

# Demonstration Use Cases in Designing Accessible Gesture Input with Gesture-A11Y

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## ABSTRACT

Gesture-A11Y is a web-based platform that allows users to find, explore, visualize, and export touchscreen gesture datasets collected on smartphones, tablets, smartwatches, and other touch devices from people with different impairments. The platform provides search and filtering tools, gesture visualizations, and dataset export to help researchers and developers reuse gesture data for interaction design, gesture recognition, and user studies. In this demonstration paper, we present two usage scenarios: one showing how a researcher can prepare a gesture study, and another showing how a developer can build a more accessible application by integrating gesture input customized for specific user groups.

## AUTHOR KEYWORDS

Gestures; accessibility; motor impairments; interfaces.

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## Introduction

Touchscreen gestures are a common way of interacting with smartphones, tablets, smartwatches, and many other touch-enabled devices [3]. As gesture interfaces continue to grow, researchers and developers increasingly rely on gesture datasets to design, evaluate, and improve interaction techniques [2], develop gesture recognition algorithms [1, 5], and conduct user studies [6, 7], including with users experiencing impairments and disabilities. However, finding a high-quality gesture dataset that matches the abilities of target users and the needs of a specific project can be difficult and time-consuming. To address this challenge, we employ Gesture-A11Y [4], a platform that supports the exploration, creation, and selection of gesture datasets. In this demo paper, we present two example scenarios that illustrate how Gesture-A11Y can support research and development tasks, which include gesture data exploration, creation of custom datasets, and selecting suitable data for practical applications.

## Application presentation

Gesture-A11Y [4] provides an intuitive interface for exploring touchscreen gesture datasets collected from a variety of devices, including smartphones, tablets, and smartwatches. Users can search and filter gestures using multiple criteria, such as device type, gesture type, users' impairment symptoms, and can indicate additional search terms as comma-separated keywords to filter the results more precisely. For each matching gesture, the platform shows a short description that includes information about the gesture, the number of strokes, the user's health condition, the impairment symptoms, and when available, various scores describing this gesture

(e.g., WHODAS score). This information helps users to understand the structure and differences of gesture data without requiring external analysis tools. Users can select individual gestures to create a custom dataset or export complete datasets. Each gesture is accompanied by fields describing the gesture and the user. Stroke gestures are stored as sequences of 2D  $(x, y)$  points that can be used to reconstruct the gesture on a touchscreen, while mid-air gestures are stored as sequences of 3D  $(x, y, z)$  points collected from the device's IMU sensors. More details are available in Terenti et al. [4].

## Demonstration

The platform is primarily intended for two types of users: researchers who study gesture interaction, and developers who want to incorporate gesture input into their applications. In this section, we present two demonstration scenarios that illustrate how each type of user can benefit from the platform.

### Demo #1

A researcher is investigating accessible interaction techniques for wearable devices and is preparing a study on gesture input for people with disabilities. They want to evaluate how suitable touchscreen gestures are when performed on smartwatches used for health monitoring, when users may need to interact with applications for medication reminders, activity tracking, or emergency calls. The researcher needs gesture datasets collected on smartwatches and wishes to identify gestures that are reliable for users with limited control.

Gesture-A11Y [4], the researcher searches for datasets containing smartwatch gestures and repeatedly refines the results by applying filters such as device type and participant characteristics (Figure 1). The gesture visualizations allow the researcher to explore gesture strokes and compare multiple samples, which helps them to assess the consistency of the gestures. The researcher repeats the filtering and gesture analysis steps until the search results meet their needs. Individual gestures from the search results can then be added to a final dataset for export.

After identifying the most relevant datasets, the researcher exports the selected gesture collections for further analysis and integration into the evaluation tool they intended to use. As a result, the platform reduces the effort required to prepare empirical studies and supports reproducible research in accessible touchscreen interaction.

### Demo #2

A software developer is building a smartphone application that uses gesture input for people with motor impairments. During development, the developer finds that the recognition model works well when trained with data from the general

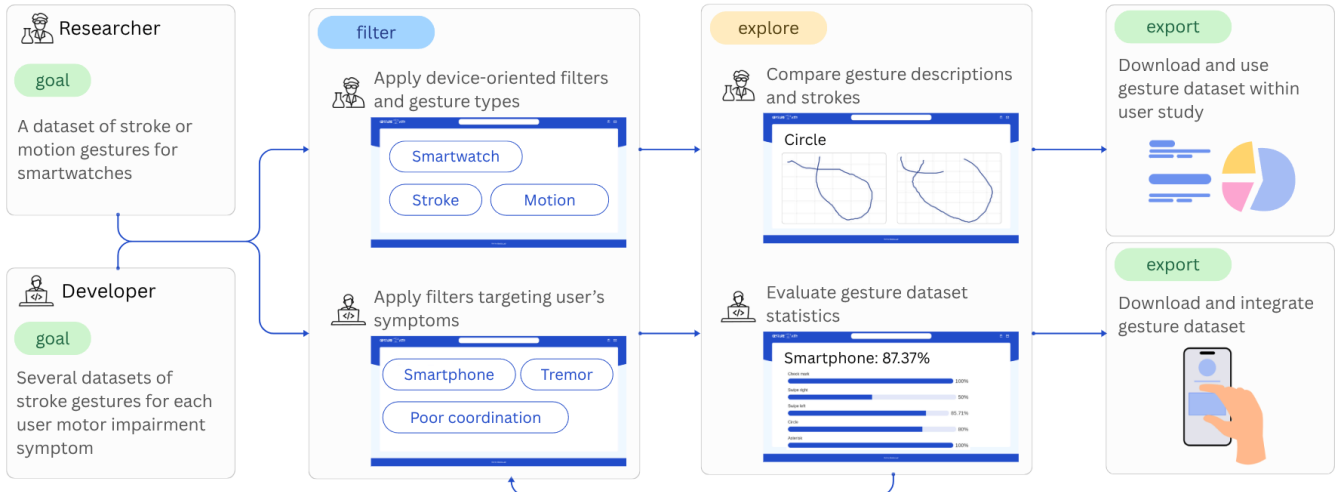


Figure 1: Workflows of a researcher and a developer for filtering, exploring, and exporting gesture datasets.

population, but performs much worse for users with impairments. Interaction differences introduced by symptoms such as hand tremor or reduced motor coordination result in gesture that significantly differ from original training data, which leads to misclassifications.

To improve the performance of a gesture recognition system, the developer uses Gesture-A11Y [4] to search for gesture datasets collected from people with different motor conditions (Figure 1). The search results are refined using filters such as device type, participant characteristics, and gesture category to find datasets that better match the target users. The developer explores the gesture visualizations to identify differences in gesture execution of different user groups. The dataset descriptions provide additional information, including the performance of \$-family recognizers on the dataset, which help developers decide whether a dataset is suitable or needs additional filtering. Eventually, the developer exports the data and uses them to train a gesture recognition model that matches the abilities of the target users.

To personalize the application, the developer adds a step during first-time use in which users select the motor conditions that best describe their symptoms. Based on this choice, the application loads a gesture recognition model trained with the matching dataset from Gesture-A11Y [4]. This allows the recognition system to better consider the movement patterns of each user group, which improves recognition accuracy and overall user experience. As a result, developers can build more inclusive applications without collecting large amounts of gesture data themselves.

## Conclusion

This paper presented two use cases of Gesture-A11Y [4], a previously developed web-based platform for exploring gesture datasets, including gesture descriptions and stroke data

collected from users with impairments. Future research could extend the platform with additional gesture data, recognizers, and LLM-based assistance for more efficient data extraction and integration into practical applications.

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