Expectation-based user interaction

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Abstract

Multimedia and multimodal interfaces reflect the growing technological possibilities of computer-based systems for interaction with the user. The ongoing increase in communication bandwidth and the growing variety of communication channels enable further improvement in the user interface. However, how this increased communication capacity can optimally be exploited is as yet unknown. Since the functionality of these computer-based systems also continues to grow, the increased complexity of interaction procedures and the difficulty of mastering them are prime issues in the design of "easy to use" multimodal user interfaces.

In order to appreciate more fully what is involved in self-evident and at the same time efficient interaction between user and system, we will first briefly describe the layered-protocol model of computer-human dialogue as proposed by Taylor (1988a). This conceptual framework emphasizes the relevance of layered feedback for the efficiency of communication. As indicated by Engel & Haakma (1993), in particular early feedback about the system's interpretation of the message part already received (I-feedback) as well as on machine expectations about message elements still to be received (E-feedback) are of relevance for the system's ease of use.

Thereafter, as an interesting example of improved human-computer interaction through layered multimodal I- and E-feedback, an experimental trackball device will be described. It provides the user, in addition to the standard visual I-feedback about the current cursor position, with tactile E-feedback about the expected cursor target position.

Lastly, our running experimental exploration of the possibilities for automatic cursor-endpoint prediction will be described, this research being of relevance for the further improvement of interaction with the mentioned trackball device with expectation-based force-feedback.

Layered interaction

In order to obtain information, to inform others (humans or machines), or to have them do things, people have to communicate their intentions (goals). These intentions are encoded into messages which are transmitted to the receiving party by modulation of the physical parameters of the communication channels concerned (e.g. via sound waves, key presses, etc.). In turn, the receiver has to decode the incoming messages back into the intentions of the originator by means of the same communication protocol.

In contrast to machine communication, where these coding and decoding processes are generally based on fixed context-independent protocols, coding and decoding in human communication are strongly correlated with the changing knowledge of the interacting parties (see e.g. Beun, 1989). Their messages generally carry just the information necessary to form a reference to the knowledge already available (see e.g. Barwise & Perry, 1983). For instance, by simply referring to what has been mentioned earlier, repeated detailed description is avoided making communication considerably faster.

This context-dependency implies, however, that errors and/or ambiguities in coding/decoding may arise, as a result of differences in the contextual knowledge assumed and applied by the originator and the recipient. It is mainly through feedback, viz. the reactions of the recipient to the message sent, that the originator is enabled to detect faults in the communication of his intention.

The human decoding process appears to be divided into a number of successive steps. Feedback concerning the intermediate decoding results is given to the originator at an early stage. This layered feedback (Taylor, 1988a) enables the originator to prevent accumulation of faults by correcting the detected misperceptions immediately. Taylor (1988b) has shown that also the efficiency of intention transfer in human-machine communication can be improved analogously to inter-human communication by layered feedback.

Layered multimodal I- and E-feedback

In human-machine communication the user often does not fully understand the use of the specific communication protocol and also is not fully aware of the context knowledge available to the machine. Engel & Haakma (1993) have claimed that human-machine communication would become more efficient and at the same time easier to learn, and hence easier to use in general, if the user were to be provided with layered machine feedback that includes both the machine's interpretation of the message part received so far (I-feedback) and the machine's expectations concerning the message part still to come (E-feedback).

In general, layered multimodal I-feedback can be observed in all kinds of human-machine interaction. When, for instance, a human uses a keyboard, a combination of visual, tactile, kinesthetic and auditory feedback gives early information about correct key selection and activation, while the interpreted symbol appears as higher level I-feedback on the screen. This I-feedback also plays a role at much higher levels of communication. For instance in the "What you see is what you get" word processors, the text layout is already displayed for the user before it is actually printed. This often allows at least the layman to realize his or her intentions more efficiently.

The use of layered E-feedback is not new either, but this type of feedback is less frequently and less consciously applied. Given some general notion of the message intention, contextual knowledge like the history of the past interaction(s) enables the recipient to predict message elements still to come. If the recipient in human communication prompts these context-dependent message expectations before the originator has completely uttered the primary message, the speed of communication at the originator's end can be increased by limiting the rest of the message to a simple confirmation.

Property sheets are a clear example of layered E-feedback in human-machine communication that help the user in formulating and communicating his or her intentions. Once the machine is made aware of the user's higher level goal, e.g. the printing of a file, it can indicate, e.g. by means of a form to be filled out, which lower level messages it expects to receive for effecting the file print-out. Frequently, the data fields in the forms are already provided with expected (default) values which only require revision in the case of discrepancies. E-feedback can also be found at rather low levels of human-machine communication, such as in rotational switches with mechanically determined expected (default) positions of the axis. In the following an example will be given of a new pointing device offering layered multimodal I-feedback as well as layered multimodal E-feedback.

