**GestARLite**: An On-Device Pointing Finger Based Gestural Interface for Smartphones and Video See-Through Head-Mounts

Varun Jain, Gaurav Garg, Ramakrishna Perla and Ramya Hebbalaguppe
TCS Research, India
{varun.in, ga.gaurav, r.perla, ramya.hebbalaguppe}@tcs.com

**Abstract**

Hand gestures form an intuitive means of interaction in Mixed Reality (MR) applications. However, accurate gesture recognition can be achieved only through state-of-the-art deep learning models or with the use of expensive sensors. Despite the robustness of these deep learning models, they are generally computationally expensive and obtaining real-time performance on-device is still a challenge. To this end, we propose a novel lightweight hand gesture recognition framework that works in First Person View for wearable devices. The models are trained on a GPU machine and ported on an Android smartphone for its use with frugal wearable devices such as the Google Cardboard and VR Box. The proposed hand gesture recognition framework is driven by a cascade of state-of-the-art deep learning models: MobileNetV2 for hand localisation, our custom fingertip regression architecture followed by a Bi-LSTM model for gesture classification. We extensively evaluate the framework on our EgoGestAR dataset. The overall framework works in real-time on mobile devices and achieves a classification accuracy of 80% on EgoGestAR video dataset with an average latency of only 0.12 s.

**Introduction**

Over the past few decades, information technology has transitioned from desktop to mobile computing. Smartphones, tablets, smart watches and Head Mounted Devices (HMDs) are slowly replacing the desktop based computing. There has been a clear shift in terms of computing from office and home-office environments to an anytime-anywhere activity (Schmalstieg and Hollerer 2016). Mobile phones form a huge part of lives: the percentage of traffic on the internet generated from them is overtaking its desktop counterparts 1. Naturally, with this transition, the way we interact with these devices also has evolved from keyboard/mice to gestures, speech and brain computer interfaces. In a noisy outdoor setup, speech interfaces tend to be less accurate, and as a result the combination of hand gestural interface and speech are of interest to most HCI researchers. Hand gesture recognition on a real-time feed or a video is a form of activity recognition, and we specifically target models that can work on smartphones.

Expensive AR/MR devices such as the Microsoft HoloLens, Daqri and Meta Glasses provide a rich user interface by using recent hardware advancements. They are equipped with a variety of on-board sensors including multiple cameras, a depth sensor and proprietary processors. This makes them expensive and unaffordable for mass adoption.

In order to provide a user friendly interface via hand gestures, detecting hands in the user’s Field of View (FoV), localising certain keypoints on the hand, and understanding their motion pattern has been of importance to the vision community in recent times. Despite having robust deep learning models to solve such problems using state-of-the-art object detectors and sequence tracking methodologies, obtaining real-time performance on-device is still a challenge owing to resource constraints on memory and processing.

In this paper, we propose a computationally effective hand gesture recognition framework that works without depth information and the need of specialised hardware, thereby providing mass accessibility of gestural interfaces to the most affordable video see-through HMDs. These devices provide VR/MR experiences by using stereo rendering of the smartphone camera feed but have limited user interaction capabilities (Hegde et al. 2016).

Industrial inspection and repair, tele-presence, and data

---

1https://stonetemple.com/mobile-vs-desktop-usage-study/
visualisation are some of the immediate applications for our framework and we aim to design a mobile-based hand gesture recognition framework which can work in real-time and has the benefit of being able to work in remote environments without the need of internet connectivity. To demonstrate the generic nature of our framework, we evaluate the detection of 10 complex gestures performed using the pointing hand pose with a sample Android application. Figure 1 shows a real world application of 3D data visualisation on an Android smartphone to be used with Google Cardboard device.

The summary of key contributions is as follows:

1. We propose GestARLite: an on-device gestural interface based on fingertip regression via a cascade of neural network blocks, consisting of, MobileNetV2 for hand detection, our architecture for fingertip regression followed by a Bi-LSTM for gesture classification. This approach is marker-less and uses only RGB data without depth information. The trained models are ported on to an Android device for validating the accuracy and real-time performance of the proposed framework.

