HCI: Model-based Design
(Individual Models of Human Factors)

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Learning Objective

- In the previous lectures, we discussed two popular models belonging to the GOMS family, namely KLM and (CMN)GOMS
  - Those models, as we mentioned before, are simple models of human information processing
- They are one of three cognitive modeling approaches used in HCI System Design

Learning Objective

- A second type of cognitive models used in HCI is the individual models of human factors
- To recap, these are the models of human factors such as the motor movement, choice-reaction, eye movement etc.
  - The models provide analytical expressions to compute values associated with the corresponding factors, such as movement time, movement effort etc.

Learning Objective

- In this lecture, let us discuss two well known models belonging to this category
  - **The Fitts' Law**: a law governing the manual (motor) movement
  - **The Hick-Hyman Law**: a law governing the decision making process in the presence of choice

Fitts' Law

- It is one of the earliest predictive models used in HCI (and among the most well known models in HCI also)
- First proposed by P M Fitts (hence the name) in 1954

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology*, 47, 381-391.

Fitts' Law

- As we noted before, the Fitts' law is a model of human motor performance
  - It mainly models the way we move our hand and fingers
- A very important thing to note that this law is not generalized one; it models motor performance under certain constraints (next slide)

Fitts' Law - Characteristics

- This law models the human motor performance having the following characteristics
  - The movement is related to some *"target acquisition task"* (i.e., the human wants to acquire some target at some distance from the current hand/finger position)
  - The movement is *rapid* and *aimed* (i.e., no decision making is involved during movement)
  - The movement is *error-free* (i.e. the target is acquired at the very first attempt)

Nature of the Fitts' Law

- Another important thing about the Fitts' law is that, it is both a descriptive and a predictive model
- Why it is a descriptive model?
  - Because it provides "throughput", which is a descriptive measure of human motor performance
- Why it is a predictive model?
  - Because it provides a prediction equation (an analytical expression) for the time to acquire a target, given the distance and size of the target

Task Difficulty

- The key concern in this law is to measure “task difficulty” (i.e., how difficult it is for a person to acquire, with his hand/finger, a target at a distance D from the hand/finger’s current position)
  - Note that the movement is assumed to be rapid, aimed and error-free

Task Difficulty

- Fitts, in his experiments, noted that the difficulty of a target acquisition task is related to two factors
  - Distance (D): the distance by which the person needs to move his hand/finger. This is also called *amplitude* (A) of the movement
  - The larger the D is, the harder the task becomes
  - Width (W): the difficulty also depends on the width of the target to be acquired by the person
  - As the width increases, then the task becomes easier

Measuring Task Difficulty

- The qualitative description of the relationships between the task difficulty and the target distance (D) and width (W) can not help in "measuring" how difficult a task is
- Fitts' proposed a 'concrete' measure of task difficulty, called the "index of difficulty" (ID)

Measuring Task Difficulty

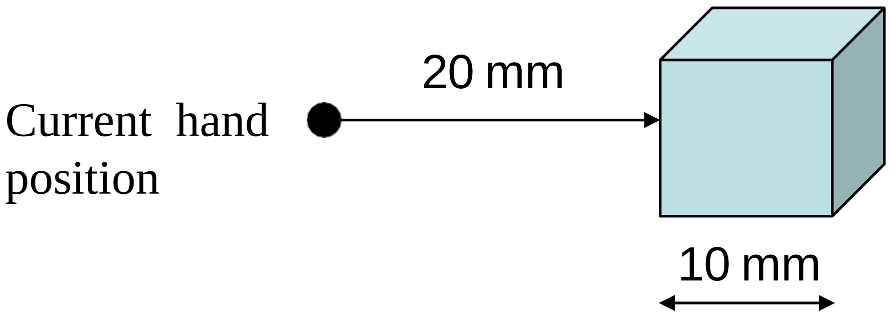
- From the analysis of empirical data, Fitts' proposed the following relationship between ID, D and W

$$ID = \log_2(D/W+1) \text{ [unit is } \textit{bits}\text{]}$$

(Note: the above formula was not what Fitts originally proposed. It is a refinement of the original formulation over time. Since this is the most common formulation of ID, we shall follow this rather than the original one)

ID - Example

- Suppose a person wants to grab a small cubic block of wood (side length = 10 mm) at a distance of 20 mm. What is the difficulty for this task?



