DOLL·E
Gesture-Controlled Automation For Remote Filmmaking

IRI Research Project 2021-2022

Presented by Olivia Loh

Introduction

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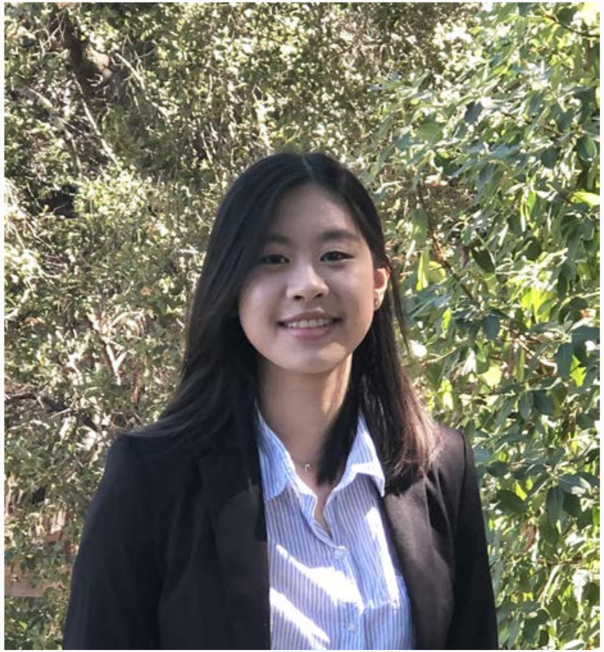
Year: Senior

Major: Computer Engineering

Minor: Film, Television, Digital Media (FTVDM)

Project: Gesture-Controlled Automation for Remote Filmmaking

Mentor: Professor Jeff Burke



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Conception

Motivation

- Effects of COVID on film industry:
  - Social, collaborative, and practical field
  - Film production slowdown due to social distancing
- Remote-filmmaking and virtual production mitigates this slowdown

- Enhance remote-filmmaking by integrating gesture-control to create a more intimate filming experience and convenient user interface

Background

- Current remote filmmaking software facilitates high-quality end-to-end live streaming service
- Gesture control implemented in automobiles and smartphone
- Ongoing research on gesture recognition using deep learning
- I propose to investigate the applications of gesture control as a new form of teleoperation for physical virtual work

Field Study and Use Cases

- When is gestural control useful?
  - The “subtlety and dynamic range of fingers” as opposed to buttons or voice control
- When is remote control useful?
  - During the pandemic. When crew members need to quarantine, they can still be “present” on set
  - Shooting at overseas locations. Flying less crew to locations cut travel costs.
  - Operating large equipment: Lighting equipment, Jibs, Dolly, Cranes, Mechanical Effects
  - Filming in difficult situations, such as aerial shots, underwater shots, cold or hot climate
- Use Cases for Different Film Set Roles:
  - Cinematographers
    - Smoothly control fluid head tripod to produce subtle moves in shot.
  - Actors
    - Can more naturally drive their own action instead of automated mechanical effects,
  - Directors
    - Communicate with their “splinter” (second) crew

