Real-time Egocentric Gesture Recognition on Mobile Head Mounted Displays

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Abstract

Mobile virtual reality (VR) head mounted displays (HMD) have become popular among consumers in recent years. In this work, we demonstrate real-time egocentric hand gesture detection and localization on mobile HMDs. Our main contributions are: 1) A novel mixed-reality data collection tool to automatically annotate bounding boxes and gesture labels; 2) The largest-to-date egocentric hand gesture and bounding box dataset with more than 400,000 annotated frames; 3) A neural network that runs real time on modern mobile CPUs, and achieves higher than 76% precision on gesture recognition across 8 classes.

1 Introduction

Mobile virtual reality (VR) head mounted displays (HMD), such as Daydream and GearVR, have made VR more accessible. Making users believe that they can interact with the virtual environment is critical to immersion. Since people interact with the real environment mostly with hands, we study how to bring hand presence to VR. In this work, we focus on hand gesture detection and localization. Our goal is to reliably recognize and localize hand gestures in real-time on mobile HMD systems.

There are two main challenges to this problem:

1. There is limited dataset available on egocentric hand gestures and bounding boxes.
2. It is challenging for high-capacity machine learning models to run at interaction framerate on mobile devices

To the first challenge, we propose to utilize mobile mixed reality headset as a tool to collect data and automatically label bounding box. With this method, we collected a large dataset of 33 people in 30 different scenes, with a total of 406,581 annotated frames. To download the dataset, please visit https://sites.google.com/view/hmd-gesture-dataset.

To the second challenge, we trained a neural network based on the TensorFlow Object Detection API [1]. The network uses MobileNet [4] as the feature extractor and SSD head [6] to generate multibox predictions. When running on mobile, one forward pass of our model takes 31.85 milliseconds on one core mobile CPU, achieving real-time performance.

2 Background

There has been extensive research on hand gesture recognition system. [10], [7], [11] provide excellent surveys on vision-based gesture recognition systems.

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Table 1: Sample images and gesture distribution in our dataset

| Gesture       | # of Frames | (% of total) |
|---------------|-------------|--------------|
| Thumbs_Press  | 113206      | (27.8%)      |
| Thumbs_Up     | 120716      | (29.7%)      |
| Thumbs_Down   | 55844       | (13.7%)      |
| Peace         | 116815      | (18.7%)      |

Figure 1: Image statistics of the dataset. (a) Distribution of bounding boxes; (b) Histogram of bounding box sizes; (c) Histogram of pixel intensity in all images; (d) Histogram of pixel intensity inside all bounding boxes;

Convolutional neural networks (CNN) such as in [8] and recurrent neural networks (RNN) such as in [3][2] have further pushed the boundary on gesture recognition results. Unfortunately none of them has shown real-time performance on mobile devices.

Building large and diverse datasets for hand gestures remains challenging. Existing gestures datasets such as those from [9] have less than 10,000 annotated frames. The closest datasets to our work are EgoFingers [5] where 93,729 frames are labeled, and EgoGesture [2] where 3 million frames have gesture labels but no bounding boxes. Compare to these datasets, our dataset contains 406,581 frames with both gesture labels and bounding boxes.

3 Dataset

3.1 Label As You Go

In order to scale data collection, we utilize mobile mixed reality headsets to collect automatically labeled data. Images in our dataset are labeled by the subjects as the images are recorded, instead of by annotators after the fact.

We used a Daydream View, a Google Pixel XL smartphone, and a monochrome USB camera that is connected to the phone and faces the world. In the headset, users can see digital video passthrough of the outward facing camera, and hence see the real world while in VR.

On top of video passthrough, we overlay a bounding box target on each frame in camera image space. For each gesture class, subjects are instructed to pose the requested gesture, and fit their hands tightly into the rendered bounding box target. With the mixed reality setting, this task is simply done through natural hand-eye coordination.

