THE PSYCHOLOGY OF USER-COMPUTER INTERACTION

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Abstracts:

1. User-Computer Interaction and Cognitive Psychology

Computer science is an asymmetric field. While many topic problems of computer technology are intimately connected with the human use of computing machinery, only the machine side of these problems is usually studied. An obvious topic that would benefit from work on both the human and machine aspects is human-computer interaction. However this is not easy to do. The need to base human factors for computer interaction on a theory of human cognition is discussed, stressing the primacy of design and the critical roles of engineering calculations. The ground is laid for such an advance by presenting the Model Human Processor, a highly approximative, but useful, engineering-level model of how humans proces information.

2. Examples of Model-based Human Factors

A series of examples are presented for how to model human-computer interactions in ways that permit approximative engineering calculations. The examples are drawn from pointing devices and editors. In each case, the advantages of having models or theories of the phenomena, as opposed to merely the results from comparative experiments are stressed.

3. Human-Computer Interaction in the Computer Science Curriculum

The point of view manifest in the prior two lectures provides a basis for discussing how human-computer interaction might become a part of the computer science curriculum. Nine issues raised by the introduction of human-computer interaction topics are discussed. Among other things, the conclusions are drawn that human engineering of actual interfaces will probably be done predominantly by computer scientists as opposed to human factors practitioners and that the teaching of human-computer interaction should be dispersed among subject courses rather than being concentrated into a course on humans. A suggested course syllabus is drawn to stimulate discussion.

LECTURE 1

USER-COMPUTER INTERACTION AND COGNITIVE PSYCHOLOGY

In recent years, the convergence of a number of forces has brought the human-computer interface forward as an area of increasing importance within computer science:

1. There is finally enough raw computing power to make it practical to expend significant resources on the interface.

2. Bitmapped raster displays have reduced the cost of graphics interfaces to where they can become widespread and made graphics easier to program.

3. The effect of the above developments has been to make it possible and practical for computers to be applied to new tasks, tasks that tend to be more cognitive and that tend to require more intimate interfaces with higher densities of userinteractions/time.

There now seem to be nearly unlimited possibilities for interacting with computing machines far beyond the teletype-oriented turn-taking of the recent past. At the same time, interfaces have become both the critical element on which the success of many programs depend and the part of the program least predictable for designing.

Our goal in these lectures is to consider this subfield of human-computer interaction and its place in the discipline and teaching of computer science. The construction of computer interfaces is a topic of many parts: user interface management systems, control structures, data structures, graphical interaction techniques, to name a few. These are topics to which the computer scientist is naturally drawn. We intend, therefore, to focus on a part of the problem that, although acknowledged important, is something of a nuisance in human-computer interaction, namely, the human.

Computer science, as it currently exists, is a curiously asymmetric field. Many problems in computers are intimately connected with the human use of computing machinery. Yet only the machine side of this interaction tends to be studied. For example, programming languages mediate between, on the one hand, something that generates a program, and on the other, something that receives a program and executes it. One would expect there to be substantial technical study on each side of the problem: On the machine side there might be studies of parsing algorithms, algorithmic efficiency, run-time environments, and storage. On the human side there might be studies of what languages are easy to learn, to understand, to generate, and to debug. A similar analysis could be repeated for other topics where computers and humans interact: the design of computer-based communications systems for organizations, team organization for software production, programming, human-computer interaction.

Of course, it is all well and good to puff about how computer science ought to be a bit less asymmetric, paying attention to the user, whereas the actual doing of this is a matter of some difficulty. The question is whether studies on the human side are possible with any acceptable degree of rigor. As a means of answering this question, we shall proceed with a particular view of the state of the art in human-computer interaction that fits what we think is needed for its progress and integration into computer science. We begin with a consideration of what is known about the human from psychology and human factors.

Classical Human Factors

There have always been applied parts of psychology: intelligence testing, personnel selection, and clinical psychology, to state some examples. The study of how people deal with machines got its major impulse during World War II with studies of vigilance (why, after several hours on watch radar operators miss blips), aircraft cockpits (knobs and dials), and manual control (the extension of control theory to include explicit models of humans). Incidently, this latter study, manual control, was so successful that it is today becoming of limited importance: theories of pilot control are good enough that they can sometimes be used to replace the pilot in many of the same tasks that these theories used to be used in for predicting the pilot! Contemporary cognitive psychology is a direct descendent of these equipment studies (although, curiously, it has avoided manual control).

In the United States, studies of people and equipment came to be called human factors: in Europe, a similar (though definitely not identical) area of studies came to be called ergonomics. The classical style of human factors work has been the *comparative experiment.* For example, Fig. 1 shows a set of dials taken from an experiment on the check-reading of instruments. The users in the experiment (Kurke, 1956) are given a task to do. During this task the dial on the pointer is moving. The experimenter measures how long it takes the subject to notice that the pointer has gone into the "danger" zone. From Fig. 1, we can see that the dial displaying a red wedge whenever the pointer is in the danger zone takes the least time to notice and the dial with no marking of the danger zone is the worst.

