Actionness Estimation Using Hybrid Fully Convolutional Networks

Limin Wang[1,3] Yu Qiao[1] Xiaoou Tang[1,2] Luc Van Gool[3]

[1]MMLAB, SIAT, CAS, China [2]MMLAB, CUHK, Hong Kong [3]CVL, ETH Zurich, Switzerland

Introduction

- **Background**
  - Action classification can simply answer the question of "whether there is an action instance present in the video".
  - Action detection is able to provide the information of "where it is if there is an action instance in the video".
  - Sliding window is computationally prohibitive due to the huge number of spatio-temporal tube candidates.
  - Action proposal is a promising direction to reduce computational costs of action detection.
- **Action and actionness**
  - Action is defined as **intentional** bodily **movement** of biological **agents** (e.g. people, animals).
  - Actionness describes the confidence score of containing an action instance at this location.
  - Two important visual cues for actionness estimation: appearance and motion.
- **Method**
  - We formulate actionness estimation as a dense estimation problem by using fully convolutional network (FCN).
  - We propose a hybrid convolutional architecture (H-FCN), including appearance FCN (A-FCN) and motion appearance (M-FCN).
  - Additionally, actionness map is new kind of visual feature and we incorporate it into RCNN framework for action detection.

An example

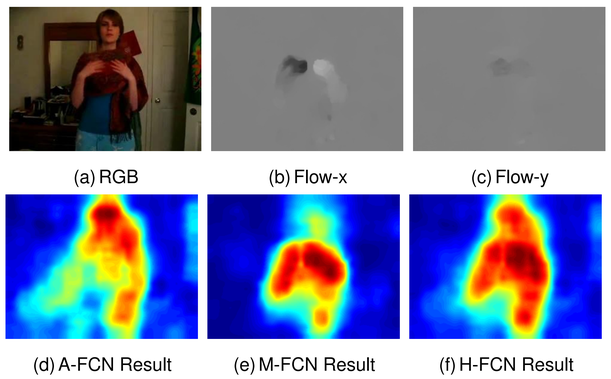

Figure 1: **An example of actionness maps**.

References

1. W. Chen, C. Xiong, R. Xu, and J. J. Corso. Actionness ranking with lattice conditional ordinal random fields. In CVPR, 2014.
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3. K. Simonyan, and A. Zisserman. Two-stream convolutional networks for action recognition in videos. In NIPS, 2014.
4. G. Gkioxari, and J. Malik. Finding action tubes. In CVPR, 2015.
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Actionness estimation with H-FCN

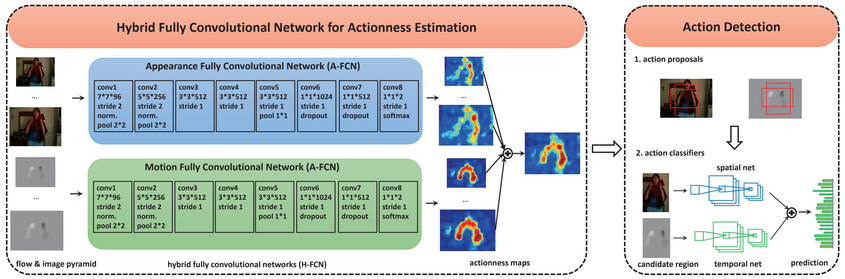


Figure 2: **Pipeline of our approach**.

- **Input**
  - A-FCN takes a single frame ($\boldsymbol{W} \times \boldsymbol{H} \times \mathbf{3}$).
  - M-FCN takes two consecutive frames ($\boldsymbol{W} \times \boldsymbol{H} \times \mathbf{4}$).
- **Architecture**
  - ClarifaiNet is adapted for H-FCN design by replacing FC layers and Conv layers.
- **H-FCN training**
  - Bounding boxes act as weak supervision signal for actionness estimation.
  - Pretraining A-FCN with ImageNet models (for object recognition).
  - Pretraining M-FCN with UCF101 models (for action recognition).
  - Training code is available at https://github.com/yjxiong/caffe.git [5].
- **H-FCN testing**
  - In realistic videos, action instances may vary in scales and we propose a multi-scale testing scheme.
  - We construct pyramid representations of RGB frames and stacking optical flow fields (four scales: $\mathbf{1}/\sqrt{\mathbf{2}}, \mathbf{1}, \sqrt{\mathbf{2}}, \mathbf{2}$).
  - These actionness maps from different scales are first up-sampled to the size of original image and then averaged.

