

Input Performance

KLM, Fitts' Law, Pointing Interaction Techniques

Input Performance 1

Input Performance Models

- You're designing an interface and would like to:
 - choose between candidate designs without building them
 - estimate performance with your new design
- Solution: use a model of how people use input devices and interfaces to predict time, error, fatigue, learning, etc.
 - models most often focus on time and error (easiest to measure)

Input Performance 2

Keystroke Level Model (KLM)

- Describe each task with a sequence of operators
- Sum up times to estimate how long the task takes
- Operator types
 - K** Keystroke = 0.8 – 1.2s (based on expertise, type of string)
 - P** Pointing = 1.10s
 - B** Button press on mouse = 0.1s
 - H** Hand move from mouse to/from keyboard = 0.4s
 - M** Mental preparation = 1.2s
- KLM is simplified GOMS, so sometimes called KLM-GOMS
- Great online resource for KLM (Kieras, 1993):
 - <ftp://ai.eecs.umich.edu/people/kieras/GOMS/KLM.pdf>
- KLM Time Calculator
 - <http://courses.csail.mit.edu/6.831/2009/handouts/ac18-predictive-evaluation/klm.shtml>

Input Performance 3

KLM Operators

main physical operators	Code	Operation	Time
	K	Key press and release (keyboard)	Best Typist (135 wpm)
			Good Typist (90 wpm)
			Poor Typist (40 wpm)
			Average Skilled Typist (55 wpm)
			Average Non-secretary Typist (40 wpm)
			Typing Random Letters
			Typing Complex Codes
			Worst Typist (unfamiliar with keyboard)
	P	Point the mouse to an object on screen	
	B	Button press or release (mouse)	
	H	Hand from keyboard to mouse or vice versa	
	M	Mental preparation	

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KLM Example (Only Physical Operators)

- Use KLM to compare the performance time of three different date entry widgets. (assume: hand already on mouse, 40 WPM typist)

PBH(Kx10) ▪ One text field

Date (MM/DD/YYYY):



(PBPB)x3 ▪ Three Dropdowns



PBH(Kx10) ▪ Three text fields



Op	Time
K	0.3
P	1.1
B	0.1
H	0.4
M	1.2

Including Mental Operators (M)

- People need to think about something before doing it
 - identify when people have to stop and think: **M**
 - difference between actions using *cognitive conscious* and *cognitive unconscious*
- Insert an **M** operation when people have to:
 - initiate a task
 - make a strategy decision
 - retrieve a chunk from memory
 - find something on the display (e.g. point to something)
 - think of a task parameter
 - verify that a specification/action is correct (e.g. display changes)
- Can use **M** to model novice and expert
 - add M in front of any action if they're a novice

KLM Critique

Benefits?

-
-
-

Drawbacks?

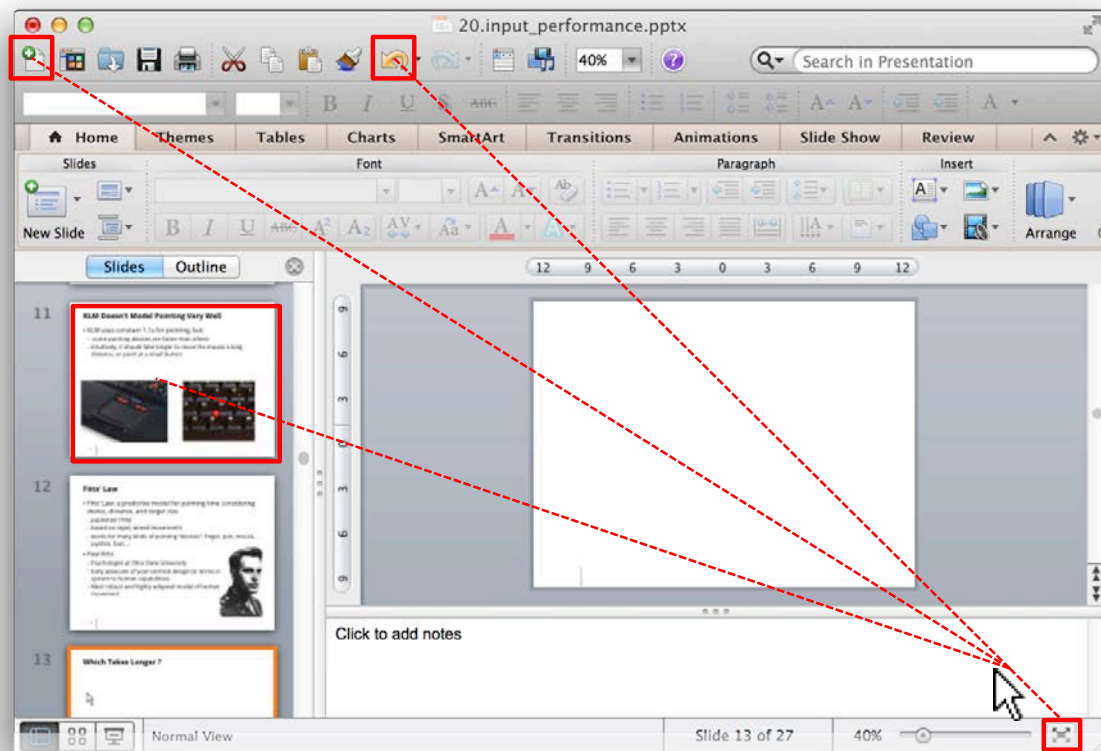
- Some time estimates are out of date
- Some time estimates are inherently variable
- Doesn't model:
 - Errors
 - Learning time
 - etc.

