A Mobility Evaluation of Tilt Panning and Offset Sensing Smart Watch Input

HongMin Kim
Ulsan National Institute of Science and Technology
Ulsan, Republic of Korea
khm489@unist.ac.kr

MyungSung Kim
Korea Advanced Institute of Science and Technology
Daejeon, Republic of Korea
myungsung.kim@kaist.ac.kr

Ian Oakley
Ulsan National Institute of Science and Technology
Ulsan, Republic of Korea
ian.r.oakley@gmail.com

ABSTRACT

Small smartwatch touchscreens restrict input and researchers have long explored how alternative modalities and techniques can enable new possibilities and boost expressiveness. However, these techniques are generally designed in and for static, stable settings; mobility issues are rarely considered. To address this omission, we conducted a mobility study that compares two recently proposed alternative smartwatch input modalities: physical movements of a watch on the wrist, and an offset touch sensor on the edge of the device. We observed high selection errors for tilt input (23.89% to 34.22%) and prolonged times for offset sensing (>1000ms). We propose a combined input technique designed to fit the constraints of mobile watch use: touches to the device edge stabilize and constrain input, while tilt and touch control and trigger it. A second study shows this design can improve target selection time while mobile to less than 800ms with error rates of 10.2%.

CCS CONCEPTS

• **Human-centered computing → Pointing**; *Interaction devices*; HCI design and evaluation methods.

KEYWORDS

HCI, Wearable Devices, Input Technique for Mobility Condition, Multi-modal Input

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1 INTRODUCTION

Smartwatches provide a novel context for input: tiny screens [10] within touchable [8], twist-able bodies [17] all attached to the highly mobile wrist [13]. Based on sensing systems as diverse as tomographic scanning of the inner structure of the arm [20], range finders that track hand angle [5], bespoke touch sensors integrated into device edges [8] or straps [11] and simple on-board inertial motion units [18], researchers have explored how to exploit the specifics of the wrist-mounted context to support a broad range of input and interaction tasks. These include staples such as pointing [19] through hand pose or gesture recognition [16], to complex, prolonged activities such as text entry [4]. Taken together, this body of work highlights the fact that, despite their diminutive size, careful design and clever implementation can yield expressive and effective smartwatch input techniques via a wide range of non-traditional means.

While this diversity showcases the potential of developing innovative input techniques for the watch form-factor, it is currently lacking in its treatment of mobility – in assessing whether the proposed techniques can be used in real world situations in which users are engaged in common tasks such as walking [7]. In such settings, input performance typically declines and careful design is required to mitigate these losses [12]. Initial work to assess performance with watches while mobile is now emerging but, to date, it has focused on traditional touch-screen input tasks and either cataloged performance in key mobile contexts [3] or contributed guidance for effective watch input technique design for mobility [14]. While this work is valuable, we note that little attention has been devoted to how effective novel smartwatch input techniques are when users are actually mobile.

This paper starts to address this issue. It re-implements two recently proposed non touchscreen based interaction techniques for watches, one based on the idea of touches to the edge or side of a watch case [2, 8], the other based on tilting the watch body [17–19]. These techniques were selected as they involve touching or gripping the watch, stable contacts that may make them inherently suitable for mobile use. We then evaluate performance using these techniques in a mobility study involving participants both standing and walking. These techniques have not previously been examined in these contexts. The results show high error rates for tilt input that increase substantially while walking (19.66% to 29.48%) and prolonged times for offset sensing (>1000ms). Building on these findings, we propose two variants of a novel interaction technique that combines the beneficial properties of these input styles and evaluate them in a follow up study. The result show improvements in error rate compared to tilt input (8.8% to 17.5%) and time compared to offset sensing input (767 to 885 ms).

The contributions of this paper include: 1) the first study of non-traditional, non-touchscreen smartwatch input in a mobility scenario; 2) a novel interaction technique design that builds on the results of this study and; 3) a validation of this design in a follow up study. The goal of this paper is to reflect on whether the diverse,

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creative techniques for smartwatch input proposed in the Human-Computer Interaction research community are practical and viable for use in real user settings – to provide a first examination of how representative examples of these techniques hold up in a mobile context.

