The Effects of Walking Speed on Target Acquisition on a Touchscreen Interface

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ABSTRACT
Studies have reported negative effects of walking on mobile human–computer interaction when compared to standing or sitting. However, the quantitative relationship between walking *speed* and user performance is unknown. In the study described here, we varied walking speed on a treadmill and measured effects on discrete aiming movements on a touchscreen interface. Their relationship was found to be non-linear with a local optimum: when walking at 40–80% of one's preferred walking speed (PWS), target acquisition performance plateaus, indicating optimal trade-off between speed and interaction. Accelerometer data showed that, despite increasing hand oscillation, users were able to maintain stable interaction performance at 74% of PWS. Interestingly, this speed coincides with the speed users *spontaneously* walk when interacting with a mobile device.

Author Keywords
Mobile human-computer interaction, walking speed, target acquisition, touchscreen interface

ACM Classification Keywords
H5.2. [User Interfaces]: *Input devices and strategies*.

General Terms
Human Factors

INTRODUCTION
Mobile device users must continuously regulate walking speed according to situational constraints and priorities on the one hand, and demands of the interactive task on the other [11]. Everyday experience tells us that slowing our walking speed is necessary in many situations. In this paper, we are interested in charting what we call the *walking speed–interaction trade-off function*; in other words, how a change in walking speed affects interaction and *vice versa*. Is there an "optimal" walking speed where one can maintain high velocity *and* high performance in an interactive task?

This trade-off function is important because, ideally, a mobile user interface should allow the user to walk at any speed without reducing interaction performance. To study this effect, we conducted a study where we gradually increase walking speed on a treadmill and measure effects on performance in a touchscreen target acquisition task. The data are linked to users' idiosyncratic walking speed (*preferred walking speed, PWS* [12]) and we measure both hand and body oscillation with accelerometers during walking.

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Previous Work
Some of the earliest field studies showed that walking can hamper input performance [2], but results from later studies have complicated the picture. One study reported *no* effect of walking [7] and another reported an effect restricted to poor lighting conditions [1]. However, these studies did not control walking speed but let users choose their own pace. The lack of control left open the possibility that users slowed down walking enough for it not to interfere with interaction. Barnard *et al.* [1] report that users *spontaneously* reduce speed by 30–37% when using a mobile device.

Three methods have been used to control walking speed: a treadmill [8], instruction to maintain a particular speed [16], and a human pace-setter [6]. In the abovementioned studies, the effect of walking has been, without exception, negative and focused on accuracy instead of reaction time (for an exception, see [9]). Alternatively, walking speed can be measured during unconstrained performance and cross-correlated with performance. Using this method, Schildbach and Rukzio [15] found that target selection time increased by 31% from standing to walking on a test track, despite the fact that the participants decreased their walking speed by 25%. Error rates, target selection times and task completion times showed performance being hampered by having to hit targets that are *small*, suggesting that oscillation of the hand is particularly detrimental to aiming movements.

These results leave open the question of what is the quantitative relationship between walking speed and interaction. For example, if users slow down 5% from regular walking speed, how much will they gain in improved performance in the interactive task? Or, if they walk extremely slowly, will they then be able to maintain the same performance as when static? Our experiment adds to the literature by systematically controlling walking speed on a treadmill. We chose a treadmill because real routes and tracks may confound walking speed with the complexity of the route. As walking speed increases, so does the *rate* of environmental cues to which the user must attend. When walking faster, the user must attend to an increasing number of turns and other cues per second. The only study that both 1) controlled walking speed, although only at four levels, and 2) used a treadmill was a study of *reading* by Mustonen *et al.* [10]. They found that reading velocity (characters/second) decreased from 27 to 22 from standing to walking at PWS.

METHOD

A calibrated Woodway treadmill was used to control the velocity of walking in our study. Treadmill *gait* has been found to be functionally equivalent to over-ground gait for healthy subjects accommodated to treadmill walking [14]. Crossan *et al.* [5] have studied effects of gait in HCI, showing that target selection time and accuracy depend on the gait *phase* [4]. A feature of our method is that we recorded hand and body oscillation with accelerometers attached to the user's body. Other key features are that we measure not only PWS but also PWS *while interacting* with a mobile device. Biomechanical studies of walking have found that people naturally adapt their walking speed to a level that is most efficient in terms of energy expenditure per kilometer [3,13] and this speed, the preferred walking speed, is idiosyncratic. PWS has been applied in studies of mobile HCI in two ways: as an independent variable [8,10], and as a dependent variable to show the effect of an interaction on walking speed: the speed to which the user decelerates walking when interacting [12,15].

Design

The experiment used a within-subject design with treadmill velocity as an independent variable. Velocity was manipulated in steps of 0.6 km/h starting from 0 km/h to the fastest walking speed that each user felt safe and comfortable. One trial was conducted at each of these steps. The fastest speed ranged from 3.6 km/h to 7.2 km/h. The order of conditions was counterbalanced. The dependent variables were target selection time and accuracy of selection.