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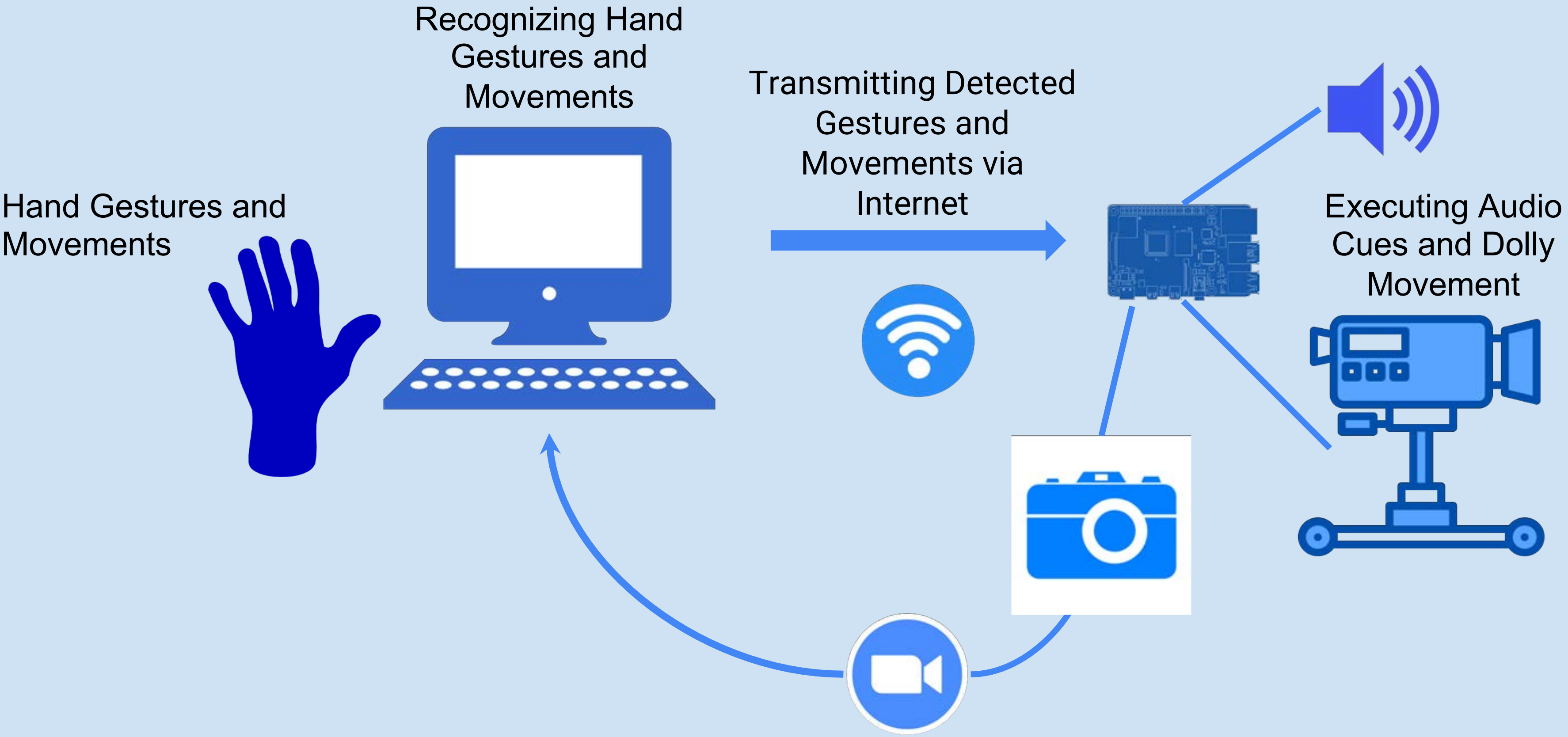
Hand Gestures and Movements
Recognizing Hand Gestures and Movements
Transmitting Detected Gestures and Movements via Internet
Executing Audio Cues and Dolly Movement

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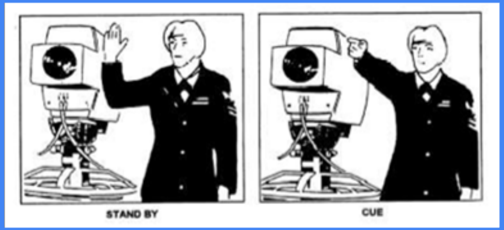
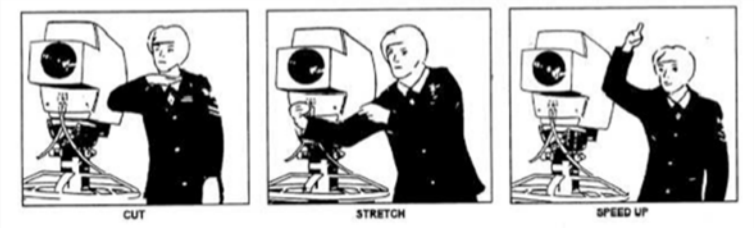
Progress