2 RELATED WORK

The emergence of consumer wearable devices in the last decade has resulted in a large and growing research literature detailing specialized interaction techniques that meet the requirements of their unique and restricted contexts. Smartwatches are no exception and numerous authors have proposed techniques to enhance watch touch screen use by, for example, optimizing tapping or stroking for tasks such as typing [15] or by exploring how temporally [9] or spatially [6] separated taps can be leveraged to support rapidly issuing commands. A related approach has been to expand input possibilities by developing additional touch surfaces, such as on the strap [11] or edge [8] of a watch. Touches to these surfaces can also be combined with traditional touchscreen inputs to increase input bandwidth, as in Ahn et al. [1]'s watch text entry system in which taps to the side of device select different sub-regions of a keyboard to be shown on the screen, thus enabling larger and more usable keys.

Other researchers have sought to leverage the wearable context to design motion sensitive systems for smartwatch input. These include systems that feature trackers capable of detecting body movement, such as the angle of the wrist [4] or simpler approaches that just rely on overt movements of the watch itself captured by bespoke [17] or built-in [18] motion sensors. This work leverages the fact that a watch is readily graspable and typically loosely attached to the body – it can be gripped and twisted, turned or tilted with relative ease. Research suggests these modalities, when combined with traditional touch screen input for disambiguation, are sufficiently expressive to support a wide range of interactions including target selection, parameter adjustment and panning.

We identify both non-traditional touch surfaces (e.g., on a watch edge) and watch-motion based input as promising candidates for next generation input techniques on wrist wearables. However, we note that, in contrast to an emerging body of work that is considering mobility issues for standard touchscreen watch input [3, 14], no prior studies have explored these techniques in realistic watch use scenarios - situations where a user may be busy, mobile or otherwise distracted. We identify this as a weakness in the data describing these new modalities for wearable input and present the first study examining the performance of these types of non-traditional watch input in a mobility setting.

3 APPARATUS

We constructed a compact and portable prototype that implements both inertial tilt input and edge based touch input. The prototype is shown in Figure 1 and consists of a 3D printed case (composed of both conductive and non-conductive elements) that contains an Arduino pro mini (5V/16Mhz), an HC-06 Bluetooth module, two MPR121 capacitive touch sensor breakout boards (each supporting 12 electrodes), a bespoke PCB that links all components and a commercial smartwatch: a 1st generation MOTO360 featuring a

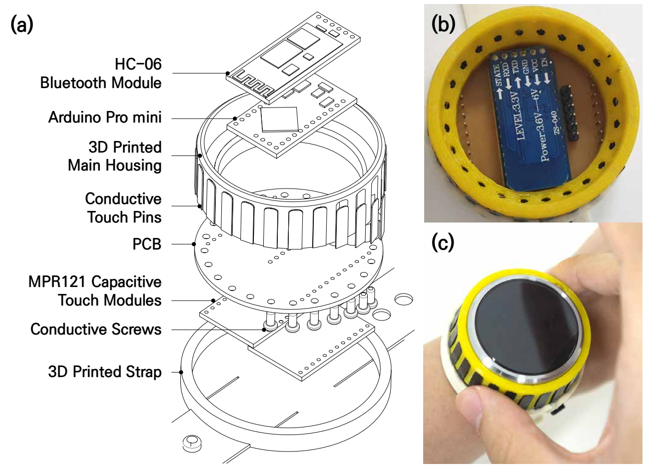


Figure 1: Offset touch and tilt sensing smartwatch prototype: (a) exploded view, (b) internals of case (c) worn on the wrist

320 by 290 pixel screen. This device was selected as it is round and does not feature external lugs, simplifying construction of a fully touch sensitive surface around its edge. The final dimensions of this device are 52mm in diameter and 27mm high (compared to the watch's 46mm by 11.5mm). The housing is mounted on a 3D printed flexible watch strap.

