Analysis of Hand Segmentation in the Wild

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Abstract

A large number of works in egocentric vision have concentrated on action and object recognition. Detection and segmentation of hands in first-person videos, however, has less been explored. For many applications in this domain, it is necessary to accurately segment not only hands of the camera wearer but also the hands of others with whom he is interacting. Here, we take an in-depth look at the hand segmentation problem. In the quest for robust hand segmentation methods, we evaluated the performance of the state of the art semantic segmentation methods, off the shelf and fine-tuned, on existing datasets. We fine-tune RefineNet, a leading semantic segmentation method, for hand segmentation and find that it does much better than the best contenders. Existing hand segmentation datasets are collected in the laboratory settings. To overcome this limitation, we contribute by collecting two new datasets: a) EgoYouTube-Hands including egocentric videos containing hands in the wild, and b) HandOverFace to analyze the performance of our models in presence of similar appearance occlusions. We further explore whether conditional random fields can help refine generated hand segmentations. To demonstrate the benefit of accurate hand maps, we train a CNN for hand-based activity recognition and achieve higher accuracy when a CNN was trained using hand maps produced by the fine-tuned RefineNet. Finally, we annotate a subset of the EgoHands dataset for fine-grained action recognition and show that an accuracy of 58.6% can be achieved by just looking at a single hand pose which is much better than the chance level (12.5%).

1. Introduction

Growing usage of wearable devices such as Google Glass, GoPro, and Narrative Clip has made egocentric research in computer vision a rapidly growing area. These cameras generate huge volumes of data which makes automatic analysis of their recorded content (e.g., for browsing, searching, and visualizing) a need, for applications such as summarizing videos, describing events in life-logging photo data, and recognizing activities of daily living. Most of the work in egocentric vision deals with understanding camera wearer’s activities and behavior. In this work, instead, we focus on a very crucial entity in egocentric videos: hands. Hands are ubiquitous in our daily life. We see them more than any other object in our life time. Their pose and configuration tell a lot about what we plan to do or what we pay attention to. Due to these, hand detection, segmentation and tracking are fundamental problems in egocentric vision with a myriad of applications in robotics, human-machine interaction, computer vision, augmented reality, etc. Extracting hand regions in egocentric videos is a critical step for understanding fine motor skills such as hand-object manipulation and hand-eye coordination.

We address the task of egocentric pixel-level hand detection and segmentation in realistic daily settings. A large number of works have addressed this problem in third-person or surveillance videos. Relatively less effort, however, has been devoted to this problem in first-person videos. Although few works exist (e.g., [3], [23] and [2]), the last analysis of hand segmentation in egocentric videos dates back to pre deep learning era [23]. Here, we plan to reiterate this topic by conducting an exhaustive analysis of hand segmentation in egocentric videos using state of the art semantic segmentation methods.

In contrast to third-person point-of-view videos – e.g., from a mounted surveillance camera or a laptop camera – egocentric videos contain rapid changes in illumination, highly dynamic and unpredictable camera motion, unusual composition and viewpoints, significant motion blur, and complex hand-object manipulations. Further, camera wearer is not captured in egocentric videos, thus other cues that can localize hands might be missing (e.g., person’s face or shoulders). Thus, hand segmentation models developed over third-person videos may not be adequate for egocentric hand detection.

We base our analysis on Bambach et al. [2], where they introduced a new hand dataset and a deep learning model for hand detection and segmentation. Their dataset, Ego-Hands, has pixel-level annotations for hands with two participants in each video interacting with each other [2]. We chose this dataset for two main reasons: 1) To the best of our knowledge, it is the only egocentric dataset with focus
on humans interactions from first-person point-of-view, and
2) It has pixel-level annotations for hands, where hands are
considered from fingers till wrist. We also utilize the GTEA
dataset which includes cooking activities indoors. Further,
we introduce a new large-scale dataset of labeled hands in
the wild which includes YouTube videos shot in realistic un-
constrained conditions, indoors and outdoors, under a wide
variety of scenarios. We call this dataset as EgoYouTube-
Hands (EYTH) dataset. An analysis is also performed to
assess how general the segmentation model could be by ap-
plying them to hands across datasets(both first-person and
third-person images).

We also study the utility of hand regions for activity
recognition, hands alone and in conjunction with manipu-
lated objects.