KLM Doesn't Model Pointing Very Well

- KLM uses constant 1.1s for pointing, but:
 - some pointing devices are faster than others
 - intuitively, it should take longer to move the mouse a long distance, or point at a small button



Which Takes Longer?



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Fitts' Law

- Fitts' Law: a predictive model for pointing time considering device, distance, and target size
 - published 1954
 - based on rapid, aimed movements
 - works for many kinds of pointing "devices": finger, pen, mouse, joystick, foot, ..
- Paul Fitts
 - Psychologist at Ohio State University
 - Early advocate of user-centred design (in terms of matching system to human capabilities)



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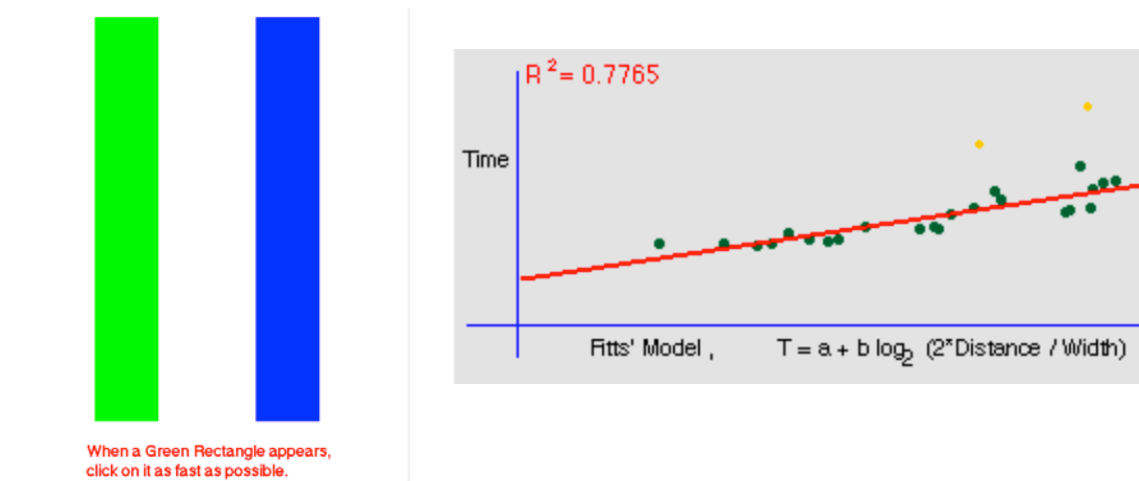
Distance vs. Size