Hand Gestures and Movements

Choosing Gestures

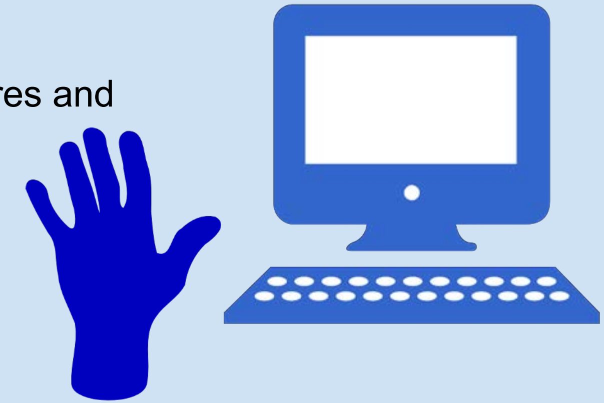
- Objectives:
  - Intuitive and Natural
- Many filmmakers with different roles on set (e.g. cameraman, lighting, etc.)
  - For the purposes of my project, I decided to focus on cinematographer
- Chose 4 hand signals:
  - Cue → Camera Rolling
  - Palm Up → Move dolly: Forwards, Backwards, Left, Right
  - Fist → Stop dolly
  - Cut → Stop





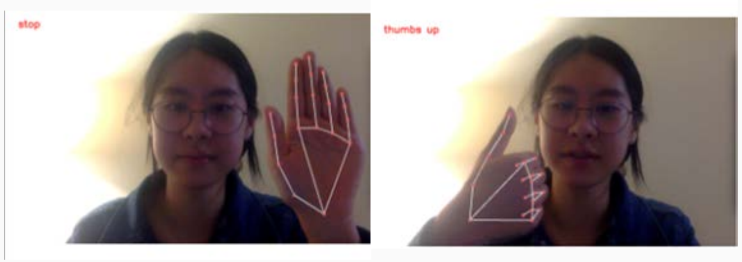
Recognizing Hand Gestures and Movements

Hand Gestures and Movements



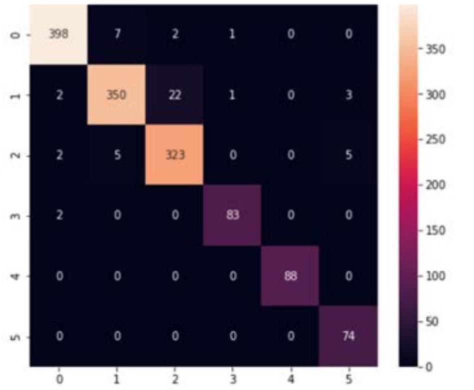
Hand Gesture Recognition: Skeletal Approach

- Computer Vision:
  - Pros:
    - Completely contactless HCI
    - A simple webcam would suffice
  - Cons:
    - Change in lighting conditions
    - Occlusion
    - Background colors (depend on vision technique)
- Skeletal method:
  - Perform hand segmentation by calculating 3D connections and Euclidean distance over hand skeleton pixels
  - Good for dynamic hand gesture recognition



Hand Gesture Recognition: Skeletal Approach

- MediaPipe API
  - Uses regression (direct coordinate prediction) to robustly locate 21 3-D points of hand. Dataset of ~30K labelled images serves as ground truth
- Tensorflow Library
  - Multi-layer perceptron network. Takes in vector input and uses two ReLU hidden layers and one softmax final layer to output class probability score
- MediaPipe and Tensorflow Open-Source Example: https://github.com/kinivi/hand-gesture-recognition-mediapipe/
  - Came with pre-trained model and dataset of poses
  - Added additional pose data and re-trained model:
    - Training data: 4 different poses with 1000 sets of 21 hand points each

