

Object Referring in Videos with Language and Human Gaze- Supplementary Material

We provide the following additional materials:

- **Annotation interface**
- **Gaze Feature encoding**
- **More qualitative results**
- **Accompany video for interface and video examples**

1. Annotation Interface

We annotate a dataset of textual attributes and descriptions for objects in videos. We collected the annotations on Cityscapes dataset [1]. We crowdsourced the annotation task on Amazon Mechanical Turk (AMT). Firstly, we show the set of instructions as in Fig. 5 to the workers. Here, we try to convey a few Do’s and Dont’s for writing descriptions for the objects along with a visual example. As described in the paper, the goal of the annotation is for cooperative conversations. That is, the descriptions need to be truthful, informative, relevant, and brief for co-observers to find the target objects easily and unambiguously.

Referring Expression annotation. The interface that we show to AMT workers is shown in Fig. 2. Worker is obliged to see the video in the beginning. We freeze all the fields of the interface and it is opened only if the video is viewed at least once. The video is embedded on top of panel of the interface. The video stops with the final frame of the video which is allowed to be annotated as shown in Fig. 2. We display all the previous annotations of the objects in the final frame to avoid repeated object annotations. We provide a Play Video button and encourage the Workers to re-watch the video for better scene understanding and object description.

The worker is then asked to draw a tight bounding box on an unannotated object. For the corresponding annotated objects, he/she fills the fields of object “Attributes” (e.g. class name, color, and size) and the “Relationship with the observer (e.g. in front, on the right side, and far away)”. Finally, the Workers need to describe the object in a short sentence that help people to identify the object uniquely among all the objects. This annotation for attributes and relationships **help** significantly; it makes sure that the Workers have

made enough effort to understand the object and the scene well. The attributes and relationships will be explored for referring expression generation in our future work.

We display the list of objects annotated by the worker on the left under the heading “Box list” and we provide an option to update/remove a particular object from the list. A Worker is allowed to annotate two objects per video at maximum for the diversity of annotations. In Fig. 3, we have shown an example of annotation of three objects with their corresponding descriptions for a particular video. Fig. 4 shows a sample annotation of Attributes and Relationships for the objects annotated in Fig. 3. Please see the accompany video for video examples and kindly refer to Fig. 2 for a better view of the interface.

Gaze recording. Fig. 6 demonstrates the web interface that we show to workers in AMT. Since the recording of gaze involves recording of the faces, we ensure that workers read the privacy policies before they start the recording task. This primarily includes that their faces will be recorded during the tasks and the recordings will be used for research purposes only. Our aim is to record all the gaze for bounding box annotations of the objects from the task of referring expression. We have explained the annotation process in the main paper. Here, we have also shown some examples of recorded frontal view of the annotators for gaze recording in Fig. 1.

2. Gaze feature encoding

Workers annotate by gazing at the corners of the image displayed on the canvas. These corner gazes are used to find the mapping function from camera coordinates to image coordinates. This mapping function is later used to compute the gaze features. Given the corners in image coordinates I_1, I_2, I_3, I_4 of gazes G_1, G_2, G_3 , and G_4 . We compute the gaze features (F) by the following procedure as shown in Algorithm. 1.

Mapping function. We find the mapping function to map the coordinates from screen/camera coordinates to image coordinates. We get the system of linear equations from the four corners which we annotated for the calibration as

Data: Gaze of corners G_1, G_2, G_3, G_4 ,
 Corners(image coordinates) I_1, I_2, I_3, I_4 and
 Bounding boxes BB

Result: Gaze Features(F)

Initialization: Corners (camera coordinates) C_1, C_2, C_3, C_4 ;

Begin:

```

 $C_i = DAN(G_i)$  [3];  $i=1,2,3,4,;$ 
 $I_i = A * C_i + B$  (as in Eq. 1) where  $A = (a_1, a_2)$  and
 $B = (b_1, b_2)$ ;
Solve for A and B (See Eq. 2);
while For all Gaze  $g_i$  and bounding box  $BB_i$  do
   $p_i = A * DAN(g_i) + B;$ 
   $heatmap = gaussian\_2d(Image, p_i, \sigma = 20);$ 
  if  $p_i$  within image then
     $F_i = mean(heatmap[BB_i]);$ 
  else
     $BB\_norm =$ 
     $heatmap[BB_i]/max(heatmap[BB_i])$ 
     $F_i = mean(BB\_norm);$ 
  end
end
Gaze Features= F;
End:

```

Algorithm 1: Extracting Gaze Features

shown in Algorithm 1. Given the system of linear equations with more number of equations than the variables, we have overdetermined equation

$$y = Hx \quad (1)$$

The solution x can be derived by minimizing the energy of error:

$$\begin{aligned}
 J &= \|y - Hx\|_2^2 \\
 J &= (y - Hx)^T(y - Hx) \\
 J &= y^T y - 2y^T Hx + x^T H^T Hx
 \end{aligned}$$

Making derivative of J to zero, we get,

$$x = (H^T H)^{-1} H^T y, \quad (2)$$

assuming $H^T H$ is invertible.