2. EgoGestAR: a dataset of spatio-temporal sequences representing 10 gestures suitable for MR applications. View our demo and the dataset at: https://varunj.github.io/gestarlite

Related Work

The efficacy of hand gestures as an interaction modality for MR applications on smartphones and HMDs has been extensively explored in the past (Hürst and Van Wezel 2013). Marker-based finger tracking (Buchmann et al. 2004) has been established as an effective way of directly manipulating objects in MR applications. However, most of the work has been based either on skin colour or on hand-crafted features for hand segmentation and interest point detection which is followed by optical flow for tracking.

Accurate hand segmentation is very important in all First-Person View (FPV) gesture recognition applications. In early attempts, it was observed that the YCbCr colour space allows better clustering of hand skin pixel data (Morero, Marcenaro, and Regazzoni 2013). In (Baraldi et al. 2014), super-pixels with several features are extracted using SLIC algorithm for computing hand segmentation masks. Li et al. (Li and Kitani 2013) observed the response of Gabor filters to examine local appearance features in skin colour regions. Most of these approaches are faced by the following challenges: (i) movement of the hand relative to the HMD renders the hand blurry, which makes it difficult to detect and track it, thereby impeding classification accuracy. (ii) sudden changes in illumination conditions and the presence of skin-like colours and texture in the background causes algorithms with skin feature dependency to fail.

To this end, we look at utilising the current state-of-the-art object detection architectures like MobileNetV2 (Sandler et al. 2018), YOLOv2 (Redmon and Farhadi 2016) and Faster R-CNN (Ren et al. 2015) for hand detection. Recently, a Faster R-CNN based hand detector was proposed (Huang et al. 2016). They used a cascaded CNN approach for jointly detecting the hand and the key point using HSV colour space information. A dual-target CNN takes input from the Faster R-CNN and localises the index fingertip and the finger-joint.

There are many classification approaches proposed in the context of hand gesture recognition. DTW and HMM based classifiers (Liu, Kehtarnavaz, and Carlsson 2014) have been used with stereo camera setup to recognise third-person view gestures. Support Vector Machines have also been explored for hand gesture recognition via bag-of-features (Dardas and Georganas 2011). All such classifiers work well given a small set of sufficiently distinct gestures but fail to extract discriminative features as one scales up to large datasets containing gestures with high inter-class similarity.

Several works (Tompson et al. 2014) use depth information from sensors such as the Microsoft Kinect that restricts its applications in head mounted devices. Moreover, most depth sensors perform poorly in the presence of strong specular reflection, direct sunlight, incandescent light and outdoor environments due to the presence of infrared radiation (Fankhauser et al. 2015). On-device gesture recognition is especially challenging due to the limited sensors present on a smartphone. A recent work (Fink, Phelps, and Peck 2018) uses a thermographic camera for detecting the infrared radiation from the hand. This method needs additional hardware in the form of an infrared transducer. To the best of our knowledge, ours is the first attempt to make an on-device
gesture classification framework for mobile devices.

**Proposed Framework**

There has been an increased emphasis on developing end-to-end networks that learn to model a number of sub-problems implicitly while training. While this has several advantages in learning joint tasks like object-detection followed by classification, it usually relies on the presence of a large amount of labelled data which has discriminative features useful for each of the sub-problems. For example, consider a scenario where one had large volumes of labelled data for object detection but only a small volume for object detection with classification. In such a scenario, an end-to-end model would be restricted to train on the small volume of data available for both tasks, whereas a model that is separately trained on a large detection dataset in conjunction with a classifier is likely to do much better owing to superior detection performance.

Hence, we propose an ensemble of architectures capable of recognising a variety of hand gestures for frugal AR wearable devices with a monocular RGB camera input that requires only a limited amount of labelled classification data. The GestARLite architecture is capable of classifying fingertip motion patterns into different hand gestures. Figure 2 shows the building blocks of our proposed pipeline: (i) MobileNetV2 (Sandler et al. 2018) takes a single RGB image as an input and outputs a hand candidate bounding box. The input images are first down-scaled to $640 \times 480$ resolution to reduce processing time without compromising on the quality of image features. (ii) The detected hand candidates are then fed to a fingertip regressor as depicted in Figure 3 which outputs the spatial location of the fingertip. (iii) The collection of these is then fed it to the Bi-LSTM network for classifying the motion pattern into different gestures.

