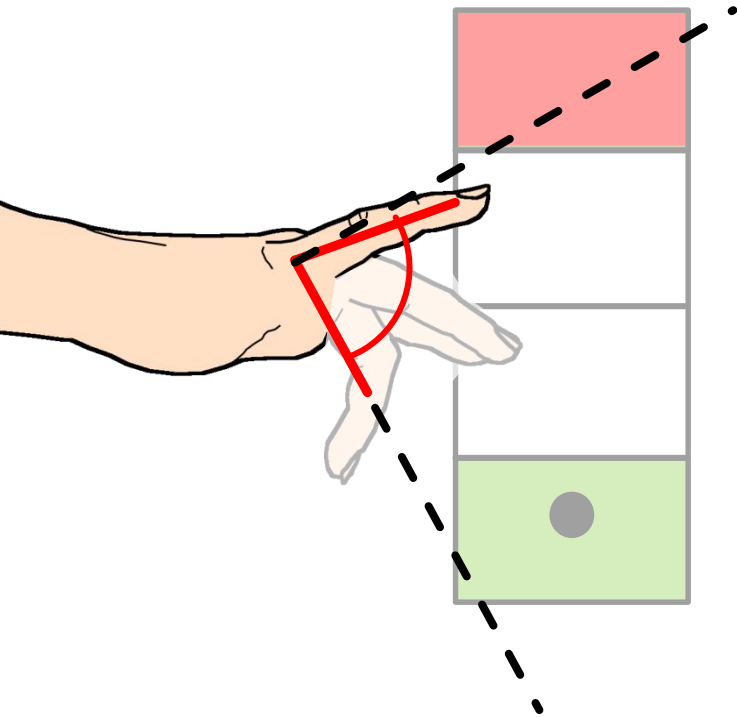


Häger-Ross and Schieber, Journal of Neuroscience, 2000

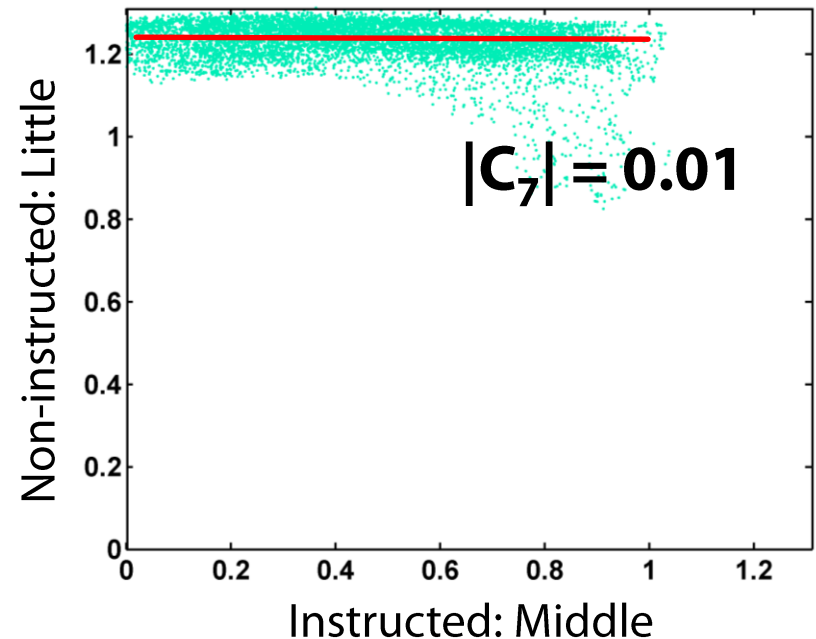
Individuation Analysis

Schieber Index

Quantify independence of uninstructed joints



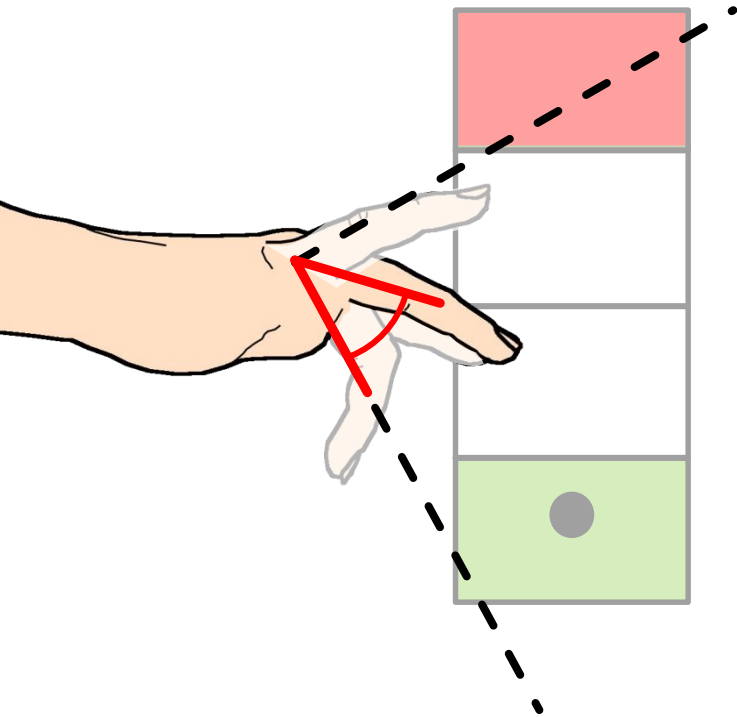
Middle vs. Little, participant 9031



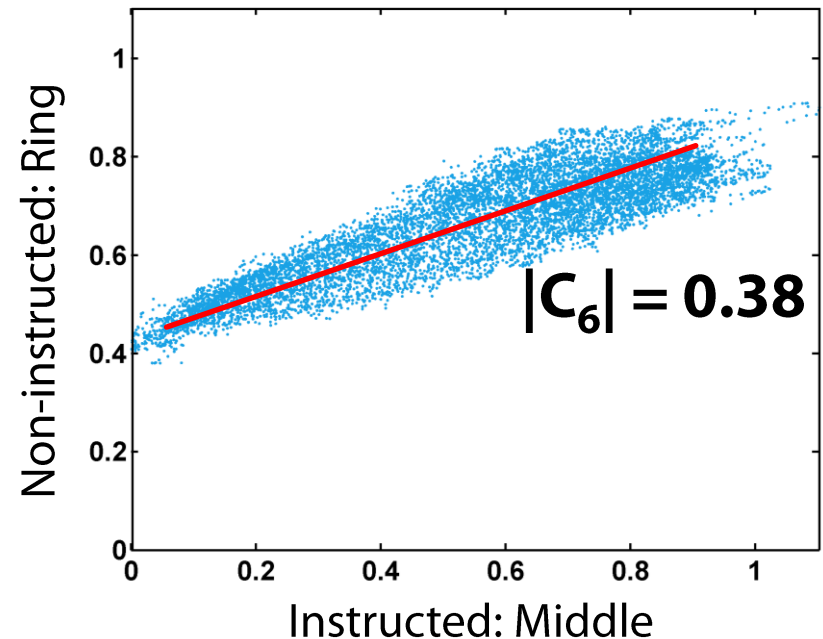
Individuation Analysis

Schieber Index

Quantify independence of uninstructed joints



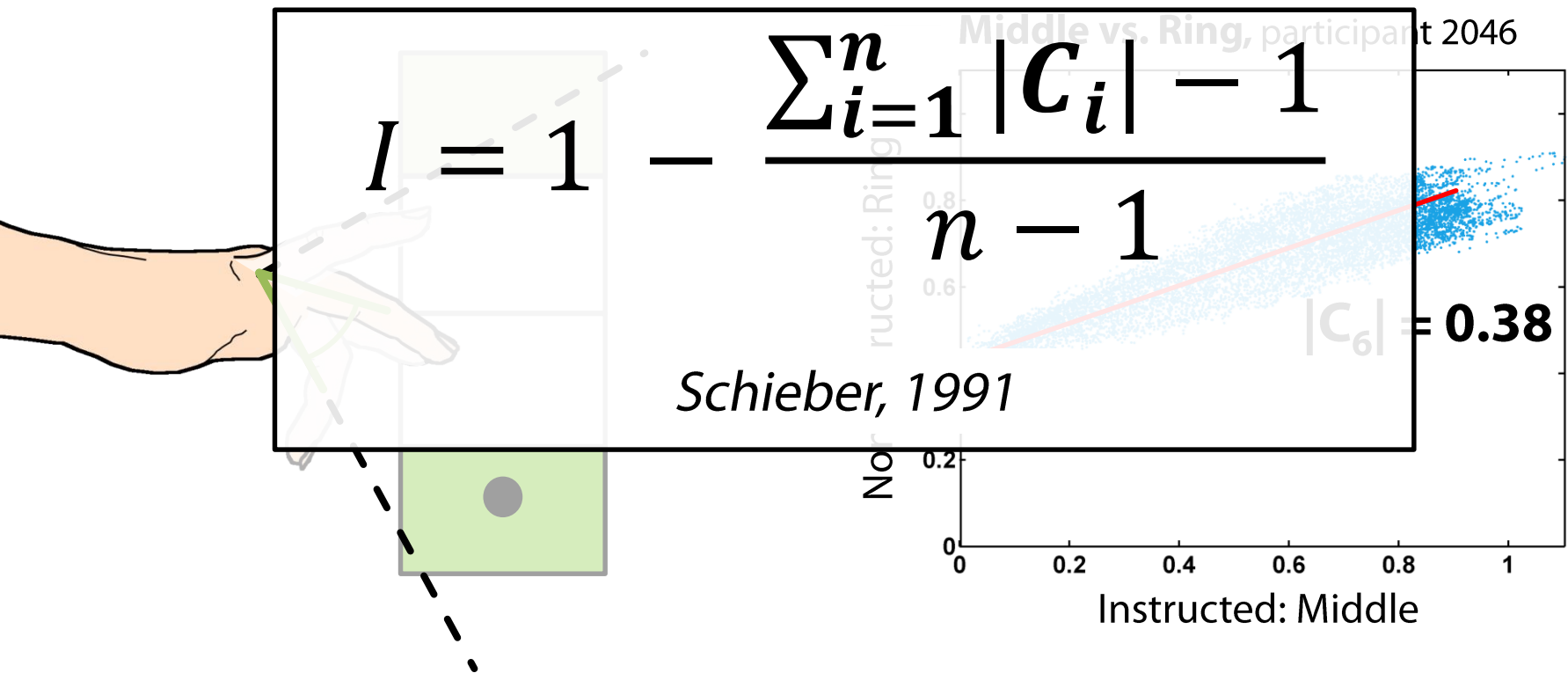
Middle vs. Ring, participant 2046



Individuation Analysis

Schieber Index

Quantify independence of uninstructed joints



Results

Models of individuation

Because of anatomical differences, we determined the range of each user experimentally, and we determined concrete target widths and distances for each joint at the beginning of each task. We asked participants to flex and extend the joint without moving their fingers too much. The corresponding movement time was then uniformly divided into 2, 3, 4, and 5 bins. We used the same four unique ID s for every user: 1, 1.1, 1.2, and 1.3. Over all discretization levels there were 10 digit pairs for each joint, resulting in $7 \times 10 = 70$ conditions.

