Connecting Gaze, Scene, and Attention:
Generalized Attention Estimation via Joint modeling of Gaze and Scene Saliency

ECCV 2018 European Conference on Computer Vision
8 – 14 September 2018 | Munich, Germany

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Problem

➢ Human gaze behaviors are complex in the real world. **Automatically detecting and quantifying various types of visual attention from images** remains an open challenge.

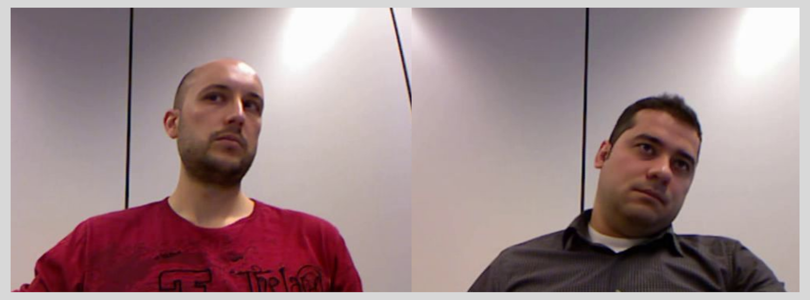
➢ Current systems have focused on constrained versions of this problem in predetermined contexts.

Our Approach

➢ We propose the new problem of **"generalized attention estimation"** and **design a system that can model the visual attention of subjects in unconstrained scenarios** which works across most natural scenarios.

➢ We exploit three public datasets that have been originally collected for different tasks to solve this problem.

Dataset



EYEDIAP dataset [1]
- ➢ Gaze and head pose variance
- ➢ Target outside, clean background
- ➢ Learn precise gaze angle representation

GazeFollow dataset [2]
- ➢ Real world pictures
- ➢ Target inside (with our additional annotation)
- ➢ Learn gaze-relevant scene saliency representation

Train

SynHead dataset [3]
- ➢ Large head pose variation
- ➢ Target outside, arbitrary background
- ➢ Complement the other datasets

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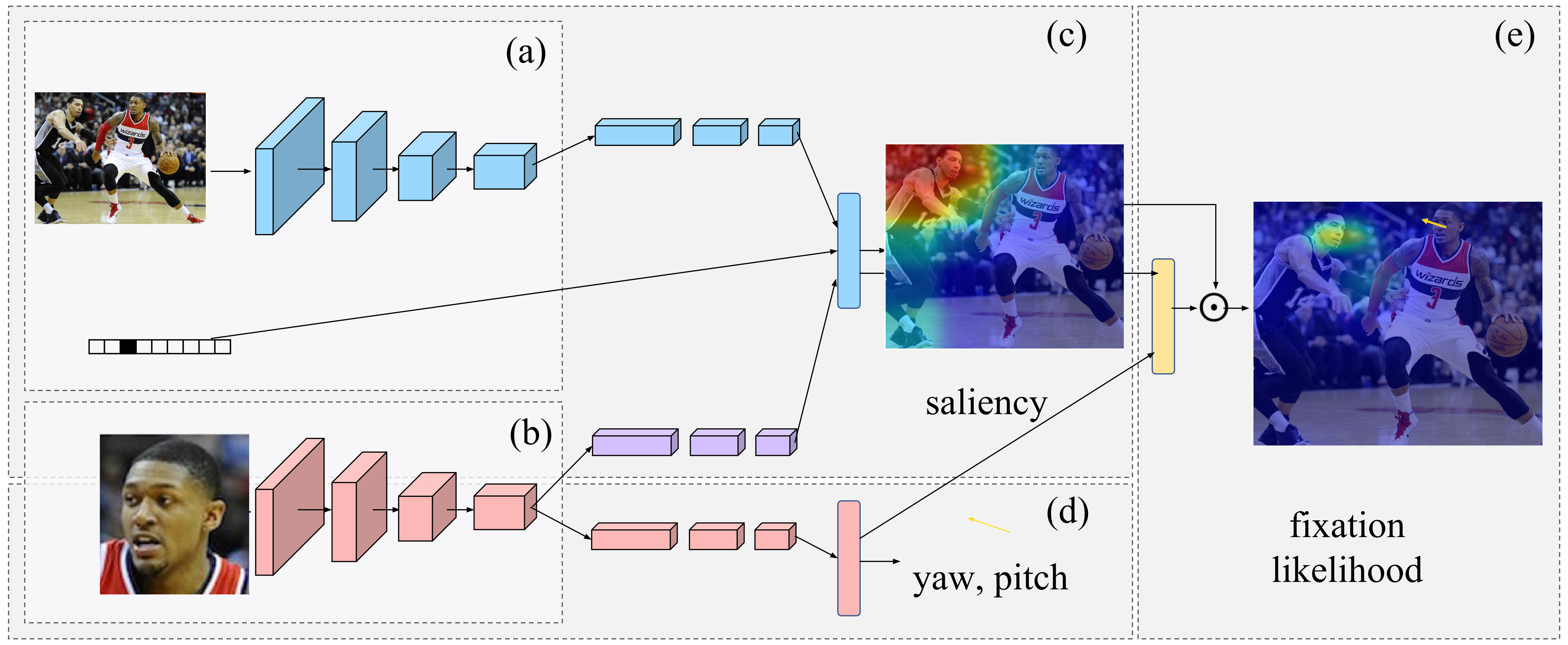
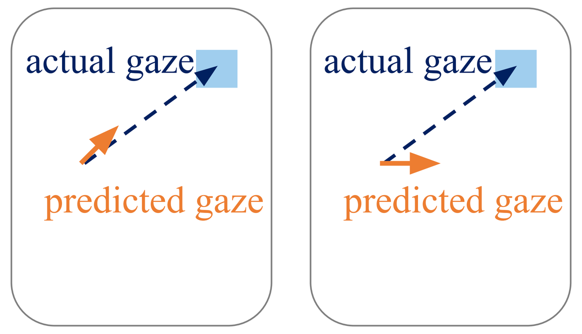
MMDB dataset [4]
- ➢ Naturalistic social interactions
- ➢ Frame-level annotations of subject's visual targets (with our additional annotation) among many other nonverbal behaviors

