# Bullseye! When Fitts' Law Doesn't Fit

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## ABSTRACT

Today's GUI interfaces require considerable visual attention for their operation. Consequently, interface events use up precious screen real estate and disenfranchise blind users from current software usage. If interfaces move to the realm of auditory and tactile designs, these problems are mitigated. However, it is not clear how much useful HCI research, particularly performance time models, will transfer from the visual to the non-visual. This paper attempts to answer a small part of this question by considering performance time models for menu selection in a non-visual bullseye menu. We chose to study non-visual bullseye menus because we have found them to be highly useful in non-visual interfaces: they can serve as effective non-visual replacements for several visual linear menus.

## MOTIVATION

Standard GUIs rely heavily on the visual modality, because it is an efficient and effective means of interaction between humans and machines. The PC of today includes a large CRT that can display high resolution graphics, but may not include high-quality speakers (or even a sound card) for emitting sounds. Tactile input/output device are not generally included either. One may think that the reason for the overwhelming popularity of visual interfaces and the rarity of non-visual ones is that non-visual interfaces are simply not needed in today's mainstream applications. We argue that non-visual interfaces are indeed needed, for several important reasons.

### Blind Users Compute Too

Users who have a visual impairment are at an extreme disadvantage. The WIMP interface provides feedback that is almost all visual. Sounds are sometimes used in this interface, but only for special purposes such as to attract the attention of the user. Some work has been performed on creating non-visual interfaces, but the emphasis of current research remains with the visual modality.

### Screen Space is a Precious Resource

If a particular display mechanism has low resolution or is designed be small, such as that of a PDA or another hand-held device, then for the sake of efficiency, the display space should be used only for output which cannot be conveyed any other way. Even in systems with large resolution screens, displayed information sometimes covers other information which the user may want to see. For example, when a users pulls down a linear menu is activated, the menu may cover important information on the screen. Thus screen space should be considered a precious resource.

### Visual Overload

Although the resolution of today's monitors is a vast improvement over the CRT's of the past, users still suffer from fatigue effects caused by looking at computer displays for a long period of time, such as dry eyes or difficulty focusing on the screen. These fatigue effects are a symptom of visual overload. If some of the visual components of interaction were replaced by non-visual components, visual overload would decrease, and users may suffer less from these fatigue effects.

### Non-visual Interfaces May Be More Intuitive

One of the main goals of interaction design is to render the interface as intuitive as possible. In our everyday environments humans receive a variety of stimuli playing upon all senses, including aural and tactile, and we instinctively respond to these stimuli. If computing systems take advantage of these instinctive responses, they will be more intuitive to use. .

### Non-visual Interfaces May Support the Visual Task

Users tend to perform better on user interface tasks they are familiar with. Hence learnability plays a central role in the usability of an interface tool. Some users may find that learning via the visual channel is effective, while others may not. We can make thus user interfaces more learnable for more users by supplying learning cues in multiple modalities.



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## MODELLING USER PERFORMANCE IN NON-VISUAL INTERFACES

Much research has been done on modelling user performance in visual interface tasks, helping both HCI researchers predict behaviour during task execution and interface designers build better interaction tools. Non-visual interface elements have also been developed, but there has been little work on modelling them. This paper provides a modest remedy. It proposes an effective non-visual user interface element called a *bullseye menu.* It then proposes and evaluates two performance time models for selecting an item from it. One of these models is Fitts' Law, which is commonly used to model performance time for visual menu selection tasks. The other is a simple linear model, which states that the time to select from this menu is a linear function of the index of the target ring. Perhaps surprisingly, Fitts' Law is shown to be inferior in this particular instance of a non-visual user interface task.