The Datasets section discusses the gesture patterns of our EgoGestAR dataset used for classification. As there is no static reference for the camera, small errors introduced due to the relative motion of the head with respect to the hand can be rectified by the Bi-LSTM network used for classification. We observe that the Bi-LSTM network is robust to unexpected impulses arising in gesture pattern due to false detections.

**Hand Detection**

We compared state-of-the-art object detection approaches (i) Faster R-CNN (Ren et al. 2015), (ii) YOLOv2 (Redmon and Farhadi 2016) and (iii) MobileNetV2 (Sandler et al. 2018) to detect the specific pointing hand pose.

MobileNetV2 (Sandler et al. 2018) is a streamlined architecture that uses depth-wise separable convolutions to build light weight deep neural networks. The depth-wise separable convolution factorises a standard convolution into a depth-wise convolution and a $1 \times 1$ convolution also called a point-wise convolution thereby reducing the number of parameters in the network. It builds upon the ideas from MobileNetV1 (Howard et al. 2017), however, it incorporates two new features to the architecture: (i) linear bottlenecks between the layers, and (ii) skip connections between the bottlenecks. The bottlenecks encode the model’s intermediate inputs and outputs while the inner layer encapsulates the model’s ability to transform from lower-level concepts such as pixels to higher level descriptors such as image categories. Skip connections, similar to the traditional residual connections, enable faster training without any loss in accuracy.

In our experiments to detect the hand candidate in RGB input images obtained from wearable devices, we evaluate the MobileNetV2 feature extractor with SSDLite (Sandler et al. 2018) object detection module. The Experiments and Results section highlights the results in comparison with YOLOv2 (Redmon and Farhadi 2016) and Faster R-CNN (Ren et al. 2015) with a pre-trained VGG-16 model (Simonyan and Zisserman 2014) consisting of 13 shared convolutional layers along with other compact models such as ZF (Zeiler and Fergus 2014) and VGG1024 (Chatfield et al. 2014) by modifying the last fully

![Figure 3: Overview of our proposed fingertip regressor architecture for fingertip localisation. The input to our network are $3 \times 99 \times 99$ sized RGB images. Each of the 2 convolutional blocks have 3 convolutional layers each followed by a max-pooling layer. The 3 fully connected layers regress over fingertip spatial location.](image-url)
connected layer to detect hand class (pointing gesture pose).

**Fingertip Localisation**

We propose a fingertip regressor based on a CNN architecture to localise the \((x, y)\) coordinates of the fingertip. The hand candidate detection (pointing gesture pose), discussed in the previous section, triggers the regression CNN for fingertip localisation. The hand candidate bounding box is first cropped and resized to \(99 \times 99\) resolution before feeding it to the network described in Figure 3.

The proposed architecture consists of two convolutional blocks each with three convolutional layers followed by a max-pooling layer. Finally, we use three fully connected layers to regress over the two coordinate values of fingertip point at the last layer. Since the aim is to determine continuous valued outputs corresponding to fingertip positions, we use Mean Squared Error (MSE) measure to compute loss at the last fully connected layer. The model is trained for robust localisation, and we compare our model with the architecture proposed by Huang et al. (Huang et al. 2016). They localise both fingertip and finger-joint while we regress fingertip alone.

**Gesture Classification**

The fingertip localisation network outputs the spatial locations of the fingertip \((x, y)\), which are then fed as an input to our gesture classification network. To reduce computational cost, we just input the \((x, y)\) coordinate instead of the entire frame to the network thereby helping achieve real-time performance. Motivated by the effectiveness of LSTMs (Hochreiter and Schmidhuber 1997) in learning long-term dependencies of sequential data (Tsironi, Barros, and Wermer 2016), we employ a Bi-LSTM (Graves and Schmidhuber 2005) architecture for the classification of gestures. We found that Bi-LSTMs perform better than LSTMs for the particular classification task since they process the sequence in both forward and reverse direction. The usage of LSTMs inherently means that the entire framework is also adaptable to videos and live feeds with variable length frame sequences. This is particularly important as the length of gestures depends on the user performing it and on the performance of the preceding two networks.