Trackball with I- and E-feedback

Engel, Goossens & Haakma (1994) were able to provide more support for their claim about the distinction between I- and E-feedback with their experimental results obtained with a trackball input device improved by the introduction of expectation-based force feedback.

Normally the user already receives I-feedback on the system's momentary interpretation of his/her manual trackball-movement messages via on-line display of the current cursor position. In a window-oriented graphical display, the system also offers the user context-dependent E-feedback by showing expected cursor target locations on the screen in the form of icons, pull-down menus, etc.

At a lower level of interaction, kinesthetic I-feedback is supplied by the mass and internal friction of the trackball itself. By simultaneously offering supportive E-feedback in the form of a machine-originated force applied to the ball as a function of the corresponding graphical display and the momentary cursor position, the user's movements can be guided towards the cursor position expected by the machine. In this way, communication efficiency on the part of the user can be increased.

Two optical sensors and two servo motors are used in the mentioned trackball device. One combination of position sensor and servo motor determines the cursor position and tactile feedback along the x axis and the other combination controls them along the y axis. As described by Engel et al. (1994), experimental results with a laboratory version of this new device showed that the expectation-based force feedback significantly enhanced speed and accuracy of pointing and dragging, while the effort needed to master the trackball device was small compared to that for the conventional trackball without contextual force feedback.

Endpoint prediction

The experimental comparison of the trackball with and without force feedback by Engel et al. (1994) was mainly based on evaluation of the speed and accuracy of cursor positioning in single target situations, for which Fitts' law was found to hold. Fitts' law (Fitts, 1954; Fitts & Peterson, 1964) predicts a logarithmic relation between movement time (MT) to a target as a function of target distance (D) and target width (W):

$$MT = a + b \log2(D / 0.5W) \qquad (1)$$

Engel et al. (1994) found a decrease of 33% in the regression coefficient for the condition with additional force feedback as well as a decrease in the percentage of acquisition errors.

In practice, however, not just a single target but a set of possible target objects will be displayed as E-feedback. To arrive at a specific target, the cursor may have to cross other possible target objects before ending at the ultimate one. To provide effective tactile E-feedback the system has to decide early on what the expected target object is. The following experiment is the first of a series aimed at the systematic exploration of the possibility of early endpoint prediction.

Predictions from linear movements

As a first step in this exploratory research, we decided to explore the predictive aspects of simple horizontal target-selection movements not influenced by force feedback from the target or other non-target objects.

Experimental setup

The subject was able to move the cursor in a straight horizontal line over the computer screen with a rotary knob of 6 cm diameter, instead of with the earlier applied two-dimensional trackball. To allow for variation in task difficulty, the display showed two horizontal rows of five rectangular objects each. One row was to the left and the other was to the right of the screen center. The width of the objects increased with distance from the screen center in such a way that their D/W, see (1), remained approximately the same. Different sets of rectangular objects were used for the three D/W values used.

In order to prevent the occurrence of rythmic motor routines, each target-selection trial started with a pause of random duration during which the outlines of the possible targets were shown on the screen. Thereafter, an audible alarm sounded until the subject pressed the start button with his/her preferred hand. The cursor then appeared at the screen center while one of the displayed rectangular objects was indicated as being target by changing its colour. Then, the subject had to release the start button and move the cursor on to the target with the same hand by the rotary knob. Arrival of the cursor had to be confirmed by pushing the computer spacebar with the other hand. Correctness of the target movement was signalled with easily distinguishable auditory signals. Incorrect movements were not allowed to be compensated.

Nine subjects participated in four sessions of about 30-minute duration each. Each experimental session consisted of three blocks of trials, each with a specific D/W. In a block, the ten possible target width-distance combinations with the same D/W were used and each combination had to be correctly performed 15 times. For verification that the subjects understood the instructions, three practice trials preceeded the experiments.

All cursor movements were electronically sampled and digitally recorded. From these data different movement characteristics were derived, including the value and moment of maximum acceleration and maximum velocity.

