

GestureSock: Exploring toe gestures as alternative input method

Vincent van Rheden
Human Computer Interaction Division
University of Salzburg
Salzburg, Austria
vincent.vanrheden@plus.ac.at

Florian 'Floyd' Mueller
Exertion Games Lab, Department of Human-Centred
Computing
Monash University
Melbourne, VIC, Australia
floyd@exertiongameslab.org

Sasindu Abewickrema
Exertion Games Lab
Monash University
Melbourne, Australia
sasindu@exertiongameslab.org

Don Samitha Elvitigala
Department of Human Centred Computing, Faculty of
Information Technology
Monash University
Melbourne, Australia
don.elvitigala@monash.edu



Figure 1: GestureSock: (Left) the sock with pressure sensors (Middle) Video still of the "extend hallux toe" gesture to play the next music track, (Right) Applications for the demonstration

Abstract

In everyday life we often find ourselves with both hands occupied, e.g. while holding a child in one hand and a dog leash in the other or riding a bicycle. These situations limit our ability to interact with our devices, leading to HCI investigating "hands-free" interactions such as voice commands. However, they are limited in noise environments and certain social situations. A recent lab study using a motion capture system has shown that toe movements might be a useful way of interacting. In this work we advance this research by exploring toe interactions through integrating pressure sensors in a sock. We address practical issues of implementation and applicability of an interactive sock capable of capturing toe interactions. We show that combining pressure with movement sensing can increase the interaction possibilities, allowing for a broad interaction vocabulary.

CCS Concepts

• **Human-centered computing** → Ubiquitous and mobile computing; Ubiquitous and mobile devices; Gestural input.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

CHI EA '25, Yokohama, Japan

© 2025 Copyright held by the owner/author(s).

ACM ISBN 979-8-4007-1395-8/25/04

<https://doi.org/10.1145/3706599.3721114>

Keywords

Foot Interaction, Augmented Foot, Gestures, Touchless Interfaces

ACM Reference Format:

Vincent van Rheden, Sasindu Abewickrema, Florian 'Floyd' Mueller, and Don Samitha Elvitigala. 2025. GestureSock: Exploring toe gestures as alternative input method. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25)*, April 26–May 01, 2025, Yokohama, Japan. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3706599.3721114>

1 Introduction

Human-Computer Interaction (HCI) research shows ample examples of hand- and touch-based interactions. Hand and touch-based interactions are omnipresent in our everyday life through smartphones, keyboards. Often in everyday situations, our hands are occupied, and we are not able to interact with our devices as intended. To overcome these challenges, researchers have explored for hands-free interaction. A prominent line of research focuses on voice commands [11, 13] but has shown to be prone to noise and its use might be reduced due to privacy issues or in social situations in which speaking is simply not appropriate, such as in the library or meditation hall. Besides voice commands, researchers have explored body-centric approaches in which body movements are used to interact, such as through eye gaze [14] or head-movements [15].

As an alternative, researchers also have utilized the lower extremities, exploring foot gestures and foot tapping [18, 19]. Recent work shows that toes can serve as an effective input method for quick and accurate interaction [12]. In this prior work researchers analyzed toe movements in the lab, deriving a potential interaction space. We see a unique advantage of using foot and toe-based gestures as an

alternative for hands-free interactions compared to other methods in the literature due to the possibility of facilitating them through an interface using everyday footwear such as socks. However, only a few works explored the foot gestures in wearable form factor, and many of them facilitate foot gestures as a whole without looking at the toe gestures. Hence, our work further advances the Muller et al.'s [12] work by:

- providing an implementation of toe interactions through a pressure sensitive sock.
- showing that toe movement in combination pressure allows for a broad(er) interaction vocabulary.

While CHI has widely explored and demonstrated the possibility of hand gestures using external and wearable tracking devices [5, 16], not much foot gesture work has been demonstrated. Hence, in this interactive demo, GestureShock aims to showcase how sock-based gesture interfaces can be utilized in daily life, providing an alternative input method to interact with our computing devices such as mobile phones, screens, and HMDs.

2 Related Work

In this section, we briefly cover foot-based interaction through the lenses of implicit and explicit interactions. Then, we delve into explicit interactions and discuss the recent explorations on the capabilities of human toe movements to perform explicit interactions to set the background for our interactive demonstration.