Method



projection of gaze angle



small loss   large loss

Project-and-Compare
- ➢ When angle is not directly available, a projection of its predicted angle is used as a measure of loss.

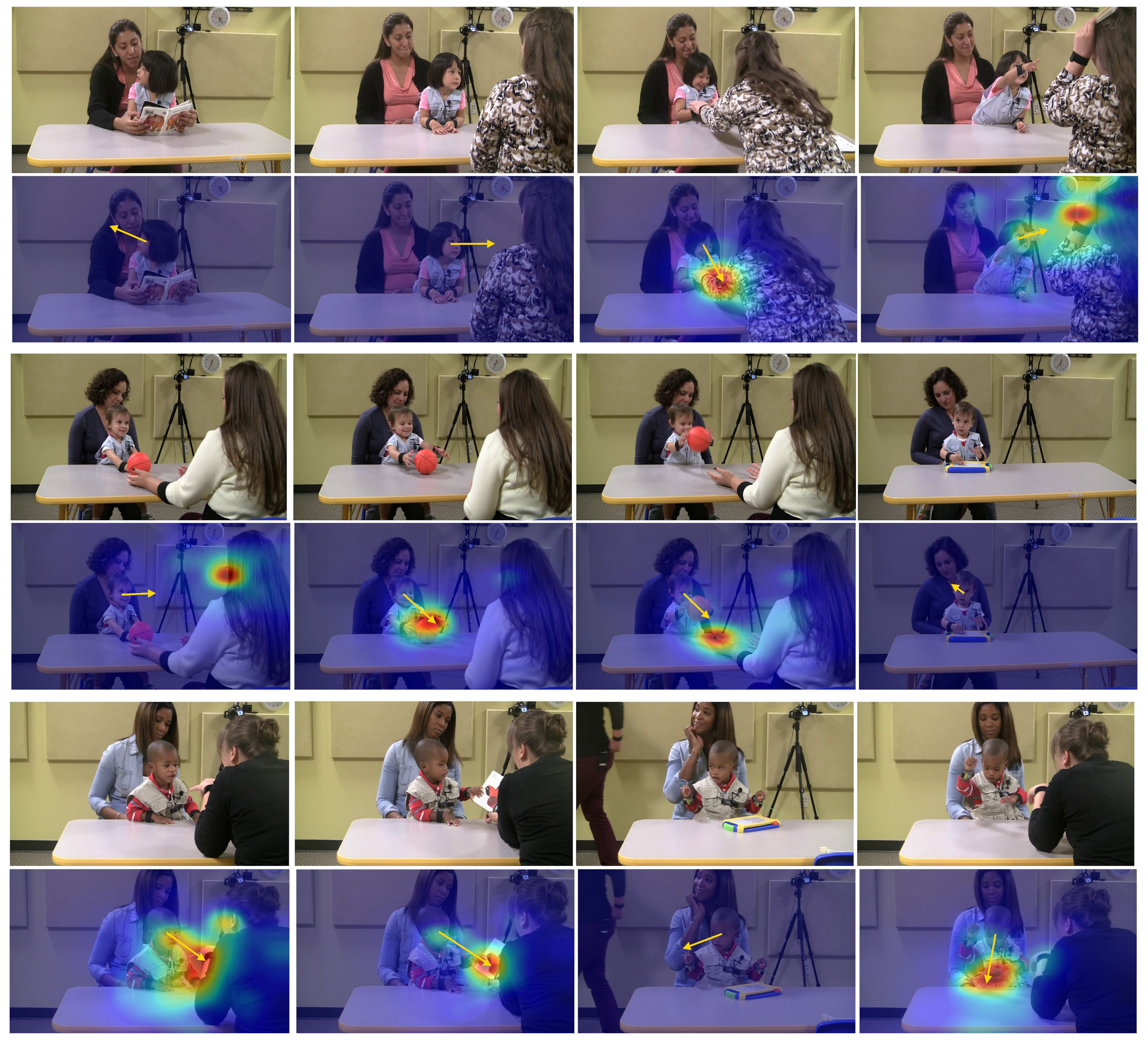
➢ Input = full scene image, a person's face location whose visual attention we want to predict, and the close-up face image.