For another example, Fig. 2 shows two possible arrangements of key pads for push-button telephones. One arrangement matches that of adding machines, the other arranges the keys in order. Users in this experiment (Conrad and Hull, 1968) "dialed" a set of telephone numbers with the result that more errors appear to have been induced by the adding machine arrangement than

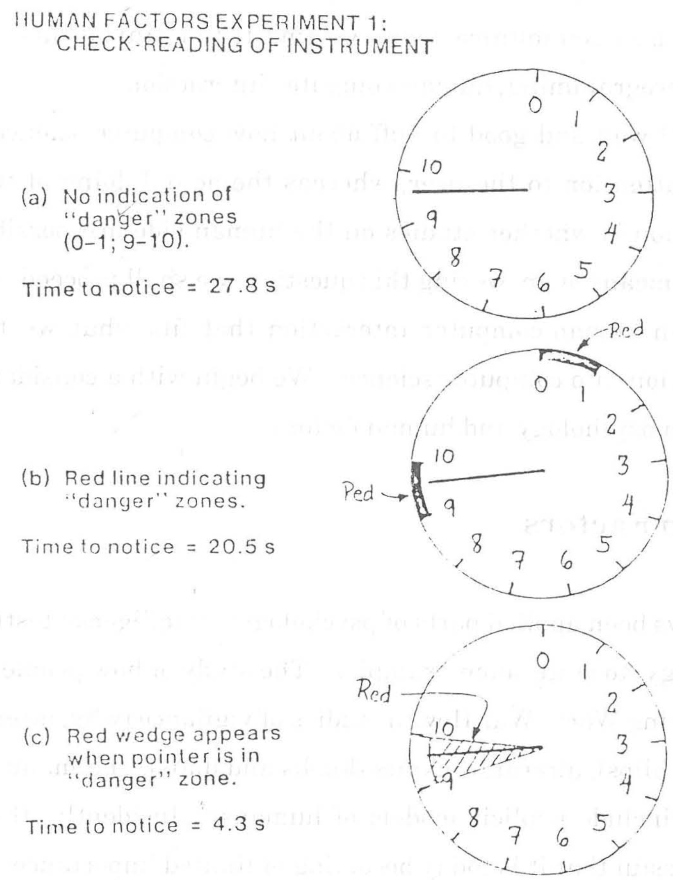


Fig. 1.

HUMAN FACTORS EXPERIMENT 2:
ERROR RATE OF TELEPHONE NUMBER PADS

ADDING MACHINE	TELEPHONE
9 8 7	1 2 3
6 5 4	4 5 6
3 2 1	7 8 9
0	0

Percentage errors:

ADDING MACHINE	TELEPHONE
8.2 %	6.4 %

Fig. 2.

by the numerical arrangement. Partly on the basis of this experiment, telephone keypads in the United States are numerically arranged.

In addition to the comparative experiment, another tool of the human factors practitioner is what might be called *task analysis*, broadly construed: The analyst writes down everything a person must do to complete a task. He uses this list to discover conflicts, awkwardnesses, potential errors, and likely execution times. For example, the airline industry conducts "time-line analyses" in which each action a pilot will perform in, say, landing his airplane is carefully scrutinized.

Of course, there are other detailed methods available in human factors (see National Research Council, 1983), but these two, comparative experiments and task analysis, are really the essence of what is available. These two tools *are* useful in investigating human-computer interaction, but they have important limitations: The problems with comparative experiments are (1) they cannot be done at design time (because the system has not been built yet) and (2) with so many potential sources of interaction around, one does not trust them to generalize to the next situation (in the absence of some theory or model). The problem with task analysis is that, as usually practiced, the analysis has a difficult time reaching highly cognitive issues, and the systems we build are increasingly cognition-intensive.

The Nature of Human-Machine Interaction

In order to gauge the purchase available from different analysis and measurement techniques, it is important to appreciate the full complexity of the human-computer interaction problem. The most general formulation of human-machine interaction is probably the case where a computer is embedded in a larger piece of equipment controlled by a human operator. Fig. 3 presents a diagram based on Sheridan's model of supervisory control (see National Research Council, 1983, Ch. 4) of a computer as part of some system such as a power plant or a space station. The computer is shown broken into two computers, one to service the task, the other to service the user interface. Evident in the diagram are a number of feedback paths indicating possible control loops for the sensors (e.g., automatic light adjustment), the activators (e.g., inner loop controls for aircraft), the display itself, and the controls the user employs. But complex interactions are also possible between the task interface computer and the human interface computer. Table 1 gives ten interaction modes between the user and the machine. A designer must choose amongst these very carefully. Of course many computing systems are simpler; but they can be thought of as degenerate cases of Fig. 3 in which the task, sensors, and effectors are all inside the computer and the human interface computer is just a user interface management system, or perhaps even code intermixed with task code.

GENERALIZED MODEL OF HUMAN-COMPUTER INTERACTION

(Based on Sheridan's Supervisory Control Model)