Apparatus

The joint angles were tracked using the Leap Motion sensor, forming its output to a kinematic skeleton. The tracking and display of the task ran on a fast computer (3.1 GHz Intel i7 at one place, 3.1 GHz i7 at another). We showed visual feedback on high refresh rate monitors (112 Hz CRT and 120 Hz LCD respectively). Leap Motion was capable of tracking at up to 10

Analysis

Performance: The design and evaluation of the task was done according to [36]. Movements were performed at a distance beyond 3 SD of the median. Accuracy was adjusted to allow an error rate common in high-performance tasks such as target shooting. Based on the remaining movements, we determined the target width $W_{50\%}$ and distance $D_{50\%}$ which compute the effective index of difficulty (ID_{eff}).

$ID_{eff} = \log_2(\frac{W_{50\%}}{W_{min}} + 1)$. This indicates the actual difficulty of the performed task and captures the speed-accuracy trade-off. To account for individual differences, we cluster the effective ID s into 5 equally sized bins and compute the average movement time within each bin. For this purpose, we excluded data points with an effective ID of 3 SD beyond the median. Least-squares linear regression was used to determine the slope and intercept of the Fitts' Law model.

Individuation: We followed the protocol described in [33] to determine individuation indices. We first plotted, separately for each user, the movement time of each joint as a function of the index of difficulty. The regression line was then computed for each joint. The regression line was then averaged across all users, taking the median. Outliers beyond 3 SD of the median were excluded. The slopes of the resulting data were determined by least-squares linear regression. While linear movement trajectories were the norm, there were a few outliers where a linear relationship could not be determined. We observed two reasons: (1) Problems in tracking the joint angle (Figure 5 (b)) and (2) drifting of fingers, a phenomenon in which the non-instructed joint gradually changes its angle due to fatigue, inattention, or corrective behavior (Figure 5 (c)). To account for this, we excluded models with a fit of $R^2 < 0.5$. As suggested by Schieber, we averaged the absolute value for each slope, to generalize the relative individuation over all participants. These values were then used to compute the individuation index. In the next section, we report findings for performance, individuation, and movement ranges.

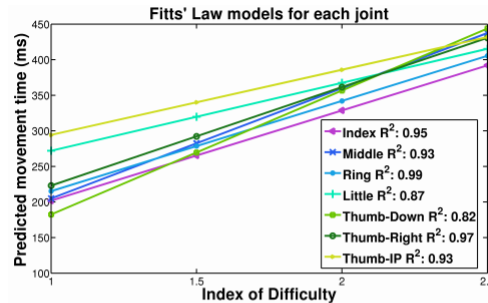


Figure 4. Performance models for each joint as given by Fitts' law. Overall, Index is the fastest, while Thumb and Little finger are the slowest.

Joint	Intercept a	Slope b	R^2
Index	75.140	126.77	0.95
Middle	49.940	155.03	0.93
Ring	88.450	126.79	0.99
Little	176.52	95.510	0.87
Thumb-Down	8.1900	174.26	0.82
Thumb-Right	84.590	138.44	0.97
Thumb-IP	202.73	91.590	0.93

Table 1. Fitts' Law models for each joint, given by intercept and slope.

$F(6, 60) = 3.3, p < 0.05$. Overall, Index had the highest performance, while Thumb-IP was the worst.

More subtle differences can be observed by looking at the cross-over points of the slopes in Figure 4. The Index finger was the fastest for most part of the ID range. However, for small ID s, all fingers are spread for the different targets (difference of 112 ms, $ID = 1$) while they become more condensed for larger ID s (51 ms, $ID = 2.5$). In other words, there is a significant individual difference in movement time.

Differences in MT for the same joint were as large as 418 ms. The top performance was 91 ms for $ID = 1$, while the worst user performed at a speed of 509 ms per movement $ID = 1$.

Individuation: Schieber Indices

Table 2 provides an overview of the findings. We report aggregate indices per finger and by finger-pair coactivation.

Individuation Index: The individuation index for each finger can be found in the second column of Table 2. The values range from 1 for perfect individuation to 0 for perfect coactivation. Thumb-IP was found to be the most individuated joint, while Thumb-Down seemed to be the one with the highest coactivation. The individuation indices of the MCP joints showed only marginal differences.