In 2015, Velloso et al. performed a survey capturing interactions with the lower limbs [20]. They identified three main categories of foot interfaces: foot-operated, foot-tracking, and foot-worn devices. Later, in 2021, Elvitigala et al. expanded on this work, focusing on mobile augmented foot interactions (AFI) [6]. They introduce AFIs as self-contained foot-worn mobile interfaces with input or output capabilities that extend human abilities. AFIs mainly enhance human capabilities in three ways: (1) sensing physical parameters of the body, such as movement and pressure (input), (2) providing feedback to the wearer (output), and (3) using a combination of input and output.

AFIs can be mainly categorised into two, based on the type of interactions: implicit interactions and explicit interactions. Many foot interfaces focus on implicit interactions such as sensing foot pressure distributions or gait for anomalies while walking or running. The actions covered by implicit interactions do not directly interact with a computerized system [17]. Using an IMU sensor to track walking to detect abnormal gait [4] is an example for implicit foot interactions [1]. Prior work has clustered explicit foot interactions into three categories: semaphoric, deictic, manipulative [9, 20]. Semaphoric actions are mainly referred to as specific foot gestures such as fore-foot tapping or heel tapping [18, 19], while in manipulative interactions, foot movements or pressure is used to control an external device [3]. Although foot interfaces have been used for deictic interactions using external tracking devices, AFI can only be categorized as semaphoric or manipulative. Reportedly, the world's first wearable computer is considered a manipulative foot interface that utilized a button hidden inside a shoe to communicate the results of a roulette machine using tap gestures to predict outcomes [19].

Many works focus on explicit interactions whilst being sedentary, such as an input device for people with disabilities who can use foot taps and gestures to control external devices such as a keyboard or prosthetic limbs [2, 18]. Several work also explored the viability of foot interactions as an input method to support hands free interactions while standing up [7, 21]. These works were primarily focused on the movement of the foot as a whole. Example gestures are foot taps or different pressure distributions that can occur based on how we exert the pressure on the foot, such as increased forefoot pressure, heel pressure, and increased pressure on the left or right side of the foot.

As a step forward in utilizing foot gestures as an input modality, Müller et al. assessed the usage of toe movements [12]. The work mainly focused on exploring the viability of toe gestures by evaluating the accuracy, efficiency, and user experience of such interfaces in a sedentary controlled study. Our focus is to develop a wearable interface that could facilitate such gestures, advancing foot-based gestures as an alternative input method. In particular, our work focuses on contributing to explicit foot interactions by developing an interface tailored to utilize the capabilities of our toes performing gestures.

3 Designing GestureSock

We conducted an elicitation study with 15 participants (11 Male, 4 Female) in the age ranged from 22 - 38 yr (Mean 28, SD 4). In this section first we describe how we collected toe gestures. Then we describe how that informed the prototype before we explain the demo setup.

3.1 Collecting Toe Gestures

To explore toe gestures we conducted a study with the goal to understand toe movements and collect toe gestures. We invited 15 participants and asked them to explore the movements they were able to make with their toes. Starting off with a baseline of gestures consisting of the ones from [12] (all flex, all extend, hallux flex, hallux extend, four lateral toes extend and flex) and three new ones (press hallux, press lateral toes, split toes, press small toe) we accumulated new gestures. Each movement they were able to recreate three times was counted as a separate toe gesture. For each new participant we asked whether they could perform the updated list of gestures and come up with new ones. All of the toe gestures were captured with video to later review them and count how many people were able to make what gesture. We found that most participants were more capable with one foot, and as such we recorded the gestures with their preferred foot. We found seventeen distinct toe gestures demonstrated by the participants using various toes, toe groups, flexing, extending, pressing, lifting, and folding (see figure 2 & 3). Note that, due to the cumulative approach, some participants that joined at the beginning might have been able to perform a certain gesture which was not included in the gesture list yet, and didn't come up with them either, potentially skewing the results. As the average number of gestures performed by the participants was 11 (SD = 3.6) we do not expect many of these cases to exist we summarized the final results in figure 2. Participants noted different levels of difficulty and comfort for the gestures. For example, for some lifting the hallux was difficult but they could

