MoveSpace: On-body Athletic Interaction for Running and Cycling

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ABSTRACT

Wearables are increasingly used during training to quantify performance and provide valuable real-time information. However, interacting with these devices in motion may disrupt the movements of the activity. We propose a method of interaction involving tapping specific locations on the body, identify candidate locations for running and cycling, and compare them in a series of controlled experiments with athletes. A purpose-built prototype measures speed of interaction and gives feedback cues for athletes to report the physical effects on the activity itself. Our results suggest that specific locations are faster and have minimal disruption to movement, even under induced fatigue conditions. The overall method is fast - 1.31s for running and 1.65s for cycling. Preferred locations differ significantly across sports, with stable body parts ranking higher. We effectively demonstrated the use of a single hand for interaction during running with two distinct tap gestures. A set of guidelines inform the design of new sports technologies.

CCS CONCEPTS

• **Human-centered computing → Interaction techniques**; *Ubiquitous and mobile computing systems and tools*; Empirical studies in ubiquitous and mobile computing;

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KEYWORDS

Running, cycling, sports training, on-body interaction, interaction in motion

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1 INTRODUCTION

Training with technology has become an essential practice among athletes [21]. The wrist-worn form-factor is the most popular platform, with devices such as the Apple Watch, Fitbit, and Garmin a common sight at sporting events. Along side these, novel form-factors are emerging in the form of smart-clothing [20], flexible and stretchable skin patches [23], and interactive tattoos [11]. Professional athletes are using these technologies in their clothing and shoes with embedded sensors [10]

Interacting with devices during training imposes certain physical constraints such as maintaining stride while running [18] or balancing when cycling. The point of interactions on the body is thus affected by the sporting activity and the athlete's individual characteristics, such as their reach and form. In addition to this, the interface itself is also fixed, composed of buttons or touchscreens, it does not adapt physically to different sports or the training demands of the athlete. As a result, interacting with these devices is not optimal in training scenarios, since the athlete may have to slow down or stop to use them [14].

To address these challenges, we propose a more direct way to interact with wearable devices, by using tap gestures on particular body locations. The underlying motivation for such an interface is to explore the interactive potential in the dynamics of the human body in motion [13]. In this view, physiological factors such as body posture, reach, and locomotion can be harnessed to promote, rather than disrupt the interaction. Other properties such as proprioception and kinesthesis have already been suggested as promoters

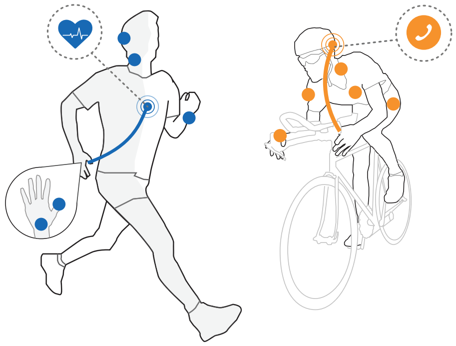

Figure 1: We propose an interface that allows input during movement by tapping the body. We map the fastest, easiest to target, and least disruptive locations which differ for the sports of running and cycling. Tapping locations can provide athletes with information about their performance in real-time, and allow them to stay in control of their devices.

of interaction [7]. Therefore, this direction of study could reveal bodily dynamics and movements appropriate for interaction that can be used to create more natural and easier to use interaction methods, which flow naturally with given physical activities.

We select the two sports of cycling and running for the study as they present different challenges in terms of demand on locomotion, form, and exertion. We asked athletes to try using their body as an input surface during a real training session and to report which locations they preferred. From this initial study we elicited eleven candidate locations for running, and six for cycling. We further evaluated these locations in a series of experiments by recording actuation time and subjective data during athletic training for both running and cycling, and noted significant differences in location performance depending on activity. We discuss the underlying factors for these results, analyze them in relation to activities, and compare to previous work.

The contributions of this paper are:

(1) A fast method of input in athletic interaction – Synthetic stimuli response times are 1.31s for running and 1.65s for cycling (Table 1 and Table 2).
(2) A map of body locations showing which are the most comfortable for input and the effect of interaction on the athletic activity (running: Figure 4; cycling: Figure 5), paving the way for many sports to use on-body interaction.

2 RELATED WORK

Interaction in sports present a unique set of design challenges in terms of demand from locomotion, form, and exertion. Previous studies have looked at the performance aspects [21] and experiences of technology use [19] during training, while we direct our attention to the interaction itself and consider it in terms of these challenges.