Edge based sensing is enabled by 24 3D printed electrodes (Protopasta Conductive PLA) tightly embedded within the main housing (Ninjatek NinjaFlex) and each bolted to the PCB using M2 screws. The MPR121 units and Arduino capture raw data from these electrodes by comparing baseline and current readings [8]. Data from each electrode is then compressed to 4 bits to create full data packets of 12 bytes in length. These are sent, via serial Bluetooth, directly to the watch at 30Hz. Tilt based sensing is enabled by the watch's built-in IMU, as in prior work [18], at 60 Hz. All software was written using a modified version of the Processing development environment that enables compiling for smartwatches.

4 STUDY 1: EXISTING INPUT TECHNIQUES

Using this hardware prototype, we implemented and adapted two different input techniques from the literature on watch tilt panning [18] and offset sensing [8]. To facilitate comparison, both techniques were modified in several ways. Firstly, both were designed to support an identical arrangement of 24 targets: three concentric rings of eight equally sized (in terms of both angle and radius) targets – see Figure 2. The tilt panning system mapped changes in the watch's orientation during touches to the side of the device to the position of a cursor at a fixed rate of 11 pixels per degree. To move the cursor to the edge of the screen therefore required tilting the watch by 15 degrees. Selection was triggered by releasing the device edge. This technique and the target selection interface were inspired by the pressure input technique described by Yeo et al. [18]. The offset sensing input technique mapped cursor movement to the direction of a single touch to the watch edge at a speed of 100 pixels per second, or 1.6 seconds to move from the center to edge of the screen. Selection was again triggered by releasing the

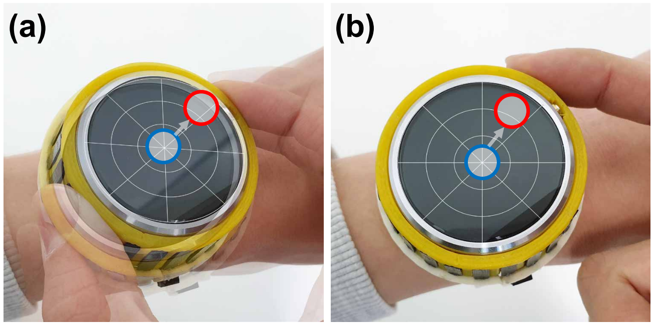


Figure 2: Input Techniques: (a) Tilt panning: hold and tilt the watch to control a cursor. (b) Offset sensing: touch the edge of watch and a cursor moves towards your finger.

finger. The mappings of tilt and time to cursor displacement were set during development and informal piloting through a process of iterative refinement.

Twenty-four participants completed the study (13 male, 11 female, all right handed and with a mean age of 22.82 (SD: 1.99)). They were recruited from the local student population and compensated with approximately 10 USD in local currency. They reported high levels of experience with touch screens (9.33/10) but limited prior experience with wearable devices (0.9/10). The study followed a repeated measures design with two independent variables: the *input* technique of either tilt panning or offset sensing and the *pose* of either standing (in a quiet lab environment) or walking (a circular route around office corridors at a uniform speed) while completing tasks. Participants completed these four conditions in a fully balanced design: one participant completed each of the 24 possible orders. In each condition, participants completed three blocks of trials, with each block composed of the full set of 24 possible target selections delivered in a random order. Participants were required to complete all trials correctly – in case of errors, trials were returned to the set of yet to be completed trials in each block. The first block of trials was discarded as practice, leaving a total of 4608 successful trials (24 by 2 by 4 by 24) for analysis. At the end of the study, participants were debriefed and given the chance to comment on the different conditions regarding issues such as the difficulty or comfort of the tasks.