In summary, the lessons learned from this study are as
follows: First, we find that fine-tuning the RefineNet model
for pixel-level hand detection dramatically improves the
state of the art (e.g., 81.4% mIOU over EgoHands dataset,
about 26% improvement vs. [2]). Second, we annotate
hands at pixel-level over approx. 1300 egocentric video
frames taken in unconstrained real world environments and
evaluated RefineNet on those images. We find that fine-
tuning RefineNet over these images generalizes well across
other datasets in terms of mIOU accuracy. Third, we intro-
duce a new HandOverFace dataset which has 300 frames
with faces occluded by hands to test the performance of
hand segmentation methods. Fourth, we applied the Con-
ditional Random Fields to refine the model segmentation
maps and found that it improves the accuracy in some cases,
although not always. Fifth, we annotated a subset of Ego-
Hands dataset (800 frames) for finer hand-level actions like
picking, placing, holding, etc. and found that a single
hand pose carry much information about activity being per-
formed, and Finally, we trained AlexNet on that subset and
achieved 58.6% accuracy (chance equals 12.5% for 8 most
frequent action classes), and 59.2% accuracy when finely
annotated hand maps were used. We find that hand maps
along with objects significantly improves activity recogni-
tion (77.3% recognition accuracy).

2. Related Works

First-person hand segmentation. Li and Kitani et al., [23]
classified hand detection approaches (pre deep learning era
models) into three categories: (1) local appearance-based
detection; e.g., those relying on skin color [16, 17, 1], (2)
global appearance-based detection; e.g., using global hand
template [35, 30, 34], and (3) motion-based detection; using
ego-motion of the camera and assuming hands (foreground)
and the background have different motion detection; e.g., those relying on skin color
template [35].

Several works have addressed egocentric hand segmen-
tation. Ren and Gu [31] and Fathi et al. [11] proposed
a method to find regions with irregular optical flow pat-
tterns that may correspond to hands. The assumption here
is that the background is static which is quite true in re-
alistic daily egocentric videos when the person interacts
with other objects or people. Li and Kitani [23] proposed
an illumination-aware approach that chooses the best local
color feature for each environment using scene-level feature
probes. However, they assumed that there are no social in-
teractions in videos, so that all hands in the video belong to
the egocentric viewer. Lee et al. [22] proposed an approach
to detect hands in social interactions in egocentric videos.
They also proposed a probabilistic graphical model to uti-

Third-person hand segmentation. Some works have ad-
ressed hand detection in videos recorded from third-person
or surveillance cameras. For example, Mittal et al. [27] used
defeasible part models and skin heuristics to detect hands.
Few other recent works have investigated 3D hand pose es-
timation and hand-object interaction using hand segmenta-
tion [39, 18]. [8, 37] present comparative studies of hand
segmentation methods from the pre deep learning era.

3. Analysis Plan

In this section, we first describe details of the datasets
used in our analysis, followed by our approach for hand seg-
mentation and hand-based activity recognition.

3.1. Hand Datasets

We employ five datasets in our analysis. Two of them
are already available (EgoHands and GTEA), and we con-
tribute 3 additional datasets including EgoYouTubeHands,
HandOverFace and EgoHands+. The first four will be used
for the segmentation task and the last one for activity recog-
nition. We used LabelMe [32] toolbox to annotate hands in
our datasets. For hand segmentation, we follow [2] and an-
notate hands only till wrist. For activity recognition, we la-

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3.1 EgoHands dataset

This dataset [2] is unique because it captures interactions among actors. It has 48 videos recorded with a Google glass. Each video has two actors doing one of the 4 activities: playing puzzle, cards, jenga or chess. These videos are recorded in 3 different environments: office, courtyard and living room. The EgoHands dataset has pixel-level ground truth for over 15,000 hand instances. Each video has 100 manually annotated frames, 4800 frames ground truth in total. The original work randomly splits these videos into training, validation and test sets with the ratio of 75%, 8% and 17%, respectively. We used the same split in our work. Fig. 2 shows the heat map for spatial occurrence of hands in this dataset. As can be seen, most of the time hands occur at the bottom of the egocentric videos.