2.1 Wearable Interfaces

Interactive devices expand the input and output capabilities of the athlete thus allowing them greater access over their information and device functions. Interactive clothing allows input using conductive fibres [12, 20], while skin sensing technology using EMG [15], acoustic [9], and waveguide [24] technologies have been explored for input. Another type of interactive material is the wearable tattoo based on gold leaf [11], and the electronic stretchable skin [23]. While the advantage of these interfaces is that they are portable and mobile, they are not informed by user studies involving the human body in motion. Our paper addresses this topic by exploring preferred body locations for tapping while running and cycling.

Smart watches conveniently combine both sensing and interaction capabilities, however, they have two key problems. Since they are necessarily wrist-mounted, they can only collect data from that location. Second, that location may not be a suitable interaction point when considered under different sporting activities. Therefore, interacting with these devices in motion may require the user to stop or interrupt the motions of the activity [14].

2.2 Interacting in Motion

Several frameworks have been created to help designers create interactions that align with the movements of the human body. Mueller et al. propose an exertion framework looking at these interactions through 4 lenses: the responding, moving, sensing, and relating body. In particular, the moving body refers to the repositioning of body parts relative to one another during physical activity [16]. Marshall et al. create a taxonomy of interactions in motion according to their relation to locomotion, and the degree to which the activity allows an interaction [13]. Applications of these ideas can be seen in projects which take advantage of existing activity movements input to their connected systems, for example, using cycling gestures [6] and foot tapping [5]. Even implicit parameters such as heart rate have been used as input during running [17]. The goal of this study is expand this space by evaluating the feasibility and effectiveness of on-body tapping as a potential non-disruptive method of interaction for multiple sports.

2.3 On-body interfaces

Very recently, Hamdan et. al [8] have explored on-body tapping for running. We distinguish from this work with the following: i) the evaluated location were different – our participants identified 3 different location: the thumb, neck, and ear. One explanation for this is that we used 3 times more users in the elicitation study compared with [8]; ii) we evaluate another cycling besides running and draw general conclusions for the implications of wearable devices for athletic interaction. Pinstripe [12] studied interaction with textile user interfaces across the body while sitting, standing still, and walking showing that pocket, forearm, upper arm, and sternum are the preferred locations. BodyScape [22] evaluated the performance of 18 body parts finding that upper body targets were faster for touching (1.4s) than lower limbs (1.6s) and upper body locations were more socially acceptable. Gesture elicitation studies for single-hand microgestures [4] showed that when comparing with other gestures, taps are preferred by users because of their ease of use and conceptual simplicity. While the human body has been explored as an input and output device in a stationary context [22], our work focuses on the interaction possibilities afforded by the moving body.

3 MOTIVATION

To more clearly address the potential of a non-disruptive form of athletic interaction, we propose a method of interaction involving tapping locations on the body which accounts for the motions of the activity. This allows us to address the issues of optimal input locations on the body without regard to device sensing and information output; a strategy lining up well with compact multitouch input and output gear [11, 15, 20, 24]. We conducted a series of studies with athletes to answer the following questions: 1) Is on-body tapping a suitable method of interaction during training? 2) Among training athletes, which different body locations do they think are suitable for interaction during training, and why? 3) How do these body locations perform in terms of speed, accuracy, workload, and the effect on their posture and movement? 4. Does the performance and ranking of the different locations vary according to different types of activities? If so, how do they vary and why? 5. Do athletes find this type of interaction desirable, and for what purpose?

4 FINDING SUITABLE BODY LOCATIONS

To answer the question regarding the suitability of the proposed method, we conducted a study with athletes and asked them to try out on-body locations during running and cycling by tapping them.

4.1 Participants and Method

We recruited 9 runners (4 female) who trained on average 4.3-6x per week. Similarly, we recruited 5 active cyclists (1 female) who practiced a minimum of 2x per week. Recruitment was done via a local sports clubs and the authorâĂŹs personal network. The instructions were the same for both sports, and stated: "While in motion, try to touch areas of your body and reflect on the comfort and performance of the interaction.". Athletes could use any location in their vicinity, including parts of their equipment, or the bike itself. There was no minimum time or number of attempts that athletes had to complete, and they were free to integrate it into their training routine as they saw fit. All participants received the same set of instructions, however, some received them via email, while others received a paper version in person. Where possible, we also requested for photographs of the exact locations chosen.