## THE BULLSEYE MENU

A bullseye menu is a series of concentric *circles* divided into *sectors*. We call the region between two neighbouring concentric circles a *ring*. Each ring has a corresponding *index*: The index of the ring containing the first set of menu items is 1, the index of the ring containing the second set of menu items is 2, etc. The direction and distance a user moves a pointing device (in our case, a stylus) from a floating origin determines the menu category. For example, selection in ring 1 in the upward sector might correspond to selecting the "File: New" command, and selection in ring 3 in the right-hand sector might correspond to selecting the "Edit: Copy" command. The bullseye menu can be implemented both visually and non-visually. Figure 1 depicts selection from it.

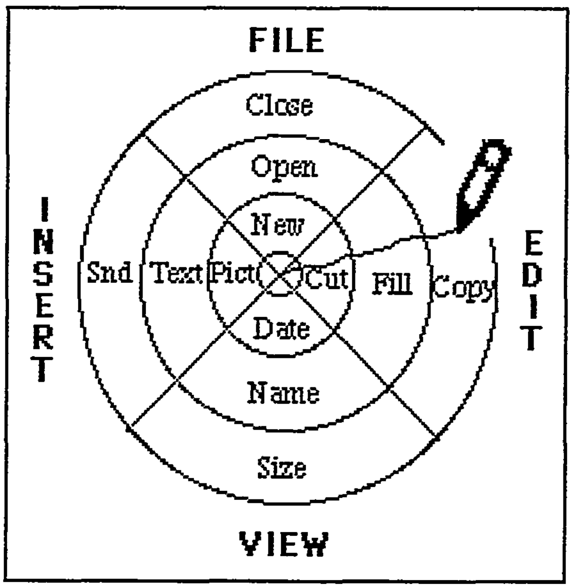


Figure 1: Selection from a bullseye menu.

### A Visual Version

In the visual implementation, the system displays a menu in response to some user interface event, such as putting pressure on a stylus. The user visually locates the target selection, moves the cursor to it, and upon seeing that the cursor is in the target area, performs some action to select that item. Clearly, we can model this task using Fitts' Law [3].

### A Non-visual Version

Our non-visual version is similar to the visual one, except the menu is not displayed and a non-visual cue signals when the user rolls the cursor over a circle. Thus, after activating the menu, the user moves the cursor in the direction of the item s/he wishes to select and counts the number of non-visual cues. For example, if the user knows that "Edit:Copy" is in ring 3 in the right-hand sector, s/he might press a mouse button and move the mouse to the right for three signals to select that particular menu item.

A bullseye menu therefore serves as a good basis for non-visual menu selections for two reasons. There is no need to move the mouse to a certain position before making a menu selection. Also, it is possible to handle a large number of menu selections or handle the menu selections represented by a number of linear menus in a straightforward and easily understandable fashion.

## STUDYING PERFORMANCE TIME

We decided to consider two different types of non-visual cues in our study: a simple "beep" sound and a tactile pulse, which was provided by a relay connected to the parallel port of the PC and controlled through the interface code (see [4], [5]). Since we were only interested in selection time and not search time, our study was designed so that the user need not think about the location of the target item: its position was explicitly given by specifying the index of the target ring and the direction to move.

### Two Possible Performance Time Models

An important criterion for determining the value of an interface is establishing how well users perform when interacting with it. Developing an appropriate model for user performance helps us predict the efficiency and effectiveness of interface usage. We can directly compare one interface to another by comparing their performance time models.

In the next subsections we give a short description of Fitts' Law, a short description of an alternative, "linear" model, and discuss which may be more appropriate for modelling performance times in a non-visual bullseye menu.

### Fitts' Law

Fitts' Law [3] predicts that the time for a user to move a pointing device to a *target* from a *starting point* is logarithmically proportional to the distance to the target and inversely logarithmically proportional to the size of the target. The original Fitts' Law formula has been updated by Mackenzie [6]. We used Mackenzie's version for our experiment.

We can use Fitts' Law to measure the effectiveness of visual menus [8] by computing that menu's mean time to target. We can then compare this to the mean times of other menu systems to determine relative effectiveness.