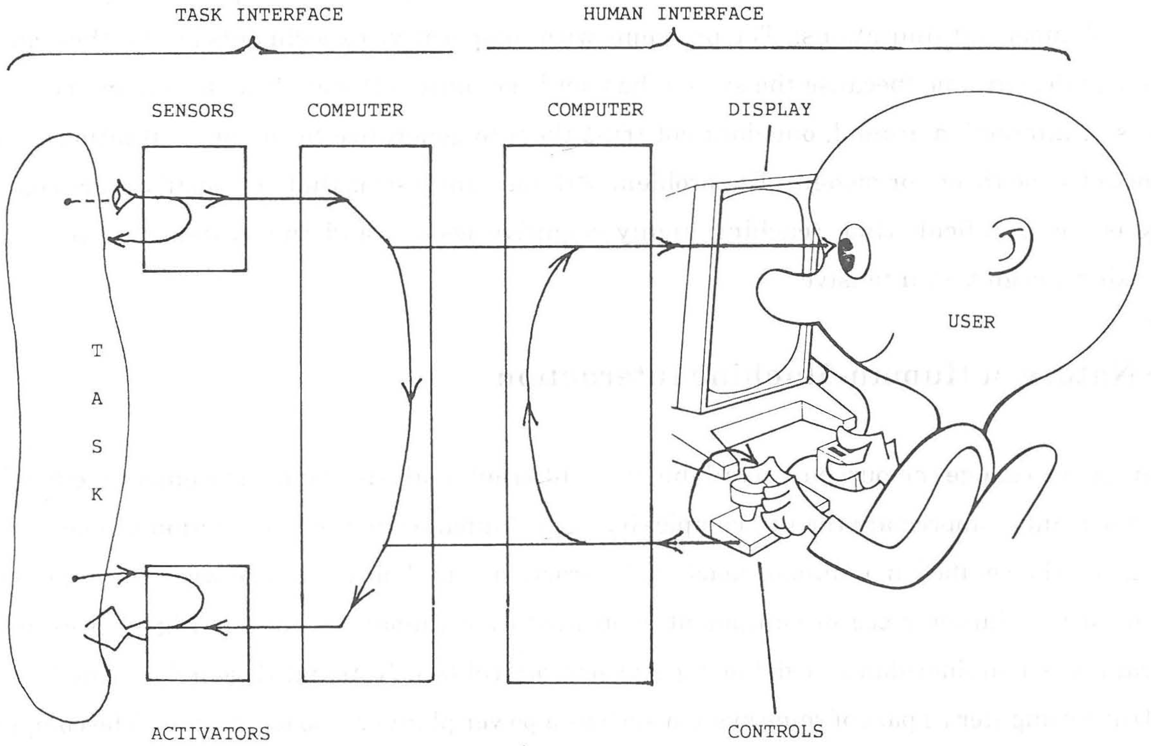


Fig. 3

TABLE 1.

Levels of Automation

100% Human Control	1.	Human considers decision alternatives, makes and implements a decision.
	2.	System suggests set of decision alternatives, human may ignore them in making and implementing decision.
	3.	System offers restricted set of decision alternatives, human decides on one of these and implements it.
	4.	System offers restricted set of decision alternatives, and suggests one, human may accept or reject, but decides on one and implements it.
	5.	System offers restricted set of decision alternatives and suggests one which it, the system, will implement if human approves.
	6.	System makes decision and necessarily informs human in time to stop its implementation.
	7.	System makes and implements decision, necessarily tells human after the fact what it did.
	8.	System makes and implements decision, tells human after the fact what it did only if human asks.
	9.	System makes and implements decision, tells human after the fact what it did only if it, the system, thinks he should be told.
100% Automated Control	10.	System makes and implements decision if it thinks it should, tells human after the fact if it thinks he should be told.

Source: Sheridan, reprinted in (National Research Council, 1982, p. 112)

A number of problems must be resolved in designing an interface. Table 1 and the feedback loops in Fig. 3 have already illustrated the *automation problem* (which parts of the task should be done by which parts of the machine and who should have the initiative when?). Other problems are the *display problem* (how can the display be employed to increase system usability?), and the *interaction techniques problem* (which interaction techniques are advantageous?). Both of these are part of the larger *communication problem* (how is it that the intentions and information of the user can be communicated to the machine and vice versa?). Like the automation problem, the analysis of communication can become complex. There are logically three active agents involved, two computers and one human. Each of these may contain models of the others such that one agent may presume to do what it thinks another requires on the basis of its model of that agent, without actually being commanded. Intelligent tutoring programs, for example, choose which exercises to display to the user on the basis of a changing model of the user's competence (Sleeman and Brown, 1982). We shall not discuss these problems of interface design directly. Instead we shall discuss an approach to the problems and in so doing try to illustrate where we believe the study of human-computer interaction fits into other knowledge of computer science.

It is a basic goal of work on human-computer interaction to make it possible to have a discipline of interface design more like standard engineering. For example, it would be useful to be able to make back-of-the-envelope calculations of human performance. Why? Not just to emulate the physical sciences, but because design time is the critical time for human-engineering. And to analyze user behavior at design time we need predictive models. In fact, we can summarize the sort of models we need in terms of three criteria: task analysis, calculation, and approximation.

> *Task analysis.* We need to be able to take a human task and to analyze what the rational courses of action are to determine the actions that will be required to accomplish the task.
>
> *Calculation.* We need to be able to make at least simple calculations concerning things like time to complete a task, time to learn a system, and errors likely to occur. Furthermore, if calculations are to be useful they must only require data that is available and they must be reasonably simple.
>
> *Approximation.* Humans, of course, are complex. If the calculations are to be simple (in fact, if they are to be done at all) they will have to be approximations. Fortunately, many of the decisions we have to make do not depend on the fine details of human performance.

The source of ideas for moving in the above direction is modern cognitive psychology. A major revolution in our understanding of human cognition has taken place since the 1950s. This increase in insight about human mental functioning ultimately derives from our new understanding of man as a processor of information. Advances in cognitive psychology, especially in the problem solving area, are closely related to developments in artificial intelligence, specifically with the development of techniques for representing complex information and with the theory of heuristic search. Many of the results from this area are highly compatible with the tools needed to study human-computer interaction (not so suprising since we are considering man in the context of information-processing machines).

The Model Human Processor

At the center of any attempt to make use of cognitive psychology for engineering purposes is a summary of human information-processing capabilities. We shall, therefore, begin with our own such summary called the Model Human Processor. Here we shall only have time for a brief summary. The complete model is contained in Card, Moran, and Newell (1983). This model is inspired by the simplified description sometimes used in computer science to describe computer systems in terms of processors, memories, and switches (Siewiorek, Bell, and Newell, 1981); we shall describe the human processor in terms of processors and memories. In the spirit of approximation, the idea is to put forward a simplified engineering model for supporting predictions of user behavior, rather than to explain in detail the many intricate phenomena of human performance.

The Model Human Processor summarizes human processing capability in terms of three processors (see Fig. 4):

a Perceptual Processor,
a Cognitive Processor, and
a Motor Processor.

