How We Look Tells Us What We Do: Action Recognition Using Human Gaze

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EYE COG LAB

Big Picture

Eye movements contain information that can be used to recognize actions in still images and enhance automatic computer vision methods.

Information in Eye Movements

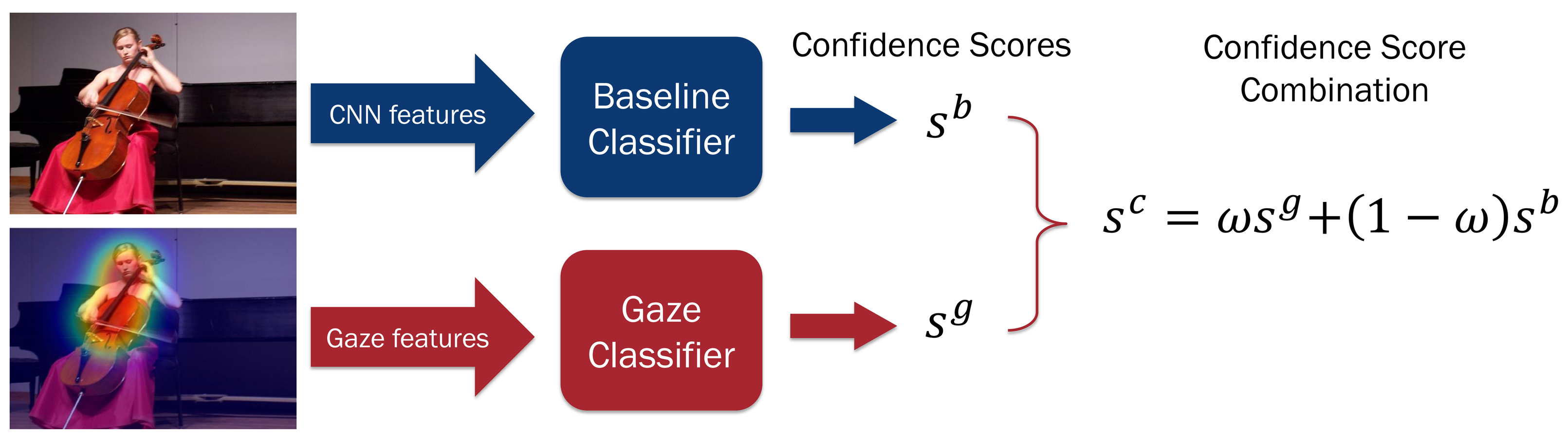
- Different action classes elicit different spatio-temporal gaze patterns from viewers.
- Gaze features are derived and used to train Support Vector Machine (SVM) classifiers.
- Confusion in the gaze classifier reveals behaviorally-meaningful action groups.

Information in Pixels

- Convolutional Neural Network (CNN) features are computed for an image and are used to train SVM classifiers for each action.

Goal

- Explore relationship between gaze patterns and pixels describing actions in images.
- Show usefulness of gaze, alone or combined with computer vision, to classify images.



Contribution

- Better understand through gaze how people comprehend and group actions.
- Propose novel gaze features for automatic action classification in still images.

Datasets

PASCAL VOC 2012 Action Classes

- 500 images selected from a total of 9157 images featuring:
  - 10 action classes: "**walking**", "**running**", "**jumping**", "**riding horse**", "**riding bike**", "**phoning**", "**taking photo**", "**using computer**", "**reading**", and "**playing instrument**".
  - All selected images depicted a single whole person performing an action.

Gaze Data

- Eye movement data collected by [1]
- 8 subjects (3 male and 5 female)
  - 3 second viewing period.
  - Task: Recognize the action in an image and select it from a list of 10 actions

[1] C. S. Stefan Mathe. Action from still image dataset and inverse optimal control to learn task specific visual scanpaths. In Advances in Neural Information Processing Systems, 2013.