We vary the location of the bounding box to increase coverage of the dataset. To further reduce time, we animate the bounding box target in a pre-defined zigzagging trajectory which sweeps across the whole frame. As the trajectory is predictable and easy to remember, the subjects are able to follow the box, even as it moves to a new location. Each subject participating in data collection was asked to pose 4 gestures on each hand: Thumbs_Press, Thumbs_Up, Thumbs_Down, and Peace. For each gesture, we instrument 3 sequences of trajectories. The bounding box size stays the same for a single sequence, but varies from sequence to sequence. We provide a clicker to the subjects to signal the start of each data collection sequence.
3.2 Dataset Details

With the label as you go approach, we built a dataset of 406,581 frames of egocentric hand gesture data. The full dataset creation process took only two days. Each frame is labeled with gesture class and the bounding box of hands. Our dataset contains data from 33 subjects and 4 gesture classes on each hand. Since the mixed reality setup is mobile, we are able to collect data in different locations. As a result, we have 30 scenes under varying lighting conditions in the dataset. Table 1 has full breakdown of the dataset, and Figure 1 has image statistics of our dataset.

4 Mobile Object Detection Model for Gesture Recognition

4.1 MobileNet SSD Architecture

We trained a gesture recognition CNN based on TensorFlow Object Detection API [1]. It is composed of two parts conceptually: a MobileNet [4] feature extractor to produce feature maps, and a SSD [6] multibox detector to predict bounding box location and gesture labels (Figure 2). For each anchor box in the SSD head, the model predicts 4 offset values of the bounding box, and 9 class labels (4 distinct gestures multiplexed with either left or right hand, and one None class). We use a cross entropy loss for classification, and smooth $L_1$ loss as in [12] for bounding box localization loss. We add the two losses together as the final loss function.

![Figure 2: Illustration of the MobileNet SSD model.](image)

After model inference, we pick the bounding box proposal with the highest confidence in label prediction, as we only expect one label per image. SSD model natively supports multi-class and multi-instance prediction too.

4.2 Experiments and Results

Our models are trained with TensorFlow. Our training set contains 342,227 frames, and evaluation set contains 64,354 frames. The same person only appears in one split. For training, we use a batch size of 32. Image sizes are $320 \times 240$, and of one single color channel. We add random data augmentation to the training dataset, including brightness and contrast perturbation, and random crop and padding.

On our evaluation dataset, we test the top confidence bounding box prediction against the groundtruth label. Detailed results of the model performance can be found in Table 2.

4.3 Mobile Inference

The trained TensorFlow models can be exported to run on mobile devices. We benchmarked them on Snapdragon 821 chipset, which is common among Android devices since 2016. All results in Table 2 reflect model inference time on one Big CPU core on device.

In our application, we chose the MobileNet-0.25 model. Our inference framerate is at 30 frames per second on device. Accounting for pre- and post-processing steps, the whole gesture detection pipeline can run at 27 fps sustainably.
| Model               | Depth multiplier | Precision | Inference latency (ms) | Total latency (ms) |
|--------------------|------------------|-----------|------------------------|--------------------|
| MobileNetSSD-25%   | 0.25             | 76.15%    | 31.8504                | 36.1658            |
| MobileNetSSD-50%   | 0.5              | 77.43%    | 77.4913                | 81.6922            |
| MobileNetSSD-100%  | 1                | 80.94%    | 265.2109               | 269.4694           |

Table 2: Results of model performance. Total latency includes inference, pre- and post-processing.

5 Conclusion

In this work, we present a mobile egocentric gesture recognition pipeline. We built a mobile mixed-reality data capture tool, with which we can automatically annotate gestures and bounding box locations. We created the largest-to-date egocentric gesture and bounding boxes dataset. We trained a neural network based on the TensorFlow Object Detection API [1], and achieved 76.41% precision and real-time performance on mobile devices.

As future work, our label as you go approach can be adapted to other data collection tasks, such as keypoint and segmentation mask annotation. It can also be deployed on smartphones, where users could be asked to move their phone such that the object in the viewfinder fits into the rendered target.

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