For single shot tasks, such as pressing a button at the sound of a signal, these processors run in a series. But for some tasks, the processors can operate pipelined-parallel: a user can type the last word while reading the next word, for example. (Actually there are several Perceptual Processors—speech and vision, for example, require different processing—but we have simplified this here.) These processors are thought of as having a processing cycle during which elementary processing takes place. As examples, events that occur within one Perceptual Processor Cycle tend to be perceived as part of a single event and movements are composed of simple micromovements.

MODEL HUMAN PROCESSOR

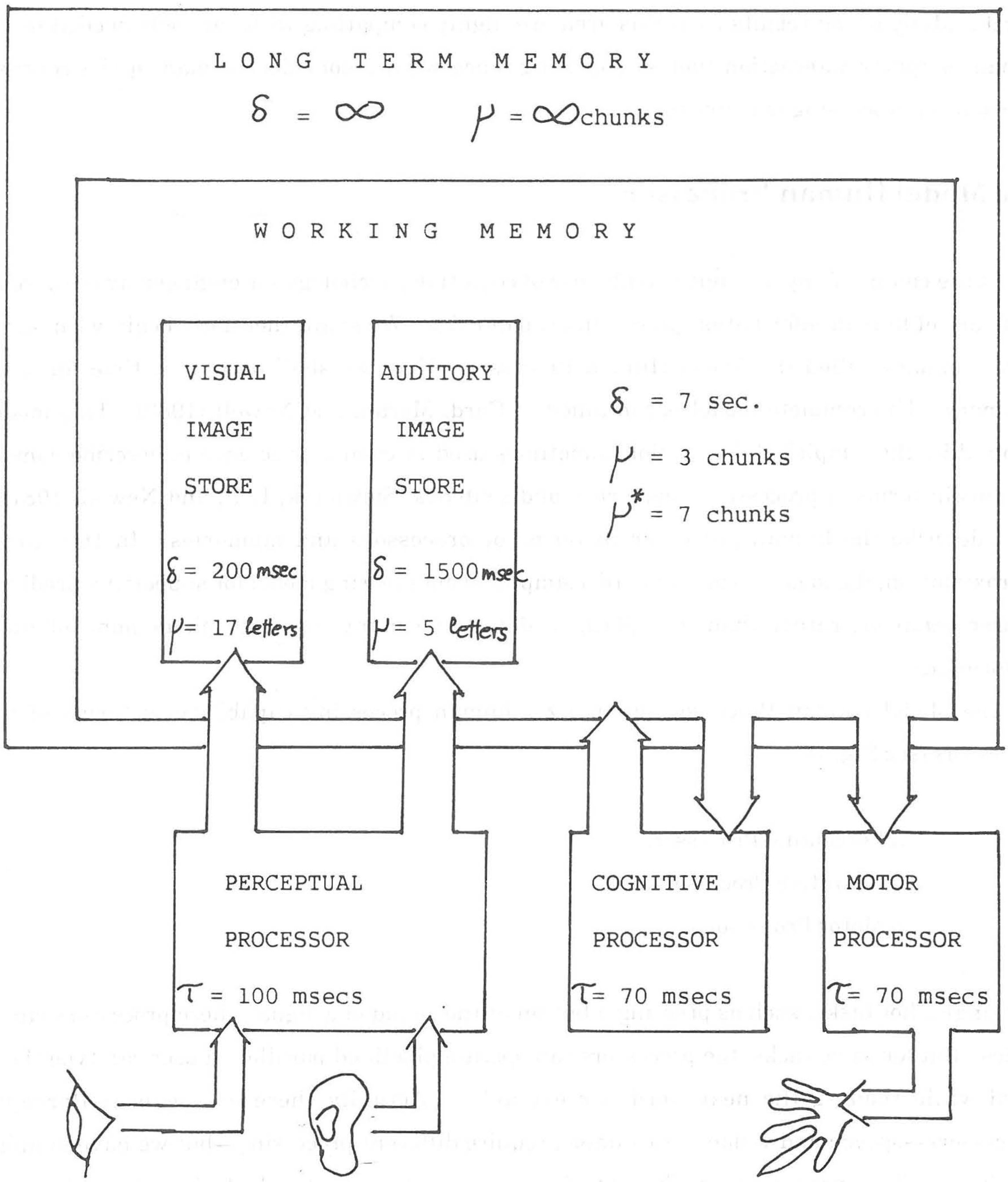


Fig. 4

Human memory is summarized in terms of four memories:

a Visual Image Store
an Auditory Image Store
a Working Memory, and
a Long-Term Memory.

Fig. 4 does not look like the usual computer memory with separate transfer paths, because human memory is actually hierarchical. Items in the Visual Image Store and the Auditory Image Store appear after a short delay symbolically coded in the Working Memory. Working Memory can be thought of as a set of activated nodes of a semantic network in Long-Term Memory (where all the knowledge resides). The Visual Image Store and the Auditory Image Store are the sample-and-hold buffers where sensory inputs are stored in a physical code (if the light is brighter, the memory of it takes longer to decay). Working Memory is sort of the general register of the mind and stores information symbolically, generally with some sort of acoustic (or even visually-based) code. It is shown surrounding the sensory buffers because these are closely connected: About 10 msec (below the time grain of our model) after the physical pattern for a letter appears in a sensory buffer, it appears in Working Memory with a symbolic code.