Hegde et al. (Hegde et al. 2016) conducted a feasibility study for ranking the available modes of interaction for frugal Google Cardboard set-up and reported that the frequent usage of magnetic trigger and conductive lever leads to wear and tear of the device and it scored poorly on usability. Hence, we propose an automatic, implicit trigger to signify the starting and ending of a user input sequence. In the event of a positive pointing-finger hand detection on five consecutive frames, the framework is triggered to start recording the spatial location of the fingertip. Similarly, the absence of any hand detections on five consecutive frames denotes the end of a gesture. The recorded sequence is fed as an input to the Bi-LSTM layer consisting of 30 units. The forward and backward activations are multipled before being passed on to the next flattening layer that makes the data one-dimensional. It is then followed by a fully connected layer with 10 output scores that correspond to each of the 10 gestures. Since the task is to classify 10 gesture classes, we use a \textit{softmax} activation function that interprets the output scores as unnormalised log probabilities and squashes the output scores to be between 0 and 1 using the following equation:

\[
\sigma (s)_j = \frac{e^{s_j}}{\sum_{k=1}^{K} e^{s_k}}
\]

where \(K\) denotes number of classes, \(s\) is a \(K \times 1\) vector of scores, an input to \textit{softmax} function, and \(j\) is an index varying from 1 to \(K\), \(\sigma (s)\) is \(K \times 1\) output vector denoting the posterior probabilities associated with each gesture. The \textit{cross-entropy} loss has been used in training to update the model in network back-propagation.

**Datasets**

**Hand Dataset**

We use the SCUT-Ego-Finger Dataset (Huang et al. 2015) for training the hand detection and the fingertip localisation modules. The dataset includes 93729 frames of pointing hand gesture including hand candidate bounding boxes and index finger key-point coordinates.

**EgoGestAR Dataset**

A major factor that has hampered the advent of deep learning in the task of recognising temporal hand gestures is lack of available large-scale datasets to train neural networks on. To our knowledge, there exists no dataset, other than the ones mentioned in this paper, that provides annotated data of a wide range of intuitive temporal hand gestures.
Hence, to train and evaluate the proposed gesture classification network, we propose EgoGestAR: an egocentric-vision gesture dataset for AR/MR wearables. The dataset includes 10 gesture patterns. To introduce variability in the data, the dataset has been collected with the help of 50 subjects chosen at random from our research lab with ages spanning from 21 to 50. The average age of the subjects was 27.8 years. The dataset consists of 2500 gesture patterns where each subject recorded 5 samples of each gesture. The gestures were recorded by mounting a tablet PC (model HP10EEG1) to a wall. The patterns drawn by the user’s index finger on a touch interface application with position sensing region was stored. The data was captured at a resolution of 640 × 480. Figure 4 describes the standard input sequences shown to the users before data collection and a sample subset of gestures from the dataset showing the variability introduced by the subjects. These gestures primarily divided into 3 categories for effective utilisation in our context of data visualisation in MR applications:

(i) 4 swipe gesture patterns (Up, Down, Left, and Right) for navigating through graph visualisations/lists.
(ii) 2 gesture patterns (Rectangle and Circle) for RoI highlighting in user’s FoV and for zoom-in and zoom-out operations.
(iii) 4 gesture patterns (CheckMark: Yes, Caret: No, X: Delete, Star: Bookmark) for answering contextual questions while interacting with applications such as industrial inspection (Ramakrishna et al. 2016).

Further, to test the entire framework, 240 videos were recorded by a random subset of the aforementioned subjects performing each gesture 22 times. Additional 20 videos of random hand movements were also recorded. The videos were recorded using a OnePlus X Android device mounted on a Google Cardboard. High quality videos are captured at a resolution of 640x480, and at 30 FPS. We have published the dataset online \footnote{https://varunj.github.io/gestarlite} for the benefit of the research community.