4.1 Results

We first examined the raw data. Figure 3 depicts selection points in all trials with blue indicating correct and red showing errors. This figure suggests that offset sensing solutions allowed more consistent and reliable angular input – compared to the dispersed results in the tilt panning technique, selection points are more clearly banded to the angular centers of the targets. Figure 4 summarizes this data as aggregate performance for time and errors. To analyze these data we conducted Repeated Measures ANOVA incorporating Greenhouse–Geisser corrections to correct for sphericity violations (where needed) . In addition to the variables of pose (standing/walking) and input technique (tilt panning/offset sensing) we also included target distance (three levels: inner, middle or outer ring) as a variable due to the strong impact it exerted on

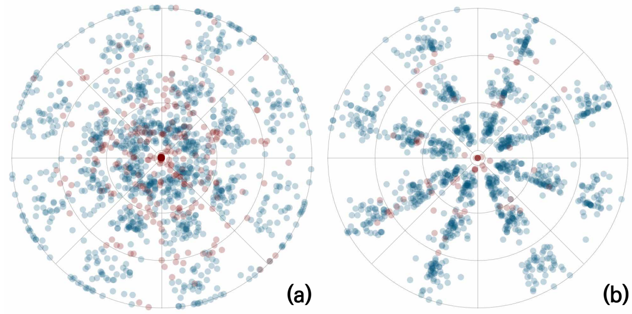


Figure 3: Selection points in study 1 from (a) tilt panning (b) offset sensing input conditions

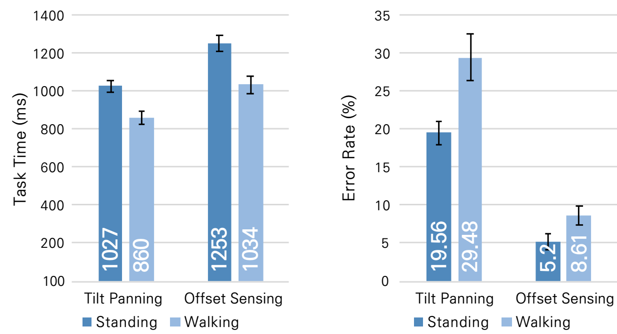


Figure 4: Mean task time and error rates from study 1. Bars show standard deviation.

performance. Table 1 summarizes the statistical results. As the variables are either binary (pose, input) or the interactions the main focus of interest (distance and another variable) we opted not to conduct *post-hoc* testing.

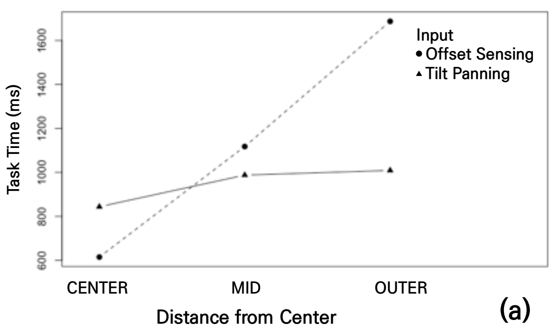
Participants' comments in the debrief echoed the objective results. Eleven mentioned that tilt panning while walking was challenging, perhaps due to there being "too many degrees of freedom" (P5, P17) or simply the inevitability of making unintentional cursor movements. The speed at which tilt panning could be performed was acknowledged (P1, P4) and there was a suggestion it would be preferred if more constrained (P15, P32). Six participants remarked offset sensing was "unfamiliar but easy" and that there was little difference between operating the technique while standing or while walking (P8). Furthermore, four appreciated that touches to the edge of the device did not obscure the screen.