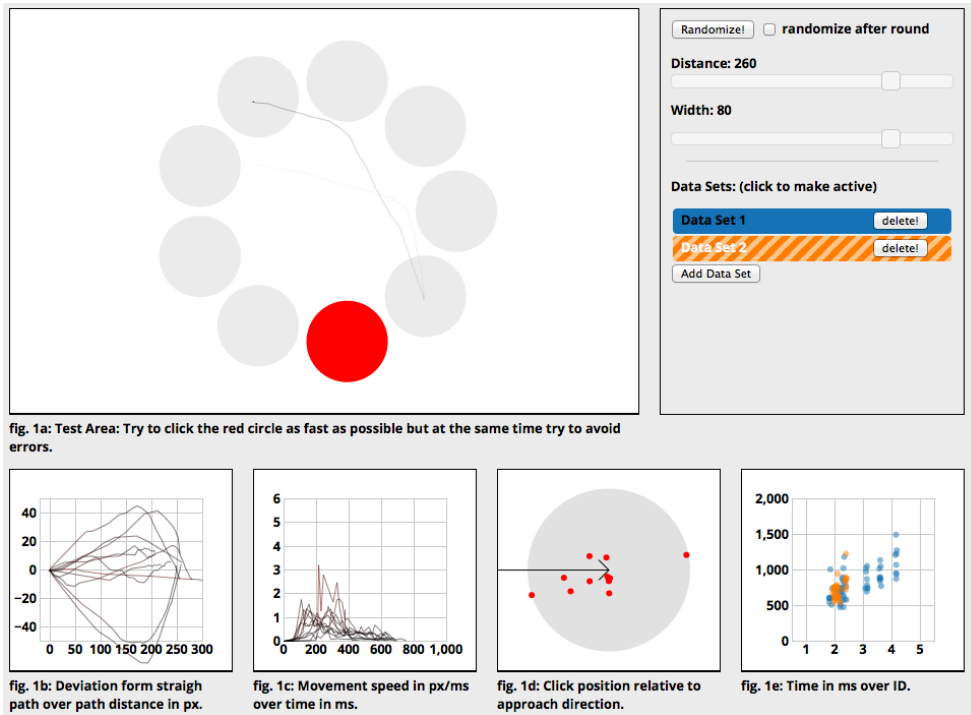
- The larger the **distance**, the longer the **time**
- The smaller the **size** of the target, the longer the **time**
- So, a proportional relationship between movement time and distance and size:

$$MT \propto \frac{D}{S}$$

- But ...
 - what is meant by target “size”?
 - a proportional relationship isn't a model ...

<http://husk.eecs.berkeley.edu/projects/fitts/>

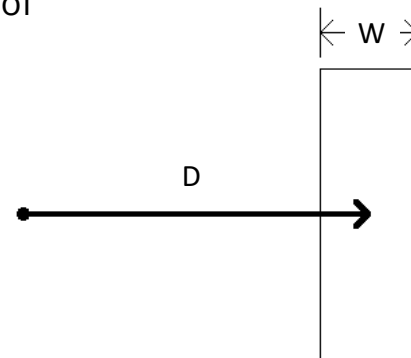




Linear Regression

- Movement time varies according to log of Distance and target "Width" (assume 1 dimension for the moment):

$$MT \propto \log \frac{D}{W}$$



- It's a linear regression, so it has a slope 'b' and intercept 'a' ...

$$MT \propto a + b \log_2 \frac{D}{W}$$

Fitts' Law

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

- MT = movement time
- D = distance between the starting point and the centre of the target (D is often shown as 'A' for Amplitude)
- W = Constraining size of the target
- a and b are characteristics of input device