**Experiments and Results**

Since the framework comprises of three networks, we evaluate the performance of each of the networks individually to arrive at the best combination of networks for our proposed application. We use an 8 core Intel® Core™ i7-6820HQ CPU, 32GB memory and an Nvidia® Quadro M5000M GPU machine for experiments. A Snapdragon® 845 chip-set smartphone was used which was interfaced with the server (wherever needed: to evaluate our method that runs on device) using a local network hosted on a Linksys EA6350 802.11ac compatible wireless router.

For all the experiments pertaining to hand detection and fingertip localisation, we use the hand dataset (Huang et al. 2015). Out of the 24 subjects present in the dataset, we choose 17 subjects’ data for training with a validation split of 70:30, and 7 subjects’ data (24,155 images) for testing the networks.

Figure 5: Hand candidate detection and fingertip localisation on sample images using MobileNetV2, YOLOv2 and Faster R-CNN with ZF networks in several challenging conditions. (a) indoor light with skin-like colours in background, (b) specular reflection, (c) low light with blurry hand, and, (d) hand in the absence of the pointing gesture. MobileNetV2 localises the hand more accurately as compared to YOLOv2 by giving tighter bounds on hands. Faster R-CNN is the most accurate, but does not work on-device.

**Hand Detection**

Table 1 reports percentage of mean Absolute Precision (mAP) and frame rate for hand candidate detection. Even though MobileNetV2 (Sandler et al. 2018) achieved higher frame-rate compared to others, it produced high false positives hence resulted in poor classification performance. It is observed that YOLOv2 can also run on-device although it outputs fewer frames as compared to MobileNetV2. At an Intersection over Union (IoU) of 0.5, YOLOv2 achieves 93.9% mAP on SCUT-Ego-Finger hand dataset whereas MobileNetV2 achieves 89.1% mAP. However, we observe that YOLOv2 performs poorly when compared to MobileNetV2 in localising the hand candidate at higher IoU that is required for including the fingertip. Figure 5 shows results

| Model     | On Device | mAP IoU=0.5 | mAP IoU=0.7 | rate (FPS) | Model Size |
|-----------|-----------|-------------|-------------|------------|------------|
| F-RCNN VGG16 | x         | 98.1        | 86.9        | 3          | 546 MB     |
| F-RCNN VGG1024 | x        | 96.8        | 86.7        | 10         | 350 MB     |
| F-RCNN ZF   | x         | 97.3        | 89.2        | 12         | 236 MB     |
| YOLOv2      | ✓         | 93.9        | 78.2        | 2          | 202 MB     |
| MobileNetV2 | ✓         | 89.1        | 85.3        | 9          | 12 MB      |

Table 1: Performance of various methods on the SCUT-EgoFinger dataset for hand detection. mAP score, frame-rate and the model size are reported with the variation in IoU.
of the detectors in different conditions such as poor illumination, blurry rendering, indoor and outdoor environments. We notice that even though both the detectors are unlikely to predict false positives in the background, YOLOv2 makes more localisation errors proving MobileNetV2 to be a better fit for our use-case.

It is worth noticing that the model size for MobileNetV2 is significantly less than the rest of the models. It enables us to port the model on mobile device and removes the framework’s dependence on a remote server. This helps reduce latency introduced by the network and can enable a enable wider reach of frugal devices for MR applications.

We evaluate the model employed for fingertip localisation on the test set of 24, 155 images. The $2 \times 1$ continuous-valued output corresponding to finger coordinate estimated at the last layer are compared against ground truth values to compute rate of success with changing thresholds on the error (in pixels) and the resultant plot when compared to the network proposed by Huang et al. (Huang et al. 2016) is shown in Figure 6. Adam optimiser with learning rate of 0.001 has been used. The model achieves 89.06% accuracy with an error tolerance of 10 pixels on an input image of $99 \times 99$ resolution. The mean absolute error is found to be 2.72 pixels for our approach and is 3.59 pixels for the network proposed in (Huang et al. 2016).

| Method        | Precision | Recall | $F_1$ Score |
|---------------|-----------|--------|-------------|
| DTW (2014)    | 0.741     | 0.76   | 0.734       |
| SVM (2008)    | 0.860     | 0.842  | 0.851       |
| LSTM (1997)   | 0.975     | 0.920  | 0.947       |
| Bi-LSTM (2005)| 0.956     | 0.940  | 0.948       |

Table 2: Performance of different classification methods on our EgoGestAR dataset. Average of precision and recall values for all classes is computed to get a single number.