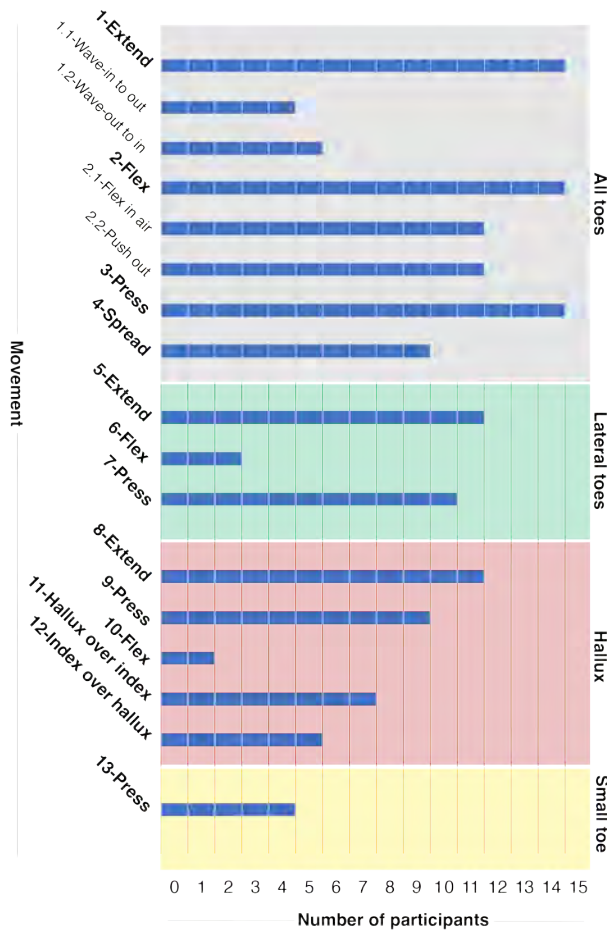


Figure 2: Left: bar graph of the amount of participants capable of performing a specific gesture.

easily move their small toe, while for others this was vice versa. The three central toes were found to move as one unit for half of participants. The small toe was individually controllable by a quarter of the participants. Eight of the participants were able to fold their big toe over their index toe, and six vice versa. Comparing to the results[12], we found that participants found the extension and flexion of all toes similarly easy. Surprisingly only three of fifteen participants were able to flex the lateral toe group and only two could flex the big toe, contrasting the results from muller et al.[12], in which the flexion of the hallux and lateral toe group was classified as the most usable gestures. Furthermore, we found that using the surface to apply pressure as a form of a gesture was achievable by many (all toes (15), lateral toe group (11), and hallux (10)).

3.2 Prototype

We engaged in an iterative prototyping process to explore what sensors could be applicable to capture toe gestures in everyday setting (see figure 4). Learning from finger-movement-capturing gloves



Figure 3: Gestures performed by the participants

e.g. [10] we explored flex sensors aligned with the toes to capture flexing and extending the toes. We found that the movement of the toes were too small to be captured sufficiently and accurately by (standard) flex sensors that work well with the fingers. In a next exploration, we used thin stretch sensors developed from a conductive rubber sheet by cutting thin bands, which increased the flexibility and sensitivity of the sensors. Though the sensitivity of these sensors was superior to the flex sensors, the pull needed to create a sufficient measurement of the toe movement would dislocate the sock and rendered this implementation unreliable. As a final exploration, we created pressure sensors from Velostat, a conductive sheet that changes resistance when pressed. By experimenting with various sizes and locations we found that this sensor is capable of capturing toe flexes (through the squeeze that the joint



Figure 4: Explorations with flex sensors (left), stretch sensors on the toe (center) and pressure sensors on the insole (right)

makes), toe lifts (based on decrease in pressure from the toe tips), and toe splits (based on decrease in pressure between toes). We found Velostat highly suitable for its flexibility and the possibility of customising it as desired.

Based on the study presented in section 3.1 we implemented the sensors in a configuration that would allow to capture most of the gestures. Each of the identified gesture able toe sections (the hallux, the three central toes, and the small toe) were equipped with a sensor on the tip to sense a press and release, and a sensor on the joint to sense a squeeze when flexing. Additionally we placed a sensor in between the small toe and the fourth toe to capture the small splitting away from the three central toes. Each sensor was individually shaped and crafted to fit the surface and placement (see figure 5). The shape was determined by cutting a piece of tape to size that functioned as a template for the shape of the sensor. The sensing principle was based on an online tutorial by Adafruit¹, in which conductive wire was taped to each side of the piece of Velostat. Then, all sensors were sewn on a split-toe sock on earlier described positions. Conductive thread was used to sew soft circuitry to the top edge of the sock to connect them to the hard circuitry held in the top of the sock (see figure 1).

