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Tapping on the Move: Fitts' Law Under Mobile Conditions

Min Lin, Kathleen J. Price, Rich Goldman and Andrew Sears
Inter. Systems Research Ctr, Infor. Systems Dept, UMBC, 1000 Hilltop Circle, Baltimore, MD 21250, USA, {mlin, kprice1, rich1, asears@umbc.edu}

Julie A. Jacko
School of Industrial & Systems Engineering, Georgia Institute of Technology, 765 Ferst Dr., Atlanta, GA 30332, USA, jack@isye.gatech.edu

ABSTRACT

Stylus-based interactions are a critical interaction technique for PDA devices due to their compact size. The validity of the classic Fitts' Law model is unclear under mobile conditions. We conducted a study, investigating the efficacy of a basic stylus operation, tapping, when performed under normal seated conditions as well as when participants walked either slow or fast on a treadmill. Although walking causes instability and difficulties coordinating PDA device with stylus, resulting in challenges with tapping tasks that require precision, Fitts' Law remained an effective tool explaining over 90% of the variance under both walking conditions. Our results indicate that the selection times for mobile interactions can be estimated by using a smaller IP value in the equation obtained under seated condition. Practical design strategies are derived to guide the development of solutions that can be used effectively under mobile conditions.

INTRODUCTION

Computers play important roles in our everyday lives, from casual tour guide systems (Cheverst et al., 2000) to mission-critical air traffic control systems. As technology advances, computers become more portable and powerful. Mobile computing has become increasingly important, and people want to have access to their computing devices anywhere, anytime. Light-weight computing devices, such as PDAs (personal digital assistants) and smart phones, are the first steps toward mobile support for everyday tasks. They are designed to be compact so that they can be easily carried all the time. Given the limited interaction mechanisms available for these devices, stylus-based interactions have replaced the traditional keyboard-and-mouse interaction paradigm as a critical technique for mobile device operations. Some research has focused on improving the usability of mobile devices when they are not used in traditional, stationary environments (Pascoe, Ryan, and Morse, 2000; Price et al., 2004), on reading comprehension using PDAs while walking (Barnard et al., 2004), and on the development of conceptual frameworks regarding the context in which the devices are used (Sears et al., 2003). However, no empirical research has been reported in literature that explicitly investigates the efficacy of stylus-based interactions under mobile conditions.

Stylus-based interactions are usually performed as the user holds the device in their non-dominant writing hand (e.g., the hand they do not use to write) and the stylus in their writing hand, similar to writing on one's palm using a pen. Experience with pen and paper suggests that completing these stylus-based interactions while walking may prove difficult. Many people have no difficulty in talking on their mobile phones while finding their way along a busy street, but we seldom see PDA users interacting with their devices while walking. Instead, we notice that these individuals usually stop, use their devices, and then resume walking. This walk-stop-use-walk pattern implies that something about interacting with PDA while walking causes the resulting activities to be less comfortable or effective. Therefore, understanding the characteristics of PDA interactions under mobile conditions will help develop or improve interfaces to better support nomadic interactions.

RESEARCH ISSUE

Mobile interactions may affect the usability of PDAs in a variety of ways. In this initial investigation, we decided to concentrate on the efficacy of Fitts' Law (Fitts, 1954) as a tool for modeling interactions when users complete target selection tasks while walking. We studied one of the most basic stylus behaviors: tapping on targets.

Generally, tapping is used for GUI (graphical user interface) object selection and cursor control. The time required to complete tapping tasks has been modeled by the classic Fitts' Law:

$$T = a + b \log_2 (D/W + 1) \qquad (1)$$

The time (T) spent to move the stylus from current position to a target depends on the distance (D) from the current position to the target and the size of the target (W). In equation (1), the values of the coefficients, *a* and *b*, are determined empirically. The $\log_2$ (D/W + 1) component is usually referred to as the index of difficulty (ID), and 1/*b* is called the index of performance (IP).

An important application of tapping is data entry using stylus-based virtual keyboards (MacKenzie and Zhang, 1999; Zhai, Hunter, and Smith, 2000). Fitts' Law is important in this context since it can be used to determine the upper limit for data entry rates given a specific keyboard layout. Since earlier studies have been conducted under stationary conditions (e.g., the user was not moving), the validity of Fitts' Law under mobile conditions remains unclear. As a result, current findings regarding virtual keyboards may or may not be applied directly to mobile situations. Testing the validity of Fitts' Law in the context of mobile interactions, therefore, is important to the field of mobile computing research.