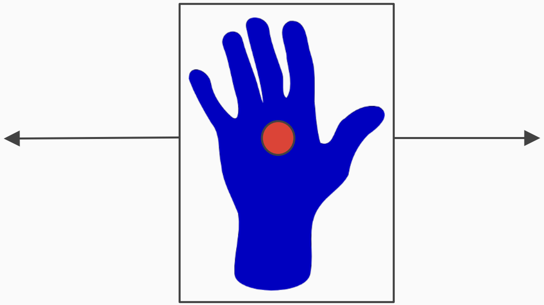


Classification Report

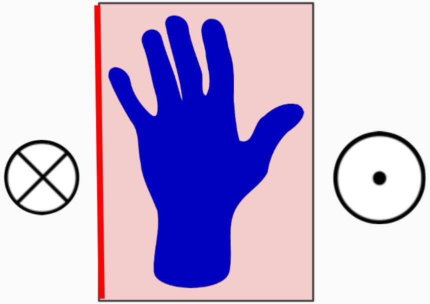
	precision	recall	f1-score	support
0	0.99	0.98	0.98	408
1	0.97	0.93	0.95	378
2	0.93	0.96	0.95	335
3	0.98	0.98	0.98	85
4	1.00	1.00	1.00	88
5	0.90	1.00	0.95	74
accuracy			0.96	1368
macro avg	0.96	0.97	0.97	1368
weighted avg	0.96	0.96	0.96	1368