3.1.2 EgoYouTubeHands (EYTH) dataset

One limitation of existing datasets is that they are collected in constrained environments. Ideally, we would like to detect any hand in first-person videos recorded in unconstrained daily settings. To meet this objective, we need pixel-level hand annotations in real world images and/or videos. Thus, we downloaded three egocentric videos (3-6 minute long) from YouTube in which users are doing different activities and are interacting with others. We annotated every 5th frame in these videos. Our dataset has ~1290 frames with pixel-level hand annotations, with variation in environment, number of participants, hand size, etc. Fig. 1 shows some images. Hands visible through transparent objects such as glass are annotated as complete object considering reflections as occlusion. This dataset has 2600 hand instances, with approx. 1800 first-person hand instances and approx. 800 third-person hands. The heatmap for EYTH in Fig. 2 shows that this dataset has most variations in hand locations. Also the histogram of this dataset has most images for smallest hand size. See Table 1 for detailed breakdown of statistics.

3.1.3 GTEA dataset

GeorgiaTech Egocentric Activity dataset (GTEA) by [29] has 7 daily activities performed by 4 subjects. Videos are collected in the same environment for the purpose of activity recognition. It does not capture social interactions and is collected under static illumination conditions annotated at 15 fps for 61 action classes. We use this dataset for hand segmentation. The original dataset has 663 images with pixel-level hand annotations considering hand till arm. Following [6], we also cropped out the arm part for our work.
for block and puzzle piece. We used also shows statistics over the occurrence of each action in the Ego-Hands+ dataset. Histogram of actions frequencies left hand right hand both hands

<table>
<thead>
<tr>
<th>Stat</th>
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<th>EgoYouTube</th>
<th>GTEA</th>
<th>HandOverFace</th>
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<td>507</td>
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<td>920</td>
<td>600</td>
<td>–</td>
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<tr>
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<td>3rd-P right</td>
<td>4510</td>
<td>534</td>
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</tbody>
</table>

Table 1: Statistics of hand datasets used in this work. 1st-P and 3rd-P stand for first-person and third-person, respectively.

3.1.4 HandOverFace (HOF) dataset

We collected 300 images from the Web in which faces are occluded by hands to study how skin similarity can affect hand segmentation. Some examples are shown in Fig. 2. This dataset has pixel-level annotations for hands along with the hand type: left or right. HOF has images for people from different ethnicities, age, and gender. See Table 1 for statistics. HandOverFace dataset has a fair share of both big and small hands. Also, visualization of hand maps across this dataset tells us that hands are mostly appearing towards the center of images (See Fig 2).

3.1.5 EgoHands+ dataset

Humans are good at guessing the action being performed by just looking at the hand pose. The original EgoHands dataset is labeled at frame-level for 4 activities. To investigate the role of hand masks in hand-pose based activity recognition, we needed action annotations at a finer level. Thus, we annotated a small subset of 8 videos (800 frames), 2 from each coarse-level activity for outdoors (courtyard) in the EgoHands dataset at hand-pose level. We labeled each hand pose with one of the following 16 activities: holding, picking, placing, resting, moving, replacing, thinking, pulling, pushing, stacking, adjusting, matching, pressing, high-five, pointing, and catching. Ambiguous hand poses are annotated with multiple possible labels (e.g., picking and placing are sometimes difficult to be inferred at a single frame-level). Additionally, most of these actions are based on the object type. For instance, adjusting and matching are actions relevant to puzzle pieces, pulling and pushing are relevant to jenga blocks, and so on. However, actions like holding, thinking, resting and highfive are general actions.

We call these additional annotations as the EgoHands+ dataset. Fig. 3 shows occurrence of each action in the Ego-Hands+ dataset. Actions like holding, picking, placing and resting are few of the most occurring ones in this dataset. Fig. 3 also shows the break down of all actions based on their hand-type i.e., whether the participant used her left, right, or both hands. Fig. 3 also shows statistics over the EgoHands+ dataset.

Figure 3: (Left) Histogram of activities occurrence in EgoHands+ dataset. Fine-level activities include holding, picking, placing, resting, moving, replacing, thinking, pulling, pushing, stacking, adjusting, matching, pressing, high-five, pointing, and catching. Left: Inset) Some statistics for EgoHands+ dataset. Objects include cards, chess_piece, jenga_block and puzzle_piece. We used this dataset for fine-level activity recognition. Right) Histogram of hand type occurrence in EgoHands+ dataset

3.2. Hand Segmentation

We treat hand segmentation as a semantic segmentation task, in contrast to Bambach et al. who formulated it as object detection. Semantic segmentation assigns one label, from a well defined set of class labels, to each pixel [28]. Similarly, we interpret the hand detection problem as a dense prediction problem where we want to detect every pixel that belongs to a hand (i.e., binary segmentation).