METHODOLOGY

Apparatus

The PDA device used in this study was a Palm m500 handheld device with 160×160 (in pixels) screen resolution and 4-bit grayscale color. A Wacom tablet connected to a Dell laptop computer running Windows® XP was set up to run a Palm emulator with m500 look and feel. It provided the opportunity for the participants to understand the task while avoiding any possible learning that could occur if they used the handheld device itself. Walking conditions were simulated using a PaceMaster ProElite treadmill.

Table 1. Demographic Information of the Participants in the Three Mobility Conditions

Mobility	Seated	Slow Walking	Fast Walking
Mean Age	25.8	20.1	20.4
Computer Experience (years)	10	8	9
Computer Usage (hours per week)	32	24	38

Participants

Forty-eight participants, 24 males and 24 females, volunteered to take part in the study. They were randomly grouped into three 16-participant groups, which completed their tasks under different mobility conditions: seated (no mobility), slow walking, and fast walking. Table 1 shows the demographic information of the three groups. The age of participants ranged from 18 to 38. They were all experienced computer users and used computers extensively at the time this study was conducted.

Task

The task, which included a total of 240 trials, was to select targets by tapping on the PDA screen using a stylus. A trial starts by tapping a black 15×15 (in pixels) square in the center of the screen. This causes the black square to disappear and a circular target appears in one of the eight directions (corresponding to primary directions on a compass) from the location where the stylus initially touched the screen. Five different sizes of targets were used: 5, 8, 11, 14, and 17 pixels in diameter. Targets appeared at three different distances from the initial tapping point: 20, 40, and 60 pixels. Therefore, there were 120 unique combinations of target sizes, distances, and directions with each combination tested twice. The 240 trials were presented in a randomly generated order. Participants must attempt to select the target by tapping. Once the participant taps the screen to select a target, the target disappears and the next trial begins, regardless of the accuracy of the tapping activity.

Procedure

Participants assigned to the walking conditions started the experiment by selecting a comfortable walking pace on the treadmill. Brief instructions as to how to adjust the walking speed were projected on the wall in front of the treadmill. The treadmill speed was slowly adjusted by the investigator while a participant walked and issued brief verbal instructions. Participants were instructed not to look at the speed display on the treadmill panel but to feel their walking pace and say “faster” or “slower” so the investigator could adjust the speed accordingly. Once the participant found a comfortable walking pace, they would say “stop” to finish the adjustment process. The speed reading on the treadmill display was recorded and served as the reference speed for calculating the slow and fast speeds used in the study. In slow walking condition, the speed was calculated as 80% of the reference speed; and in fast walking condition the speed was calculated as 120% of the reference speed. The participants were not told about their group membership so that they could not adjust their task strategies based on this information. We believed that it was important to set walking speeds relative to the comfortable pace selected by each individual instead of forcing everyone to accept an arbitrary predetermined pace. This process helps ensure that the walking pace is natural and makes the terms “slow” and “fast” contextually accurate for every participant. For the participants who were assigned to the seated condition, this adjustment process was skipped.

Verbal instructions were given to each participant regarding how to perform the tapping tasks using a stylus. Participants were allowed to practice three target selection trials on the Wacom tablet. The size of the targets, the distance participants had to move the stylus, and the actions required were all similar to what participants would ultimately experience using the PDA. Additional practice was optional. After confirming that they understood the tapping operation as well as the required task, participants were handed the Palm device to begin the experimental task under the mobility condition they were assigned to. There was no time limitation for participants to complete the task.

Table 2. Mean Target Selection Time with Standard Deviations in Parentheses

Mobility Time (ms)		Seated			Slow Walking			Fast Walking		
		Distance (pixel)								
		20	**40**	**60**	**20**	**40**	**60**	**20**	**40**	**60**
Size (pixel)	**5**	1099 (231)	1173 (266)	1258 (238)	1155 (212)	1194 (164)	1293 (164)	1147 (237)	1220 (215)	1319 (235)
	8	1004 (179)	1061 (174)	1168 (185)	1063 (150)	1096 (181)	1230 (194)	1085 (204)	1135 (226)	1205 (239)
	11	946 (152)	1006 (144)	1075 (132)	968 (155)	1049 (166)	1128 (171)	990 (186)	1046 (175)	1129 (181)
	14	930 (194)	1001 (175)	1065 (153)	916 (107)	993 (140)	1099 (160)	940 (165)	1016 (180)	1095 (180)
	17	921 (156)	991 (227)	1034 (149)	897 (137)	959 (130)	1034 (126)	912 (164)	961 (174)	1045 (174)

RESULTS AND DISCUSSION

As Fitts’ Law equation (1) implies, stylus movement time is determined by target size and the distance to the target. Table 2 lists the average target selection time for various sizes and distances under the three mobility conditions. Smaller sizes make target more difficult to select, and result in longer selection times. Similarly, longer distances require larger movements, and result in longer selection times. These results are consistent with Fitts’ Law.