Participants

Twenty university students (17 males) with a mean age of 22.4 years (SD 3.9) participated. 19 were right handed. Mean height was 176 cm (SD 11), and mean weight 69.75 kg (SD 13.19). Their average daily walking distance was 5.4 km/day (SD 2.4). Five users used a treadmill (Mean 2.2 hours/week, SD 1.3). All participants received a payment of £6 for their involvement.

Task

The task was to select crosshair targets appearing on a touchscreen as quickly and accurately as possible. The device was held in the non-dominant hand and targets selected with the dominant index finger. Twenty-five targets were equally spaced on a 5 by 5 grid with one below being the start position for each selection (Figure 1). Targets were displayed one at a time and the finger had to be returned to the starting position after each selection, resulting to a total

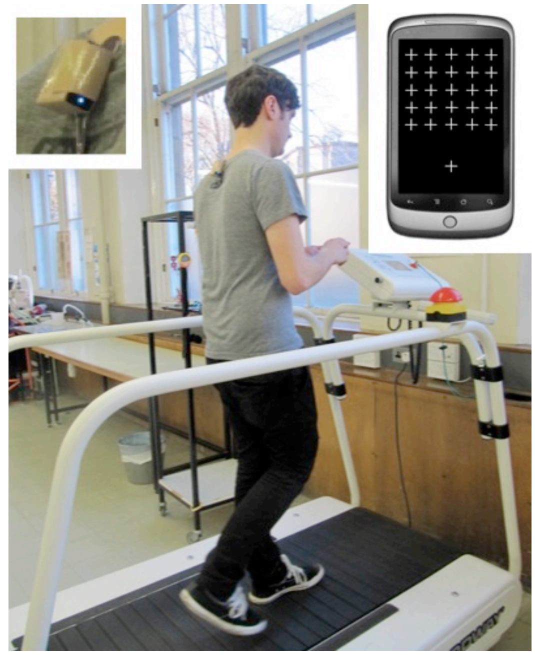

Figure 1. A participant walking on the Woodway treadmill with a SHAKE sensor pack attached to the shirt collar (Left). The targets were shown in a grid of crosshairs on a mobile phone touchscreen (Right).

of fifty targets per condition. The order and timing of target presentations were randomized, the latter within a 0.5-1.5 second inter-target interval. The inter-target interval was randomized to prevent participants adapting to a rhythm between cadence and target selections.

Apparatus and Measurement

The experiment was conducted on an HTC Nexus One Android mobile phone with a 3.7 inch, 480x800 pixel touchscreen. The phone's internal accelerometer measured the oscillation of the non-dominant hand holding the device. A SHAKE SK7 sensor pack's accelerometer (code.google.com/p/shake-drivers) measured body oscillation with a 50Hz sampling rate from the back of the neck (Figure 1). The frequency of gait (*cadence*) was calculated from recorded oscillations. Amplitudes of the body and hand oscillations were calculated as standard deviations of vertical average accelerations. The experimental software recorded target onset and selection times (in milliseconds), and selection accuracy in pixel coordinates. The SHAKE sensor pack was connected to the phone via Bluetooth and all data were logged on-device.

Procedure

The safety features of the treadmill were first introduced and a brief training session on walking on the treadmill was given. A training session for the selection task was conducted standing still. To determine individual PWS, participants were asked to think about their normal walking speed when heading for example, to school or shops, and asked to instruct the experimenter to either increase or decrease the speed of the treadmill until this speed was reached. *PWS*

Figure 2. Average target selection accuracy by percentage of PWS. Vertical bars denote 95% CIs.

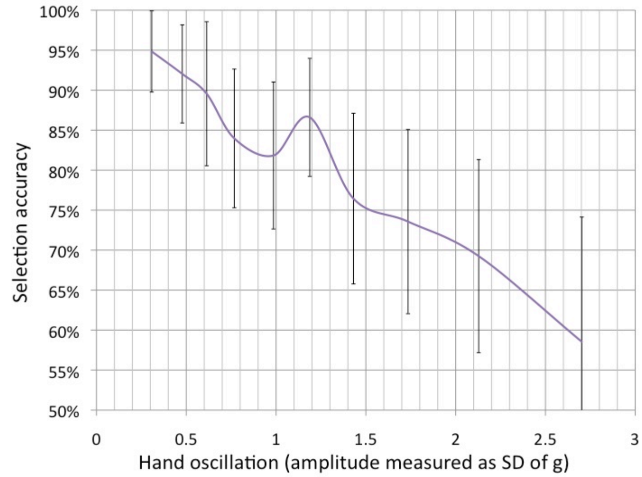

Figure 3. Average target selection accuracy by hand oscillation amplitude. Vertical bars denote 95% CIs.

while interacting was determined similarly by asking participants to think about the speed they would normally walk if simultaneously interacting with a touchscreen device. Before each trial, participants were given time to adjust to the trial's walking velocity so that they felt comfortable and safe.