Boritz, Booth and Cowan [4] performed what is probably the most relevant Fitts' Law study to non-visual bullseye menus. They showed that Fitts' Law is a good predictor of the time to target for circular menus and that time to target is affected mainly by target size and distance, and only slightly by direction. This effect is small enough that it is possible to use one set of Fitts' law constants for all directions.

We thus considered Fitts' Law to be a possible performance model for selection from a non-visual bullseye menu. There is an analogous physical movement – a user moves toward a target and homes in on it. The direction to the target is already known, and through aural or haptic feedback, the user is aware of when the cursor is in the target area. It also appeared that menu selection could be modelled by Fitts' Law from casual observation of the task. We observed that when users select from a non-visual menu they tend to move the stylus more quickly through the inner rings of the menu, and slow down when the target ring is close. These changes in the speed of movement are comparable to deceleration in a Fitts' Law task. We also noted that Fitts' Law has often been used to model visual menus. We therefore considered it worthwhile to investigate whether it can adequately model non-visual bullseye menus.

### Why Consider an Alternative to Fitts' Law?

There are characteristics of visual Fitts' Law tasks that are quite different from non-visual bullseye menu selection. First, Fitts' Law tasks generally involve visual, instead of auditory or tactile feedback. It was unclear whether these communication channels are sufficiently similar to the visual channel for Fitts' Law to apply. With visual feedback, the user is constantly aware of the exact position of the target. With tactile and auditory feedback, the user can only approximate the position of the target, given the distance s/he has already moved the stylus and the speed at which the stylus is moving.

Second, typical Fitts' Law tasks have no intermediate targets between the original position of the pointing device and the target. The feedback signals at each of the inner circles on the path to the target in a non-visual bullseye menu can be considered intermediate targets. If the user wishes to select from ring 4, then s/he knows s/he must detect 4 feedback signals in order to reach it. The first three signals are intermediate targets: they must each be reached before the fourth (and ultimate) target is reached. The user aims for the first signal, then the second, then the third, and finally the fourth, and then stops. It seems likely that the presence of these intermediate targets has on effect on user performance.

#### *The Linear Model*

The linear model discussed in this paper predicts that the mean time to hit a target is a linear function of inputs (possibly including the size of the target and the index of the target ring), rather than a logarithmic function, as in Fitts' Law. Our literature review uncovered only one other instance of a linear model being used for predicting time to target, Accot and Zhai [1]. They point out that while Fitts' Law adequately describes performance time for most pointing tasks, it inadequately describes performance time for trajectory-based pointing tasks. They describe a "steering law" which states that the time to select a target along a trajectory is a linear function of the width of the path and length of the distance travelled to the target. They perform a series of experiments involving various angles of movement and differing "tunnel" widths in which the cursor must be moved. The results show that this "steering law" does indeed explain user behaviour in trajectory-based tasks.

Although this work involves visual tasks, it is related to the task of selecting from the non-visual bullseye menu. The "tunnels" through which Accot and Zhai's users travelled constrained an otherwise unrestrained motion: users moved the pointing device with more prudence.

The same restrained motion may exist in the task of selection from a non-visual bullseye menu. Each signal produced by traversing a circle on the way to the target ring must be counted, and therefore may be considered an intermediate target. These intermediate targets may act as speed regulators: the user must accurately count the number of signals traversed, which might cause the speed of movement to be more constant or more restrained. Also, there is a ceiling on how fast humans can count: users need to move the stylus slowly enough so that they can count the signals. Since the target position in a non-visual bullseye menu is ambiguous, users must carefully keep track of their orientation in the menu in order to avoid over- or undershoot. A constrained movement similar to that found in trajectory-based visual pointing tasks may therefore result, which prompted us to investigate the possibility of a linear model of performance.