➢ Scene and face images go through separate convolutional layers in such a way that **(a) (b) and (c) contribute to saliency**, and **(b) and (d) contribute to gaze angle** prediction. In the last layer, the final feature vectors for two tasks are **combined to estimate how likely the person is actually fixating** at a gaze target in the frame.

➢ Loss = Cross Entropy + Euclidean + Project-and-Compare.

Result

GazeFollow dataset (test split)



MMDB dataset

Table 1 Gaze-saliency evaluation on the GazeFollow test set

Method	AUC	L2 Distance	Min Distance
Random	0.504	0.484	0.391
Center	0.633	0.313	0.230
Judd [17]	0.711	0.337	0.250
GazeFollow [23]	0.878	0.190	0.113
Our	*0.896*	*0.187*	*0.112*

➢ Our model achieves state-of-the-art result on the gaze following task, which consists in identifying the location of the scene the subject is looking at.

Table 2 Gaze angle evaluation on EYEDIAP

Method	Angular Error (degree)
Wood [29]	11.3°
iTracker [18]	8.3°
Zhang [32]	*6.0°*
Our	6.4°

➢ Our model also competes with the state-of-the-art on the 3D gaze estimation task

Table 3 Evaluation on MMDB - gaze target grid classification

Grid Size	Method	Precision	Recall
2x2	GazeFollow [23]	0.344	0.715
	Our	0.744	0.851
5x5	GazeFollow [23]	0.210	0.437
	Our	0.614	0.683

Table 4 Evaluation of fixation likelihood on MMDB

Method	Average Precision
SVM with GazeFollow [23]	0.311
SVM with GazeFollow [23]+gaze [32]	0.531
SVM with GazeFollow [23]+headpose [2]	0.620
SVM with gaze [32]+headpose [2]	0.405
SVM with GazeFollow [23]+gaze [32]+headpose [2]	0.624
Random Forest with GazeFollow [23]	0.707
Random Forest with GazeFollow [23]+gaze [32]	0.727
Random Forest with GazeFollow [23]+headpose [2]	0.785
Random Forest with gaze [32]+headpose [2]	0.512
Random Forest with GazeFollow [23]+gaze [32]+headpose [2]	0.773
Our, trained only with GazeFollow dataset	0.737
Our, trained only with GazeFollow and EYEDIAP dataset	0.820
Our final	*0.902*

➢ We evaluate our full model on a new challenging task on the MMDB dataset.

➢ We are the first to report attention estimation results on this problem. We compare our results to a variety of baseline tests.

References

[1] Mora, et al. EYEDIAP: A Database for the Development and Evaluation of Gaze Estimation Algorithms from RGB and RGB-D Cameras. ETRA 14.
[2] Recasens, et al. Where are they looking? NIPS 15.
[3] Gu, et al. Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network. CVPR 17.
[4] Rehg, et al. Decoding Children's Social Behavior. CVPR 13.