4.2 Discussion

The results show clear differences, and substantial effect sizes, in both time and errors. The main effects of input indicate that tilt panning was faster than offset sensing but led to an increased error rate; the main effects of pose show a surprising reduction in task time while walking and an expected increase in error rates. Based on comments from several participants highlighting an increased sense of urgency in the walking condition, we attribute these changes to a speed/accuracy trade-off – in the walking condition, instabilities in

Measure	*Variable(s)*	*F-value*	*P-value*	η_p^2
Task Time	Input	F(1,23) = 60.04	<.0001	0.723
	Pose	F(1,23) = 65.858	<.0001	0.741
	Dist	F(1.98,45.5) = 225.2	<.0001	0.907
	Input X Pose	F(1,23) = 2.379	0.137	0.094
	Pose X Dist	F(1.98,45.5) = 5.05	0.011	0.180
	Dist X Input	F(1.96,45.1) = 137.79	<.0001	0.855
Error Rate	Input	F(1,23) = 1807	<.0001	0.987
	Pose	F(1,23) = 156.5	<.0001	0.872
	Dist	F(1.58,36.34) = 190	<.0001	0.892
	Input X Pose	F(1,23) = 32.71	<.0001	0.587
	Pose X Dist	F(1.86,42.78) = 56.02	<.0001	0.709
	Dist X Input	F(1.46,33.6) = 99.7	<.0001	0.813

Table 1: RM-ANOVA results from Study 1 for all main and interaction effects for input technique, pose and target distance



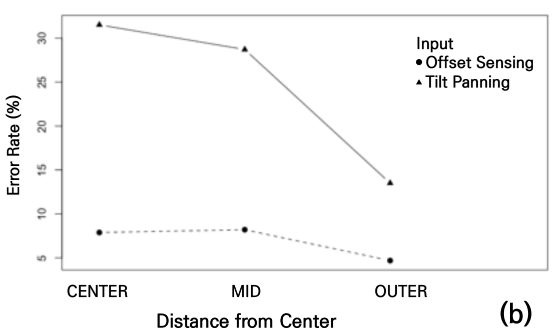


Figure 5: Interaction plots in study 1: a) task time (Input by Distance) and b) error rate (Input by Distance)

performance of prolonged tasks led to an increased desire for speed which, in turn, contributed to greater error rates. The input by pose interaction in errors is due to the offset sensing input technique being more resilient to the change in pose from standing to walking – the increase in errors for offset sensing is smaller than for tilt panning.

The main effects of distance simply represent the increased challenge of reaching further targets. The interactions with this variable (Figure 5) show two trends. Firstly, error rates between the two techniques converge in the edge targets. This reflects the fact that these targets could be selected by points on the boundary of the possible cursor input space – in Fitts' law parlance, the edge targets were infinitely deep. Secondly, in terms of time, the interaction indicates a reversal: offset sensing is most rapid for selections on inner targets and tilt panning most rapid for selections on outer targets. This reflects a fundamental difference in the way the techniques worked – for center targets offset sensing demanded a rapid tap and release, while for edge targets participants held down their finger while the cursor moved to the edge at a fixed velocity. For tilt panning, cursor position depended on entirely small changes in watch orientation, meaning no such linear effect was present in the task completion time.

Its worth comparing the current data to prior accounts. There are close similarities: task times and error rates for a prior study of offset sensing with 24 targets, albeit in a different spatial arrangement, are 1386ms and 5.4% [8], broadly similar to data from the standing condition in the present study. There are also differences: prior work on tilt input has relied on dwell selection and reported substantially longer (2.1 to 2.6 seconds) and more accurate input (0.2% to 1.6% errors) [18]. The difference between dwell and lift-off selection mechanisms is likely responsible. Dwell improves accuracy by not requiring a potentially unstable finger lift action and, as a consequence, doubles task times. We also note that the increased stability of dwell would not likely be maintained in an inherently unstable walking scenario - it would be hard to dwell via tilt while walking. This highlights the importance of assessing wearable input techniques in mobile contexts.

5 STUDY 2: NOVEL INPUT TECHNIQUE

We developed a novel input technique to combine the quick task times of tilt panning with the lower error rates of offset sensing and reflect participants comments and opinions. The technique requires a user to touch the side of the watch with two fingers, as in tilt panning, but constrains cursor movement to a line connecting the finger touches, thus reflecting the offset touch positions. Actual movements of the cursor along this line are achieved by tilt panning the watch with either the zero order *tilt-position* mapping used in the first study or a new first order *tilt-velocity* mapping, in which a degree of tilt is mapped to a cursor velocity of 10 pixels/second. The technique has a number of beneficial properties: increased stability of movement in response to watch tilting (only one degree of freedom) and reversibility (tilting can move the cursor in either direction along the line).