3. Qualitative Results

In this section, we present more qualitative results on Cityscapes dataset from different models to show the advantage of using multiple modalities: NLOR [2], Ours:(I,D,O) and Ours:(I,D,O,G) in Fig. 7. From column 4, we see how gaze improve the object localization results over already given depth information, motion information and the temporal-spacial context information.

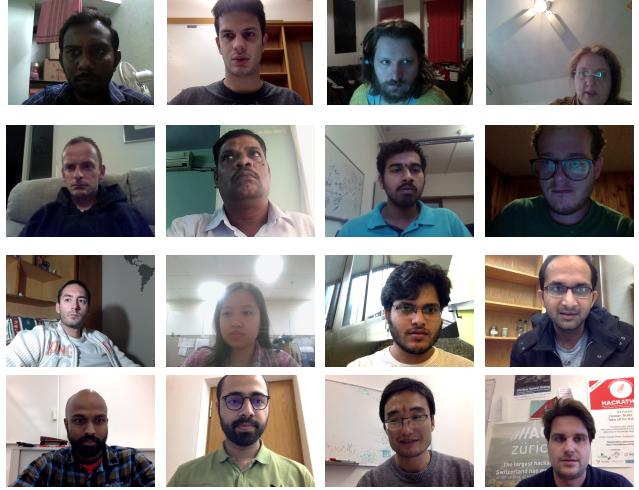


Figure 1: Selected images of gaze recording from our annotations.

References

- [1] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele. The cityscapes dataset for semantic urban scene understanding. In *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 1
- [2] R. Hu, H. Xu, M. Rohrbach, J. Feng, K. Saenko, and T. Darrell. Natural language object retrieval. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4555–4564, 2016. 2
- [3] M. Kowalski, J. Naruniec, and T. Trzcinski. Deep alignment network: A convolutional neural network for robust face alignment. *arXiv preprint arXiv:1706.01789*, 2017. 2

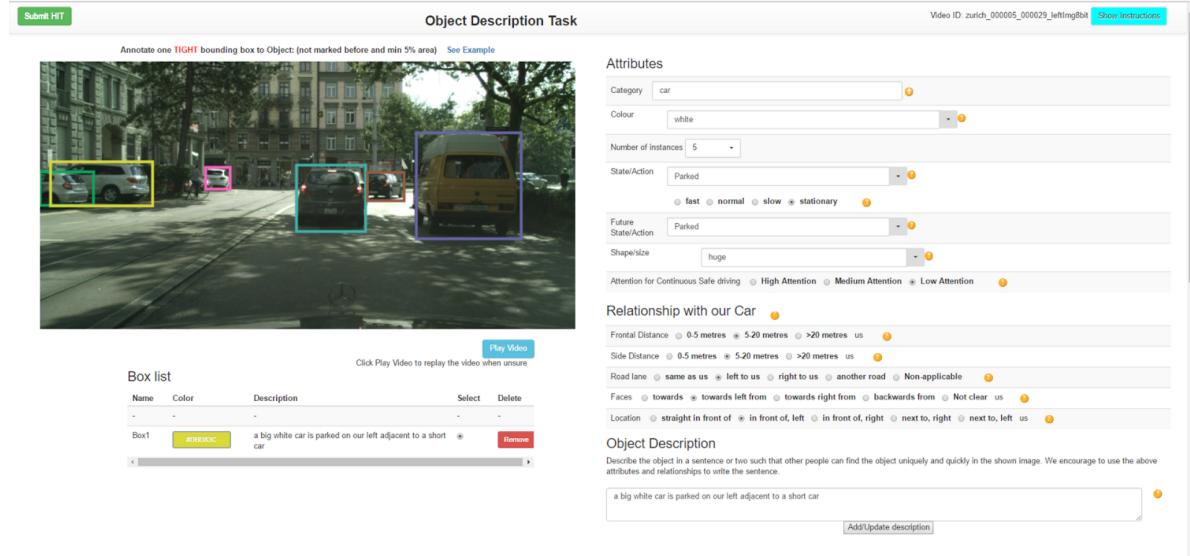


Figure 2: Snapshot of the annotation interface that we show to the workers for Object Description task.

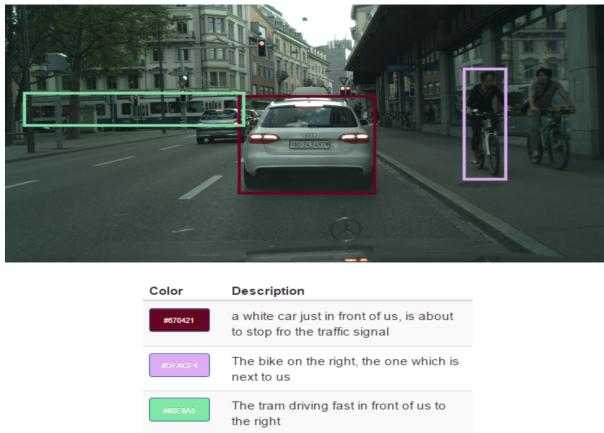


Figure 3: Sample annotations of objects and their descriptions.