Action proposal and action detection

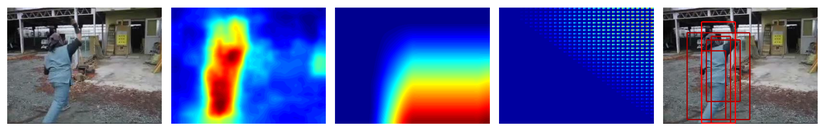


Figure 3: **Procedure of generating action proposals**.

- **Action proposal**
  - We first resize actionness maps into size of $\mathbf{32} \times \mathbf{32}$.
  - We then use integral image representation to speed up the calculation of average actionness score in any boxes.
  - We sample boxes according to their scores and spatial overlaps.
- **Action detection**
  - Following R-CNN, we train an action classifier with two-stream CNNs by cropping positive examples and mining negative examples.
  - At test time, we directly use the output of two-stream CNNs as the detection score for each action proposal.

Experimental results

Evaluation datasets: Stanford40, UCF Sports, and JHMDB.

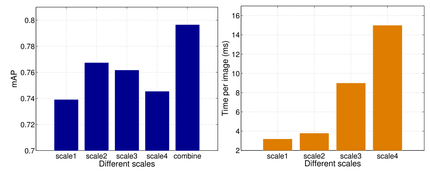


Figure 4: Exploration of multi-scale image representation for actionness estimation.

Method	Stanford 40	UCF Sports	JHMDB
L-CORF [1]	72.5%	60.8%	69.1%
DPM	**85.6%**	54.9%	58.2%
RankSVM	55.8%	21.9%	-
MBS	-	22.8%	-
A-FCN	79.7%	75.0%	80.7%
M-FCN	-	77.2%	80.6%
H-FCN	-	**82.7%**	**86.5%**

Table 1: Evaluation of actionness estimation.

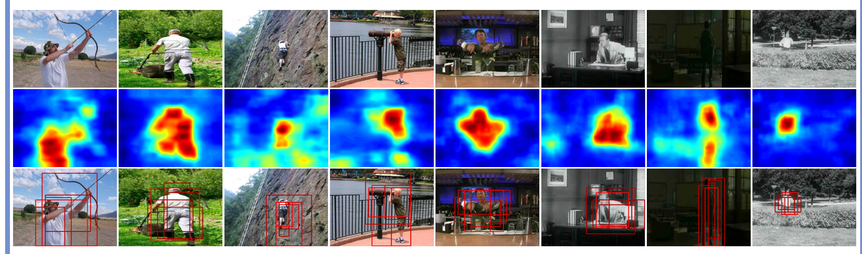
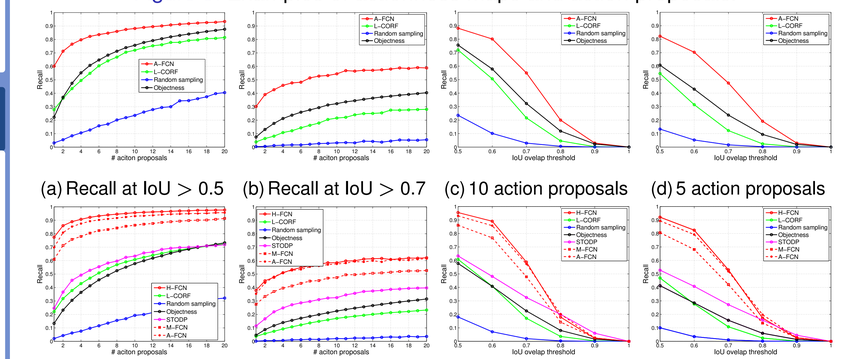


Figure 5: Examples of actionness maps and action proposals.