**Gesture Classification**

We use our *EgoGestAR* dataset for training and testing of the gesture classification network. We also tried classification with an LSTM network in the same training and testing setting as the Bi-LSTM. During training, 2000 gesture patterns of the training set were used. A total of 8, 230 parameters of the network are trained with a batch size of 64 and validation split of 80 : 20. Adam optimiser with learning rate of 0.001 has been used. The networks are trained for 900 epochs and achieved validation accuracy of 95.17% and 96.5% for LSTM and Bi-LSTM respectively. LSTM and Bi-LSTM achieve classification accuracy of 92.5% and 94.3% respectively, outperforming the traditional approaches that are being used for similar classification tasks. We present comparison of the proposed LSTM and Bi-LSTM approach with DTW (Liu, Kehtarnavaz, and Carlsohn 2014) and SVM (Fan et al. 2008) classification in Table 2. Additionally, we observe that the performance of traditional methods like DTW and SVM deteriorate significantly in the absence of sufficient data-points. Hence, they rely on complex interpolation techniques to give consistent results.

Figure 6: Comparison of our proposed finger localisation model with Huang et al. (Huang et al. 2016). (above) our model achieves a higher success rate at any given error threshold. (below) The fraction of images with low localisation error is higher for our proposed method.

Fingertip Localisation

We evaluate the model employed for fingertip localisation on the test set of 24, 155 images. The $2 \times 1$ continuous-valued output corresponding to finger coordinate estimated at the last layer are compared against ground truth values to compute rate of success with changing thresholds on the error (in pixels) and the resultant plot when compared to the network proposed by Huang et al. (Huang et al. 2016) is shown in Figure 6. Adam optimiser with a learning rate of 0.001 has been used. The model achieves 89.06% accuracy with an error tolerance of 10 pixels on an input image of $99 \times 99$ resolution. The mean absolute error is found to be 2.72 pixels for our approach and is 3.59 pixels for the network proposed in (Huang et al. 2016).

Figure 7: The overall performance of our proposed framework on 240 egocentric videos captured using a smartphone based Google Cardboard head-mounted device. The gesture is detected when the predicted probability is more than 0.85. Accuracy of our proposed framework is 0.8 (excluding the unclassified class).
Table 3: Analysis of gesture recognition accuracy and latency of various models against the proposed framework. Our framework GestARLite works on-device and effectively has the highest accuracy and the least response time.

| Method          | Accuracy | Time taken | On Device |
|-----------------|----------|------------|-----------|
| Tsironi et al.  | 32.27    | 0.76       | ✗         |
| VGG16+LSTM      | 58.18    | 0.69       | ✗         |
| C3D             | 66.36    | 1.19       | ✗         |
| GestARLite      | 80.00    | 0.12       | ✓         |

Framework Evaluation

Since the proposed approach is a series of different networks, the overall classification accuracy in real-time will vary depending on the performance of each network used in the pipeline. Therefore, we evaluate the entire framework using 240 egocentric videos captured with a smartphone based Google Cardboard head-mounted device. The MobileNetV2 model was used in our experiments as it achieved the best trade-off between accuracy and performance. Since the model can work independently on a smartphone using the TFLite engine, it removes the framework’s dependence on a remote server and a quality network connection.

The framework achieved an overall accuracy of 80.00% on a dataset of 240 egocentric videos captured in FPV as shown in Figure 7. The MobileNetV2 network works at 9 FPS on 640 × 480 resolution videos, and the fingertip regressor is capable of delivering frame rates of up-to 166 FPS working at a resolution of 99 × 99. The gesture classification network is capable of processing a given stream of data in less than 100ms. As a result, the average response time of the proposed framework is found to be 0.12s on a smartphone powered by a Snapdragon® 845 chip-set. The entire model has a very small memory footprint of 16.3 MB.