RESULTS

We analyze target selection accuracy because selection times were approximately constant over the conditions. To enable comparison between participants, accuracy was normalized by dividing accuracy in each velocity condition with the participant's baseline performance (accuracy level while standing still). To assess the effect of PWS, the data were grouped into eight intervals: 0–19%, 20–39%, 40–59%, 60–79%, 80–99%, 100–119%, 120–139% and 140–159% of PWS. For comparing the obtained means, we use 95% confidence intervals (CIs) calculated from the Student's t-distribution. Accidental double taps were removed.

Mean PWS over all participants was 3.90 km/h (SD 0.64). Mean PWS *while interacting* was 2.97 km/h (SD 0.63), a 24% reduction from PWS.

Accuracy

Figure 2 shows the decrease in accuracy as a function of preferred walking speed (PWS). Three observations can be made:

First, there is always a cost of walking, no matter how slow the pace. When compared to standing still (where accuracy is at the maximum of 100%), accuracy decreases to 89% when walking just 20–40% of PWS. This difference is significant, $t(21)=27.23$, $p<0.05$.

Second, performance decreases approximately linearly (but slowly) when speed increases from 30% of PWS to 90% of PWS. The mean accuracy at 90% of PWS (81.6%, CI±7.4%) is significantly worse than at 30% of PWS (89.1%, CI±8.5%), $t(32)=32.75$, $p<0.05$. However, the decrease in accuracy is not significant when increasing speed from 30% to 70% of PWS (83.5%, CI±7.2%), nor from 50% of PWS (85.9%, CI±7.6%) to 90% of PWS, suggesting that, although the trend is slightly decreasing, target selection performance remains relatively stable in relation to speed when walking speed is in the range of about 40 to 80% of PWS.

Third, performance starts to deteriorate very quickly when walking beyond speeds of 100% of PWS.

Hand and Body Oscillation

The data show that target selection accuracy deteriorates in relation to both hand and body oscillation. We here concentrate on hand oscillation, which we found to be a stronger predictor of accuracy (Figure 3).

A surprising anomaly was identified at the oscillation amplitude of 1.2 g, where performance (86.6%, CI±7.8%) was improved over both the weaker (81.8%, CI±9.7%) and stronger (76.4%, CI±11.3%) amplitudes. This finding indicates that users were able to aim their hand relatively accurately at this amplitude compared to other hand oscillation amplitudes. To associate this optimal point back to walking speed, we fitted a linear trend between hand oscillation amplitude and PWS (Figure 4; $R^2=.767$). This trend suggests that this optimal point of selection accuracy occurs at 74% of PWS, which coincides with the mean PWS while interacting with a mobile device (76%) shown above.

DISCUSSION AND CONCLUSIONS

Reinforcing previous findings, the data suggest that all walking—no matter if it is only at 20% of PWS!—is costly. If one needs to prioritize performance in the interactive task then it makes sense to stop walking entirely. But the data yield a more intriguing finding, suggesting that when walking at a speed of about 40–80% of PWS, users are able to maintain a more stable level of performance than expected. Performance costs plateau within this range of speeds. The accelerometer data tentatively indicate that this is *not* due to improved stabilization of the holding hand at this pace, as non-dominant hand oscillation increases, suggesting that

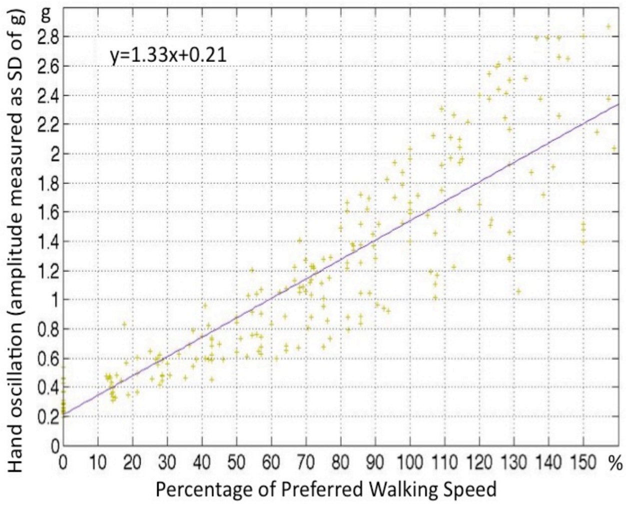

Figure 4. Hand oscillation amplitudes by percentage of PWS. Vertical bars denote 95% CIs.

the dominant hand is able to compensate for the effects of walking in this speed range against the increasing oscillation of the non-dominant hand holding the device.

Interestingly, this walking speed range matches with the range our users themselves determined as their preferred walking speed while interacting with a touchscreen device (76% of PWS), and it matches with results from previous studies where users spontaneously decelerated by 20–40% when interacting [1,12,15]. As humans are aware of their “natural” walking speed, experienced users of mobile devices seem to be aware of the walking speed that is efficient for mobile interaction.

Further investigations are needed to understand performance in the range of 40 to 80% of PWS. It will be necessary to replicate the present experiment with a larger sample size, and other tasks and interfaces. Comparing the walking speed–performance trade-off functions of different interface types is important for mobile HCI, as previous studies have found that some interfaces are less susceptible to the effects of walking [12,16]. Ideally, we will be able to develop interaction techniques that are optimized to reduce the detrimental effects of increasing walking speed.

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