We conducted a study of this technique with a new set of 16 participants (11 male, five female, all right-handed, mean age 24.6 (SD: 2.19)), again recruited from the local student body and compensated with approximately 10 USD. Self reported data on experience with touch screens (9.1/10) and wearables (1.7/10) were similar to the initial set of participants. The task structure and study design closely followed the first study with the exception of the use of a Latin square arrangement to balance the repeated measures conditions (due to the lower number of participants). The input variable was composed of the tilt-position and tilt-velocity techniques and we again used both standing and walking poses. After excluding trials for practice, we retained a total of 3072 trials (24 by 2 by 4 by 16) for analysis.

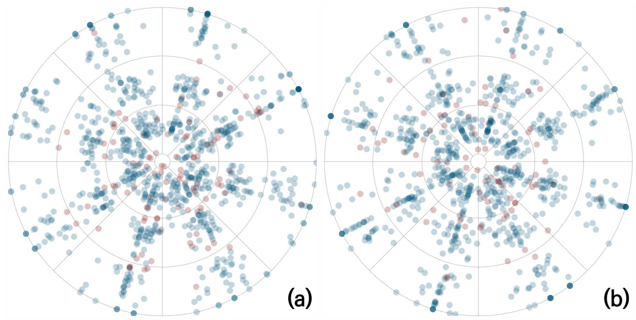


Figure 6: Selection points in study 2 from (a) tilt position (b) tilt velocity

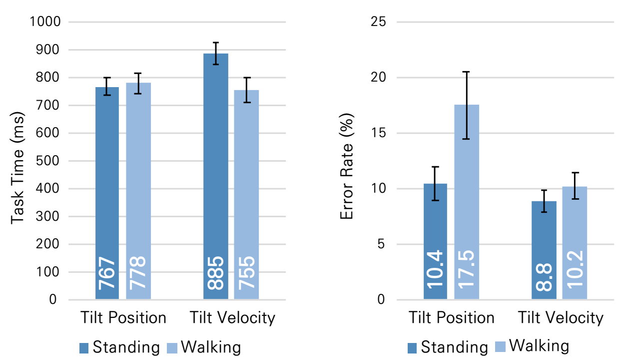


Figure 7: Mean task time and error rates from study 2. Bars show standard deviation.

Measure	*Variable(s)*	*F-value*	*P-value*	η_p^2
Task Time	Input	F(1,15) = 1.48	0.243	0.090
	Pose	F(1,15) = 5.523	0.033	0.269
	Dist	F(1.56,23.4) = 8.792	0.003	0.370
	Input X Pose	F(1,15) = 13.366	0.002	0.471
	Pose X Dist	F(1.32,19.8) = 0.295	0.656	0.019
	Dist X Input	F(1.29,19.3) = 2.851	0.099	0.160
Error Rate	Input	F(1,15) = 59.897	<.0001	0.800
	Pose	F(1,15) = 119.32	<.0001	0.888
	Dist	F(1.72,25.8) = 50.195	<.0001	0.770
	Input X Pose	F(1,15) = 12.433	0.003	0.453
	Pose X Dist	F(1.76,26.4) = 40.873	<.0001	0.732
	Dist X Input	F(1.34,20.1) = 0.177	0.751	0.012

Table 2: RM-ANOVA results from Study 2 for all main and interaction effects for input, pose and distance

5.1 Results and Discussion

We again examined the raw data. Figure 6 shows selection points in all trials with blue indicating correct and red showing errors. Selection points are aligned reasonably well to the center of targets, as in the offset sensing technique in study 1, and there are no clear differences between the plots. This figure suggests that the combined input technique achieved consistent and reliable angular input in both its tilt position and tilt velocity variants.