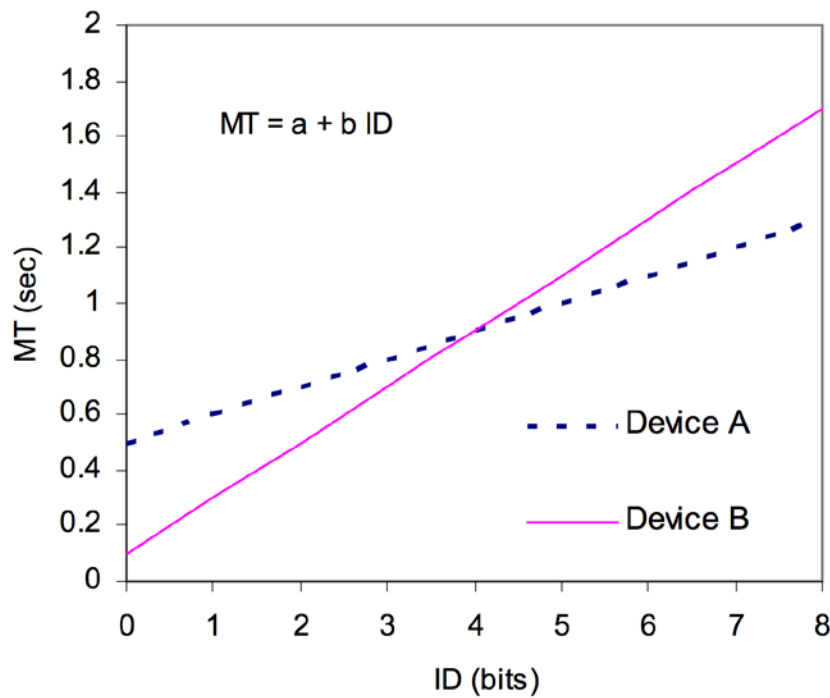
Fitts' Law: Index of Difficulty

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

IP = "Index of Performance" = 1/b ID = "Index of Difficulty"



Device Characteristics (a and b parameters)



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a, b, and IP for different devices

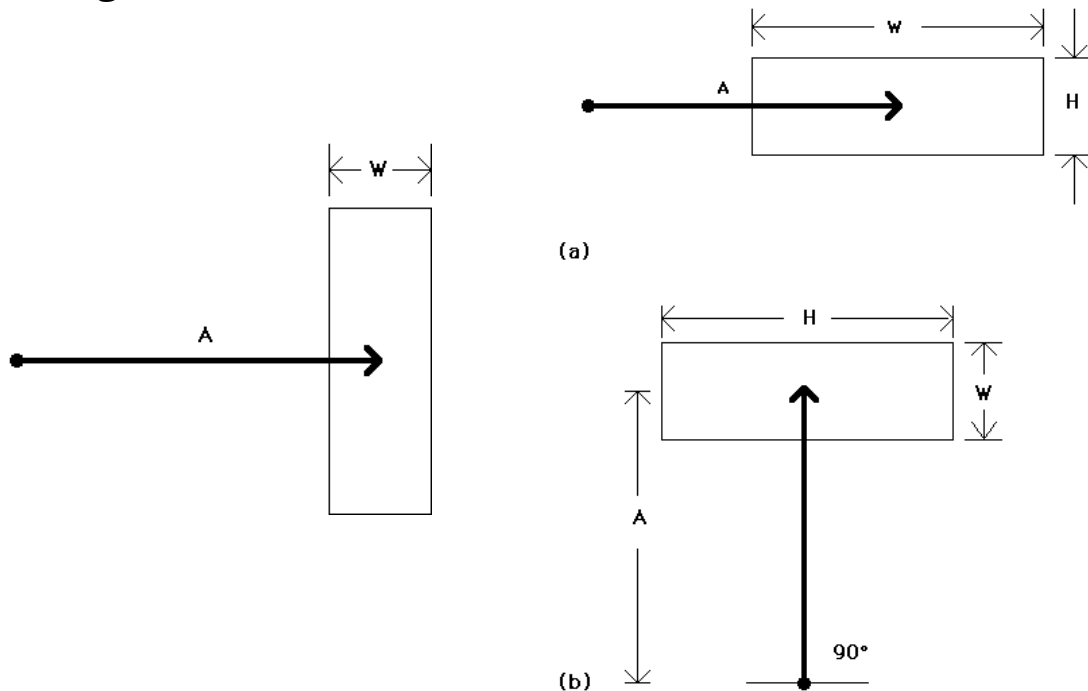
Regression Coefficients				
Device	r^a	Intercept, a (ms)	Slope, b (ms/bit)	IP (bits/s) ^b
*** Pointing ***				
Mouse	.990	-107	223	4.5
Tablet	.988	-55	204	4.9
Trackball	.981	75	300	3.3
*** Dragging ***				
Mouse	.992	135	249	4.0
Tablet	.992	-27	276	3.6
Trackball	.923	-349	688	1.5

^a $n = 16, p < .001$

^b IP (index of performance) = $1/b$

Figure 7. Fitts' law models. A regression analysis for each device-task combination shows the correlation (r), intercept (a), slope (b), and index of performance ($IP = 1/b$). Prediction equations are of the form $MT = a + b ID$, where $ID = \log_2(A/W + 1)$.

2D Targets?