Metrics for Movement Detection: Two-Axis

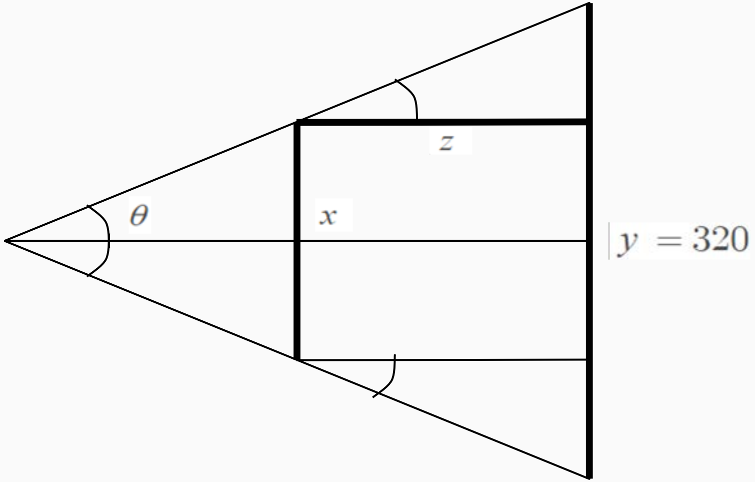
- X-axis
  - Midpoint of bounding box



- Z-axis
  - Length of bounding box
  - Area of bounding box

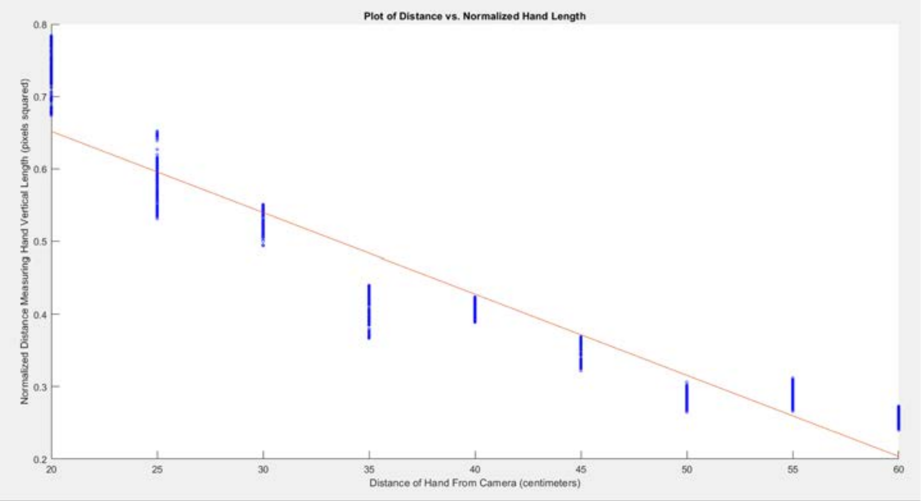


Least Squares Regression: Curve Fitting for Depth as a Function of Length



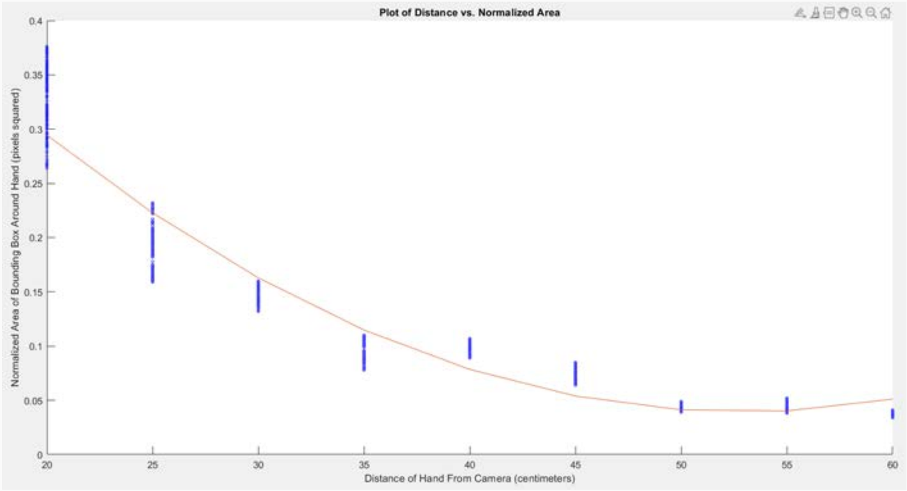
$$(x-y)^2 = 4z^2a^2 \text{ , where } a^2 = \left(\frac{1}{cos^2\theta} - 1\right)$$

$$x = y - 2az,\ y + 2az$$



Least Squares Regression:
Curve Fitting for Depth as a Function of Area

- Quadratic model
- Yields lower bias and variance

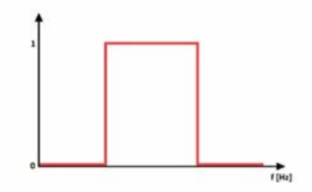


Noise Corrections

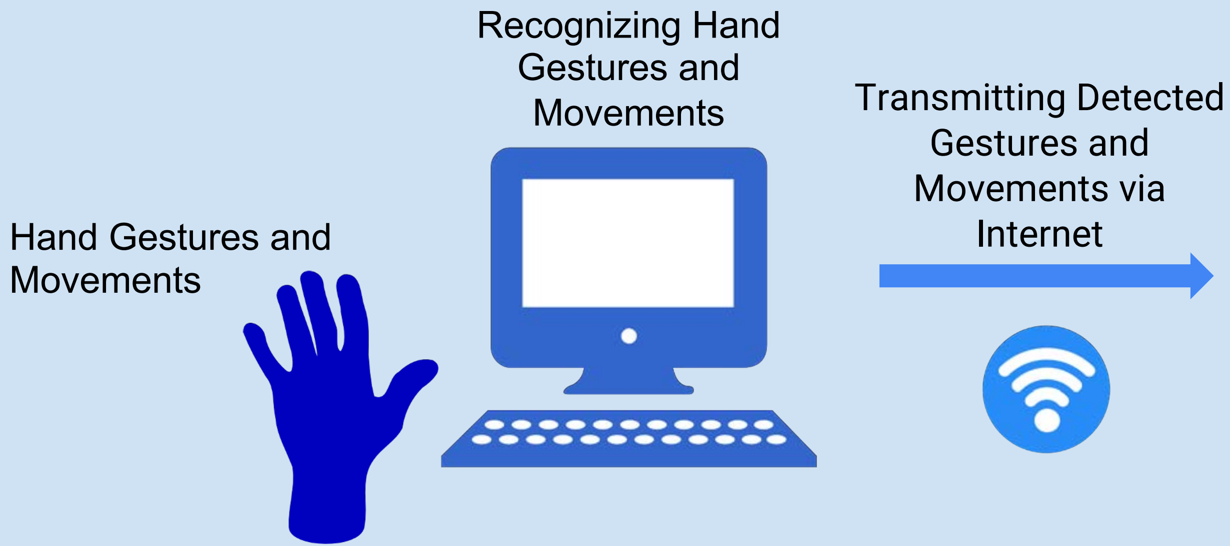
1. Utilize the area of bounding box and previously fitted function to determine instantaneous velocity.