¹<https://learn.adafruit.com/firewalker-led-sneakers/make-velostat-step-sensors>



Figure 5: Crafting the prototype, determining the size of the sensors, creating the pressure sensors, sewing them on the sock

For this prototype we created a custom circuit board to create voltage dividers and used an ESP32 microcontroller to capture the sensor data. When capturing sensor data, a moving average filter was implemented in the Arduino code to get stable sensor data.

For the gesture recognition, a dataset consisting of 470 samples corresponding to four distinct gestures (Hallux Press, Hallux Up, Extend all toes, Flex all toes) was collected using a python script. The data set was pre-processed and cleaned to ensure consistency and quality. Two machine learning models, Random Forest Classifier² and XGBoost³, were explored to fit the dataset. The Random Forest model achieved an accuracy of 95.6%, while XGBoost outperformed it with an accuracy of 97.5%. Consequently, the XGBoost model was selected for deployment.

Initially, the XGBoost model was implemented in a Python script to predict gestures using a laptop. To enhance portability, the model was re-configured to deploy on an ESP32 microcontroller. The XGBoost model was converted into a library and integrated into the Arduino environment, enabling the ESP32 to predict gestures accurately in real time. The ESP32 BLE Keyboard library⁴ was used to establish a Bluetooth connection with compatible devices such as Android Smartphones, Apple Smartphones and Apple Vision Pro. This allowed gesture-based media control, demonstrating the system's ability to translate predicted foot gestures into media control commands on paired Bluetooth-enabled devices. In the Arduino code, simple logic was implemented to prevent double

²<https://scikit-learn.org/1.5/modules/generated/sklearn.ensemble.RandomForestClassifier.html>

³<https://xgboost.readthedocs.io/en/stable/>

⁴<https://github.com/T-vK/ESP32-BLE-Keyboard>

gesture recognition. Also, to prevent glitches and for a smooth transition dynamic delay periods were implemented.

3.3 Demo Setup

To demonstrate GestureSock, we connected the functionality of a simple music application with the aim of using it in the context of cycling. Whilst cycling, the hands are engaged with steering and changing music on the mobile phone is difficult, dangerous, and in some countries even illegal, through the conventional touch screen [8]. We selected pause/play, skip song, volume up, volume down, to be operated by the toe gestures. Pause/play: press hallux as if pressing a button, skip song: lift hallux as if flicking up to the next song, volume up: extend all toes, pointing them up, volume down: flex all toes pointing them down. Visitors will be able to wear GestureSock and explore the interactions in a VR cycling set-up as shown in figure 1, right.

4 Conclusion and Future Work

We presented GestureSock, a wearable allowing for explicit toe interactions. We based our work on a elicitation study, informing the design and implementation of GestureSock. Through six integrated pressure sensors we showed it is possible to capture five different gestures. For demonstration purposes, we, enable cyclists to interact with music without using their hands. In future work, we aim to quantify our elicitation study and expand the use case to different physical activities, such as walking and running. Additionally, we aim to explore dynamic explicit toe gestures as input for video games and VR applications using GestureSock.

Acknowledgments

Vincent van Rheden gratefully acknowledges the financial support from the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology, the Federal Ministry for Digital and Economic Affairs, and the federal state of Salzburg under the research programme COMET - Competence Centers for Excellent Technologies - in the project DiMo-NEXT Digital Motion in Sports, Fitness and Well-being (Project number: FO999904898). Florian ‘Floyd’ Mueller thanks the Australian Research Council, especially DP190102068, DP200102612 and LP210200656.