An intuitive explanation of the difference between these two models is as follows. Imagine a driver looking for a parking spot in a busy parking lot. S/he finds one and wishes to reach it before any other drivers have a chance to park there. S/he drives quickly to the spot but applies brakes in time so that s/he won't drive past the spot. This scenario is analogous to a Fitts' Law task – the user moves toward the target quickly but applies a stopping function to avoid overshoot. Imagine another scenario: a driver with failing headlights wishes to find a spot in the fourth row of an unilluminated parking lot at night time, and knows s/he must cross four speed bumps to get to it. The driver proceeds slowly enough to count the speed bumps (and to avoid damage to the automobile) in order to know when s/he reaches the fourth row. This scenario is analogous to a linear model: the driver's speed is more constant and regulated – the time to reach the fourth row of parking spots is a linear function of the number of speed bumps to cross.

## THE EXPERIMENT

The aim of the experiment was to determine, for both tactile and auditory feedback, whether times to target aggregated over all users could be better modelled by Fitts' Law or a linear function of the index of the target ring.

### Experimental Design Overview

The experiment used a four-factor, 7 x 3 x 4 x 2 design. The first factor was number of signals to target. Number of signals to target varied from 1 to 7. We considered it important to vary the target ring so that we could be assured that the hypothesis was proved for a variety of target distances. The second factor was ring width. Ring widths were 2.5 mm, 4.2 mm and 5.8 mm. We chose to vary the width of the ring between trials so that the data would include a variety of target sizes. It should be noted that we did not vary the widths of the rings within each trial: in other words, for each trial, the circles in the menu were equidistant. The third factor was direction. Directions were up, down, left and right. This variable was used for another study, but was not considered in determining the best performance time model. The fourth factor was type of nonvisual feedback, auditory or tactile. The dependent variable in the study was the time to reach the menu target. Both correct trials and error trials involving overshoot and undershoot were used in the analysis.

### Subjects

Twelve subjects between the ages of 19 and 46 participated in this study. They were all undergraduate or graduate students in the Department of Computer Science at the University of Toronto. Eight subjects were male and four were female. All except one of the participants had 4 or more years of experience with computers on a daily basis, and one had two years of experience. Nine of the participants had 4 or more years of experience with a mouse on a daily basis, one had 1 year of experience, one had 2 years of experience, and one had 3 years of experience. All except one participant had little or no experience with a stylus in the past, and one had some experience.

### Apparatus

We used an NEC PowerMate V100 pentium computer, a WACOM Digitizer II tablet, and the tactile feedback mechanism described in Friedlander, Schlueter and Mantei [4]. The operating system was Windows 95. We used the standard Windows system beep for the auditory feedback. We also used a fan to cool the tactile feedback mechanism. The tablet driver was developed by LCS/Telegraphics for the Wintab™ 16- and 32-bit API. The experiment was implemented using Visual C++™.

### Method

The experiment consisted of four one-hour sessions. The sessions were on four consecutive days – we wanted subjects to have one night's sleep in between sessions to alleviate fatigue effects and at the same time to ensure that any learning that had taken place during that day's session would not be forgotten. Each participant attended all four sessions at approximately the same time over the four days. These times varied between participants but were always between 9 am and 6 pm. Each session took one hour. The experiment type (auditory vs. tactile feedback) was alternated between sessions, and the feedback type used on the first day was counterbalanced over the 12 subjects.

Each *trial set* consisted of 32 trials. It began with 4 practice trials, where the user was instructed to move in one of four directions for 4 signals. These practice trials were not included in the data analysis: they were included so that users could familiarize themselves with the particular ring width used in that trial set before the actual trials took place. The remaining 28 actual trials were unique combinations of the 4 directions and 7 target ring indexes in random order. One block of trials contained three trial sets: at the beginning of the experiment each of the three ring widths was randomly and uniquely assigned one of the three trial sets; thus, in each block, each trial set used a particular ring width once in random order. The order in which each ring width was tested was maintained for each block of trial sets within that particular session. The first two sessions consisted of 10 blocks, and the last two consisted of 13 blocks. (As users became better at the selection task, they could perform the task more quickly, and we could fit more trials in a one-hour session.) We were only interested in measuring performance and not learning. Thus, only the last two sessions were analyzed.