Adopting RefineNet for hand segmentation: Fully convolutional networks [25] have been successfully used for dense prediction tasks. In recent years, deep residual nets have been used as the backbone in several models such as PSPNet [38] and RefineNet [24]. RefineNet is a multi-path refinement network which exploits all the features at multiple levels along the downsampling path. A RefineNet block typically consists of Residual Convolution Units (RCU), Multi-Resolution Fusion of features coming from the RCU blocks and Chained Residual Pooling. RefineNet is a cascaded architecture of multiple RefineNet blocks which is based on Residual net features. It computes features from ResNet at different levels and fuses them to produce a high resolution prediction map. We picked off-the-shelf 4-cascaded RefineNet model to evaluate it on the EgoHands dataset. We performed off-the-shelf evaluation of leading semantic segmentation methods ([7] and [38]) on the Ego-Hands dataset, and find that RefineNet gives better results than other models. Since [7] and [38] were trained on PASCAL VOC for person class, we evaluated their performance only on hand regions to give them an advantage, but off-the-shelf RefineNet beats [7] with a significant margin (~17%) and [38] with a slight difference (~2%). Therefore, we chose it for our analysis on hand segmentation datasets.

We used RefineNet-Res101 pre-trained on Pascal Person-Part dataset in all our experiments. We used pre-trained RefineNet-Res101 with a new classification layer
with 2 classes: *hand* and *no hand*. We trained the model on EgoHands, EYTH, GTEA, and HOF datasets. RefineNet-Res101 uses feature maps from ResNet101. After fine-tuning, we perform multi-scale evaluation for scales: [0.6, 0.8, 1.0] as mentioned in [24] which gives us consistently better results than single scale evaluation. On EgoHands dataset, RefineNet significantly outperformed the baseline (See Fig. 4). Thus, we used this fine-tuned model as our pixel-level hand detector.

**Cross dataset evaluation.** We believe that along with a robust segmentation method, appropriate hand segmentation datasets are also important for accurately segmenting hands in the wild. To find the essential ingredients for a robust hand segmentation setup, we measure generalization capabilities of RefineNet across datasets. After training RefineNet on each dataset, we test it across datasets to study its generalization capability (See Table 2).

**Further refinement with CRFs.** CRFs are well known for being useful in refining pixel-level predictions for computer vision problems such as saliency detection and semantic segmentation. Our initial task is to segment hands from an input image which is a binary semantic segmentation problem and thus, is quite similar to foreground/background estimation. We employed unary and pairwise potentials from [26] to refine initial maps obtained by our hand detector (Fig. 4 shows results on EgoHands dataset and Fig. 6 shows results on all datasets).

**Small hands vs. big hands.** For further analysis, we selected images with small hands and big hands from all datasets based on a threshold on bounding box area of hand relative to the image, and evaluated each trained model on small and big hands from the same dataset, respectively.

**3.3. Hand-based Activity and Action Recognition.**

Hand regions can tell us about the activities a person is doing. Bambach et al. showed a correlation between hand regions and activity being performed. Here, we extend their task. Given a single hand map, we aim to predict the fine-level action (1 out of 8 over EgoHands+ dataset). We consider activity recognition at two levels: coarse-level - where activity label is available at the frame level, and fine-level - where we have action labels for each hand region.

**Coarse-level activity recognition.** Similar to [2], we also perform hand-based activity recognition but we aim to test it using better segmentation maps that we generate to see if better segmentation helps activity recognition. Note that EgoHands dataset has frame-level annotations for different activities. The task is to classify activity only using hands without any background information. For coarse-level activity recognition, we used the same classification model used by [2] and trained it on EgoHands dataset to reproduce their results. We find that better hand maps lead to better activity recognition.