Instructed Joint	Index of Individuation	Relative Coactivation						
		Index	Middle	Ring	Little	Thumb-Down	Thumb-Right	Thumb-IP
Index	0.819	1	0.24	0.20	0.19	0.29	0.11	0.06
Middle	0.817	0.16	1	0.41	0.14	0.20	0.11	0.07
Ring	0.808	0.16	0.20	1	0.36	0.15	0.22	0.06
Little	0.806	0.18	0.35	0.29	1	0.14	0.12	0.08
Thumb-Down	0.792	0.12	0.12	0.10	0.08	1	0.69	0.14
Thumb-Right	0.853	0.07	0.09	0.10	0.09	0.27	1	0.26
Thumb-IP	0.889	0.11	0.13	0.11	0.09	0.12	0.12	1

Table 2. Individuation index and relative coactivation describe the involuntary motion of joints. The individuation index is an aggregate that describes the independence of a finger when averaged over all other fingers (1 = perfect individuation). Relative coactivation denotes the movement of an non-instructed joint when the instructed joint (each row) is moving. A value of 1 denotes that the two joints always move together.

Joint	Min°(SD)	Max°(SD)	Range(SD)
Index	48.39 (12.25)	-21.19 (8.70)	69.58 (11.81)
Middle	37.58 (11.95)	-18.69 (8.02)	56.27 (12.54)
Ring	44.66 (8.320)	-12.24 (7.70)	58.90 (11.46)
Little	39.47 (15.78)	-20.81 (8.64)	60.28 (14.89)
Thumb-Down	27.31 (1.680)	-6.280 (6.54)	33.58 (7.130)
Thumb-Right	22.18 (10.53)	-11.99 (8.43)	31.32 (12.59)
Thumb-IP	62.97 (12.94)	-27.41 (4.37)	90.38 (13.93)

Table 3. Angular limits and movement range of each joint. The table shows values averaged over all users together with standard deviations.

vides an elegant way to summarize the independence of each finger, greater insight is provided by the relative coactivation of joints, which denotes the movement of a non-instructed finger when the instructed finger is moved. In Table 2, we observe the relative coactivation averaged over all users. It shows that the coactivation of the non-instructed finger, i.e. the relative coactivation, is the opposite to the individuation index, where 1 is better. We observe that Thumb-Down is closely correlated with Thumb-Right, explaining why it is the most coactivated joint. This indicates that the two fingers cannot be reliably distinguished and thus are often combined when implementing thumb movements for gestural input. Particularly high values were also observed for the movement of Ring during instructed movement of Middle, and the other way around (Figure 6). Thumb-IP shows low values throughout all joints which explains the good individuation index.

Comfortable Movement Ranges

The average angular limits and movement range for each joint are given in Table 3. The values represent joint limits that are comfortable for the user in this setting and reachable without moving the other joints too much. One-way repeated measures ANOVA (subjects with missing data excluded) showed statistically significant differences between movement ranges: $F(6, 60) = 39.19, p < 0.0001$. We observe that the CMC joint of the thumb has the smallest movement range in both movement directions (34° and 31°). The range of the MCP joints is twice that, and Index has the largest range (70°). Thumb-IP has overall the largest movement range with an average of 90° .

Observations on Individual Differences

Large differences among users were observed. Some users were able to keep their non-instructed finger nearly static (slope close to 0), while others moved them to a large extent along with the instructed joint (slope = 0.4). Figure 7

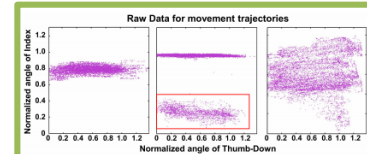


Figure 5. Raw data for movement of Index relative to instructed movement of Thumb-Down. Left (a): Example of high individuation, Middle (b): Tracking errors (red box), and Right (c): "drifting finger".

shows the coactivation of Index relative to Middle. Movement strategies vary too, resulting in a positive slope (moving along with the instructed joint) or even a negative slope (moving opposite to the instructed joint). If a joint could not be kept static, users either moved it along with the instructed joint or opposite to it. Attempts at "counteracting" movement like this were also observed in the original work by Schieber [33]. It may represent a strategy for preventing non-instructed fingers from moving along instructed digits. This suggests that these strategies are applied unconsciously.

We also observed what we denote as the *drifting finger effect*: the position of non-instructed fingers may change gradually over time for some users, as they "forget" to keep the finger still. For some users, this poses no problem, they are able to produce the exact same movement over and over (Figure 5 (a)). We show raw data of this "drifting finger" problem in Figure 5 (c). Due to user-specific differences like this, the linear model of Schieber does not always fit to a user's motion. On average, an R^2 of 0.77 (SD 0.14) was found, ranging from 0.5 to excellent fits of 0.99. As discussed above, we excluded the data where no sufficient linear relationship could be found. On average, this amounted to excluding data from 4 users per joint-condition.

Finally, despite our efforts to ensure the ergonomics of the posture and to provide enough breaks, some users complained about fatigue, especially with their wrist or arm getting tired. This suggests that these motions are tiring even if they do not require the use of large forces.