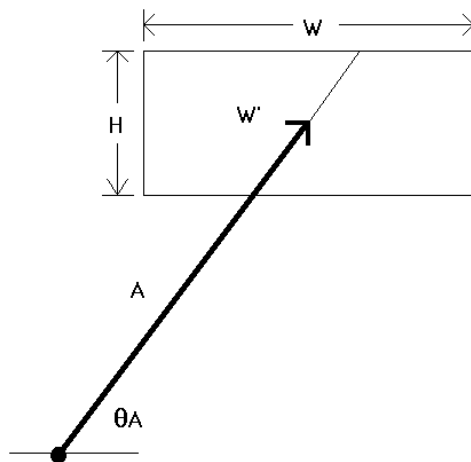
<http://www.yorku.ca/mack/CHI92.html>

(remember 'A' = Amplitude = 'D' = Distance)

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2D Targets: W' as Cross Section Given Approach



- But hard to know approach angle a priori ...

<http://www.yorku.ca/mack/CHI92.html>

(remember 'A' = Amplitude = 'D' = Distance)

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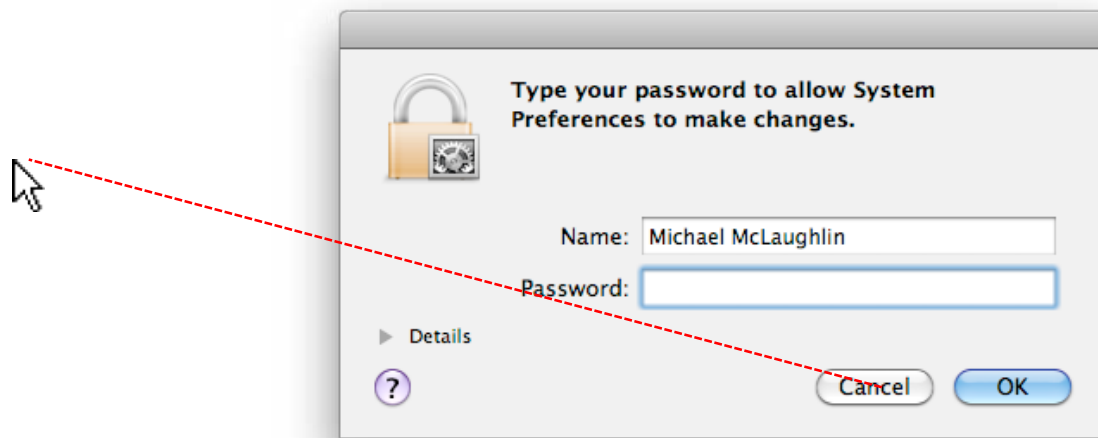
2D Targets: “W” is Minimum of Target W and H

$$MT = a + b \log_2 \left(\frac{D}{\min(W, H)} + 1 \right)$$

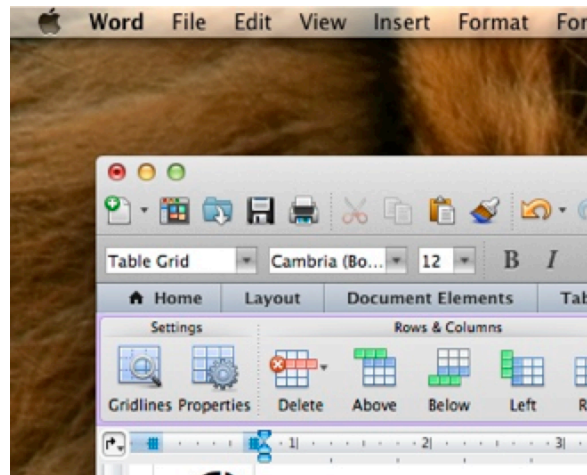
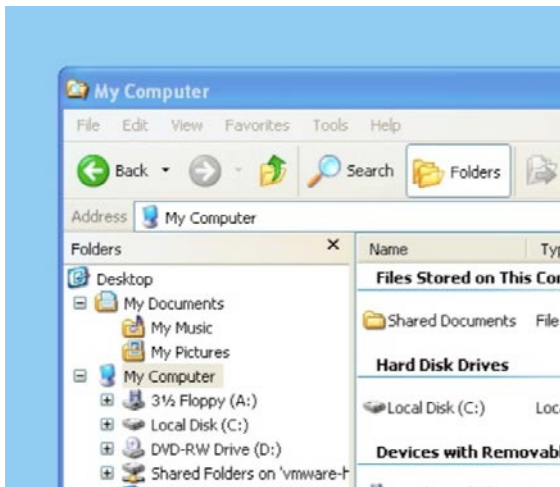
... but usually just write W assuming it's the minimum of target W and H

Fitts' Law Example

- Using a mouse to point ($a = -107$ and $b = 223$), what is the movement time to click on a 80 pixel by 32 pixel Cancel button located 400 pixels away?