4.1.1 Body Locations for Running. We collected 11 candidate locations: Neck, Ear, Dominant Chest, Center Chest, Non-Dominant Chest, Belly, Hip, Inner Wrist, Outer Wrist, Palm and Fingers. The hand locations could be activated in two distinct modes: touching the finger with the thumb, and activating the palm using the middle finger. Some participants felt that they could accidentally activate the palm position if they make a fist while running, thus they preferred the finger-to-thumb interaction. Areas on the front torso were chosen for their stability: *"The centre-line of my body stays relatively stable while running, it was almost as easy to touch this area as accurately as my hands/wrists."* (P2, M, 33, Marathon Runner)

The hip and thigh area were included due to its proximity to the motion of the arm swing. Locations on the wrist and ear were primarily selected due to previous experience in interacting with devices in these areas. Participants also reported trying out the shoulder, knees and ankles, but they were not recommended as they were difficult to target, too far away, or affected the runners stride negatively. Two athletes also attempted swipe gestures instead of taps, but found the direction difficult to control. The motion of the arm is tied to the phases of stride, thus the point of contact could coincide with the landing step which pulls the hand down. Swipe gestures could also interfere with input intended as a tap: "I donâĂŹt want to swipe it, but my hand automatically goes down. My intention was to do a tap, but I did a slide instead" (P7, M, 29, Ultra Marathoner)

Based on these results, the subsequent studies concentrated solely on tap gestures and we incorporated into the prototype the ability to perform both input on the whole body and micro-interactions using a single hand.

4.1.2 Body Locations for Cycling. We elicited 6 locations from the participants who cycled: Helmet, Neck, Chest Center, Upper Arm, Wrist and Thigh. Participants preferred the top half of the body like the neck, helmet, chest, and upper arm in order to maintain balance while cycling. Dominance did not seem to play an important role in location selection. No participants suggested touching the bicycle itself as input, despite the instructions stating that this is acceptable. This may be due to existing biases, e.g., the bike is for controlling steering etc. the set of recommended locations allows us to focus solely on using the body itself as input. One limitation of this study is the inability to control the cycling posture. In the cycling experiment, we control for this variable by using only the brake-hood position.

Figure 2: Hardware prototype as worn by one of our participant demonstrating its ability to accommodate to various hand postures.

5 HARDWARE PROTOTYPE

The prototype was designed to fit the task of usage during training. The hardware consisted of two main components: a ring-mounted RFID reader connected via flexible wires to a wrist-mounted enclosure containing an Arduino Bluno and a 1,000 mAh Lithium-Polymer battery connected to an MFRC522 RFID reader. RFID stickers on the body provide a passive means of detecting which body part was touched. Each tag is 30mm in diameter and can be triggered from any angle, through clothing and the finger itself, from a distance of 0-2cm. This solution is designed to be robust and allows near instant recognition, does not require machine learning, and is not affected by conditions like heat and sweat [15]. We tested the prototype in a series of pilot studies to make sure there were no discomfort or range of motion issues due to the form factor. The final prototype can be seen in Figure 2.

6 EXPERIMENT 1: RUNNING ON A TREADMILL

Based on results from our elicitation study, we identified 11 possible candidate locations for on-body interaction: Neck, Ear, Dominant Chest, Center Chest, Non-Dominant Chest, Belly, Hip, Inner Wrist, Outer Wrist, Palm and Fingers. The goal of the next experiment was to a) narrow down the number of locations, b) answer the most important questions regarding the effectiveness of the method and its impact on form and the ability to target. We used a treadmill study so that we could control speed of running in order to investigate the effects of fatigue.

6.1 Participants

Ten participants (2 females, 1 left-handed) ranging from 20 to 40 years old ($M = 24, SD = 5.87$) were recruited from within the university community. All the participants were running between 8 and 20 times per month ($M = 12$).

6.2 Task and Stimuli

During each trial, the participant hears the name of a body location via audio and then must tap on the correct location using our system. A trial finishes when the participant taps on any location, and binary audio feedback was given to the participant. There was a 3 second break between trials.

6.3 Apparatus

Participants wore our hardware prototype on their dominant hand with the ring mounted on the middle finger. Before use, each tag was wrapped in plastic and adhered on the body using KT tape. We collected data using our custom software on a Nexus 5 smartphone running on Android 6.0.1 which communicates with our prototype via Bluetooth LE. Our participants ran on a FreeMotion Reflex T 11.8 Treadmill.

6.4 Procedure

Participants began the experiment by filling a pre-test questionnaire with demographic information. The experimenter would then describe the experiment to the participant, show them how to operate the system, and assist the participant in putting all the eleven stickers on the correct body locations. Body locations were placed in specific locations which could be accurately reproduced. A brief training session was performed until they understood and were able to tap each location.

Participants would then proceed to a warm-up run of 3 minutes at 11.5 km/h, followed by 6 test blocks, also at 11.5km/h. To induce fatigue, the last two blocks involved first running for 3 minutes at 14 km/h before proceeding to the trials. These speeds were chosen based on average human endurance running and sprinting speeds [18].

6.5 Design

A within-subject design was used with two independent variables: *Body Location { Ear, Neck, Non-Dominant Chest, Center Chest, Dominant Chest, Non Dominant Inner Wrist, Non Dominant Outer Wrist, Dominant Palm, Dominant Thumb, Belly, Thigh}* and *Block {Training1, Training2, Test1, Test2, Test3, Test4}*. The *Body Location* was randomized within blocks.