APPLICATION TO TEXT ENTRY

The results of the study offer a nuanced picture of the two characteristics of finger motions. The performance and independence of fingers differ and are inter-connected in sub-

Joint-specific performance models

Objectives and Approach

Goal: *Inform the design of high throughput mid-air gestures.*

1

Dexterity

Single Experiment

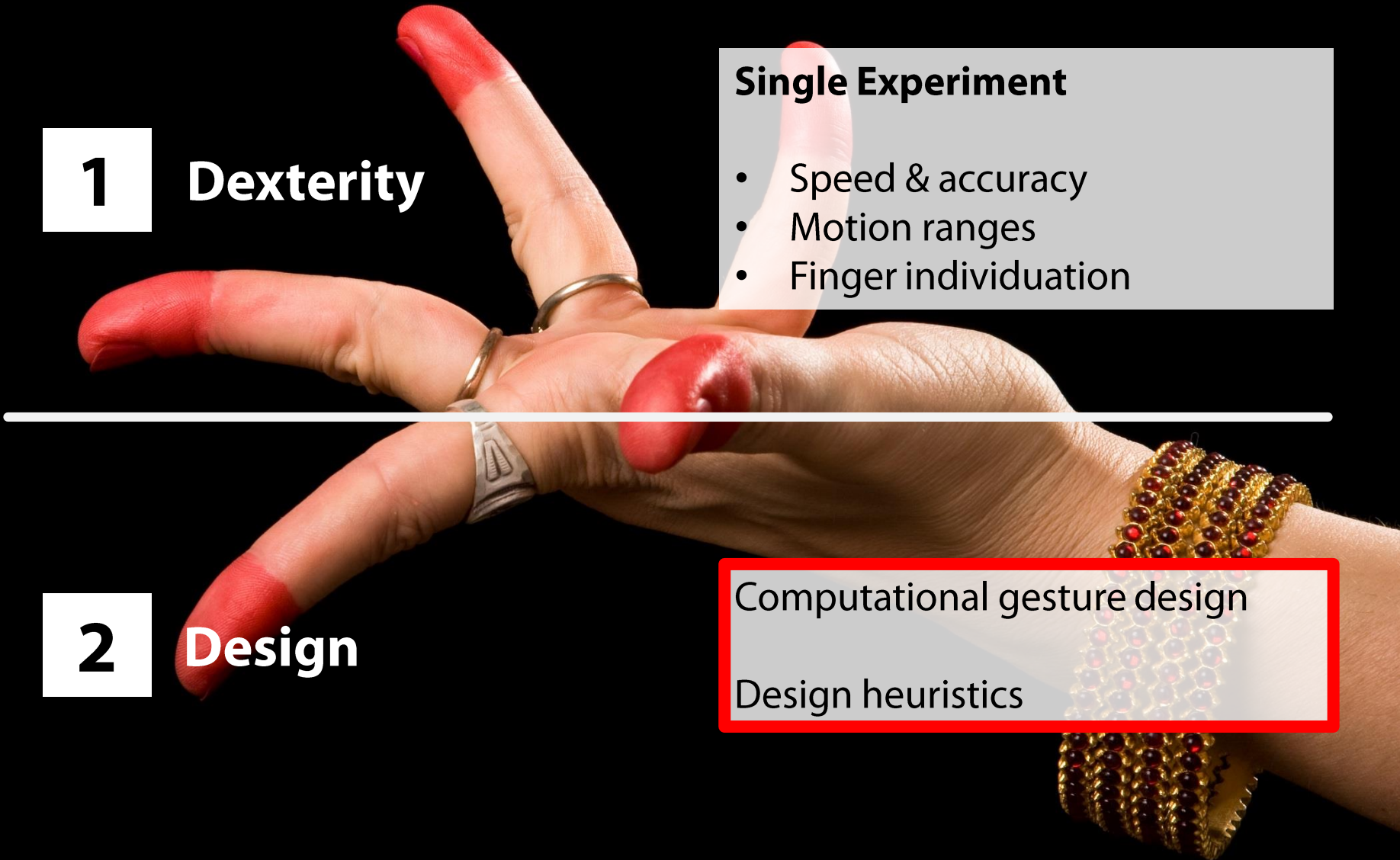
- Speed & accuracy
- Motion ranges
- Finger individuation