$$\frac{dA}{dt} \cdot \frac{dz}{dA} = \frac{dz}{dt}$$

1. Attenuating resulting values that surpass the lower and upper threshold.



1. Map into a suitable value for varying speed: [-0.4, 0.4] → [-30, 30]
2. Baseline speed + this value: [70 - 30, 70 + 30]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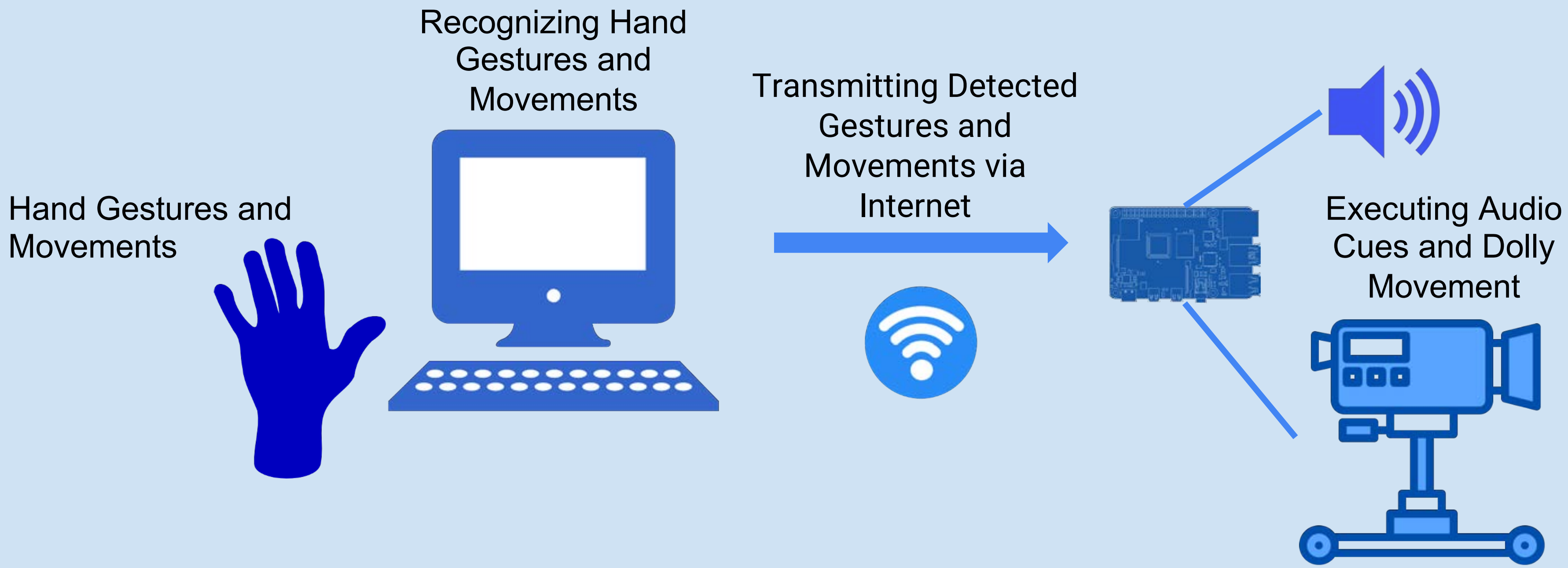
Communications

- Uni-directional Communication
    - Traditional Server Client Model
    - MQTT Protocol:
        - Publish/Subscribe to organized topics
        - Suitable for controlling IoT devices
        - Lightweight, easy to implement for prototyping
        - Low power consumption
        - (also capable of bi-directional communication)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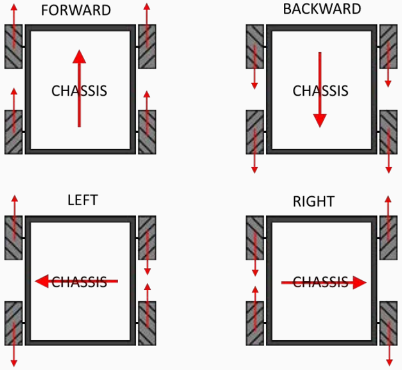
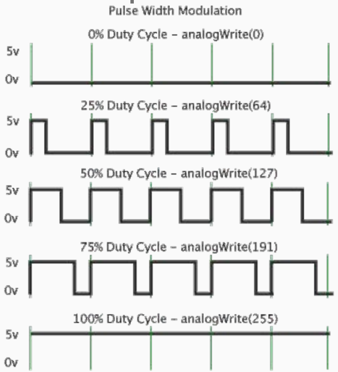
Executing Dolly Movement