We measured accuracy, execution time, as well as perceived ability to target and perceived effect on stride as dependent variables. A trial was considered accurate if the user successfully tapped on the location corresponding to the stimulus. Since we used audio stimuli, the execution time was defined as the time elapsed between the moment when the system starts speaking a location name until the moment where the participant taps on a specific location. Since each body location has a name of varying length, we used non-ambiguous stimuli of variable duration. Due to this variance in stimuli time, we could not compare completion time between locations. Our focus was more on subjective preference in order to reduce the number of locations to only choose desirable ones.

Ability to target and effect on stride were measured at the end of each block, using a 7 point Likert-Scale (1: Hard to target/High impact on stride, 7: Easy to target/Low impact on stride).

Each participant completed the experiment in about 1 hour, including short breaks between blocks. The design included the following: 10 participants $\times$ 11 body locations $\times$ [2 training blocks + 4 test blocks] $\times$ 5 repetitions = 3300 trials.

6.6 Results

We excluded the actuation time data from the training blocks for analysis. Thus, results are only taken from the four test blocks. We use ANOVA for statistical analysis and pairwise t-tests with Bonferroni correction for post-hoc comparisons.

6.6.1 Time. Our participants were quite fast at tapping on target, with a global average time of 1.43 second. A one-way ANOVA with repeated measures showed a significant main effect of Block on execution time ($F_{3,27} = 3.01, p = .04$). The Block Test1 was the slowest ($M = 1.55s$) compared to Test2 ($M = 1.39s$), Test3 ($M = 1.38s$) and Test4 ($M = 1.39s$). The difference was significant between Test1 and Test3 ($p = .05$).

6.6.2 Accuracy. The participants were very accurate during the experiment, reaching an overall accuracy average of 97.4%. A two-way ANOVA with repeated measures on both factors did not show any significant main effect of either *Block* ($p = .08$) or *Body Location* ($p = .44$) and no interaction ($p = .12$).

6.6.3 Ability to Target. The average ability to target was 5.37/7. A two-way ANOVA with repeated measures on both factors showed a significant main effect of *Body Location* on ability to target ($F_{10,90} = 2.66, p = .018$), an interaction between *Body Location* and *Block* ($F_{30,270} = 1.67, p = .019$) but no effect of *Block* ($p = .07$). The average ability to target for each location is shown in Figure 4. We observed 12 significant pairwise comparisons: Ear ($M = 6.33/7$) with 4 other locations with lower scores, Thigh ($M = 4.08/7$) with 3 other locations, Dominant Chest ($M = 4.55/77$) with 5 better scoring locations, and Non Dominant Chest ($M = 4.82/7$) with 3 other locations with higher scores. Note that three pairwise comparisons are counted twice in the previous sentence. Figure 3 summarizes these pairwise comparisons.

Chest (C)	-									
Chest (ND)	-	-								
Chest (D)	A	-	-							
Ear	A/E	E	A/E	A/E						
Thigh	E	E	E	-	A/E					
Neck	E	-	A	A	-	A/E				
Palm	-	-	-	-	-	E	-			
Thumb	-	-	-	-	-	A/E	-	-		
Inner Wrist	-	-	-	A	-	A/E	-	-	-	
Outer Wrist	-	-	A	A/E	-	A/E	-	-	-	-
	Belly	Chest (C.)	Chest (ND)	Chest (D)	Ear	Thigh	Neck	Plm	Thb	I. Wr

Figure 3: Statistical significance of (1) ability to target performance and (2) effect on stride differences. 'A' shows significance for ability to target, 'E' for effect on stride.

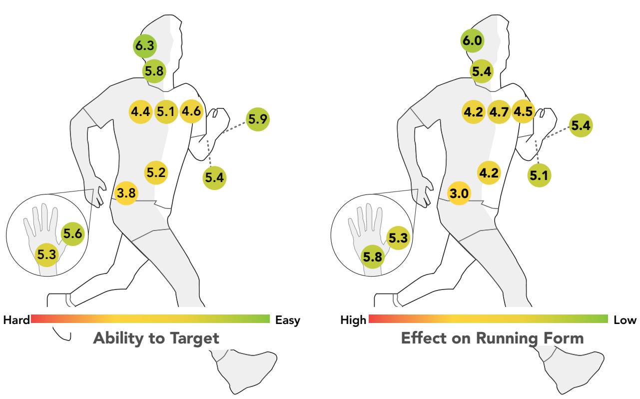

Figure 4: Body Map for Running: ability to target (left) and effect on running stride (right) using 7 point Likert-Scale (1: Hard to target/High impact on stride, 7: Easy to target/Low impact on stride).