Many of the limits of the human processor can be summarized in terms of a few parameters:

(for memories)
δ Decay time
μ Capacity, and
κ Code type

(for processors)
τ cycle time

For example, if a long list of numbers is read to a person and he is unexpectedly asked in the middle to recall as many numbers back as possible, he will be able to recall about $\mu_{WM} = 3$ numbers. But, if a person is tested for his ability to recall 4-digit numbers, then 5-digit number, then 6-digit numbers, etc. He is likely to start having difficulty above $\mu_{WM}{}^{*} = 7$-digit numbers. In this latter case he is employing not only Working Memory, but also some Long-Term Memory as well to give the famous 7 ± 2 number.

Fig. 5 summarizes the values of this set of parameters. The values available in the literature for the parameters vary somewhat depending on the exact operational definition employed in an

CONSTANTS FOR THE MODEL HUMAN PROCESSOR

MEMORIES:	LTM	Decay	infinite
		Capacity	infinite
		Code	semantic
	WM	Decay	7 [5-226] sec 7 [5-34] sec (3 chunks) 73 [73-226] sec (1 chunk)
		Capacity	3 [2.5-4.1] chunks 7 [5-9] chunks (with LTM)
		Code	acoustic, visual
	VIS	Decay	200 [70-1000] msecs
		Capacity	17 [7-17] letters
		Code	physical
	AIS	Decay	1500 [900-3500] msecs
		Capacity	5 [4.4-6.2] letters
		Code	physical
PROCESSORS:			
	Perceptual	Cycle time	100 [50-200] msecs
	Cognitive	Cycle time	70 [25-170] msecs
	Motor	Cycle time	70 [30-100] msecs
	Eye movement	Fixation	230 [70-700] msecs

Fig. 5

experiment, which experimental paradigm is used to measure it, or which human subjects are measured. This is the sort of variation that drives psychologists to distraction and despair. What is amazing is that there is, in fact, a good deal of concordance in the results of psychological experiments if only one spends as much time searching for the similarities as for the differences. For example, there must be hundreds of experiments that discover an operation with a time constant on the order of .1 sec. These regularities are generally underappreciated, probably because of the extreme emphasis in psychology on detecting statistically significant differences rather than in looking for approximations and idealized models. Many engineering disciplines based on the physical sciences also have to contend with variation: heating design (what temperatures will the building experience?), soil engineering (the composition of soils in a piece of land can only be sparsely sampled), bridge building (what will the wind speed and gusting behavior be? what will be the exact structural consequences of rust?) We handle this problem of parameter variation by having a lower and upper bound on the parameter set by the literature. Since these bounds represent unlikely extremes, we also set a more typical number. So we write the cycle time of the Perceptual Processor as

$$\tau_P = 100\,[50\sim200]\ \text{msec.}$$

The lower bound is 50 msecs; the upper bound is 200 msecs; and 100 msec is a typical value that appears under typical light levels in many experiments. This is the form in which parameters appear in Fig. 5.

Deriving Parameters from the Psychological Literature

Evidence for the value of these parameters comes from experiments in the psychological literature. Fig. 6a shows measurements of the decay time for the Visual Image Store. An array of letters is shown to a subject for a very short interval (50 msec). At some interval after the letters disappear a visual or auditory cue indicates to the subject which row of letters he is to report (He cannot be expected to recall more than the effective capacity of Working Memory $\mu_{WM}*$, even if these letters were in the Visual Image Store, so a cueing arrangement is used to sample). The curve plots the extra letters (in excess of Working Memory capacity) that the subjects could report as a function of the time that elapsed before they were cued. The curve shows an exponential decay whose slope we can characterize by the half-life δ. The family of curves shows that there is more regularity that we could parameterize (the number of letters visible has an important effect on the half-life). In this case we judge the gain is not worth the increase in fussiness for application, and

