Localization using Faster R-CNN and Multi-Frame Fusion

Ryosuke Yamamoto, <u>Nakamasa Inoue</u>, Koichi Shinoda Tokyo Institute of Technology

Outline

Motivation: detect an action concept "SittingDown"

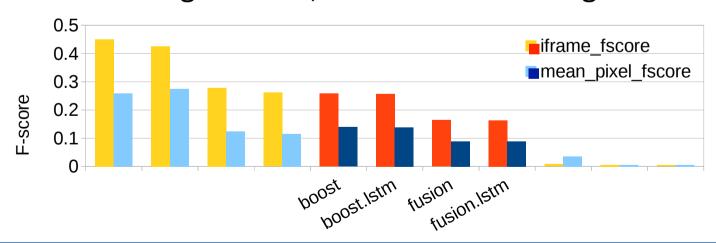
Our method: Faster R-CNN + LSTM + Re-scoring

Annotation: Frame-wise annotation for SittingDown,

Key-frame annotation for other concepts

Results:

2nd among 3 teams, best result at SittingDown



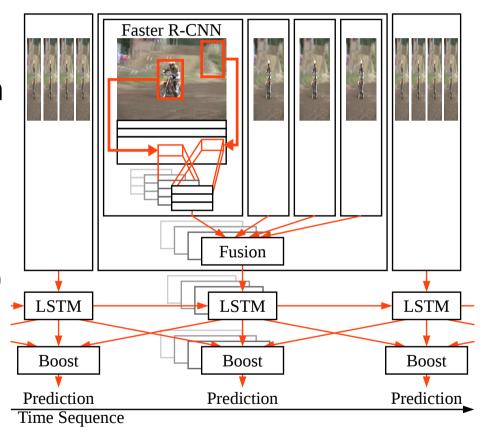
Motivation

- Localization task focuses not only on static objects, but also on action concepts
- We focus on SittingDown, one of action concepts
- How to distinguish between Sitting and SittingDown?
- → Dynamic information is important for precise detection



Our Method

- Faster-RCNN (Ren 2015)
 - Efficient object localization
- LSTM (Donahue 2015)
 - Precise action localization
 - Applied to SittingDown
- Re-scoring (Yamamoto 2015)
 - Multi-frame Score Fusion
 - Multi-Shot Score Boosting



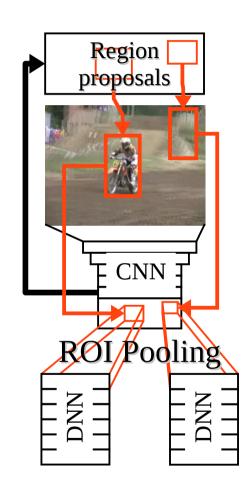
Faster R-CNN (Ren 2015)

Efficient End-to-End object localization

- 1. Generate region proposals by a network
- 2. Predict scores for each region by using CNN features

Example CNNs:

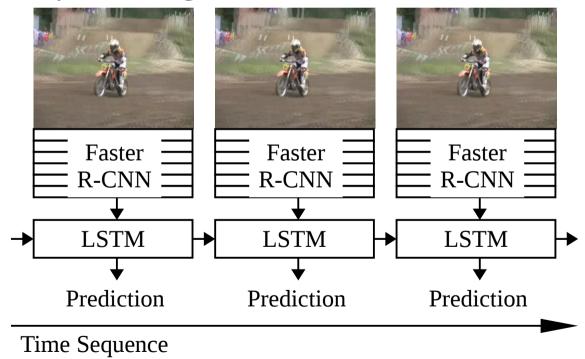
- ZF Net (Zeiler 2014) ← we use
- VGG-16 (Simonyan 2014)
- GoogLeNet (Szegedy 2015)
- ResNet (He 2016)



Long Short-Term Memory (LSTM)

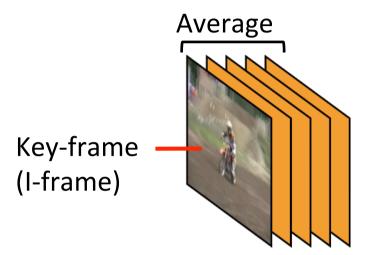
An LSTM layer is introduced to Faster R-CNN

- memorize long and short term information
- applied only to SittingDown



Multi-Frame and Multi-Shot (Yamamoto 2015)