6.6.4 Effect on Stride. The average effect on stride as perceived by our participants ranged from 4.38/7 (Thigh) to 6.05/7 (Ear), for an average of 5.03/7. A two-way ANOVA showed significant main effect of *Block* ($F_{3,27} = 5.59, p = .004$), *Body Location* ($F_{10,90} = 2.57, p = .008$) and an interaction *Block* × *Body Location* ($F_{30,270} = 1.64, p = .02$). The effect of stride varied over the four tests blocks as follows: 4.96/7 for Test1, 5.19/7 for Test2, 5.09/7 for Test3 and 4.89/7 for Test4, with significant differences between on one hand Test2 and on the other hand Test1 and Test4, suggesting that our participants felt that interacting with the system had more effect on the stride after Test2, since a higher score suggests a least effect on the stride.

In terms of *Body Location*, we found 14 significant pairwise comparisons. Tapping the Thigh had the highest impact on the stride ($M = 4.38/7$) scoring significantly worse than 9 other locations; Ear had less impact ($M = 6.05/7$) and scored significantly better than 5 other locations, and finally, Belly ($M = 4.45/7$) received significantly lower scores than 3 other locations. Note that two pairwise comparisons are counted twice. More details can be seen in Figure 3.

6.7 Body Location Analysis

We observed an interaction *Block* × *Body Location* on the effect on stride which suggests that the perceived effect on stride can improve on some locations, or to the contrary decrease on others. On Belly, Palm and Thumb, the perceived effect score increased over time, suggesting that tapping on these locations seems to have less impact on the stride over time, whereas the inverse effect was observed on Non Dominant Chest, Dominant Chest, Neck, Inner Wrist and Outer Wrist. This score stayed steady for Ear, Hip and Center Chest.

When asked about the number of locations for interactions, participants responded that, on average, 6 is a comfortable number. This matched the average number of submitted locations during our exploratory study, which was also 6. Therefore, we selected only the six best locations. We discard Hip and Belly because of their low scores in Qualitative Feedback. After discussing with participants at the end of the experiment, we also discarded Inner Wrist as it was confusing to differentiate the two locations for some participants. Finally, after comparing the general performance of the three chests position, we also discarded the Non Dominant and Dominant Chest and kept Center Chest. Our reduced set of optimal Body Locations is thus: Ear, Neck, Center Chest, Non Dominant Wrist, Palm and Thumb.

The results of this experiment show a very high accuracy overall. Our participants were consistently accurate for each location showing that our system is reliable. In terms of execution time, we notice an interesting trend as execution time decreased between blocks to reach an average of 1.38-1.39 seconds by the end of the experiment. This significant decrease of time can likely be explained by a learning effect, however the effects of fatigue on the performance is not really clear. We found no significant effects that show fatigue was affecting actuation performance.

6.8 Study Limitations

The analysis of the time data revealed that we could not reliably compare between locations due to a variance in the length of the audio stimuli - i.e. 'Center Chest' takes longer to pronounce than 'Hip'. Therefore we could only assess actuation time on an aggregate and block level. We resolve this limitation in the follow-up track experiment, where each audio stimuli is exactly 300ms in length and encoded in a single word (Please see supplementary materials for audio stimuli).

7 EXPERIMENT 2: RUNNING ON THE TRACK

The first running experiment allowed us to come up with a reduced set of six suitable body locations: *Ear, Neck, Chest, Wrist, Palm and Thumb*. In this new experiment, we test the validity of the method in a more realistic context by asking our participants to run on a track without stopping.

7.1 Participants

Twelve participants (6 females, 1 left-handed) ranging from 19 to 28 years old ($M = 22.39, SD = 3.07$) were recruited from within the university community. All the participants were running between 4 and 21 times per month ($M = 9.61$).

7.2 Task and Stimuli

Similarly to experiment 1, we used the same audio stimuli process, with binary audio feedback given to the participant at the end of a trial and a three seconds break between two trials.

7.3 Apparatus

The participants wore the same hardware prototype on their dominant wrist and hand, connected to the same Nexus 5 Android Phone. The experiment was done on an outdoor track within the university campus. The track is a standard 400 meters track. We also used a Garmin 735 XT smartwatch to track their running speed and collect biometric measurements.

7.4 Procedure

The procedure is the same as in experiment 1. During the main experiment, we asked the participants to run at a comfortable, but constant speed. Our participants ran at speeds ranging from 7.3 km/h to 14.4 km/h ($M = 11.05km/h, SD = 2.41$). Participants maintained a constant speed throughout the experiment, including a 2 minute break between blocks. We also reduced the number of blocks from 6 to 5, by removing one of the training blocks. After the experiment, we asked participants to map any functions they may use during training on the set of body locations. A brief interview concluded each experiment.