(a) Recall at IoU $>$ 0.5 (b) Recall at IoU $>$ 0.7 (c) 10 action proposals (d) 5 action proposals

(e) Recall at IoU $>$ 0.5 (f) Recall at IoU $>$ 0.7 (g) 10 action proposals (h) 5 action proposals

Figure 6: Evaluation of action proposals.

frame-AP(%)	brush-hair	catch	clap	climb	golf	jump	kick-ball	pick	pour	pullup	push	run	shoot-ball	shoot-bow	shoot-gun	sit	stand	swing-baseball	throw	walk	wave	mAP
spatial-CNN [4]	55.8	25.5	25.1	24.0	77.5	1.9	5.3	21.4	68.6	71.0	15.4	6.3	4.6	41.1	28.0	9.4	8.2	19.9	17.8	29.2	11.5	27.0
motion-CNN [4]	32.3	5.0	35.6	30.1	58.0	7.8	2.6	16.4	55.0	72.3	8.5	6.1	3.9	47.8	7.3	24.9	26.3	36.3	4.5	22.1	7.6	24.3
full [4]	**65.2**	18.3	38.1	**39.0**	79.4	7.3	9.4	25.2	**80.2**	**82.8**	**33.6**	11.6	5.6	66.8	27.0	**32.1**	34.2	33.6	15.5	**34.0**	**21.9**	36.2
our s-net	56.5	34.7	40.1	43.1	76.9	2.7	17.7	15.6	71.2	51.5	17.9	12.4	12.9	65.4	53.3	5.3	16.4	22.6	27.6	13.2	15.3	32.5
our t-net	42.9	19.0	49.6	28.9	71.8	14.0	20.4	36.6	60.1	66.0	18.0	17.3	8.3	73.5	26.0	11.6	44.1	53.7	17.6	22.4	11.5	34.0
our full net	60.1	**34.2**	**56.4**	38.9	**83.1**	**10.8**	**24.5**	**38.5**	71.5	67.5	21.3	**19.8**	**11.6**	**78.0**	**50.6**	10.9	**43.0**	**48.9**	**26.5**	25.2	15.8	**39.9**
video-AP(%)																						
spatial-CNN [4]	67.1	34.4	37.2	36.3	93.8	7.3	14.4	29.6	80.2	93.9	17.4	10.0	8.8	71.2	45.8	17.7	11.6	38.5	20.4	40.5	19.4	37.9
motion-CNN [4]	66.3	16.0	60.0	51.6	88.6	18.9	10.8	23.9	83.4	96.7	18.2	17.2	14.0	84.4	19.3	72.6	61.8	76.8	17.3	46.7	14.3	45.7
full [4]	**79.1**	33.4	53.9	**60.3**	**99.3**	18.4	26.2	42.0	**92.8**	**98.1**	29.6	24.6	13.7	**92.9**	42.3	**67.2**	57.6	66.5	27.9	58.9	**35.8**	53.3
our s-net	66.2	45.7	54.6	42.2	83.9	4.2	33.5	31.7	75.0	76.6	24.8	18.5	28.3	82.3	70.8	18.2	32.6	31.7	31.7	23.9	18.8	42.6
our t-net	64.2	38.1	80.1	39.0	91.8	34.7	57.4	74.6	74.5	77.6	31.3	40.9	18.5	89.4	59.0	32.3	69.3	82.9	25.8	46.1	22.2	54.8
our full net	76.4	**49.7**	**80.3**	43.0	92.5	**24.2**	**57.7**	**70.5**	78.7	77.2	**31.7**	**35.7**	**27.0**	88.8	**76.9**	29.8	**68.6**	**72.8**	**31.5**	**44.4**	26.2	**56.4**

Table 2: Evaluation of action detection on JHMDB dataset.