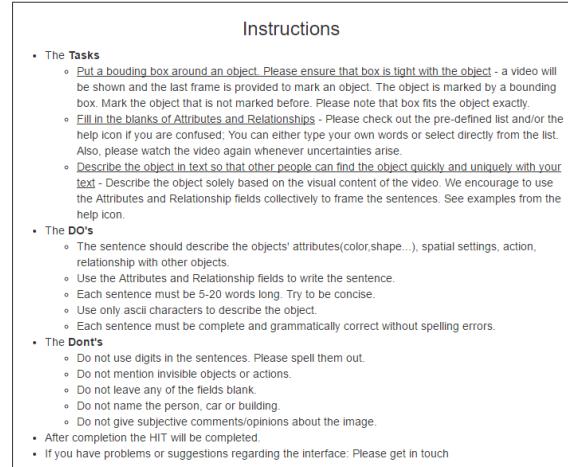


Figure 4: Sample annotation of object attributes.

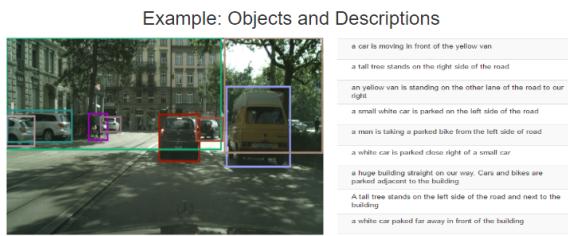


Figure 5: The set of instructions shown to the workers. An example of annotation is also shown on the bottom.

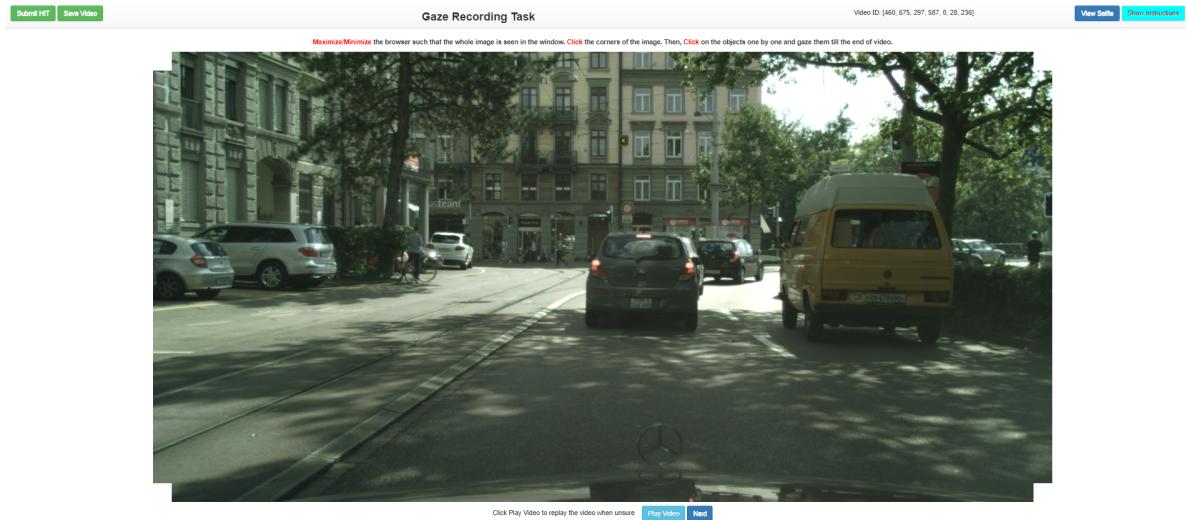


Figure 6: Snapshot of the annotation interface that we show to the workers for the task of Gaze recording.

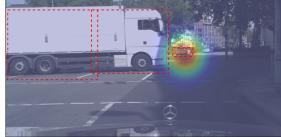
NLOR

Intermediate Results

Ours:(I,D,O)

Ours:(I,D,O,G)

A white car at a far distance in front is moving on left side of the road



A white car in front is waiting to move in signal



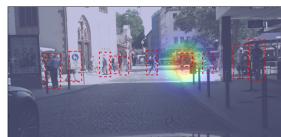
A huge car is parked on the right side of the road along with other cars



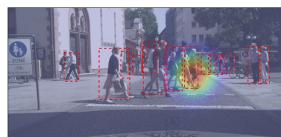
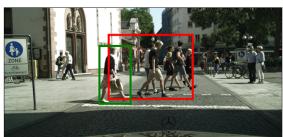
A white car is moving towards right side of the road along with black car



A women in maroon top crossing the road from left side of the road to right side



A women in black top holding a bag crossing the road from left side right side of the road along with other person



A car in front in front is just waiting to move in signal on right side of the road



Figure 7: Some qualitative results: NLOR, Ours(I,D,O) and Ours:(I,D,O,G). These results are obtained on the Cityscapes dataset. **Green** boxes represent ground truth box and **Red** boxes represent the predicted box. We mainly show how gaze helps in improving the results.