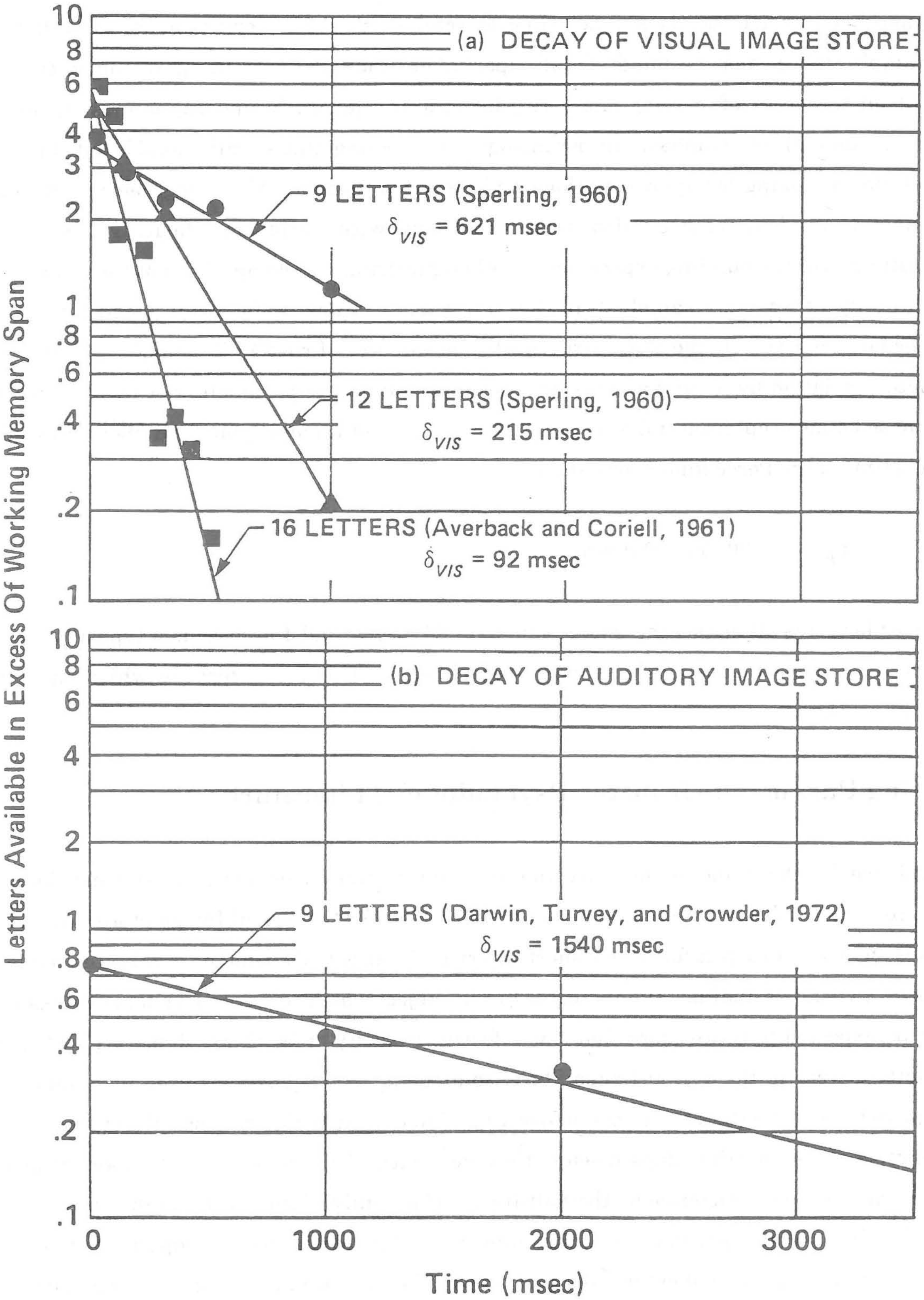

(a) DECAY OF VISUAL IMAGE STORE
9 LETTERS (Sperling, 1960)
δ_{VIS} = 621 msec
12 LETTERS (Sperling, 1960)
δ_{VIS} = 215 msec
16 LETTERS (Averback and Coriell, 1961)
δ_{VIS} = 92 msec
(b) DECAY OF AUDITORY IMAGE STORE
9 LETTERS (Darwin, Turvey, and Crowder, 1972)
δ_{VIS} = 1540 msec
Letters Available In Excess Of Working Memory Span
Time (msec)
0
1000
2000
3000
10
8
6
4
3
2
1
.8
.6
.4
.2
.1

Fig. 6.

so we accept the wider range of the parameter rather than a smaller range but more difficult application. Fig. 6b shows a similar measurement for the Auditory Image Store.

Fig. 7 illustrates that the unit of memory is a chunk (information treated as a single unit) and that the number of chunks makes more difference than what the chunks are composed of. The subject is given either one chunk or three chunks to remember, then maliciously prevented from rehearsing by having to count backward by sevens. After a time, he is asked to recall the original chunk. The curve plots the percentage of chunks correctly recalled as a function of time. Again there is roughly an exponential decay that can be characterized by a half-life.

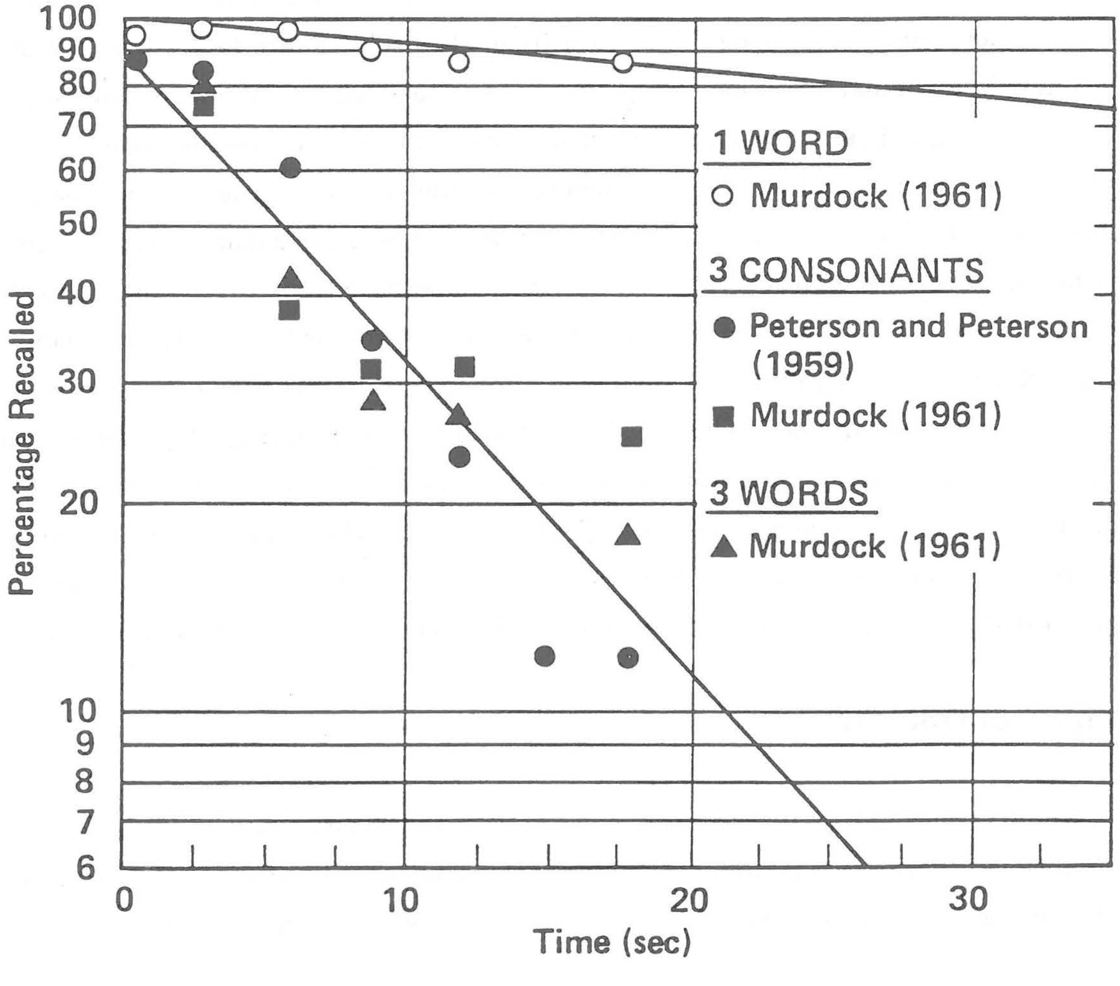
As a final example of the origins of these parametric values, Fig. 8 gives estimates of the Cognitive Processor rate. One series of experiments involve presenting to the subjects a number of numbers or other items, then giving them a test item. The subjects are to say whether the test item was one of the original set. It has been found that this task takes time linear with the number of items in the original set. Currently accepted models of the task have the subject mentally matching the test item one at a time with members of the set, and hence it is one estimate of cognitive cycle time. Experiments with everything from numbers to random shapes give times in the neighborhood of 27 to 93 msec/item. Another way to perform the measurement is to show a person a number of dots or other shapes and see how long it takes for him to say how many there are. Depending on how many there are, the shape, and the person, this number ranges from 40 to 172 msec/item. The measurement with the slowest times is silent counting. A person is asked to count to some number (saying the unit digits silently to himself) and the time measured. This measurement gives a number of about 167 msec/digit. When we put these and other measurements together, we find that there is a range, but that they are all somewhere in the neighborhood of a tenth of a second. Our summary of the literature is $\tau_C = 70[25 \sim 170]$ msec.