For each trial, a black compass was displayed at the center of the screen (Figure 4), with the north, south, east and west arms marked "N", "S", "E" and "W" respectively. The centre of the compass contained a letter (either N, S, E, W) and a number (1 to 7) indicating the direction and ring index of the target selection. The compass arm corresponding to the direction (denoted by the letter at the center) was highlighted in red. The user was to place the stylus anywhere on the tablet, press down the stylus button, move the stylus in the given direction for the given number of signals (either tactile pulses or beeps) while keeping the stylus button pressed, and release when the target was reached. An error tone was played if the user missed the target. A message indicating whether the user's error rate was acceptable was displayed at the bottom right-hand side of the screen ("Error rate is OK." or "Error rate is a little high."). A count of the number of errors of the last 10 trials was used as the error rate: if 20% or more of these trials were unsuccessful, the error rate was considered high, otherwise the error rate was considered satisfactory. The purpose of displaying whether the error rate was acceptable was to ensure that users did not become too careless in performing the selection task. The screen display used in the experiment is shown in Figure 2.

### The Hypothesis

Our hypothesis, H, is: the mean time to select a menu item from a non-visual bullseye menu aggregated over multiple users and multiple trials is linear to the index of the target ring, as opposed to following Fitts' Law. The null hypothesis, $H_{null}$, is the negation of H.

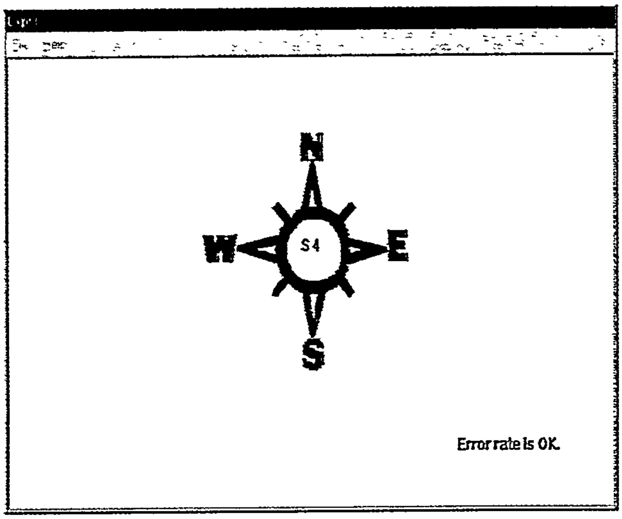


Figure 2: The Experiment Interface. According to the directions at the centre of the compass, the user is to move downwards for four signals.

To elaborate, Fitts' law in this case predicts that

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

where A is the distance to target, MT is the time to target, and W is the size of the target. (The values of a and b are determined through linear regression.) We define $r$ to be the width of a ring, and all rings have equal widths. Mackenzie discusses applying Fitts' Law to two-dimensional tasks [7] via two different methods: one by designating the width of the target as the trace of the approach vector through the centre of the target and the other by choosing the smaller of the width and height of the target. This work helped us to determine the target size of non-visual bullseye menu items: we set $W$, the size of the target, to the length of the one-dimensional trace of the stylus moving in a line perpendicular to the tangent of the ring. The length of this trace is the ring width, $r$. Thus, the width of the target is:

$$W = r$$

The distance to the target is measured from the starting point to the midpoint of the target ring. Thus, if the index of the target ring is $x$, then the distance from the centre of the menu to the midpoint of the target is the width of that ring; is the sum of the $x$-$1$ intermediate ring widths plus half the target ring width. Therefore, the distance from the starting point to the centre of the target is a multiple of the distance between the rings:

$$A = r(x - 0.5)$$

Thus, for our experiments, Fitts' Law becomes:

$$MT = a + b \cdot \log_2(x + 0.5)$$

The Linear model is much simpler:

$$MT = a + b \cdot x$$

As in Fitts' Law, $MT$ is the mean performance time, and $a$ and $b$ are constants determined from linear regression.