Results

Fitts' Law (1) was found to hold in this experiment as well. We found the following regression equation over all sessions and subjects for the Mean Movement Time (MMT) as a function of the D/W:

$$MMT \text{ [sec]} = 0.32 + 0.10 \log_2(D / 0.5W) \qquad (2)$$

with Pearson correlation coefficient r = 0.94

With regard to the initial movement parameters, we found an exponential relation between target distance D in degrees knob rotation and the movement's maximum acceleration Amax [degree/sec2]:
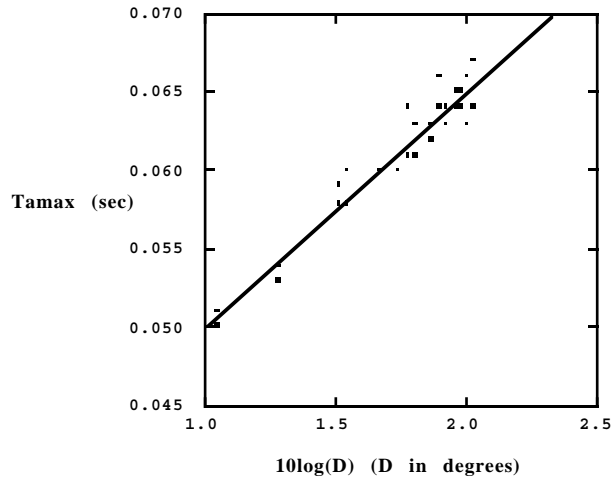
$$D \text{ [degree]} = 10 \ (0.00024 \ \text{Amax} + 0.71) \ ; \qquad r = 0.98 \qquad (3)$$
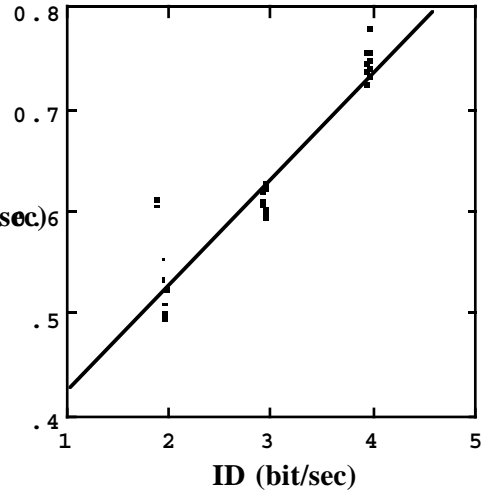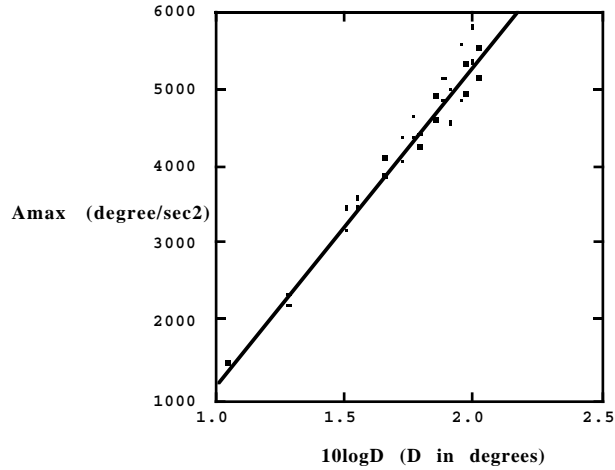
The Amax occurred TAmax seconds after the actual start of the movement. TAmax was also found to have an exponential relation with target distance D in degrees knob rotation:
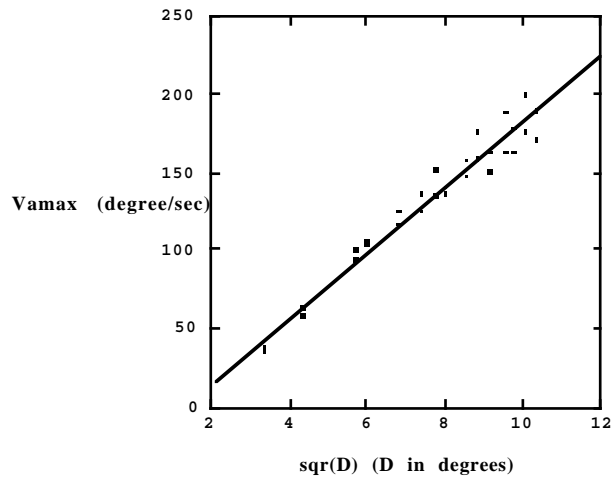
$$D \text{ [degree]} = 10 \ (67 \ \text{TAmax} - 2.3) \ ; \qquad r = 0.97 \ (4)$$