Principles of Operation

In addition to the architecture and parameters we have talked about, we also need to describe a sort of Principles of Operation to capture some of the dynamic behavior these miss. Fig. 9 lists the Principles of Operation for the Model Human Processor. A few comments about these:

Recognize-Act Cycle.

The human does not have a fetch-execute cycle like a classical computer (that is, a plan with a pointer). Instead, on each cycle, data that is in Working Memory matches best something that is in Long-Term Memory. The match becomes the new contents of Woking Memory. Another way of saying this is that certain nodes of Long-Term Memory are activated. On each cycle these activate other nodes, and so on.



100
90
80
70
60
50
40
30
20
10
9
8
7
6
Percentage Recalled
0
10
20
30
Time (sec)
1 WORD
○ Murdock (1961)
3 CONSONANTS
● Peterson and Peterson (1959)
■ Murdock (1961)
3 WORDS
▲ Murdock (1961)

Fig. 7.

COGNITIVE PROCESSOR RATE : Tc

MATCHING ITEMS:	27-93 msec/item
DIGITS	33 [27-39] msec/item
LETTERS	40 [24-65] msec/item
WORDS	47 [36-52] msec/item
GEOMETRICAL SHAPES	50 msec/item
RANDOM FORMS	68 [42-93] msec/item
NONSENSE SYLLABLES	73 msec/item
COUNTING FEW OBJECTS:	40-172 msec/item
DOT PATTERNS	46 msec/item
3-D SHAPES	94 [40-172] msec/item
PERCEPTUAL JUDGEMENT	92 msec/inspection
CHOICE REACTION TIME	153 msec/bit
SILENT COUNTING	167 msec/digit

Fig. 8

Variable Perceptual Processor Rate.

More intense stimuli reduce the cycle time of the Perceptual Processor.

Encoding Specificity Principle.

To retrieve an item from Long-Term Memory, the user has to use the links that were encoded at the time the itemwas stored.

Discimination Principle.

The more similar things in memory are, the harder it is to recover them.

Variable Cognitive Processor Rate.

The Cognitive Processor cycle time can be reduced somewhat with effort or practice.

Fitts's Law.

The time to move the hand to a target is proportional to the log of the ratio of the distance to the target and target size.

Power Law of Practice.

When one plots learning curves on log-log paper, they tend to give a straight line.

Uncertainty Principle.

The more uncertainty in an action, the greater the reaction time.

Ratinality Principle.

The way to predict peoples' behavior in task-oriented situations is to understand their goals. The more one can understand, the better one can predict.

Problem Space Principle.

Goal-oriented behavior can be described in terms of a small number of operations performed over and over by the user.

Sample Calculations

Finally, let us consider an example of the Model Human Processor description of the computer user in action.

PROBLEM. When a symbol appears on a CRT, a user is to press a key. What is the time between signal and response.

SOLUTION. The user sees the signal and processes it with his Perceptual Processor. This requires a nominal 100 msec and results in a physical code for the symbol in the Visual Image Store and a symbolic code in Working Memory. The code in Working Memory requires one 70 msec cycle of the Cognitive Processor to trigger the response of pushing the response key. Pushing

P R I N C I P L E S   O F   O P E R A T I O N

0. RECOGNIZE-ACT CYCLE OF THE COGNITIVE PROCESSOR
1. VARIABLE PERCEPTUAL PROCESSOR RATE PRINCIPLE
2. ENCODING SPECIFICITY PRINCIPLE
3. DISCRIMINATION PRINCIPLE
4. VARIABLE COGNITIVE PROCESSOR RATE PRINCIPLE
5. FITT'S LAW OF MOVEMENT TIMES
6. POWER LAW OF PRACTICE
7. UNCERTAINTY PRINCIPLE
8. RATIONALITY PRINCIPLE
9. PROBLEM SPACE PRINCIPLE

Fig. 9

the key requires one 70 msec cycle of the motor processor to carry out. The entire action requires a nominal

$$\tau_P + \tau_C + \tau_M = 100 \text{ msec} + 70 \text{ msec} + 70 \text{ msec} = 240 \text{ msec}.$$

This is, in fact, a typical response time. The value can be recalculated using the upper and lower bounds for the parameters to give a range of times that includes most experiments.