The linear model can be best compared to Fitts' Law by noting that one obtains the former from the latter by removing the logarithm. The implication is that $MT$ increases more quickly with increasing $x$ in the linear model than in Fitts' Law.

In both cases, we average the data over ring size and the index of the target ring; thus, twenty-one data points are generated for our regression analysis. The analysis compares the actual mean time to target to the calculated mean times to target in both the linear and Fitts' Law models.

## RESULTS

We tested our hypothesis separately for each feedback mechanism. For both auditory and tactile feedback, a simple regression analysis was performed on the nonerror cases and the overshoot/undershoot error trials. The results of this are shown in Figure 3 and Figure 4. It appears from these that the linear model is more accurate for both modalities. Looking at the linear model regression fits, we see that the data points are everywhere distributed evenly on both sides of the fitted line. In the Fitts' Law regression fit, the central data points sag below the fitted line, while the outermost data points fall above it. These observations are confirmed by the r-squared

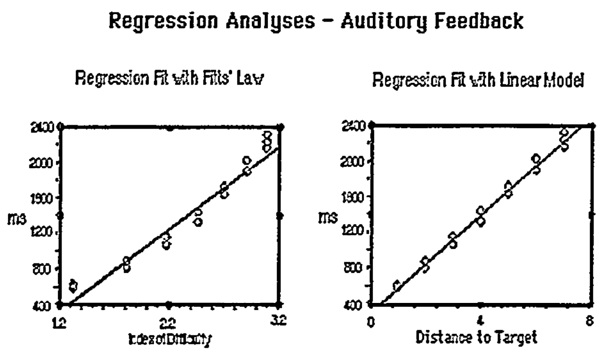


Figure 3: A comparison of the regression analyses of the observed data vs. Fitts' Law and the linear model in the auditory feedback case.

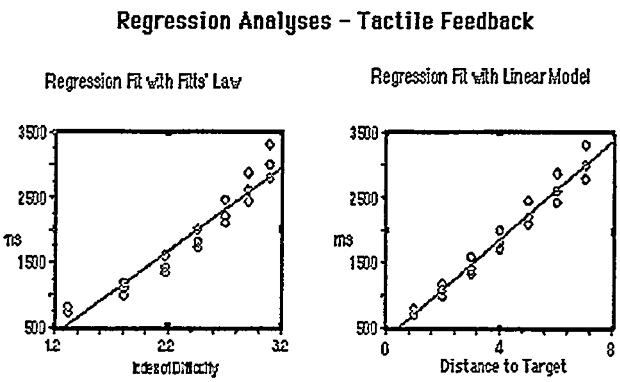


Figure 4: A comparison of the regression analyses of the observed data vs. Fitts' Law and the linear model in the tactile feedback case.

error terms for the regression. These values can be found in Figure 5.

| | Auditory Feedback | Tactile Feedback |
|---|---|---|
| $r^2$, Linear vs. Observed Data | 0.992 | 0.968 |
| $r^2$, Fitts' vs. Observed Data | 0.949 | 0.931 |

Figure 5: Resulting $r^2$ values from regression analysis, Fitts' Law vs. Observed Data and Linear Model vs. Observed Data, in both the auditory and tactile cases.

However, these observations are not enough to confirm our hypothesis. We need to verify that the difference in regression fits is significant. This was done as follows:

Both the linear model and Fitts' law are of the form $T = a + Db$, where $a$, $b$ are constants, and $D$ is the Index of Difficulty for the Fitts' Law comparison and the index of the target ring for the linear model comparison. It is therefore true that the $D$ term in both Fitts' Law and the linear model are positively correlated with $T$. Asking which of the regression lines fits the data most closely is therefore equivalent to asking which of the $D$ terms is most positively correlated with $T$. In our experiment, the values for $r_F$ (the correlation coefficient for Fitts' Law) and $r_L$ (the correlation coefficient for the linear model) are 0.996 and 0.974 respectively for auditory and 0.984 and 0.965 for tactile. Hotellings' T-test can be used to determine the probability that the true value of $r_F$ is greater than or equal to the true value of $r_L$. This is equivalent to determining the probability that our null hypothesis is true.