**Fine-level action recognition.** We extended Bambach et al.’s work to finer level as different hand poses are used for different actions like holding or writing. Given a single hand instance, we aim to tell what fine-level action is being performed. For instance, while playing cards is a coarse activity, a person can use his hands for *picking* and *placing* cards which are fine-level actions. Since, few actions like *highfive, catching, replacing, and pushing* rarely occur, we trained a CNN for 8 most frequent action classes which uses a single hand instance to classify which fine-level action is being performed. We trained the same CNN [21] in all of our experiments related to activity/action recognition, except that the last layer changes according to the number of classes.

4. Experiments and Results

**Evaluation metrics.** For *hand segmentation*, we report three metrics: pixel-level mean Intersection over Union (mIOU), mean Precision, and mean Recall. For *activity recognition*, we report classification accuracy.

4.1. Segmentation Results

Our baseline method [2] detects hand instances (bounding boxes), aggregates them, and then runs GrabCut to generate a segmentation map. This map can be converted to binary and compared with our model. Whereas, we use RefineNet-Res101 pre-trained on Pascal Person-Part dataset. We chose this model since it already has been trained to parse human hands on Person-Part dataset. The model parses human hand till elbow whereas we consider hands till wrist. For training RefineNet, we used a learning rate of 5e-5 with an increased learning rate by a factor of 10 for our binary classification layer. All models were trained till convergence, and multi-scale evaluation is used with three scales: [0.6, 0.8 and 1.0].

In the following, we first report results over the egocentric video datasets, and then proceed to some analyses.

1) **EgoHands dataset:** For fine-tuning pre-trained RefineNet-Res101 on EgoHands dataset, we used the same data split as in [2] with 3600, 400 and 800 images for training, validation and testing, respectively. We fine-tuned RefineNet-Res101 on EgoHands dataset for 80 epochs. After multi-scale evaluation, we obtained an mIOU of 81.4%
Table 2: Hand segmentation results on 4 datasets using RefineNet trained on one dataset and tested on others. Numbers in bold text show the best results on a particular dataset, whereas the blue font shows second best results for that dataset (Vertical: Train; Horizontal: Test).

![Failure cases](image_url)
Performance analysis on small vs. big hands.

Apart from hand segmentation, we were also interested in investigating the relationship between hand size and segmentation accuracy. We selected images with small hands and big hands from test sets for all four datasets (See Fig. 7 for few examples), and evaluated their respective models on those test images. We consider hands with relative area less than 0.015 as small hands, except for GTEA where we thresholded hands smaller than 0.025 as small hands. The reason for choosing higher threshold for GTEA is because this dataset has very few images with smaller hands. Please see Fig. 2 for histogram of relative area of hands. Hands with relative area larger than 0.15 are treated as big hands for all datasets. For evaluating these images from each dataset, we used the model trained on the same dataset. For instance, for EgoHands dataset, we used model trained on EgoHands dataset, and so on.

Our results show that the mIOU is consistently lower for small hands on all datasets, except for EgoHands, where the mIOU for small hands is slightly higher than big hands. The possible reason for this is that, in EgoHands dataset, most hands are smaller in size. In addition to that, Ego-Hands has a constrained setting of first-person and third-person interactions, due to which, same image with small hand for third-person may have a big hand for first-person (See Fig 2). Therefore, it makes the performance better than big hands for the chosen thresholds, but with a low margin(3.7%). Whereas, for other three datasets, the mIOU for big hands is higher with a large margin(~8%-33%), validating that small hands are more challenging for segmentation. Overall, we find that the model struggles with segmenting small hands as compared to big hands.(See Table 3).

### 4.2. Activity and Action Recognition Results

**Coarse-level activity recognition:** Our baseline [2] trained a Caffe [15] based CNN as a 4-way classifier (coarse level) for 4 activities: cards, chess, jenga and puzzle. To reproduce their results, we trained the same Caffe based CNN [20] on ground truth segmentation maps for 6K iterations. After training for 6K iterations, we tested the trained model on ground truth maps, prediction maps from baseline method and prediction maps produced by RefineNet trained on EgoHands.

Using the fine-tuned RefineNet, we obtain 13.6% improvement over the baseline with recognition accuracy of 64.5% which is closer to 66.5% accuracy using ground truth hand maps. We also studied how well the action classifier performs on CRF- based maps and learned that it still performs better than the baseline by 5.3%. See Table 4 for detailed comparisons. We continued to train the network until it converged after 230K iterations and obtained an accuracy of 71.1% using ground truth maps. While we were able to reproduce accuracy on ground truth maps as mentioned in [2], testing it on baseline maps gives us lower accuracy than reported in the baseline paper. Therefore, we report the performance for their maps from their paper. Our converged model achieved 41% accuracy on their hand maps.