- Robot Design:
  - Simulating a real-life film dolly
  - Mecanum wheels for smooth forwards, backwards, right, left movement. No turning required
  - Motors driven by PWM pins to control speed





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Results

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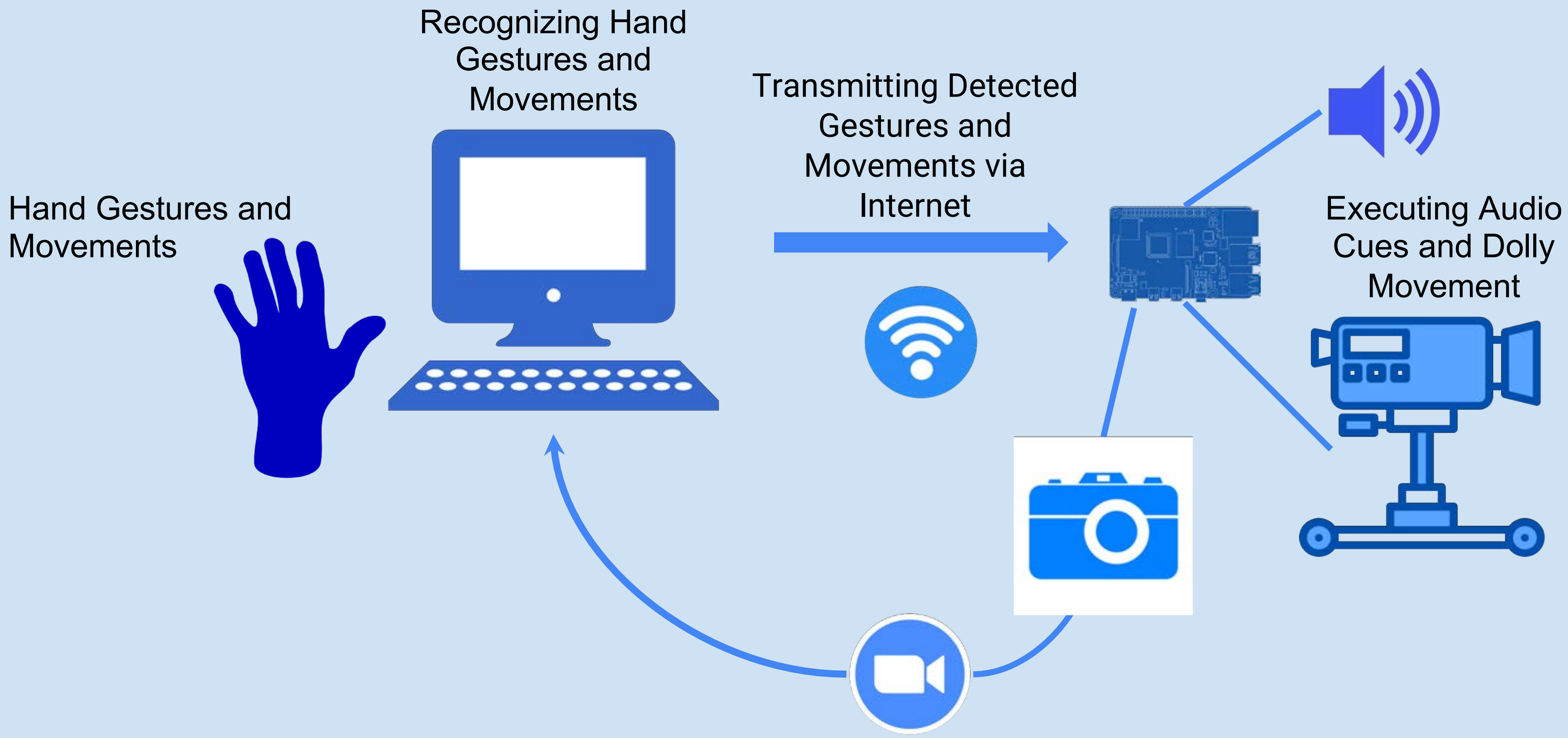
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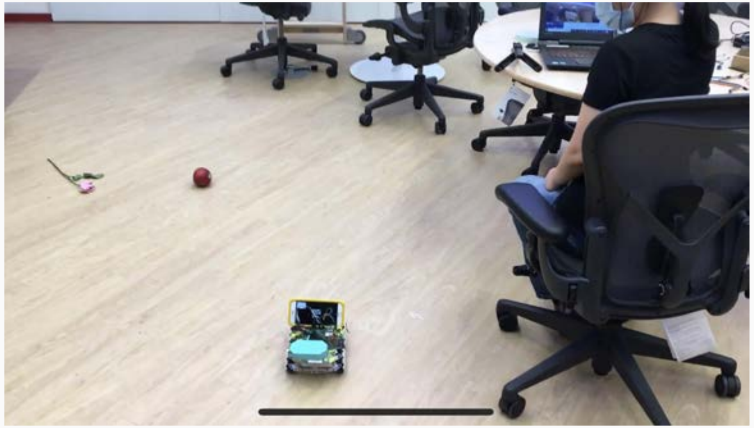
User Study