- Multi-Frame Score Fusion
 Average pooling of scores over
 5 frames in a shot
- Multi-Shot Score Boosting Add adjacent shot scores





$$score^{boost}(r_i^t) = score(r_i^t) + \beta \max_{j} \frac{r_i^t \cap r_j^{t\pm 1}}{r_i^t \cup r_j^{t\pm 1}}$$

 r_i^t : *i*th region in time t; β : multiplier

Key-Frame Annotations

Bounding-box annotation on the representative key-frame for each shot labeled as positive in collaborative annotation



Con	cept	# frames	# boxes	Concept	# frames	# boxes
Anir	mal	11,545	9,155	Inst.Musician	4,923	7,229
Bicy	cling	599	1,355	Running	945	1,394
Boy		1,848	2,492	SittingDown	-	-
Dan	cing	2,118	5,199	Baby	898	895
Expl	osionFire	2,483	2,402	Skier	320	521

I-Frame Annotations for SittingDown

- I-Frame annotation for SittingDown to train LSTM
- Annotation results

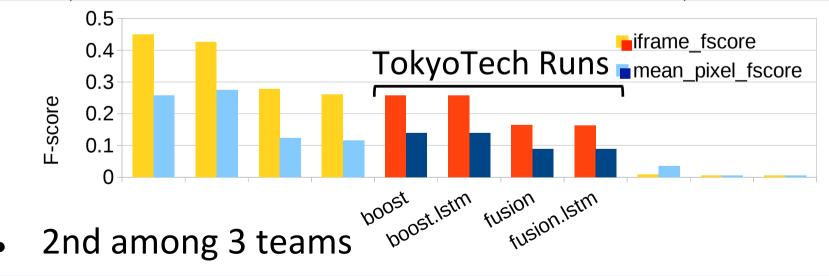
```
# shots = 92
# frames = 481
# bounding-boxes = 515
```



* We found SittingDown in only 92 shots in the 3K shots labeled as positive in collaborative annotation

Results

ID	Method	RunID
1*	Faster R-CNN + Multi-Frame Score Fusion	fusion
2*	1 + Multi-Shot Score Boosting	boost
3*	1 + LSTM(4096units) for SittingDown	fusion.lstm
4*	2 + LSTM(4096units) for SittingDown	boost.lstm
5	2 + LSTM(64units) for SittingDown	(post exp.)



Results for SittingDown

Best result for SittingDown with run #2 LSTM with 4096 units (run #4) did not work

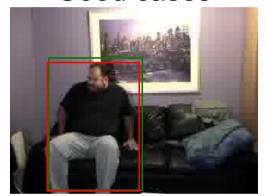
→ LSTM with 64 units (run #5) avoided over-fitting and worked in post submission experiment

ID	Method	I-Frame F-score	Pixel F-score
2*	Fusion + Boosting	0.63	0.22
	2 + LSTM (4096units)	0.00	0.00
5	2 + LSTM (64units)	11.96	4.51