7.5 Design

We used a similar within-subject design with two independent variables: *Body Location {Dominant Ear,Dominant Neck,Center Chest, Non Dominant Wrist, Dominant Palm, Dominant Thumb }* and *Block { Training1, Test1, Test2, Test3, Test4 }*. The *Body Location* was randomized within blocks. We measured accuracy and execution time again for each location in the post-experimental questionnaire. Each participant performed the experiment in around 1 hour, including around 20 to 24 minutes of running. The design included the following: 12 participants × 6 body locations × [1 training + 4 test blocks] × 5 repetitions = 1800 trials.

7.6 Results

7.6.1 Time. The execution time includes the time to play the stimulus and the time for the participant to tap on the body location using our system. The average execution time was quite fast at 1.31 second on average. A two-way ANOVA found an effect of *Body Location* ($F_{5,55} = 2.94, p = .021$), but no interaction ($p = .1$) between factors. On average, wrist was the slowest location to acquire ($M = 1.49s$). Table 1 shows the performance of each location and significant pairwise comparisons.

We also analyzed improvement of *Body Location* over time, excluding the first training block. A two-way ANOVA did not show any significant main effect of *Block* on execution time ($p = .2$). On average, execution time over all locations improved by 0.08 seconds. The palm and the thumb showed no improvement at all, while the chest improved the most by 0.22 seconds.

Table 1 shows the performance of each location and significant pairwise comparisons.

Table 1: Average time for each location in experiment 2. α,β,γ show significant pairwise comparisons.

Location	**Wrist**	**Chest**	**Neck**	**Ear**	**Palm**	**Thumb**
Average Time (s)	$1.49^{\alpha,\beta,\gamma}$	1.25	1.25^{β}	1.26^{α}	1.25	1.25^{γ}

7.6.2 Accuracy. The participants were also very accurate in this experiment, with an average accuracy of 96.9%. A two-way ANOVA with repeated measures on both factors showed no significant effect of *Body Location* ($p = .19$), *Block* ($p = .75$) or interaction between the two factors ($p = .63$). The accuracy between blocks stays nearly constant as it ranges from 96.7% in Test1 to 97.2% in Test4.

7.7 Body Location Analysis

In general, the six locations we chose for this study were good, with very high accuracy and low time to acquire them.

Neck and Ear also performed well and confirm the trend we found in Experiment 1. Neck seems to require more focus than the ear but is still a good candidate.

One of the most interesting result in this experiment is the relatively low performance of the Wrist. Most athletes use a wearable device usually worn on the wrist as a companion while exercising, which might suggest that Wrist is a good location for on-body interaction while doing sports. It appears that the Wrist takes significantly more time to tap on (up to 200 milliseconds). This difference may not seem important, but in a competitive sports context it can be an issue. As stated by P8: *"Because itâĂŹs on the other side. It would affect my movement, because when youâĂŹre jogging, you do this, you tend to lose balance."* (P8, F, 20, Recreational Jogger).

While all locations showed a significant effect between the first training block and the second, we found no further learning effects. Thus, our approach requires on average 2.5 minutes to learn. Certain locations such as the Palm and the Thumb achieved their lowest actuation time in the 2nd block, while the Chest showed the most improvement through the full experiment.

7.8 Study Limitations

We note that false positive of certain body locations such as the palm and hip can be a potential issues that are worth more design consideration, but overall, these incidents were rare in our studies. On average, we noticed about 1 false positive every 2 hours.

We see that the ear was the most desired for a music player, while the chest was thought to be particularly intuitive for biometric data.

8 EXPERIMENT 3: CYCLING ON THE TRACK

Our elicitation study for on-body touch during cycling yielded 6 candidate locations: Non Dominant Arm, Center Chest, Dominant Helmet, Dominant Neck, Dominant Thigh and Non-Dominant Wrist.

In this activity, no narrowing down was needed, and testing in a gym setting was not appropriate. Thus we conducted only 1 study using the same procedure as experiment 2, and taking all measures from both running experiments. The goal of this experiment was to investigate how the preferences for body location change depending on activity, and explore the reasons why.

8.1 Participants

Eight participants (1 female) ranging from 20 to 40 years old ($M = 26.5, SD = 7.31$) were recruited from within the university community and bicycle enthusiast groups from social media. All the participants were cycling between 2 and 31 times per month ($M = 12.25$).

8.2 Task and Stimuli

The experiment was very similar to experiment 2 with audio stimuli of exactly 300 ms, binary audio feedback given to the participant at the end of a trial and a three seconds break between two trials.