- Here D = 20 mm, W = 10 mm Thus, ID = $\log_2(20/10+1)$

  $= \log_2(2+1)$

  $= \log_2 3 = 1.57$ bits

Throughput

- Fitts' also proposed a measure called the *index of performance* (IP), now called *throughput* (TP)
  - Computed as the difficulty of a task (ID, in bits) divided by the movement time (MT, in sec) to complete the task
- Thus, TP = ID/MT bits/sec

Throughput - Example

- Consider our previous example (on ID). If the person takes 2 sec to reach for the block, what is the throughput of the person for the task

Here ID = 1.57 bits, MT = 2 sec

Thus TP = 1.57/2

= 0.785 bits/sec

Implication of Throughput

- The concept of throughput is very important
- It actually refers to a measure of performance for rapid, aimed, error-free target acquisition task (as implied by its original name “The Index of Performance”)
  - Taking the human motor behavior into account
- In other words, throughput should be relatively constant for a test condition over a wide range of task difficulties; i.e., over a wide range of target distances and target widths

Examples of Test Condition

- Suppose a user is trying to point to an icon on the screen using a mouse
  - The task can be mapped to a rapid, aimed, error-free target acquisition task
  - The mouse is the test condition here
- If the user is trying to point with a touchpad, then touchpad is the test condition
- Suppose we are trying to determine target acquisition performance for a group of persons (say, workers in a factory) after lunch
  - The "taking of lunch" is the test condition here

Throughput – Design Implication

- The central idea is - Throughput provides a means to measure user performance for a given test condition
  - We can use this idea in design
- We collect throughput data from a set of users for different task difficulties
  - The mean throughput for all users over all task difficulties represents the average user performance for the test condition

Throughput – Design Implication

- Example – suppose we want to measure the performance of a mouse. We employ 10 participants in an experiment and gave them 6 different target acquisition tasks (where the task difficulties varied). From the data collected, we can measure the mouse performance by taking the mean throughput over all participants and tasks (next slide)

Throughput – Design Implication

D	W	ID (bits)	MT (sec)	TP (bits/sec)
8	8	1.00	0.576	1.74
16	8	1.58	0.694	2.28
16	2	3.17	1.104	2.87
32	2	4.09	1.392	2.94
32	1	5.04	1.711	2.95
64	1	6.02	2.295	2.62
			Mean	2.57

Each value indicates mean of 10 participants

The 6 tasks with varying difficulty levels

Throughput = 2.57 bits/sec

Throughput – Design Implication

- In the example, note that the mean throughputs for each task difficulty is relatively constant (i.e., not varying widely)
  - This is one way of checking the correctness of our procedure (i.e., whether the data collection and analysis was proper or not)

Summary

- In this lecture, we introduced to the concept of throughput and how to measure it
- In the next lecture, let us see more design implications of throughput
- We will also discuss the predictive nature of the Fitts' law
- And, we shall discuss the Hick-Hyman law

Learning Objective

- So far, we got introduced to the Fitts' law
  - The Fitts' law models human motor behavior for rapid, aimed, error-free target acquisition task
- The law allows us to measure the task difficulty using the index of difficulty (ID)

Learning Objective

- Using ID and task completion time (MT), we can compute throughput (TP), which is a measure of task performance

$$TP = ID/MT$$

Unit of ID is bits, unit of MT is sec

Thus, unit of TP is bits/sec

Learning Objective

- We saw how TP helps in design
  - We estimate the user performance under a test condition by estimating TP
  - The TP is estimated by taking the mean of the TP achieved by different persons tested with varying task difficulty levels under the same test condition

Learning Objective

- In this lecture, we shall extend this knowledge further and learn about the following
  - How TP can help in comparing designs?
  - How the Fitts' law can be used as a predictive model?
- Also, we shall learn about the Hick-Hyman law, another model of human factor (models the choice-reaction time)

Throughput – Design Implication

- In the case of Fitts' law, we discussed one design implication of throughput in HCI
  - That is, to estimate user's motor performance in a given test condition
- We can extend this idea further to compare competing designs

Throughput – Design Implication

- Suppose you have designed two input devices: a mouse and a touchpad. You want to determine which of the two is better in terms of user performance, when used to acquire targets (e.g., for point and select tasks). How can you do so?