2

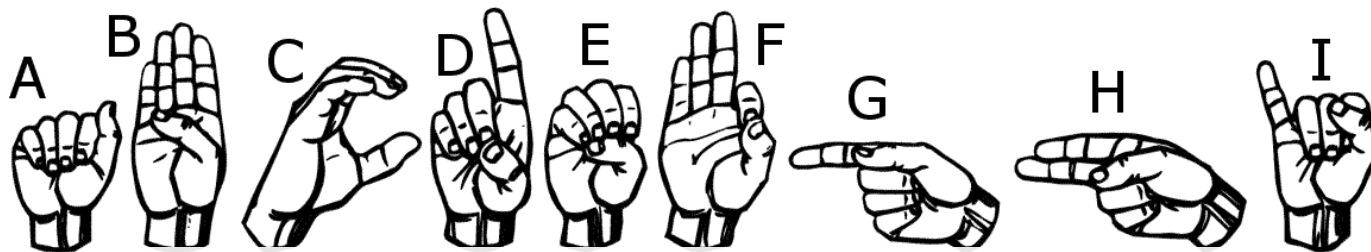
Design

Computational gesture design

Design heuristics



Performance Prediction



Fingerspelling

pred. **43.9 WPM**

obs. **40–45 WPM**

Ricco and Tomasi, 2010

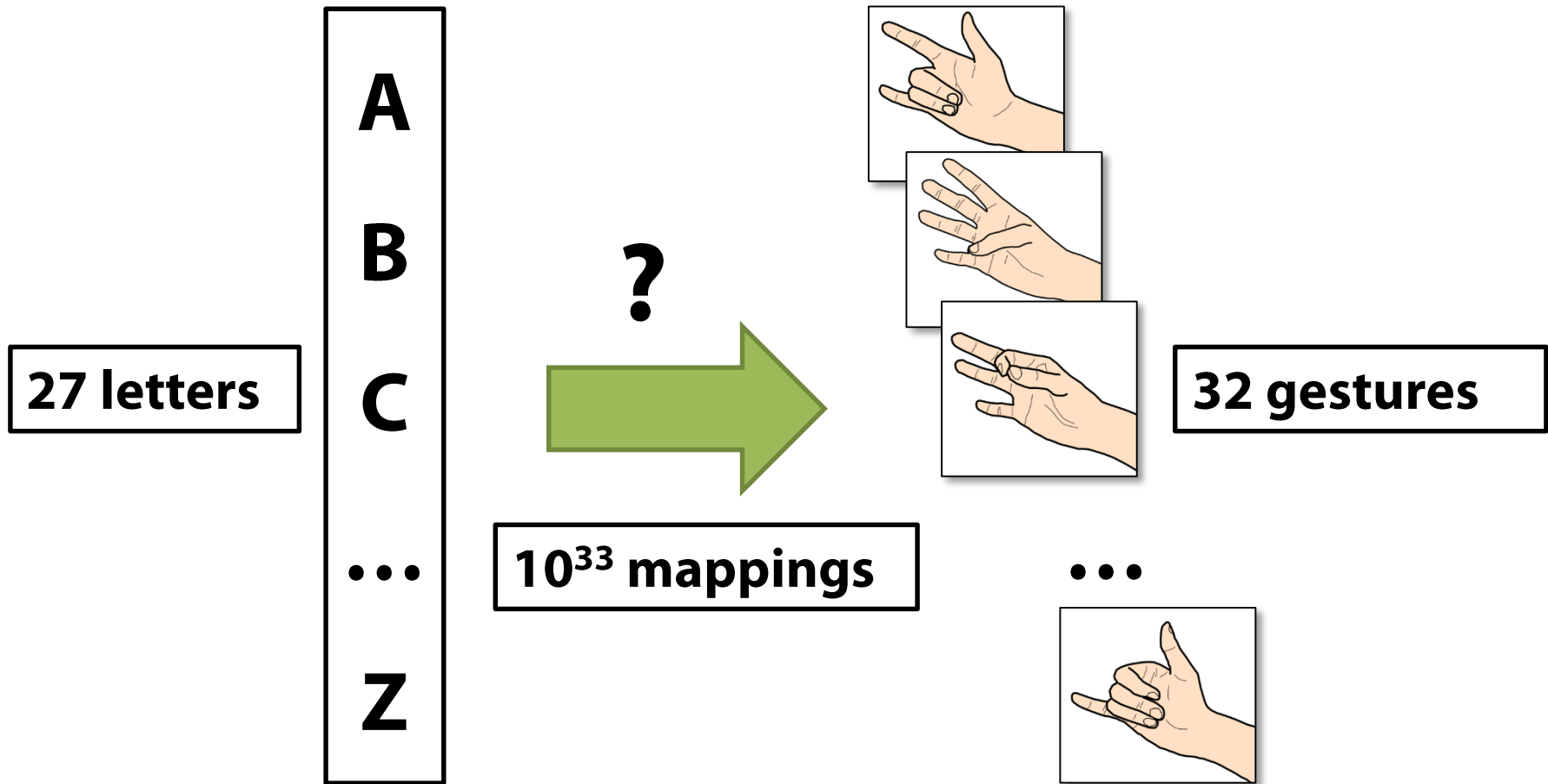


H_



Letter assignment problem

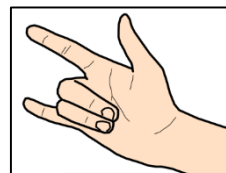
Goal: Find the best letter–posture mapping.



Letter assignment problem

Goal: Find the best letter to gesture mapping

A



Maximize:

27

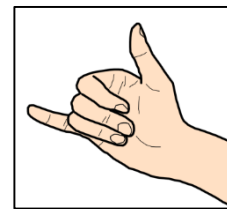
$$U = w_P \cdot P + w_A \cdot A + w_L \cdot L + w_M \cdot M$$

...