Menu Target Size in OSX and Windows

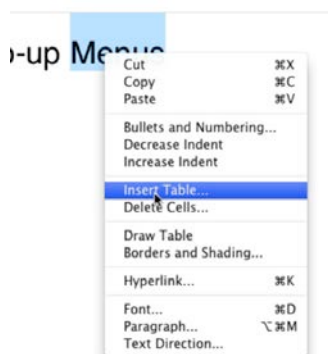


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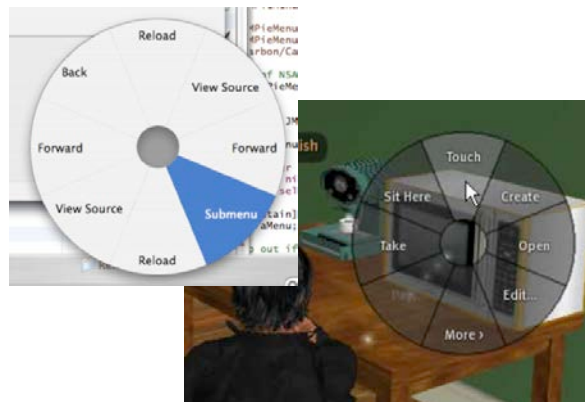
Context Menus, Pie Menus, Marking Menus

- Context Menu lowers D, but some items closer than others
- Pie Menus near mouse, all items same D (optimal)

context menu

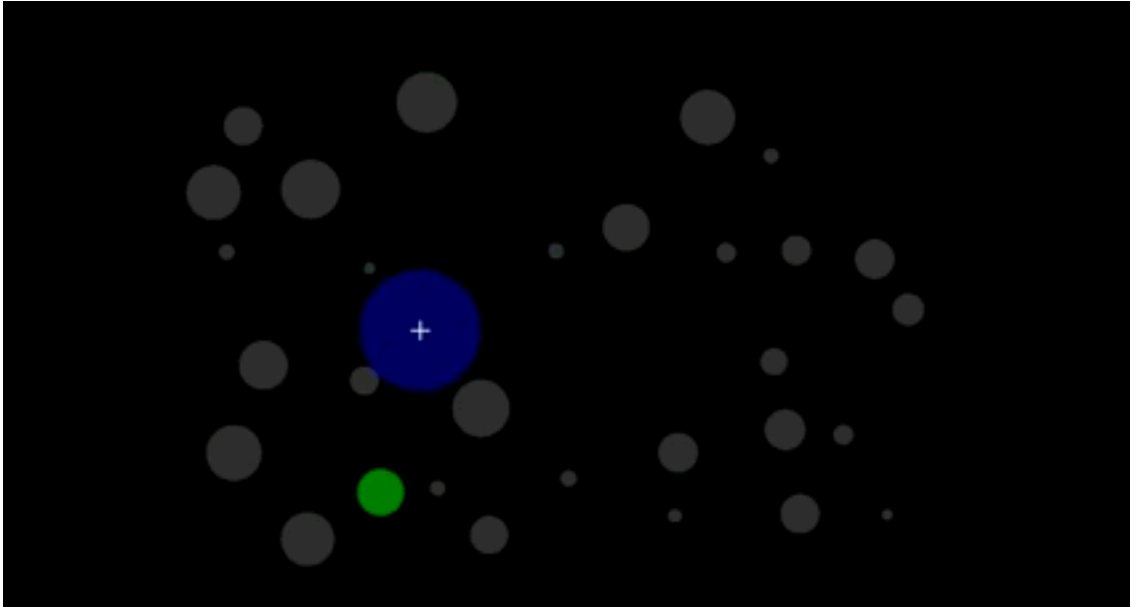


pie menu



<http://elementaryos.org/journal/argument-against-pie-menus>
http://instruct.uwo.ca/english/234e/site/secondlife_2.html