To perform Hotellings' T-test, we need two more values. One is the coefficient of correlation between $D_F$ and $D_L$, which we will call $r_{F,L}$. We calculated this to be 0.985, for both tactile and auditory experiments. The other is $N$, the number of data points in the regression analysis, which is 21 (7 target ring indexes * 3 ring widths). The quantity given by [5]:

$$t = (r_L - r_F)\sqrt{\frac{(N-3)(1+r_{F,L})}{2\left(1 - r_{F,L}^2 - r_L^2 - r_F^2 + 2 r_{F,L} r_L r_F\right)}}$$

is therefore a T distribution with 18 degrees of freedom. For the auditory experiment, $t = 6.78$. Thus,

$$p[t \geq 6.78] = p[H_{null}] < 0.0005$$

In the tactile feedback case, $t = 2.64$. Thus,

$$p[t \geq 2.64] = p[H_{null}] < 0.01$$

In both cases, the null hypothesis is rejected: the linear model is a better predictor of performance time than Fitts' Law.

## IMPLICATIONS

A linear model for performance time fits selection in a non-visual bullseye menu more closely than Fitts' Law. We can think of two reasons for this. Users tend to restrain movement when performing this task in order to count accurately. They also seem to prefer counting at a particular speed, and adjust their movements in order to do so.

The better fit of the linear model means that performance times for non-visual bullseye menu selections are likely not as fast as for equivalent visual bullseye menus, for which selection times are modelled by Fitts' Law. In Fitts' Law tasks, performance time increases logarithmically with increased distance. They will thus be increasingly superior to performance times that are linear functions of distance as the distance to the menu selection increases. However, this also implies that there may be little difference when selection distances are short. Thus, UI designers should put frequently accessed menu items near the centre of a non-visual bullseye menu. It may also be wise for them to increase the number of sectors, so that more selections are closer to the centre.

Our results are evidence that selection tasks are performed differently when simple non-visual feedback is given instead of visual. Probably because the former gives less information to the user than the latter, selection tasks cannot be performed as efficiently. It is interesting to ask whether and how the non-visual feedback we describe can be augmented to improve user performance so that it is equivalent to visual feedback. Perhaps information about distance travelled can be communicated progressively using various qualities of sound, such as frequency and timbre. Users may then be able to "home in" on their selection as they can when they can see it. One could measure the degree of improvement achieved by enhancing the non-visual feedback by comparing performance time data to that predicted by the linear model and by Fitts' Law. The linear model would serve as the baseline, and Fitts' Law would be the presumed upper bound. Our performance time model for our simple non-visual feedback task is not that far from that for the equivalent visual feedback task (i.e. a linear model is closer to a logarithmic model than a quadratic or cubic one). We are thus optimistic that enhancing non-visual feedback will bring user performance close to that of visual feedback.

It should be noted that the results from the regression analysis of the Fitts' Law case are quite good: in both the auditory and tactile cases the $r^2$ value of these analyses are higher than 0.9. Without consideration of the linear model it would be quite understandable to assume that Fitts' Law is the best predictor model for the task at hand. An important implication of our work is that Fitts' Law should not be the only performance model tested for new user interface tasks. Even if it fits the task quite well, there may be a better choice.

## CONCLUSIONS

Using non-visual bullseye menus, dependence on visual feedback in menu selection can be eliminated at the cost of increased performance time, if users are able to memorize the configuration of the menu.

