**Gesture Recognition for Enabling Control of Electrical Devices**

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# Dedication

I would like to dedicate this research to my family [todo]

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# Abstract of Praxis

**Gesture Recognition for Enabling Control of Electrical Devices**

Individuals with mobility impairments, particularly wheelchair users, often face challenges in accessing and controlling electrical devices. A gesture-based control system can greatly enhance accessibility for this group. This research praxis aims to develop and evaluate a user-friendly, cost-effective machine-learning approach that enables users to control devices through pointing gestures. Specifically, it focuses on extending DeePoint, a 3D pointing direction prediction model (Nakamura et al., 2023), into a unified machine learning system capable of identifying the electrical devices a user is pointing at. The goal is to lay the groundwork for future applications that empower individuals with mobility impairments to intuitively and efficiently control household devices using simple, natural gestures.

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# List of Symbols

State of the system

Output of the system

Noise

# List of Acronyms

ADA Americans with Disabilities Act

YOLO You only look once is a state-of-the-art, real-time object detection system

CNN Convolutional Neural Network

DL Deep Learning

ML Machine Learning

U.S. United States

# Chapter 1—Introduction

## 1.1 Background

As the number of older adult households continues to grow in the decades ahead, more homeowners are expected to undertake expensive accessibility renovations (JCHS, Harvard, 2023). One of these projects' most critical and costly aspects is improving access to electrical devices, particularly for individuals with mobility impairments who rely on wheelchairs for movement. Accessible housing design features can significantly enhance the independence of people with mobility disabilities within their homes (JCHS, Harvard, 2023). Despite advances in assistive devices, laws, and technology aimed at improving safety and aiding daily activities, people with mobility disabilities continue to face barriers in accessing electrical devices, reducing their capacity to live independently.

Over the years, various solutions have been developed to assist individuals with mobility impairments control household devices, including voice-activated systems and augmented reality or mixed reality smart glasses (Zhou, K. *et al*., 2023). Despite their potential, these technologies are not yet ready to be widespread within this group due to several challenges. Voice-activated systems, for instance, often underperform in noisy environments, making them unreliable in busy or public settings. Additionally, they are unsuitable for environments where quiet is essential, such as a baby’s room or a shared living space. While smart glasses provide a hands-free solution, they come with drawbacks, such as high costs and discomfort when worn for extended periods, which limits their practicality for long-term, daily use.

Moreover, many existing gesture-based control systems rely on specialized hardware, like RGB-D sensors, which can be effective but are often expensive, bulky, and cumbersome to use and maintain. These limitations prevent widespread adoption, particularly for individuals seeking affordable and convenient solutions to improve their independence. As a result, there is a growing need for more user-friendly, intuitive, and cost-effective approaches to overcome these barriers and provide greater accessibility in daily device control (Chang, V., *et al*., 2022).

Our solution uses finger-pointing gestures, a natural and efficient way to indicate objects or devices of interest. Implementing an intuitive system that allows device control through pointing gestures could significantly benefit individuals with mobility impairments. For example, a person in a wheelchair could navigate a room and point at devices like lights or appliances to control them, with the scene being captured by cameras mounted in the corners, which may already be available or simple to install.

In this work, illustrated in Fig. 1, We propose a multi-stage machine learning system that extends the 3D pointing direction prediction model, DeePoint (Nakamura et al., 2023). This system incorporates a device classification transformer, which utilizes the predicted pointing direction and images from DeePoint's outputs to form a unified device classification system capable of identifying which devices the user is pointing at. This classification system can process video input that monitors the wheelchair user, detecting their intent to control devices by pointing at the device and generating a command for the device to act.

A diagram of a transformer

Description automatically generated

##### Figure 1. The architecture of the device classification system.

With the proposed classification system, our contribution establishes a foundation for future touchless device control applications extending beyond household devices to include elements like elevator buttons. This system aims to empower individuals with mobility impairments to intuitively and efficiently control devices through natural pointing gestures

## 1.2 Research Motivation

The motivation behind this research arises from the persistent challenges faced by individuals with mobility impairments, particularly wheelchair users, in controlling household devices. While offering a degree of autonomy, existing solutions like voice-activated systems and smart glasses have notable limitations, such as reduced effectiveness in noisy environments, physical discomfort, and high costs. Additionally, hardware-dependent systems, such as those utilizing RGB-D sensors, are often expensive and cumbersome, further restricting accessibility.

More natural, intuitive, and affordable solutions that enable individuals with mobility impairments to interact seamlessly with devices are needed. Gesture recognition, especially through pointing direction, offers a promising alternative. However, research on the visual interpretation of 3D pointing gestures is still limited (Nakamura et al., 2023). To bridge this gap, this study seeks to develop a machine-learning model that leverages standard RGB cameras for 3D pointing recognition, to provide a practical and cost-effective solution for device control.

## 1.4 Problem Statement

## *Individuals using wheelchairs often face challenges accessing electrical devices, so approximately 35% of U.S. housing units may need to be modified to meet the accessibility requirements of the devices (U.S. Department of Housing and Urban Development, n.d., 2015).*

## Even in places that comply with the Americans with Disabilities Act (ADA), individuals using wheelchairs are often required to stretch to reach electrical switches.

## Furthermore, Assistive devices, such as canes, robotic arms, intelligent eyewear, mobile phones, or AI-enabled wearables, are expensive.

## 1.4 Thesis Statement

*A two-stage classification system is needed to identify the electrical devices a wheelchair user points at, enabling touchless device control and enhancing accessibility.*

## The primary research product is a device classification system developed in Python, designed to enhance device accessibility for wheelchair users. This technology enables integrators and developers to improve accessibility. The research presents a new contribution by developing a classification system that identifies electrical devices pointed at by a wheelchair user, leveraging DeePoint and object detection as its core machine learning technologies. The methodology incorporates machine learning, transformers, deep learning, computer vision, and object detection. Input data will consist of videos of a seated individual pointing at electrical devices, while the system’s output will classify the device and provide a probability score.

## 1.5 Research Objectives

Lorem

## 1.6 Research Questions and Hypotheses

Lorem

**RQ1:** Does a …?

**RQ2:** Does a …?

**RQ3:** Does a …?

**H1:** There is a significant correlation between …. **(Do not include the Null H)**

**H2:** If we do X, Y happens.

**H3:** By using …

## 1.7 Scope of Research

## 1.8 Research Limitations

## 1.9 Organization of Praxis

# Chapter 2—Literature Review

## 2.1 Introduction

## 2.2 Another Section

## 2.3 Another Section

**2.4 Summary and Conclusion**

# Chapter 3—Methodology

## 3.1 Introduction

## 3.2 Another Section

# Chapter 4—Results

## 4.1 Introduction

## 4.2 Another Section

# Chapter 5—Discussion and Conclusions

## 5.1 Discussion

## 5.2 Conclusions

## 5.3 Contributions to Body of Knowledge

1. [todo]

## 5.4 Recommendations for Future Research

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# Appendix A

#### Table A-1. Parametric Correlations of X and Y

|  |  |  |  |
| --- | --- | --- | --- |
|  | | | |
| Pearson Correlation | 1 | .627\*\* |
| Sig. (2-tailed) |  | .000 |
| Sum of Squares and Cross-products | 960.119 | 607.382 |
| Covariance | .559 | .354 |
| N | 1719 | 1719 |
| Pearson Correlation | .627\*\* | 1 |



##### Figure A-1. Histogram of XYZ.