**Fine-level action recognition:** To investigate action recognition at hand instance level, we additionally annotated a subset of EgoHands dataset for 16 hand-pose level actions and refer to it as EgoHands+ dataset. We then selected 8 most frequent actions (resting, holding, picking, placing, matching, pressing and stacking) for training an 8-way

### Table 3: Performance analysis on small vs. big hands.

| Datasets    | Small Hands | | Big Hands | |
|-------------|-------------|-------------|-----------|
|             | mIOU | mRecall | mPrec | mIOU | mRecall | mPrec |
| EgoHands    | 0.787 | 0.917 | 0.850 | 0.750 | 0.925 | 0.802 |
| EYTH        | 0.537 | 0.643 | 0.693 | 0.867 | 0.914 | 0.944 |
| GTEA        | 0.732 | 0.787 | 0.913 | 0.894 | 0.927 | 0.962 |
| HOF         | 0.713 | 0.866 | 0.808 | 0.792 | 0.932 | 0.840 |
CNN classifier with the same architecture used for coarse level activity recognition. We used base learning rate of 1e-4 with step size of 10K iterations. Additionally, we annotated same videos for finer hand maps and tried to segment hand details like fingers as much as possible. We then trained CNNs for 3 setups: 1) hands only, 2) object only, and 3) hand+object (See Fig. 8). We further split them on the basis of coarse hand maps and fine hand maps (where we have details about fingers).

We used the same split ratio as [2] for EgoHands+ dataset with the ratio of 75%, 8% and 17% for training, validation and testing, respectively. Each input image was split for one hand map per image and then we trained a CNN using 5 setups: 1) Using coarse hand maps only, we achieved 58.6% accuracy on test data where the chance level is 12.5%. 2) Using fine-level hand maps slightly improves accuracy, 3&4) Using objects along with both coarse and fine hand maps gives us the same results with accuracy of 77.3%. As manipulated object along with hand improves accuracy by approx 18%, we were curious to see how much the manipulated object carries information on its own. Thus, we trained a CNN on 5) Using objects only, we achieved an accuracy of 55.1%. This suggests that objects carry useful information but not more than hands. Albeit, hands along with objects lead to a significant boost in performance. Fig. 9 (right) shows ROC curves averaged over all actions for all 5 setups.

To further explore the fine-level action recognition, we test the classifier trained on GT hand maps over predicted hand maps from RefineNet and achieve accuracy of 57.1%. Testing on maps generated by RefineNet + CRF gives 54.4% accuracy. We find that RefineNet maps give accuracy close to when using GT maps (59.2%).

5. Discussion and Conclusion

Accurate segmentation of hands is challenging yet useful for many applications, mainly in robotics and surveillance. We trained a hand segmentation model which gives improved results over the previous state of the art hand segmentation method [2]. We also proposed 3 new datasets: 1) EYTH, a challenging dataset with real world settings, which is proved to be more versatile than existing egocentric datasets based on our results, 2) HandOverFace dataset, which is useful to study similar appearance occlusions when dealing with hands, and can help identify how we can deal with hand-to-skin occlusions, and 3) EgoHands+ dataset with action labels along with hand types (left, right, first-person, third-person) for each pixel-level annotated hand. For activity recognition, besides showing that improved hand maps improve recognition accuracy, we also reported baseline performance for fine-level action recognition and showed that even single hand instances are useful for finer level action recognition. Recent sophisticated deep networks are expected to give even higher performance.

Our work suggests some areas for improvement where even leading methods fail (e.g., hand-to-hand occlusion, small hands, poor lighting conditions, hand over face occlusions, etc). Along with models that handle these challenges, we also need large datasets with pixel-level annotations for hands in the wild. Conditional random fields although did not help us much quantitatively, but generated visually appealing segmentation maps. We experimented with Dense-CRF on EgoHands dataset, but our preliminary results show no improvement. We will consider using some better high level information like superpixels to improve the results.

In summary, we took a deep look into the problem of hand segmentation in realistic unconstrained environments, proposed a model that outperforms the state of the art, introduced several datasets, and identified challenges that need to be addressed in future works. All code and data will be freely available to the public.

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