8.3 Apparatus

The participants wore the same hardware prototype on their dominant wrist and hand, connected to the same Nexus 5 Android Phone. The experiment was done on the same outdoor track. The participants were asked to bring and ride their own bicycle during the experiment.This was done to accommodate for fit, since providing one bicycle with seat adjustment would only provide height adjustment. We also used a Garmin 735 XT smartwatch to track their cycling speed.

8.4 Procedure

The procedure is shared with experiment 2. During the main experiment, we asked the participants to cycle at a comfortable speed. There would be a 30 seconds break between two blocks during which there would be no stimulus. Participants were instructed to ride and perform interactions in the brake-handle (BH) position, even if their bicycles had aero-bars or drop-handles. The thigh position sticker was mounted on top of the clothing. All participants used their right hand to actuate the locations on the body. After the experiment, participants were asked to rate the perceived ability to target and effect on the cycling posture using 7 levels Likert Scale as in in Experiment 1. Participants also completed a function mapping exercise like in Experiment 2.

8.5 Design

We used a similar within-subject design with two independent variables: *Body Location { Helmet, Neck, Thigh, Arm, Wrist, Chest }* and *Block { Training1, Test1, Test2, Test3, Test4 }*. The *Body Location* was randomized within blocks.

We measured accuracy and execution time again, as well as the ability to target and effect of cycling posture for each location in the post-experimental questionnaire. Each participant performed the experiment in around 1 hour, including 20 to 24 minutes of cycling. The design included the following: 8 participants × 6 body locations × [1 training + 4 test blocks] × 5 repetitions = 1200 trials.

8.6 Results

Our participants cycled at speeds ranging from 12.8 km/h to 19.9 km/h ($M = 16.21 km/h, SD = 2.18$). Our results are therefore not applicable to high performance scenarios, but typical cruise speeds achieved in the city.

8.6.1 Time. The average time to tap on a specific location while cycling was 1.65 seconds. We found no significant main effect of *Body Location* ($p = .35$), *Block* ($p = .78$) and no interaction between the factors ($p = .96$). All the six locations we considered had an average time ranging from 1.58 to 1.78 seconds. Table 2 shows individual performance of each location with pairwise comparisons. Average time did not vary between blocks, in a short range between 1.62 seconds (Test3) and 1.68 seconds (Test2).

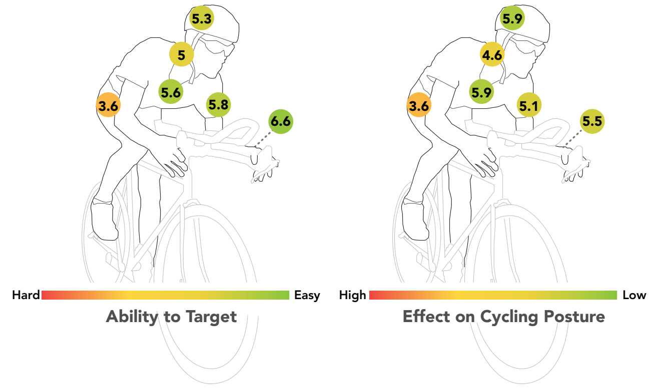

Figure 5: Results for cycling: ability to target (left) and effect on cycling posture (right) using 7 point Likert-Scale (1: Hard to target/High impact on stride, 7: Easy to target/Low impact on stride)

8.6.2 Accuracy. Accuracy was once again very high, with an average of 99.3%. There were no significant main effect of either *Body Location* ($p = .51$), *Block* ($p = .41$) or interaction between the factors ($p = .33$). Accuracy increased over time, from 98.74% in Test1 and Test2 to 100% in Test4.

8.6.3 Ability to Target. Our participants reported that they were overall able to target the different locations easily, except for Thigh. We found a significant main effect of *Body Location* on this score ($F_{5,35} = 5.38, p < .01$). Table 2 summarizes the performance of each location.

8.6.4 Effect on Cycling Posture. The average effect on cycling postures was 5.06/7, suggesting a slightly positive opinion, i.e. a not-so-strong effect on posture. We found a significant main effect of *Body Location* on this score ($F_{5,35} = 4, p < .001$). Thigh, once again, obtained the lowest score ($M = 3.25/7$). The effect on posture of each location is presented in Table 2 and Figure 5.

Table 2: Average scores for time, ability to target and effect of posture by location in Experiment 2. α, β, γ show significant pairwise comparisons.

Location	**Wrist**	**Chest**	**Neck**	**Helmet**	**Arm**	**Thigh**
Average Time (s)	$1.58^{\alpha,\beta,\gamma}$	1.58	1.585^{β}	1.695^{α}	1.69	1.78^{γ}
Ability to Target	6.63^{α}	5.63	5	5	5.75	3.635^{α}
Effect on Posture	5.63	5.88	4.63	5.885^{α}	5.13	3.255^{α}

8.7 Body Location Analysis

The quantitative results of the experiment imply that all the six locations are suitable, as the time to acquire them is quite low (less than 1.78s) and accuracy very high (up to 100% in our last block). Our system is thus usable while cycling.