Discussion and Comparison

Further analysis of the results shows that the CheckMark gesture is slightly correlated with the Right gesture since they both involve an arc that goes from left to right. Hence we observe a drop in the classification accuracy due to the inherent subjectivity of how a user draws a given gesture. Further, there are cases when the user’s hand goes out of the frame which can lead to a gesture not getting classified. Our framework is currently limited to a single finger in the users’ FoV and the accuracy drops if multiple fingers are present at roughly the same distance. However, we observe that the framework performs equally well in cases where the user is wearing nail paint or has minor finger injuries. In such cases, the fingertip regressor outputs the point just below the nail and tracks it. Further, it is also robust to different hand colours and sizes. The EgoGestAR dataset can potentially be extended to a number of pointing gestures as per the requirement of the MR application since the framework can accommodate a number of sufficiently distinct gestures.

We also make an important observation regarding our approach for including dedicated modules in our pipeline in contrast to an end-to-end framework. We compared our modular pipeline against several end-to-end trained gesture classification methods Table 3. Tsironi et al. (Tsironi, Barros, and Wermter 2016) proposed a network that works with differential image input to convolutional LSTMs to capture the body parts’ motion involved in the gestures performed in second-person view. Even after fine-tuning the model on our egocentric video dataset, it produced an accuracy of only 32.14% as our data involved a dynamic background and no static reference to the camera.

The VGG16+LSTM network (Donahue et al. 2015) uses 2D CNNs to extract features from each frame. These frame-wise features are then encoded as a temporally deep video descriptor which is fed to an LSTM network for classification. Similarly, a 3D CNNs approach (Tran et al. 2015) uses 3D CNNs to extract features directly from video clips. Table 3 shows that both of these methods do not perform well. A plausible intuitive reason for this is that the network might be learning noisy and bad features while training.

Attention based video classification (Sharma, Kiros, and Salakhutdinov 2015) also performed poorly owing to the high inter-class similarity. Since we require features from only a small portion of the entire frame, that is, the fingertip, such attention models appear redundant since we already know the fingertip location.

Conclusion

We have presented GestARLite to enable mass market reach of gestural interfaces that works in a resource constrained environment like on a smartphone or a video see-through HMD. GestARLite works in real-time and on-device achieving an accuracy of 80.00% with a model size of 16.3 MB. Our approach is marker-less and uses only RGB data from a single smartphone camera. The framework is tested on GPUs and Android devices with a Snapdragon® 845 chip-set. To the best of our knowledge, our proposed work is the first of its kind, deep learning based attempt to build on-device gestural interface for frugal head-mounted devices without the built-in depth sensors and having no need of network connectivity.

In the future, we intend to use the GestARLite architecture to come up applications of gesture recognition in second person view on Android phones exclusively for the visually challenged. Further, we aim to develop applications for huge display screens and boardrooms as an attempt to replace the mouse pointer with fingertip for controlling presentations.

References

Baraldi, L.; Paci, F.; Serra, G.; Benini, L.; and Cucchiara, R. 2014. Gesture recognition in ego-centric videos using dense trajectories and hand segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 688–693.

Buchmann, V.; Violich, S.;Billinghurst, M.; and Cockburn, A. 2004. Fingartips: gesture based direct manipulation in augmented reality. In Proceedings of the 2nd international conference on Computer graphics and interactive techniques in Australasia and South East Asia, 212–221. ACM.
Chatfield, K.; Simonyan, K.; Vedaldi, A.; and Zisserman, A. 2014. Return of the devil in the details: Delving deep into convolutional nets. arXiv preprint arXiv:1405.3531.

Dardas, N. H., and Georganas, N. D. 2011. Real-time hand gesture detection and recognition using bag-of-features and support vector machine techniques. IEEE Transactions on Instrumentation and Measurement 60(11):3592–3607.

Donahue, J.; Anne Hendricks, L.; Guadarrama, S.; Rohrbach, M.; Venugopalan, S.; Saenko, K.; and Darrell, T. 2015. Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2625–2634.

Fan, R.-E.; Chang, K.-W.; Hsieh, C.-J.; Wang, X.-R.; and Lin, C.-J. 2008. Liblinear: A library for large linear classification. Journal of machine learning research 9(Aug):1871–1874.