Z

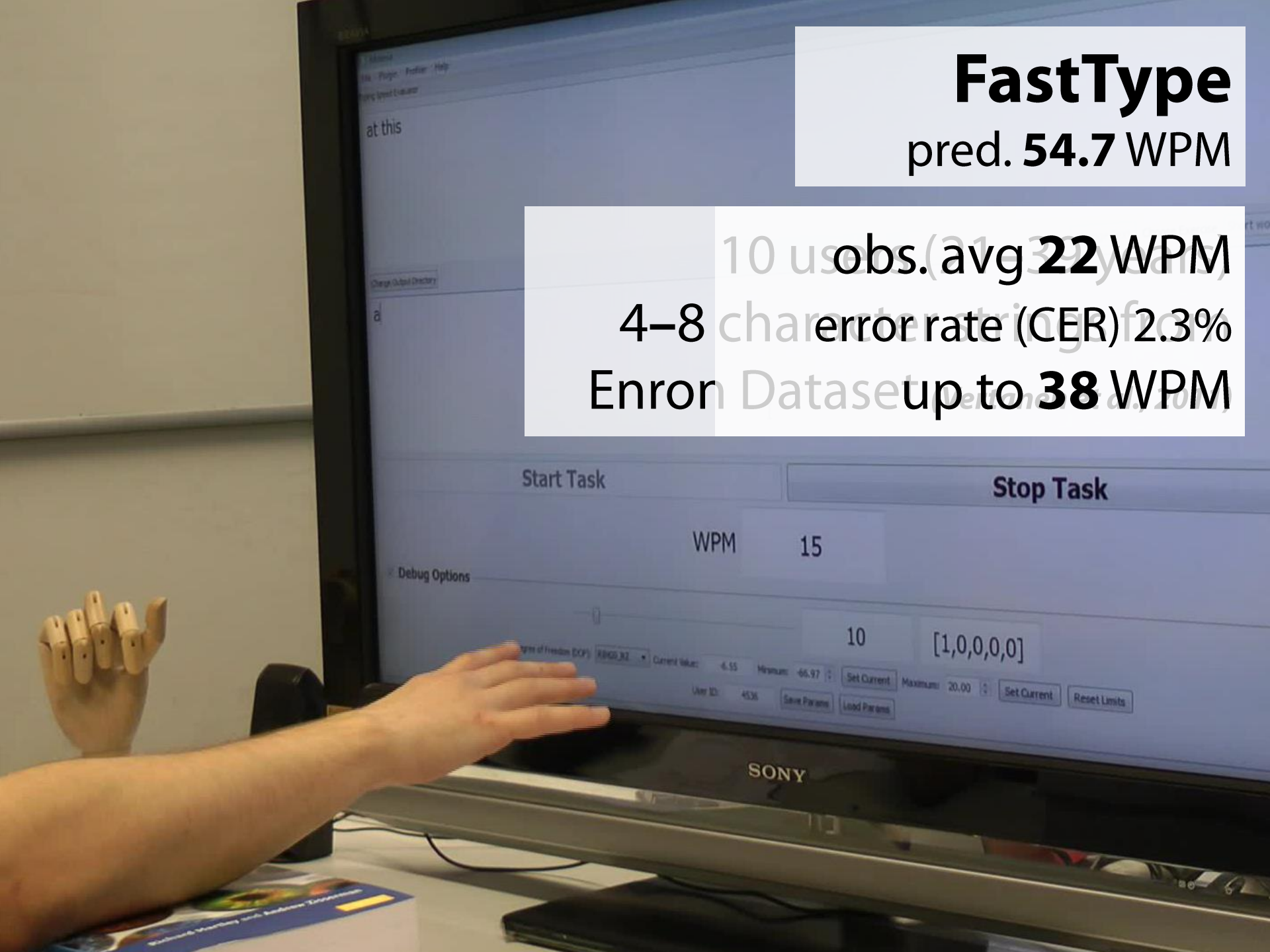
10^{33} mappings

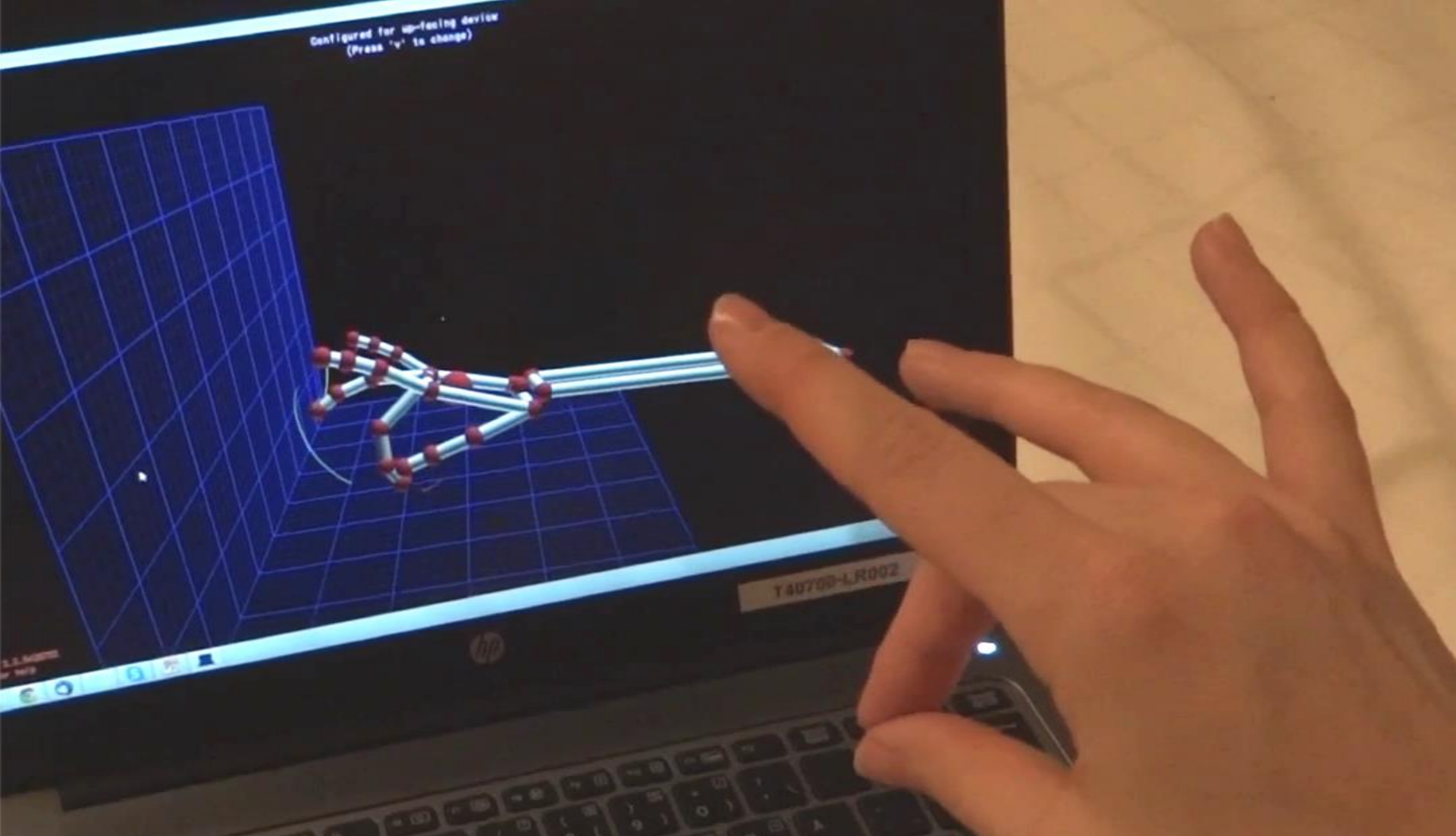
...