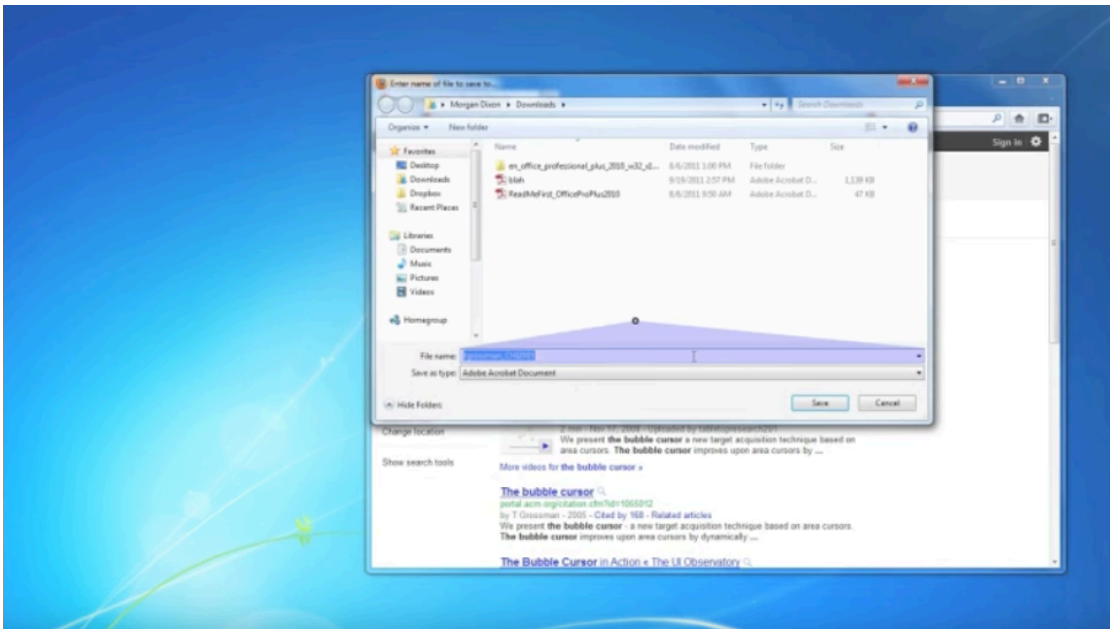
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Bubble Cursor (Grossman and Balakrishnan, 2005)

- http://youtu.be/JUBXkD_8ZeQ

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A General-Purpose Bubble Cursor using Prefab (Dixon et al. 2012)

- https://youtu.be/46EopD_2K_4

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OSX Dock Expansion

- OSX Dock expands in visual space, but not motor space ...
- Fitts's law says selecting an expanded target on the dock is **no easier** than the default small targets



McGuffin, M. J., & Balakrishnan, R. (2005). Fitts' law and expanding targets: Experimental studies and designs for user interfaces. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 12(4), 388-422.

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Motor Space vs. Screen Space

- Dynamically change CD Gain based on position of cursor
 - Making the cursor move more slowly when over the save button makes it larger in “motor space” even though it looks the same size in “screen space”.
 - LOOKS the same on screen, but “Save” button is “sticky”.
 - Faster to click “Save” (if Fitts' Law calculated in motor space).



visual space



motor space

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Steering Law

- Steering Law is an adaptation of Fitts' Law
- Developed by Zhai and Acott
- Choose a paradigm which focuses on steering between boundaries
- Applicability?