Experiments & Analyses

Visualizing gaze patterns

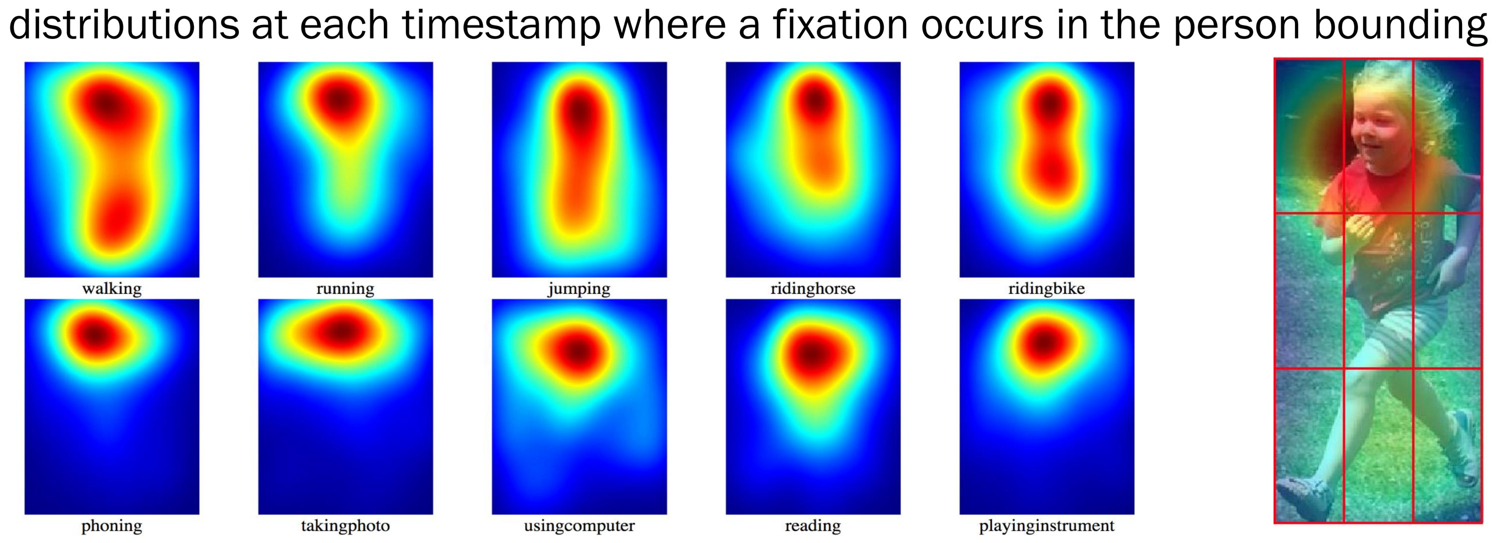
Aggregate fixations from all subjects, with darker circles denoting earlier fixations.

Fixations clustered with a Gaussian Mixture Model.

Fixation Density Maps (FDMs) using 2D Gaussian distributions weighted by fixation duration.

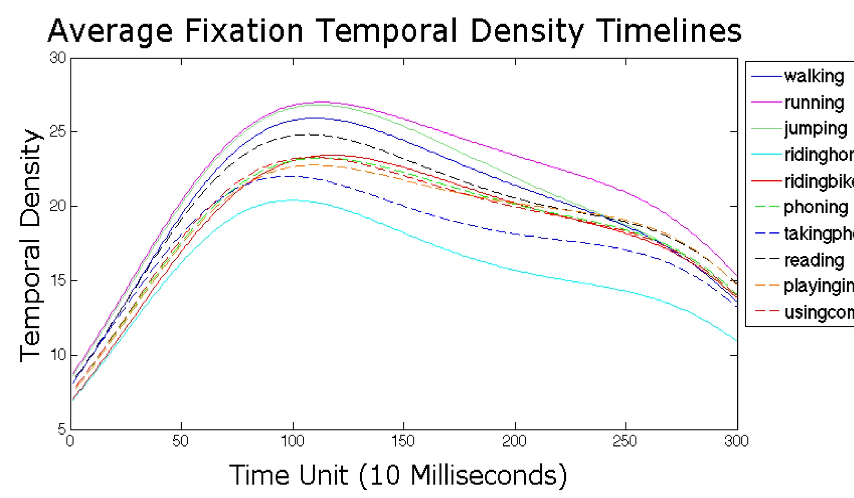
Gaze Features

- Some features used 9 grid regions, others used 3 (upper-body/lower-body/context).
- Fixation Density Maps (FDMs) generated by placing duration-weighted 2D Gaussian distribution at the location of each fixation on an image.
- Transitions between upper-body, lower body, and context segments were measured.
- Temporal Density Timelines generated by placing duration-weighted Gaussian distributions at each timestamp where a fixation occurs in the person bounding box.



Average FDMs for each action class, and the 9 segments from which features are extracted.

Gaze transitions measured between upper-body, lower-body and context segments.



Subjects looked at the person in the image within a second, then looked to context relevant objects.

Gaze Feature	Dim.
9 Region (FDM mean/max)	18
9 Region (transitions)	36
Upper/Lower/Context (fixation duration)	3
Upper/Lower/Context (transitions)	3
Temporal Density Timeline (mean/max)	12

Summary of feature types and dimensions.