Throughput – Design Implication

- You are asked to set up two experiments for two test conditions: one with the mouse and the other with the touchpad

- Determine throughput for each test condition as we have already done before (i.e., collect throughput data from a group of users for a set of tasks with varying difficulty level and take the overall mean)

Throughput – Design Implication

- Suppose we got the throughputs TP1 and TP2 for the mouse and the touchpad experiments, respectively

- You are asked to Compare TP1 and TP2

  - If TP1>TP2, the mouse gives better performance

  - The touchpad is better if TP1<TP2

  - Performance-wise they are the same if TP1=TP2 (this is very unlikely as we are most likely to observe some difference)

Predictive Nature of Fitts’ Law

- The throughput measure, derived from the Fitts’ law, is descriptive
  - We need to determine its value empirically
- Fitts’ law also allows us to predict performance
  - That means, we can “compute” performance rather than determine it empirically

Predictive Nature of Fitts' Law

- Although not proposed by Fitts, it is now common to build a prediction equation in the Fitts' law research
- The predictive equation is obtained by linearly regressing MT (movement time) against the ID (index of difficulty), in a MT-ID plot
- The equation is of the form $MT = a + b.ID$

  Where, a and b are constants for a test condition (empirically derived)

Predictive Nature of Fitts' Law

- As we can see, the equation allows us to predict the time to complete a target acquisition task (with known D and W)
- How we can use the predictive equation in the system design?
  - We determine the constant values (a and b) empirically, for a test condition
  - Use the values in the predictive equation to determine MT for a representative target acquisition task under the test condition
  - Compare MTs for different test conditions to decide (as with throughput)

Speed-Accuracy Trade-off

- Suppose, we are trying to select an icon by clicking on it. The icon width is D
  - Suppose each click is called a "hit". In a trial involving several hits, we are most likely to observe that not all hits lie within D (some may be just outside)
  - If we plot the *hit distributions* (i.e., the coordinates of the hits), we shall see that about 4% of the hits are outside the target boundary

Speed-Accuracy Trade-off

- This is called the speed-accuracy trade-off
  - When we are trying to make rapid movements, we can not avoid errors
- However, in the measures (ID, TP and MT), we have used D only, without taking into account the trade-off
  - We assumed all hits will be inside the target boundary

Speed-Accuracy Trade-off

- We can resolve this in two-ways
  - Either we proceed with our current approach, with the knowledge that the measures will have 4% error rates
  - Or we take the effective width D_e (the width of the region enclosing all the hits) instead of D
- The second approach requires us to empirically determine D_e for each test condition

The Hick-Hyman Law

- While Fitts' law relates task performance to motor behavior, there is another law popularly used in HCI, which tell us the "reaction time" (i.e., the time to react to a stimulus) of a person in the presence of "choices"
- The law is called the Hick-Hyman law, named after its inventors

Example

- A telephone call operator has 10 buttons. When the light behind one of the buttons comes on, the operator must push the button and answer the call
  - When a light comes on, how long does the operator takes to decide which button to press?
- In the example,
  - The "light on" is the stimulus
  - We are interested to know the operator's "reaction time" in the presence of the stimulus
  - The operator has to decide among the 10 buttons (these buttons represent the set of choices)

The Hick-Hyman Law

- As we discussed in the example (previous slides), the Hick-Hyman law can be used to predict the reaction times in such situations
- Thus, this law models the human's reaction time (also called *choice-reaction time*) under *uncertainty conditions* (the presence of choices)
  - The law states that the reaction (decision) time T increases with uncertainty about the judgment or decision to be made

The Law

- We know that a measure of uncertainty is referred to as the entropy (H)

  Thus, T α H

  or equivalently, T = kH, where k is the proportionality constant (empirically determined)

- We can calculate H in terms of the choices in the following way

  let, pi be the probability of making the i-th choice

  Then, H = $\sum_{i=1} p_i \log_2(1/p_i)$

The Law

- Therefore,

$$T = k\sum_{i=1} p_i \log_2(1/p_i)$$

- When all the probabilities of making the choices becomes equal, we have H = $\log_2 N$ (N = no of choices)
  - In such cases, T = k $\log_2 N$

Example Revisited

- Then, what will be the operator's reaction time in our example?
  - Here N = 10
  - A button can be selected with a probability 1/10 and all probabilities are equal
  - Thus, $T = k \log_2 10$

    $= 0.66$ ms (assuming a = 0, b = 0.2)