References

- [1] Kamiar Aminian, Farzin Dadashi, Benoit Mariani, Constanze Lenoble-Hoskovec, Brigitte Santos-Eggimann, and Christophe J. Büla. 2014. Gait analysis using shoe-worn inertial sensors: how is foot clearance related to walking speed?. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Seattle, Washington) (*UbiComp '14*). Association for Computing Machinery, New York, NY, USA, 481–485. doi:10.1145/2632048.2632071
- [2] Maria Chiara Carrozza, Alessandro Persichetti, Cecilia Laschi, Fabrizio Vecchi, Roberto Lazzarini, Vincenzo Tamburrelli, Pierpaolo Vacalebri, and Paolo Dario. 2005. A novel wearable interface for robotic hand prostheses. In *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005*. IEEE, 109–112.
- [3] Maria Chiara Carrozza, Alessandro Persichetti, Cecilia Laschi, Fabrizio Vecchi, Roberto Lazzarini, Pierpaolo Vacalebri, and Paolo Dario. 2007. A wearable biomechatronic interface for controlling robots with voluntary foot movements. *IEEE/ASME Transactions on Mechatronics* 12, 1 (2007), 1–11.
- [4] Meng Chen, Bufu Huang, and Yangsheng Xu. 2008. Intelligent shoes for abnormal gait detection. In *2008 IEEE international conference on robotics and automation*. IEEE, 2019–2024.
- [5] James Davis and Mubarak Shah. 1994. Recognizing hand gestures. In *Computer Vision—ECCV'94: Third European Conference on Computer Vision Stockholm, Sweden, May 2–6, 1994 Proceedings, Volume I 3*. Springer, 331–340.
- [6] Don Samitha Elvitigala, Jochen Huber, and Suranga Nanayakkara. 2021. Augmented Foot: A Comprehensive Survey of Augmented Foot Interfaces. In *Proceedings of the Augmented Humans International Conference 2021* (Rovaniemi, Finland) (*AHs '21*). Association for Computing Machinery, New York, NY, USA, 228–239. doi:10.1145/3458709.3458958
- [7] Koumei Fukahori, Daisuke Sakamoto, and Takeo Igarashi. 2015. Exploring subtle foot plantar-based gestures with sock-placed pressure sensors. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 3019–3028.
- [8] Graeme Horsman and Lynne R Conniss. 2015. Investigating evidence of mobile phone usage by drivers in road traffic accidents. *Digital Investigation* 12 (2015), S30–S37.
- [9] Maria Karam et al. 2005. A taxonomy of gestures in human computer interactions. (2005).
- [10] Piyush Kumar, Jyoti Verma, and Shitala Prasad. 2012. Hand data glove: a wearable real-time device for human-computer interaction. *International Journal of Advanced Science and Technology* 43 (2012).
- [11] Nicholas Mulhern, Neil McCaffrey, Nicholas Beretta, Eugene Chabot, and Ying Sun. 2013. Designing android applications using voice controlled commands: For hands free interaction with common household devices. In *2013 39th Annual Northeast Bioengineering Conference*. IEEE, 265–266.
- [12] Florian Müller, Daniel Schmitt, Andrii Matvienko, Dominik Schön, Sebastian Günther, Thomas Kosch, and Martin Schmitz. 2023. Tictactoes: Assessing toe movements as an input modality. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [13] Christine Murad, Cosmin Munteanu, Leigh Clark, and Benjamin R Cowan. 2018. Design guidelines for hands-free speech interaction. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*. 269–276.
- [14] Susanna Nilsson, Torbjörn Gustafsson, and Per Carleberg. 2009. Hands Free Interaction with Virtual Information in a Real Environment: Eye Gaze as an Interaction Tool in an Augmented Reality System. *PsychNology Journal* 7, 2 (2009).
- [15] Vladimir I Pavlovic, Rajeev Sharma, and Thomas S. Huang. 1997. Visual interpretation of hand gestures for human-computer interaction: A review. *IEEE Transactions on pattern analysis and machine intelligence* 19, 7 (1997), 677–695.
- [16] Prashan Premaratne, Quang Nguyen, and Malin Premaratne. 2010. Human computer interaction using hand gestures. In *International conference on intelligent computing*. Springer, 381–386.
- [17] Albrecht Schmidt. 2000. Implicit human computer interaction through context. *Personal technologies* 4 (2000), 191–199.
- [18] Yanbo Tao, Tin Lun Lam, Huihuan Qian, and Yangsheng Xu. 2012. A real-time intelligent shoe-keyboard for computer input. In *2012 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. IEEE, 1488–1493.
- [19] Edward O Thorp. 1998. The invention of the first wearable computer. In *Digest of Papers. Second international symposium on wearable computers (Cat. No. 98EX215)*. IEEE, 4–8.
- [20] Eduardo Velloso, Dominik Schmidt, Jason Alexander, Hans Gellersen, and Andreas Bulling. 2015. The Feet in Human-Computer Interaction: A Survey of Foot-Based Interaction. *ACM Comput. Surv.* 48, 2, Article 21 (Sept. 2015), 35 pages. doi:10.1145/2816455
- [21] Weizhong Ye, Yangsheng Xu, and Ka Keung Lee. 2005. Shoe-Mouse: An integrated intelligent shoe. In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 1163–1167.