The mean time for non-visual bullseye menu selection follows a linear function of the ring number rather than Fitts' Law when feedback is given at equidistant intervals. This is likely due to the constraining effect of counting the signals. In spite of the limited information conveyed by non-visual feedback in comparison to visual feedback, the performance time model is not as different as one might expect. This suggests that user performance with enhanced non-visual feedback can closely approximate that with visual feedback, especially when the distance to the target is not large.

## FUTURE WORK

### Consider other non-visual menu designs

A bullseye menu is essentially a pie menu modified to permit more efficient selection from a large number of options. Both of these characteristics make bullseye menus attractive for non-visual interfaces. Marking menus [6] [7] have very similar properties and are thus a logical alternative for non-visual menus. It would be interesting to implement marking menus non-visually to study their advantages and disadvantages vs. bullseye menus as well as to see if a non-visual performance model for them differs from a visual one.

### Consider an alternative predictor model

Walker [9] found that times to select from a pull-down menu were always better than those for a walking (or cascading) menu. Walking menus involve a series of Fitts' Law targets (one in each linear portion of the configuration) rather than just one target in the corresponding pull-down menu. The amount by which the series of start-up times increased total performance time was longer than the amount by which the series of targets with shorter distances reduced it. Perhaps the intermediate targets of a non-visual bullseye menu are analogous to the intermediate targets in a visual walking menu. Thus, future work may include developing a predictor model for selection from a non-visual bullseye menu as a summation series of Fitts' Law tasks, one for each of the intermediate targets (i.e. the intermediate signals perceived) on the way to selecting the non-visual bullseye menu target item.

### Consider directional influences.

This work does not take into account directional influence on performance time. It would be useful to verify whether the linear model predicts performance time better than Fitts' Law for each direction, rather than just for data aggregated over all directions.

### Implement a real non-visual bullseye menu

The experiment discussed in the thesis used an abstraction of the selection task in a non-visual bullseye menu. It would be useful to construct and conduct usability studies on an actual instance of such a menu, and do some longitudinal data collection on performance to study learning effects. A preliminary implementation could also have 4 sectors and 7 rings, and each of the sectors could correspond to a familiar menu, such as File or Edit. The menu could be activated by a right-button mouse click, and if no mouse movement is detected within a certain dwell time (perhaps 500 milliseconds) a corresponding visual bullseye menu would appear to remind the user of the menu configuration.

Several aspects of the implementation of non-visual bullseye menus can be studied. Learning can be explored. Expert performance can be compared to expert performance in other menu systems. Studies of user satisfaction can be performed to see what elements of non-visual bullseye menus they find appealing, and what elements do not work well. The auditory feedback implementation on adjacent machines could be problematic for users: studies can be performed on this type of interference and which types of sounds to select to minimize interference.

### Rerun experiment on blind participants

The original goal of the research into non-visual bullseye menus was to develop an interface for the visually impaired. Although the results of our experiment indicate that the non-visual bullseye menu is a viable menu system which allows users to make "eyes-free" selections, we have not verified that it can be used by visually-impaired users. We would like to rerun the experiment on only visually-impaired participants, and perform some usability studies for this target group.

### Rerun the experiment with slight changes to investigate particular performance issues

Our experiment did a somewhat basic analysis of selection in a vanilla bullseye menu. The menu always had four sectors, and the circles were equidistant. We only implemented two non-visual feedback mechanisms, and didn't look into their visual equivalents.

Part of this paper discusses Fitts' Law as a possible model for human performance. The linear model fit better, but perhaps this was due to the fact that the circles of the bullseye menu were equidistant. Would Fitts' Law be more suitable for a bullseye menu that had distances between circles increase logarithmically? Would performance improve if the non-visual feedback were enhanced to give users more precise information about the position of the pointing device? Having more sectors potentially decreases the distance to the selection and reduces the advantage that visual bullseye menus have over non-visual ones. However, does increasing the number of sectors make selection in non-visual bullseye menus more difficult? Investigations such as this would give researches more insight into the workings of Fitts' Law and the effect of non-visual feedback.

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