However, the qualitative results also suggest that Thigh was not that convenient for our participants. This trend was confirmed after discussing with our participants *"It's disruptive. Every time I try to touch my thigh, my bike just goes to the other direction. Then after I've done my gesture, I have to put it back to the track." (P2, M, 20, Cycling Enthusiast).* On the other hand, Wrist was seen as one of the top locations. This can be explained by the posture while cycling, which makes Wrist one of the closest and thus easiest to acquire location.

In terms of functions and their mapping, we found that participants wanted to use the helmet for phone functions such as answering a phone call and similarly to running, the chest for biometric data.

9 DISCUSSION

9.1 Properties of the Proposed Method

In general, our method of tapping locations on the body during training performed well – 1.31 seconds on average for running on a track, and 1.65 seconds on average during cycling. We found eleven suitable locations for running that we shortened to six after experiment 1: Ear, Neck, Chest, Wrist, Palm and Thumb; as well as six for cycling: Helmet, Neck, Chest, Wrist, Thigh, Arm. With the exception of the thigh, all of the selected locations had either neutral or low impact on the form of the activity and the ability to target them, meaning it is *non-disruptive* to the movements of the activity. In addition, this method is *easy to learn*: all participants were able to use this method with less than 2.5 minutes across activities. Our results can be generalized to multiple contexts as we test it in the gym and in the real-world. BodyScape [22] showed that upper body targets are faster for touching (1.4s) than lower limbs (1.6s) while standing. Although the context of BodyScape is fixed (tapping while standing), we can say that these times are in line with completion times we achieved in MoveSpace: 1.31s for running and 1.65s cycling.

Our work complements Hamdan et. al [8] which shows that the wrist was found to be the most comfortable for tapping while running. For the rating of ability to target in running, we found that outer wrist scored the second highest, right after the ear, which was not considered in their study. While the wrist is one of the most accurate locations, this contrasts with our results showing that it is also the slowest during running. We also provide actuation times and additional locations for both running and cycling. To our knowledge, these results are the first of this kind for on-body tapping for Athletic Interaction.

9.2 Explaining Performance Differences of Body Locations

Our participants were very accurate, thanks to proprioception [7]. The high accuracy of our studies shows that our participants were quickly use the system. In general, participants favor locations that require less additional movement to reach. For example, reaching across the center body line was undesirable for participants and resulted in overall lower rankings than locations on the dominant side of the body. Participants also favor locations which lie directly on the path of the swing motion: the ear, the neck, the center chest, and the non-dominant chest, were considered more natural to tap. While it appears that the thigh and hip also lie on the swing path, the motion to tap requires jutting the elbow outward, creating as one participant put it - 'a multi-dimensional movement', making them less desirable. We also see this effect when comparing the chest locations, noting that the dominant side had the lowest scores despite its proximity to the swing motion, requiring an awkward twist of the arm to tap.

Comparing the wrist across the 2 activities leads to the following insights. During running where the wrist is in motion, it is ranked the lowest and had the slowest performance, but in cycling, where the wrist is stable, it is among the fastest and most preferred body locations.

9.3 Novel Athletic Interfaces

Our studies demonstrated that single-handed interaction during running is feasible and performs well. Previous studies have looked at eliciting single-handed microgestures in a stationary context [4], however, we have evaluated a representative subset: finger-to-palm, and thumb-to-finger, and demonstrated their effectiveness in a realistic training context. The technology to enable these interactions in a mobile form factor is becoming rapidly available [2], even on commercial products: the Apple Watch can already be modified for better placement [1].

Multi sport-activities can benefit from a body-based interface, for example by being *customized* to the movements of the sport, and the frequency at which interaction is required. Our interface is also *portable* across different sports such as in a triathlon activity, which is supported by study results showing overlapping preference for locations such as the chest and ear, which could be consistently be used across activities.

Our results contribute to sport technology by suitable locations for on-body interactions using: (1) Novel sports garments, which use muscle activity signals (EMG) to monitor performance [3]; (2) Conductive fabric [20], which has high potential for training use during sports; and (3) Wearable devices, making interaction safer and less intrusive.

10 CONCLUSION AND FUTURE WORK

We presented MoveSpace, motion based interaction for running and cycling using the body as input. In our future work, we would like to create higher fidelity sensing systems to reconstruct the full paths of each targetting motion. This could answer questions regarding the exact impact on the stride during running, and guide us towards even better methods of interaction during athletic training.

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