Summary data are shown in Figure 7 and the results of statistical testing in Table 2. The key result in task time is the interaction

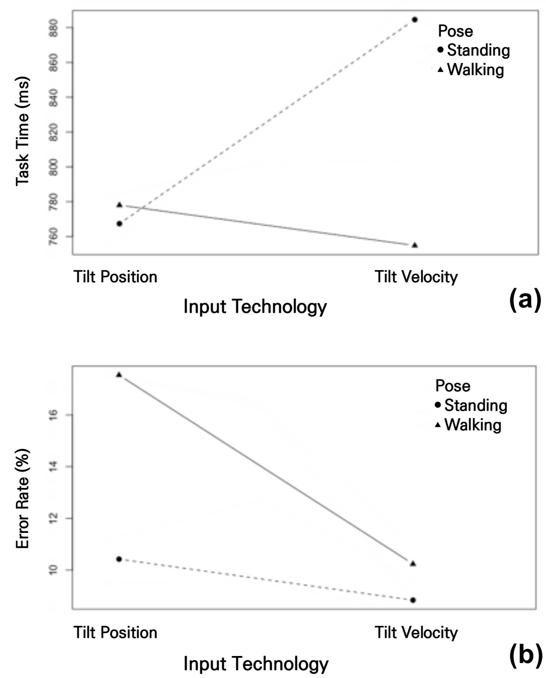


Figure 8: Interaction plots in study 2: a) task time (Input by Pose) and b) error rate (Input by Pose)

between input and pose (see also Figure 8) that indicates that while the tilt-position technique performs stably across the standing and walking poses, the tilt-velocity technique, like the techniques in the first study, is slower while standing than while walking. The interaction in the error data shows the opposite trend: tilt-velocity is fairly static, while tilt-position shows a substantial increase in errors during walking. In comparison to data from study 1, task completion times are generally reduced while error rates show modest increases compared to offset sensing (and substantial improvements over tilt panning). We interpret these outcomes to suggest our revised techniques represent a meaningful compromise in performance between the two extremes examined in study 1. Comments from the participants provide supportive evidence for this – half (eight) commented on the learning curve required to use the technique, but that it was ultimately "highly adjustable" or precise. Three explicitly mentioned the line constraint increased the stability of their input. We also note that closer similarity between the two input conditions meant target distance had limited impact on performance: interactions between input/pose and distance have small effect sizes compared to those observed in study 1.

6 CONCLUSION

This work explores how non-traditional input on watch wearables performs in realistic conditions such as standing and walking – to provide a clearer picture of how these novel techniques might work in real world settings. The initial study shows shortcomings. Due to the inherent instability caused by walking, input based on tilt panning a watch led to a high error rate while input based on offset sensing was slow. The second study investigated how to combine these techniques to yield improvements by constraining the rapidly executed but unstable tilt movements with constraints from the more stably maintained offset touches. The results indicate it was partly successful: while we did not formally compare data between the studies, task performance times were modestly reduced over both original conditions and the most accurate tilt-velocity condition offered comparable error rates to the original offset sensing conditions, particularly in the most challenging walking setting.

Future work should refine our designs, for example by optimizing the mappings between sensor inputs/time and cursor position/speed. A limitation of this work is that these relationships, despite attempts to determine reasonable settings, may not be optimal. Indeed, gain values for input devices are often personalized - allowing customization may result in the best performance. Beyond this practical detail, we emphasize the importance of evaluating wearable input techniques in wearable settings. A reliance on lab-based studies in ideal input environments such as seated at a desk will likely return results that do not scale or apply to real world wearable use scenarios. Just as recent work has started to examine this issue for standard touchscreen input [3, 14], this paper highlights the importance of considering mobility in studies of non-traditional input techniques involving alternative touch surfaces or device motion. We contribute the first work to assess this issue and show how careful designs can adapt promising techniques to the challenges of mobile use.

7 ACKNOWLEDGEMENT

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