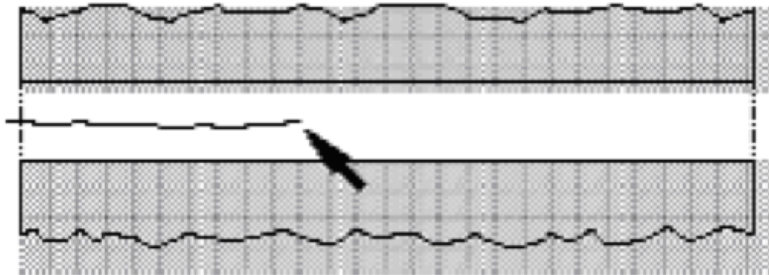
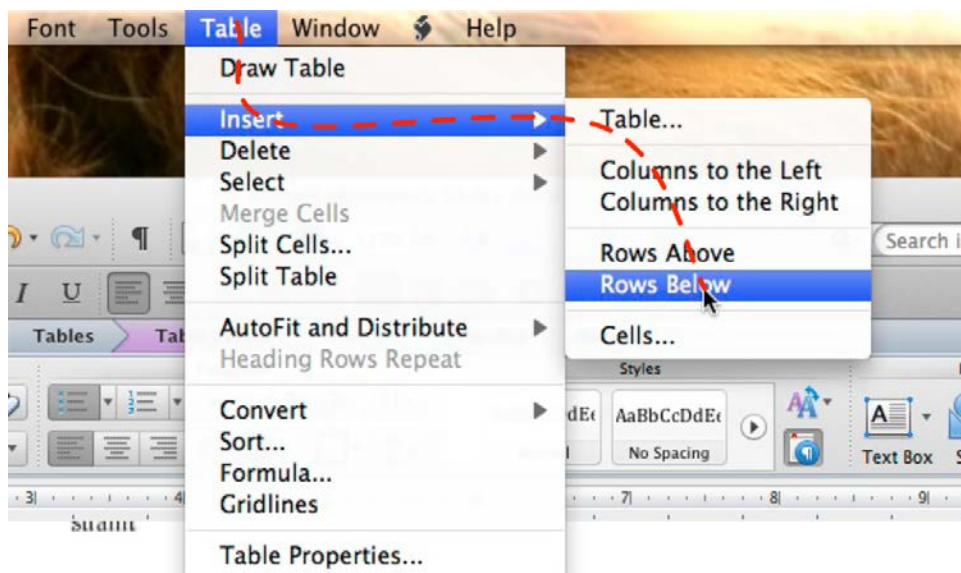


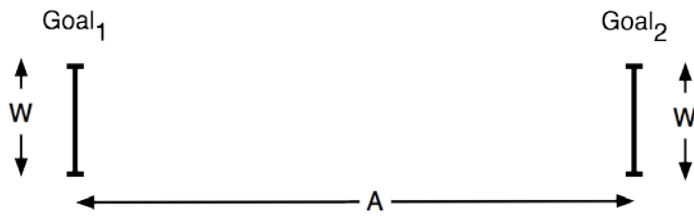
Figure 1: Self-paced movement with normal constraint

Steering Law

- Tracking a constrained path takes longer



Steering Law: Goal Passing



- Subjects passed a stylus from one end to the other
 - As fast as possible
 - Between each goal
 - Several trials with different amplitudes (A) and widths (W)
- Result: Same law as Fitts' tapping task

CS 349 - Input Performance

Steering Law: Goal Passing

- With only goals at the endpoints:

$$ID_1 = \log_2 \left(\frac{A}{W} + 1 \right)$$

- Adding N goals:



$$ID_N = \log_2 \left(\frac{A}{N \times W} + 1 \right)$$

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Steering Law: Goal Passing

- When N approaches infinity, the task approaches steering through a tunnel (hierarchical menu).
- Index of Difficulty:

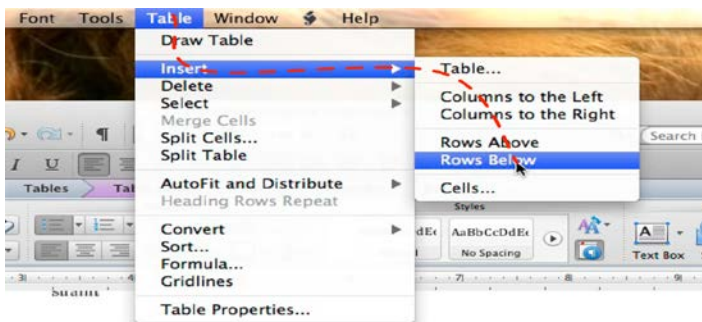
$$T = \lim_{N \rightarrow \infty} \sum_{i=1}^N b \log_2 \left(\frac{A/N}{W} + 1 \right)$$

$$T = b \frac{A}{W}$$

- So difficulty is not related to $\log(A/W)$ but just A/W

Hierarchical Menus

- Sum the parts of the path:
 - Wide path (but short stopping distance)
 - Narrow path (but wide stopping distance)
 - Wide path (with short stopping distance)



Summary

- We have mathematical models for acquiring a target, both when the path is unconstrained and constrained
 - Larger/closer is faster
- Gives some ideas for speeding things up
 - Keep things close (contextual, pie-menus)
 - Make things larger (bubble cursors)
 - Manipulate motor space to make intended targets stickier