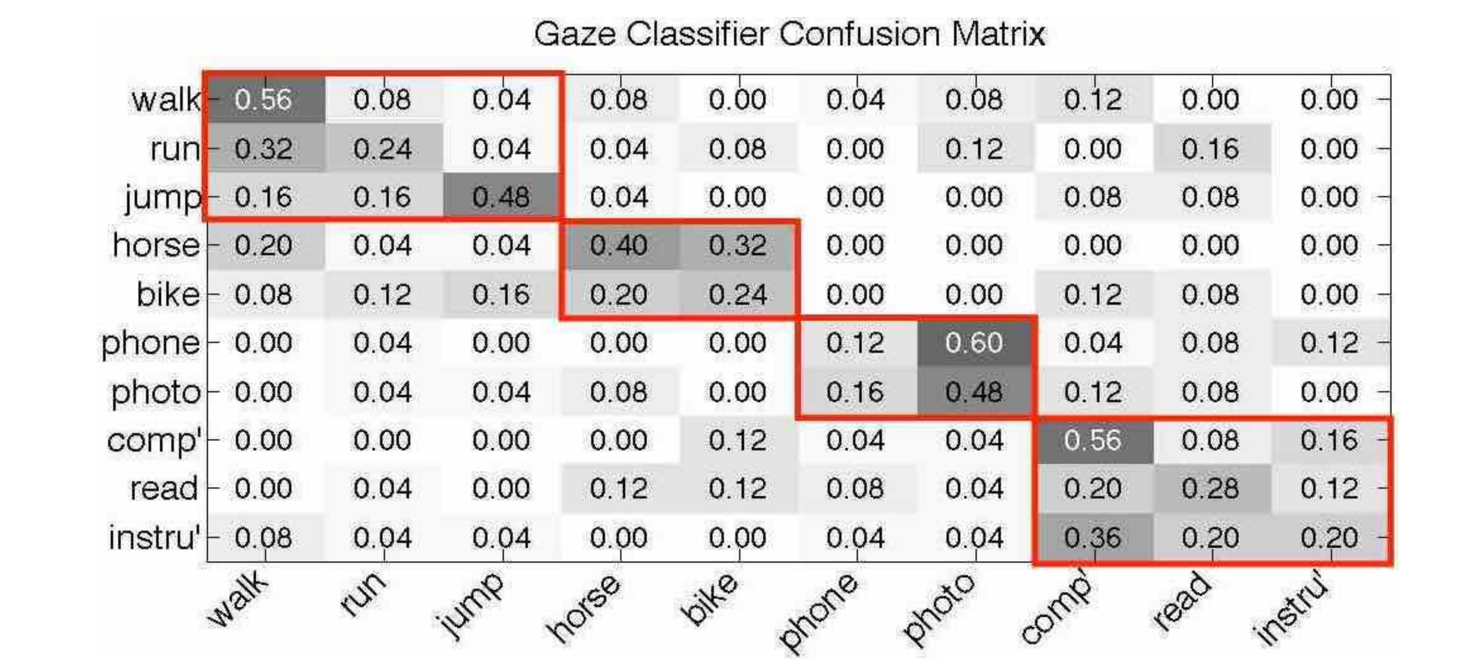
Classification results for 10 action classes

- Separate SVM classifiers were trained using gaze and CNN features.
- 2 different versions of baseline: CNN and CNN-MultiReg.
- Gaze and baseline were combined by summing weighted confidence scores.

	Gaze Features	CNN	CNN-MultiReg	Gaze + CNN	Gaze + CNN-MultiReg
walk	46.72	35.22	**58.03**	35.22	**58.03**
run	41.75	74.69	**77.70**	74.68	**77.70**
jump	41.65	74.03	**87.47**	78.59	**87.47**
horse	70.63	91.22	**98.41**	92.99	94.75
bike	34.15	**98.70**	96.63	**98.70**	96.63
phone	47.58	36.20	**49.29**	36.20	**49.29**
photo	46.24	42.53	**57.94**	42.54	**57.94**
comp'	38.74	**74.34**	72.84	**74.34**	72.84
read	35.01	59.73	58.46	**60.19**	58.46
instru'	36.08	60.95	**67.24**	60.96	**67.24**
mAP	43.86	64.76	**72.40**	65.44	72.04

Average Precisions (APs) for classification of 10 actions. Higher APs are bolded.

Gaze Classifier Confusion Matrix



The confusion matrix shows four groups of commonly-confused classes that are behaviorally meaningful. We retrained classifiers to discriminate between these groups.

Classification results for four class groups

- SVM classifiers were retrained to discriminate between four action groups:
  - walking + running + jumping
  - riding horse + riding bike
  - phoning + taking photo
  - using computer + reading + playing instrument

	Gaze Features	CNN	CNN-MultiReg	Gaze + CNN	Gaze + CNN-MultiReg
walk + run + jump	80.33	86.39	88.72	**92.29**	90.21
horse + bike	79.21	97.53	97.63	**98.99**	98.32
phone + photo	**81.64**	61.13	65.35	76.09	76.36
comp' + read + instru'	83.48	92.21	92.32	93.93	**94.10**
mAP	81.17	84.32	86.01	**90.33**	89.75

Average Precisions (APs) for classification of four action groups. A combination of gaze and CNN features performs best overall. Higher APs are bolded.

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