> PROBLEM. A second symbol occurs just after the first. The user is to push the key if the second symbol is identical to the first. What is the time between signal and response?

SOLUTION. This just adds one Cognitive Processor cycle to determine if the signals are identical. The total time will now be

$$\tau_P + 2\tau_C + \tau_M = 100 \text{ msec} + 2(70 \text{ msec}) + 70 \text{ msec} = 310 \text{ msec}.$$

> PROBLEM. A programmer is programming a video game version of billiards. Frequently during the game one ball will bump into another causing the two balls to change speed and direction. How much time is available after the collision to compute the trajectories of the balls before they must be moved to preserve the illusion of causality?

SOLUTION. Movement must occur within one cycle of the Perceptual Processor, that is, within about 100 msec to have collision and subsequent movement appear part of the same event. Of course 100 msec is the time at which the illusion breaks down. To be sure we should use the lower bound of 50 msec. An experiment by Michotte (1946/1963) shows that these numbers are approximately correct. Michotte showed people animated sequences of balls colliding with varying delays between when the first ball hit the second and the second ball moved. He asked them to judge whether the first ball caused the second one to move. If the delay was less than about 100 msec, people said the causality was immediate; if greater than 100 msec, they said the movement of the balls were independent events. If the collision was around 100 msec (from about 50 msec to about 150 msec) sometimes people said that the first ball had caused the second to move but that the collision was "sticky." Hence, if the balls are moved in less than 50 msec the illusion would remain in tact.

This completes the first lecture on user-computer interaction and cognitive psychology. The point can be stated thus: Most work in computer science concentrates on the machine side of what is really a two-sided relationship between man and machine. Yet it will likely be difficult to understand the human side from the use of such techniques as comparative experiments alone. What would seem to be required is what might be called a *model-based human factors* in which analytical models of performance capable of calculation and prediction are used to understand and drive experiments. The Model Human Processor is at the lowest level of these, summarizing the basic capabilities of the user. In the next lecture, we will give examples of how engineering calculations relevant to the design of human-computer interfaces can be built upon this base.

DISCUSSION

Professor Randell referred to the three processors in the model of the human processor, and asked whether parallel operation was considered, as, with practice, and with highly skilled tasks, there would surely be overlap between the three. **Dr. Card** replied that this observation was true, and that if the human processor is viewed as serial, then complex and skilled behaviour such as typing or playing musical instruments could not be accounted for.

In answer to the query "Will improved models for predicting performance be developed?" Dr. Card replied that the model he had outlined was a very reductionist one, but was the basis for the next higher model. In order to predict performance, for example in terms of number of cognitive processing cycles, the basic model is used to justify the next model up, which can predict performance on higher level tasks. Dr. Card pointed out the problem of accuracy of prediction, as decay times and capacity of memory, and speed of processing, are expressed as ranges. The more complex the task, the less precise the predictions can be.

Professor Rogers asked about transfer between working memory and long term memory. Dr. Card said that this transfer cannot be done voluntarily. (If it could, then education would be a trivial process!) Generally, the more often a piece of information got into working memory, the more likely it would be transferred to long term memory. The probability of this also increases with number of associations. There is also an asymmetry in the process - it takes longer per ´chunk´ to get information into long term memory than out again.

Dr. Card was asked to comment on simple stimuli which however involve a lot of processing, ie. compute-bound rather than I/O bound tasks. In reply, he said that in this case specifying the steps needed becomes much more difficult, and the next higher model has to be invoked in order to get a better estimate of the number of cycles required. This model cannot be used accurately where more than 5 or 6 steps are involved. However, one reason that ranges are used in the model is that in many applications one does not need to know the exact value of the number, but only whether it is above or below a certain threshold.

Dr. Larcombe requested elucidation of the use of the term ´perceptual processes´. Dr. Card defined the term as taking sensory inputs and producing physical/memorial representations of them.

Mr. Nichols raised the issue of individual differences within the population. Dr. Card agreed that there is variation, but that the ranges specified cover this. However, psychologists have a tendency to draw their ´representative´ samples from groups of American college sophomores...

Professor Ercoli asked for comment on male/female variation in division of cognitive function between the two hemispheres of the brain. Dr. Card replied that many alleged sex differences in cognitive function turn out not to be true, and the situation is still contentious.

Mr. Bridle asked weren´t individual differences very great? Dr. Card reasserted that there was individual variation, but some experimental results should be interpreted with caution, as individuals not only show variability in performance of tasks, but sometimes are adopting completely different types of strategies for doing the same thing, therefore experiments may not be measuring the same phenomena. He gave the example of memorising directions, where some people remember a series of right´s, left´s and straight-on´s, whilst others visualise a spatial map.

Professor Randell queried the impression inherent in the model that long term memory has infinite capacity. Dr. Card replied that long term memory is finite, but very large. It is almost impossible to give accurate estimates of capacity, although it is known that there are approximately 10 to the power 11 neurons in the brain, and a branching factor of more than 1000. The model does, however, use infinity as the parameter for the capacity of long term memory. In connection with the finitude of long term memory, Professor Randell was reminded of the ichthyologist who strenuously avoided meeting new people, as, every time he was introduced to a new person, he forgot the name of another fish...