We ran a regression on the data collected under each mobility condition to validate the effectiveness of Fitts’ Law. The time unit used in table 2 is millisecond since many tasks required less than one second. For Fitts’ Law, we follow the traditional expression and use seconds as the time unit. Equation (2) is the Fitts’ Law equation generated using the data from the seated condition. As expected, Fitts’ Law is effective for describing the results from the seated condition. The Pearson correlation coefficient is 0.97, which indicates that 95% of the variance is explained by the model.

$$T_{seated} = 0.759 + 0.129\ ID \qquad (2)$$

The index of performance (1/*b*) is 7.8bps (bits per second), similar to the value of 7.9bps reported in stylus-based virtual keyboard taping behavior by Zhai et al. (2002). The large variance explained and the similarity to previously reported IP value confirm the reliability of our experimental design as well as the data collected.

The Fitts’ Law regression equations for the two walking conditions are listed below:

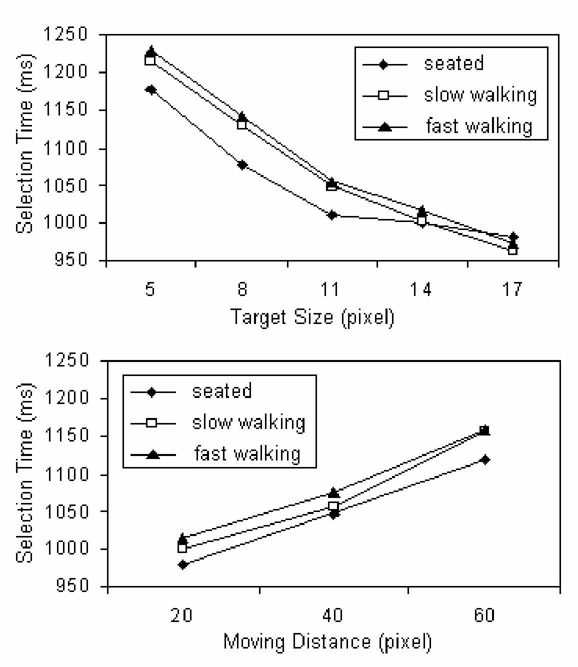
$$T_{slow\_walking} = 0.726 + 0.154\ ID \qquad (3)$$

$$T_{fast\_walking} = 0.726 + 0.151\ ID \qquad (4)$$

The Pearson correlation coefficients are 0.96 for both walking conditions. That is, the Fitts’ Law explains approximately 92% of the variance in selection times under these conditions, suggesting that it remains an effective tool for modeling stylus tapping behavior even when users are on the move.

Equations (3) and (4) are very similar to each other. The *a* values are identical, the *b* values are very similar, and both equations explain a similar portion of the variance. All these facts indicate that Fitts’ Law not only can be applied to walking conditions but that it can be reliably applied to a wide range of walking speeds. The two parameters remain constant when walking speed varies, suggesting that the parameters obtained in this study can be applied to the walking speeds ranging from 80% to 120% of a user’s normal walking speed.

Figure 1. Target Selection Time on Size and Distance Under the Three Mobility Conditions



The empirically identified index of performance value in equation (3) and (4) is 6.6bps. This is lower than the value of 7.8bps obtained when participants were seated. This indicates that walking does introduce some difficulties when users attempt to complete stylus-based tapping tasks. However, it is important to note that this value may not be applied directly to virtual keyboard text entry tasks which is not exactly the same as our target selection task. Stylus-based text entry normally lasts longer than our target selection task since most words include multiple letters. Additionally, as people need to pay attention to the environment around them while walking, longer interactions may result in more frequent attention shifts between the environment and the task, and therefore affect the overall performance (e.g. longer task completion time and higher error rate). Further investigations, using more complex tasks, such as text entry using virtual keyboard, will be helpful.