Fankhauser, P.; Bloesch, M.; Rodriguez, D.; Kaestner, R.; Hutter, M.; and Siegwart, R. Y. 2015. Kinect v2 for mobile robot navigation: Evaluation and modeling. In 2015 International Conference on Advanced Robotics (ICAR), 388–394. IEEE.

Fink, R.; Phelps, R.; and Peck, G. 2018. Gesture recognition systems and devices for low and no light conditions. US Patent 9,990,043.

Graves, A., and Schmidhuber, J. 2005. Framework phoneme classification with bidirectional lstm and other neural network architectures. Neural Networks 18(5):602–610.

Hegde, S.; Perla, R.; Hebbalaguppe, R.; and Hassan, E. 2016. Gestar: Real time gesture interaction for ar with egocentric view. In International Symposium on Mixed and Augmented Reality. IEEE.

Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. Neural computation 9(8):1735–1780.

Howard, A. G.; Zhu, M.; Chen, B.; Kalenichenko, D.; Wang, W.; Weyand, T.; Andreetto, M.; and Adam, H. 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

Huang, Y.; Liu, X.; Jin, L.; and Zhang, X. 2015. Deepfingert: A cascade convolutional neuron network approach to finger key point detection in egocentric vision with mobile camera. In Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on, 2944–2949. IEEE.

Huang, Y.; Liu, X.; Zhang, X.; and Jin, L. 2016. A pointing gesture based egocentric interaction system: Dataset, approach and application. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 16–23.

Hurst, W., and Van Wezel, C. 2013. Gesture-based interaction via finger tracking for mobile augmented reality. Multimedia Tools and Applications 62(1):233–258.

Li, C., and Kitani, K. M. 2013. Pixel-level hand detection in ego-centric videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3570–3577.

Liu, K.; Kehtarnavaz, N.; and Carlsohn, M. 2014. Comparison of two real-time hand gesture recognition systems involving stereo cameras, depth camera, and inertial sensor. In SPIE Photonics Europe, 91390C–91390C. International Society for Optics and Photonics.

Moriero, P.; Marcenaro, L.; and Regazzoni, C. S. 2013. Hand detection in first person vision. In Information Fusion (FUSION), 2013 16th International Conference on, 1502–1507. IEEE.

Ramakrishna, P.; Hassan, E.; Hebbalaguppe, R.; Sharma, M.; Gupta, G.; Vig, L.; Sharma, G.; and Shroff, G. 2016. An ar inspection framework: Feasibility study with multiple ar devices. In 2016 IEEE International Symposium on Mixed and Augmented Reality (ISMAR-Adjunct), 221–226.

Redmon, J., and Farhadi, A. 2016. Yolo9000: better, faster, stronger. arXiv preprint arXiv:1612.08242.

Ren, S.; He, K.; Girshick, R.; and Sun, J. 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, 91–99.

Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; and Chen, L.-C. 2018. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4510–4520.

Schmalstieg, D., and Hollerer, T. 2016. Augmented reality: principles and practice. Addison-Wesley Professional.

Sharma, S.; Kiros, R.; and Salakhutdinov, R. 2015. Action recognition using visual attention. arXiv preprint arXiv:1511.04119.

Simonyan, K., and Zisserman, A. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

Tompson, J.; Stein, M.; Lecun, Y.; and Perlin, K. 2014. Real-time continuous pose recovery of human hands using convolutional networks. ACM Transactions on Graphics (ToG) 33(5):169.

Tran, D.; Bourdev, L.; Fergus, R.; Torresani, L.; and Paluri, M. 2015. Learning spatiotemporal features with 3d convolutional networks. In Proceedings of the IEEE international conference on computer vision, 4489–4497.

Tsironi, E.; Barros, P.; and Wermter, S. 2016. Gesture recognition with a convolutional long short-term memory recurrent neural network. In Proceedings of the European symposium on artificial neural networks computational intelligence and machine learning (ESANN), 213–218.

Zeiler, M. D., and Fergus, R. 2014. Visualizing and understanding convolutional networks. In European conference on computer vision, 818–833. Springer.