FastType
pred. **54.7** WPM

10 users (21-32 years)
obs. avg **22** WPM
4-8 character strings (CER) 2.3%
Enron Dataset up to **38** WPM

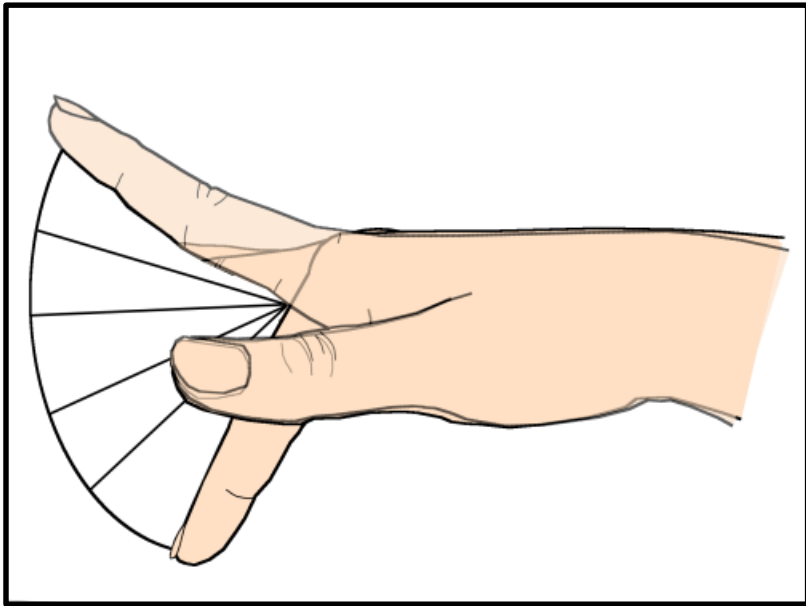




Tracking & recognition | Learnability | Ergonomics

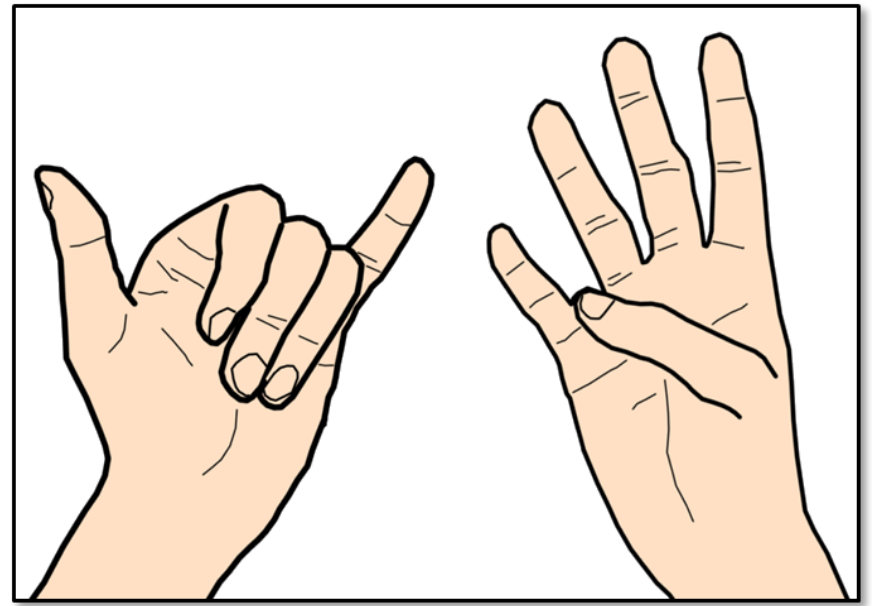
Further Predictions

65 WPM



More levels per joint

70–85 WPM



Two hand input





***Design of mid-air gesture is hard,
but our data makes it easier.***

- 1.** Joint specific models for **dexterity**
- 2.** Directly **applicable** to **design**
- 3. Methodology** applicable in other settings

Thank you!

handtracker.mpi-inf.mpg.de

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Acknowledgments

ERC Starting Grant projects **CapReal** and **COMPUTED**, and
the **Academy of Finland**