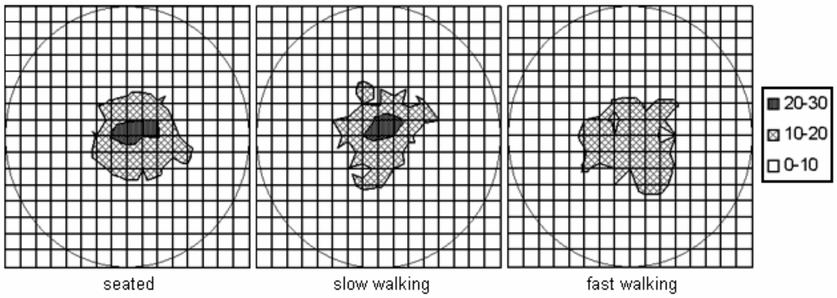
Although the IP values for the Fitts' Law equations under the seated and the walking conditions are not the same, the intercepts, *a*, are very close. More specifically, the intercepts differ by just 0.033 second, which is sufficiently small compared to the intercept values that it could be ignored. In our experimental design, targets appear in one of eight directions after the user taps on the central square. Therefore, the intercept of 0.7 seconds represents the time required by the user to identify the target prior to moving the stylus. The similarity of the intercepts indicates that the target acquisition process is not affected by mobility conditions. Therefore, if the constants *a* and *b* are known from studies conducted with participants seated, and tasks are sufficiently simple and quick like those explored in the current study, selection times for walking conditions can be approximated by using a smaller IP value (larger *b*) while holding the intercept constant. At present, it is unclear if this transformation will hold true for more complex tasks such as drag and drop interactions.

Fitts' Law describes how the target selection time is affected by target size and moving distance. The following section further examines the impact of target size and distance (Figure 1).

As illustrated in figure 1, selection times for the two walking conditions partially overlap, explaining the similarity of the Fitts' Law equations (3) and (4). For the seated condition, selection times can be reduced by approximately 3.5ms/pixel by moving the target closer to the starting location. Making targets larger resulted in a savings of approximately 28ms/pixel when targets were smaller than 14 pixels in diameter. Therefore, when designing a system that my be used under walking conditions, designers should consider making GUI objects bigger before moving them closer together as this will allow for greater reductions in target selection times. We also noticed that when targets become large enough (e.g. 14 pixels), selection times no longer differ based on mobility conditions. On the other hand, for targets smaller than 14 pixels in diameter, it is clear that the seated condition will result in shorter selection times. Therefore, in order to limit the impact of mobility on tapping-based interactions, GUI objects should be at least 14 pixels, or 0.21 inch, in diameter. Our data implies that text entry speed will decrease using current virtual keyboards (e.g. 12 pixels on Palm OS devices) when a user is walking simply because the soft keys on the screen are not large enough to compensate for the increased difficulties introduced by motion.

Since the Fitts' Law IP values and the time-size plot all indicate the existence of mobility effects on tapping behavior, we examined the distribution of stylus taps on targets. Figure 3 presents an example of the distribution plot when tapping the largest targets, 17 pixels in diameter, under the three mobility conditions studied. In general, the most frequent tapping points were around the center of the targets. However, the distribution patterns appear to differ among the three mobility conditions. When the task was performed while participants were seated, the shape of high-frequency points is symmetric, with a little bias toward the right side of the target, which may be the result of the fact that most participants were right-handed. When the task was performed while walking, the shape of the distribution becomes less regular. Importantly, the frequently tapped area (e.g. number of taps >= 20) became smaller when walking slowly and disappears when walking fast. Such a change in the distributions highlights the difficulty users experience keeping either the display or the stylus stable. As a result, when precision is important for task completion (e.g. avoid tapping on adjacent keys on a soft keyboard), designers should consider making the targets larger or leaving larger gaps between nearby objects to help reduce tapping errors.

Figure 2. Stylus Tapping Point Distribution on the 17-Pixel Target (the circles indicate the boundary of the target)



Although we studied a critical stylus-based PDA interaction technique, tapping, this is not the only operation users must perform. Our data confirms that mobility affects tapping behaviors, suggesting that similar effects may be observed for other, more complex operations such as handwriting, gesture-based input, or drag-and-drop interactions. In addition, PDA interactions in real situations are more complex than the single tap scenario investigated in this study. Multi-step operations, information representation, and nomadic interfaces are some areas where further investigation is warranted.

CONCLUSIONS

We verified the efficacy of Fitts' Law under mobile conditions. Within the walking speed range evaluated in this study, 80% - 120% of an individual's normal walking speed, Fitts' Law remained an excellent model, accounting for more than 90% the variance in target selection times. Selection times increased when tasks were completed while walking, with target size having a greater impact than distance. When targets are sufficiently large, users are able to compensate for mobility to maintain selection times that are comparable to those observed when the user is seated. In contrast, bringing targets closer to the starting location does not mediate the effects of mobility on task completion times. The distribution of taps, as illustrated in figure 2, confirms the instability of either the device or the stylus under walking conditions. Our results highlight the need for careful design if devices are intended to be used under mobile conditions. More importantly, our results underline the need for additional investigations of nomadic interactions exploring more complex interactions such as gesture-based input, handwriting recognition, and drag-and-drop interactions.

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