- Users were asked to move the dolly around to frame a shot of an apple and a rose lying next to each other



Demo Video

Survey Results

- Tasks Timing:
  - Each user took around 40s to 80s to complete the tasks
- Gestural Control & UI
  - Easy to Learn Controls: 4.83
  - Intuitive Interface: 4.33
  - “Natural-ness”: 4.5
  - Lag: 4.167
- Remote Control & Mechanical Automation
  - Speed of robot reflects hand speed: 2.5
  - Direction of robot reflects hand direction: 3.833
  - Lag: 4
- Filming with the Robotic Dolly
  - Fluidity of robot motion, “cinematic-ness”: 3.417
  - Time spent setting up a shot: 3.667

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Conclusion

Conclusion

- Using the Mediapipe open source tool for skeletal-based computer vision yielded noise that affected the program's performance.
- Area as a more reliable metric than distance.
    - Although this could have been be affected by noise
- Users agree that hand gestures for controlling the robotic dolly felt natural, but the speed of dolly movement did not fully reflect the speed of their hand motion.
- Speed determined by pixel distance or area was harder to model than I expected
    - Longer sample window → higher accuracy
        - Instantaneous velocity is not accurate due to jitter from inaccurate samples
    - Trade-offs:
        - Shorter sampling window → faster processing and message transmission

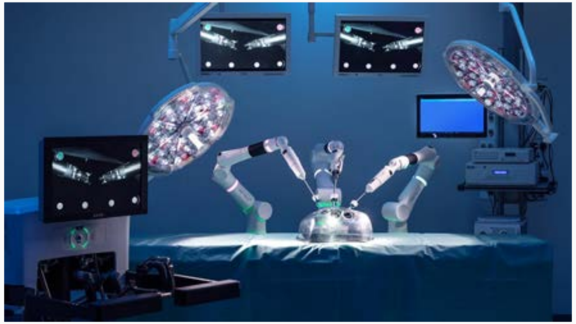
Next Steps

- Techniques for better sampling and noise elimination
- Issue of “resetting” hand motion upon hand reaching edge of screen
  - Most students found this unnatural and cumbersome
- Better hardware
  - Most students attributed dissatisfaction of mechanical automation to hardware limitations
  - Motors with more torque
  - PCB and soldered components instead of breadboard and loose wires
- Optimize algorithms for less lag and higher efficiency
- Implement a third axis (y-axis) to enable a tilt up and tilt down option on dolly’s camera

Other Applications

- Disabled
- Elderly
- Physical labor
- High risk construction work
- Surgical robotics
- Medical treatments



Special Acknowledgments

Professor Jeff Burke

Professor Leonard Kleinrock

Zhaoyu Wu

Professor Susan Littenberg

Professor William McDonald

Thank you! Any questions?