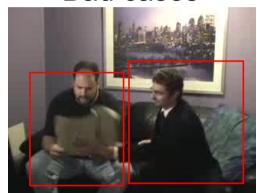
SittingDown

Re-trained network with LSTM 64 units

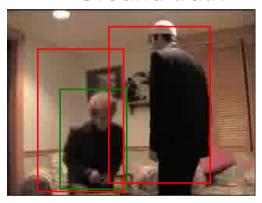
Good cases



Bad cases



System output Ground truth



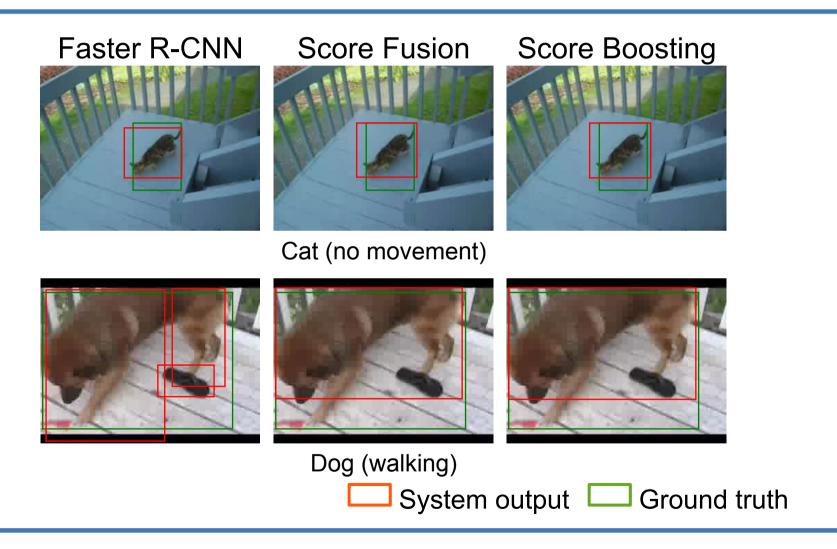




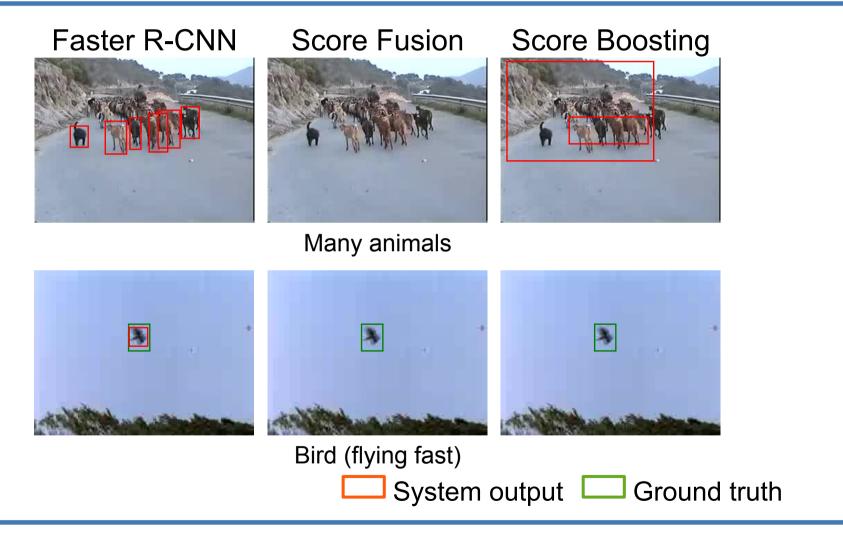
Sitting down

Moving but not sitting down Moving around a chair

Animal, Good Results



Animal, Bad Results



Faster R-CNN Score Fusion **Score Boosting** Bicycling Boy System output Ground truth

Faster R-CNN



Score Fusion



Score Boosting



Dancing







ExplosionFire





Faster R-CNN



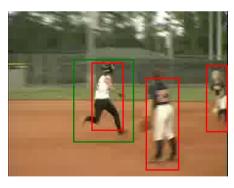
Score Fusion



Score Boosting



InstrumentalMusician





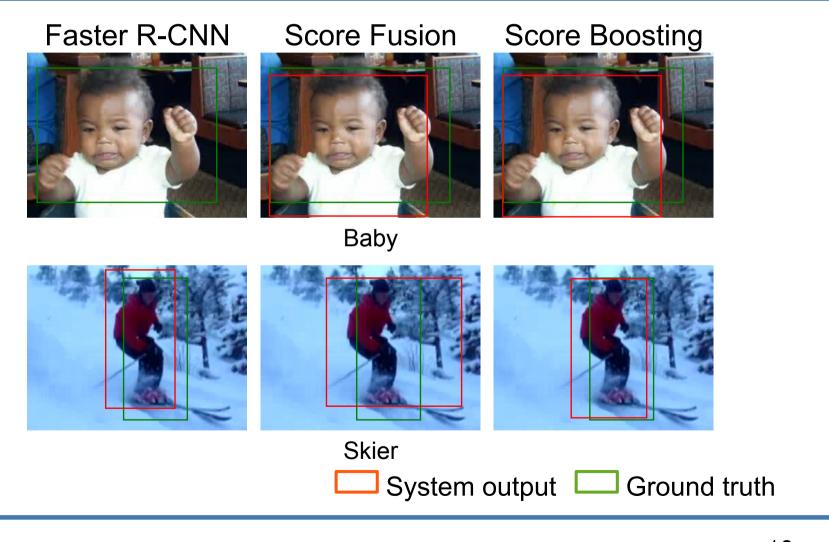


Running



System output Ground truth





Conclusion & Future Work

- We proposed a localization system
 - Faster R-CNN + LSTM + Re-scoring
- Manual annotation
 - 31K bounding boxes
- Results
 - 2nd among 3 teams, best result at SittingDown
 - LSTM with 64 units was effective for SittingDown
- Future work
 - Find a better way to localize action