while the following relation with the knob velocity at the moment of maximum acceleration VAmax [degree/sec] was found:
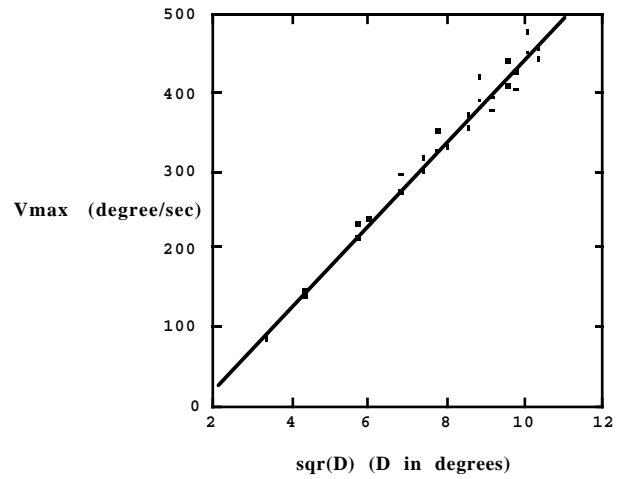
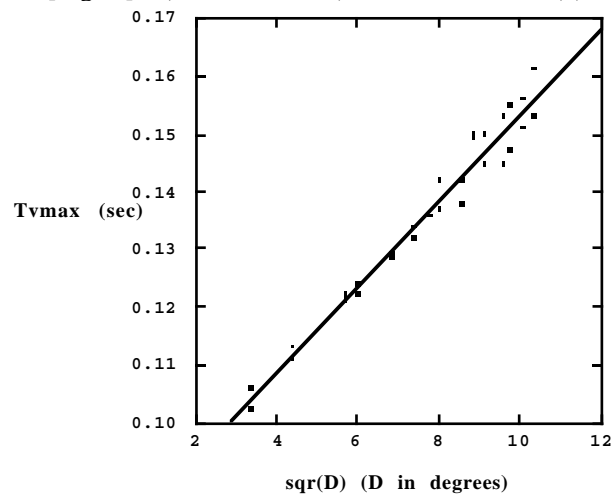$$D \text{ [degree]} = (0.048 VAmax + 1.3)2 ; \qquad r = 0.98 \text{ (5)}$$

With regard to the maximum velocity Vmax [degree/sec] and the moment TVmax [sec] and distance XVmax at which this velocity occurred we found the following experimental relations:

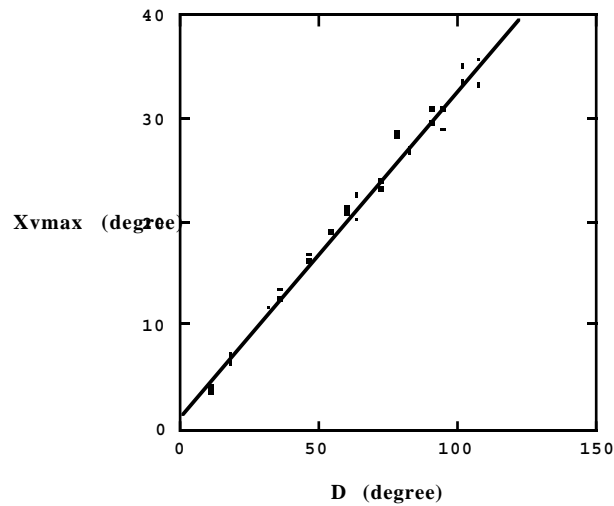$$D \text{ [degree]} = (0.019 Vmax + 1.6)2 ; \qquad r = 0.99 \qquad (6)$$

$$D \text{ [degree]} = (140 TVmax - 11)2 ; \qquad r = 0.84 \quad (7)$$

$$D \text{ [degree]} = 3.2 XVmax - 3.5 ; \qquad r = 0.99 \quad (8)$$

Equations (3, 4, ..., 8) were used to calculate the percentages of individual trials for which the predicted cursor endpoint was actually located within the borders of the target. We found XVmax to be the best predictor and TAmax the worst; see the following table.

The low percentage of correct predictions derived from TAmax and TVmax in the time domain can be explained by the relatively low sampling frequency (150 Hz) of the measurements. The predictions derived from first-derivative in time Vmax yield more accurate results than those derived from the second derivative Amax for the same reason. As expected, D/W also influenced the percentage of correct predictions; larger targets and smaller target distances yielded a higher predictive power.

Parameter	D/W = 2	D/W = 4	D/W = 8
Amax	22.1%	8.6%	4.4%
TAmax	8.8%	6.4%	2.7%
VAmax	27.1%	15.2%	7.0%
Vmax	34.5%	18.1%	7.0%
TVmax	10.0%	5.9%	3.2%
XVmax	36.9%	21.7%	9.9%

Conclusions

With help of an experimental trackball device provided with additional force feedback we have shown the relevance of multimodal layered I- and E-feedback

for communication efficiency and ease of use in human-system interaction. E-feedback requires the system to generate context dependent expectations about message elements still to be received from the user. Exploratory experiments are reported about the predictive information derivable from the initial part of straight cursor movements. We found XVmax to be the best cursor-endpoint predictor.

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