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Gesture-Controlled Automation For Remote Filmmaking

IRI Research Project 2021-2022

Presented by Olivia Loh
Introduction

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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
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
Transmitting Detected Gestures and Movements via Internet

Recognizing Hand Gestures and Movements

Executing Audio Cues and Dolly Movement

Hand Gestures and Movements
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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
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

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

\[x = y - 2az, \quad y + 2az\]
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] \rightarrow [-30, 30]\]
2. Baseline speed + this value: \([70 - 30, 70 + 30]\)
Transmitting Detected Gestures and Movements via Internet

Recognizing Hand Gestures and Movements

Hand Gestures and Movements
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)
Transmitting Detected Gestures and Movements via Internet

Recognizing Hand Gestures and Movements

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

Recognizing Hand Gestures and Movements

Hand Gestures and Movements

Executing Audio Cues and Dolly Movement

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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.
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 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
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Thank you! Any questions?