

DL Seminar

MOTDT

REAL-TIME MULTIPLE PEOPLE TRACKING WITH DEEPLY LEARNED CANDIDATE SELECTION AND PERSON RE-IDENTIFICATION



인공지능 연구실 김지성

Introduction

Detector, Tracker



Detector



Frame 1



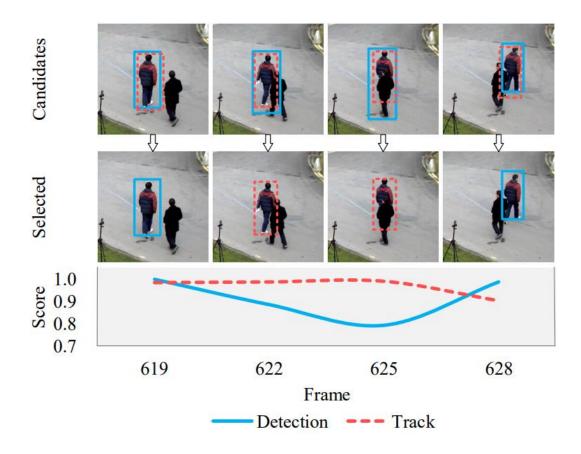
Frame 2

Frame 3



Introduction

Candidates



후보 필터링

Algorithm 1: The proposed tracking algorithm.

```
Input: A video sequence v with N_v frames and object detection
              \{\mathcal{D}_k\}_{k=1}^{N_v}
    Output: Tracks \mathcal{T} of the video
 1 Initialization: \mathcal{T} \leftarrow \emptyset; appearance of tracks \mathcal{F}_{trk} \leftarrow \emptyset
 2 foreach frame f_k in v do
          Estimate score maps z from f using R-FCN
          /* collect candidates */
          C_{det} \leftarrow \mathcal{D}_k; C_{trk} \leftarrow \emptyset
          foreach t in T do
                Predict new location x^* of t using Kalman filter
                C_{trk} \leftarrow C_{trk} \cup \{\mathbf{x}^*\}
 8
          end
          /* select candidates */
          C \leftarrow C_{det} \cup C_{trk}
          S \leftarrow unified scores computed from Equation 3
          C, S \leftarrow \text{NMS}(C, S, \tau_{nms})
          C, S \leftarrow \text{Filter}(C, S, \tau_s) // \text{ filter out if } s < \tau_s
          /* extract appearance features */
          \mathcal{F}_{det} \leftarrow \emptyset
13
          foreach x in C_{det} do
14
                I_x \leftarrow Crop(f_k, x)
15
               \mathcal{F}_{det} \leftarrow \mathcal{F}_{det} \cup H_{reid}(\mathbf{I_x})
17
          /* hierarchical data association */
          Associate T and C_{det} using distances of F_{trk} and F_{det}
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          Associate remaining tracks and candidates using IoU
19
          \mathcal{F}_{trk} \leftarrow \mathcal{F}_{trk} \cup \mathcal{F}_{det}
          /* initialize new tracks */
          C_{remain} \leftarrow remaining candidates from C_{det}
21
          \mathcal{F}_{remain} \leftarrow \text{features of } C_{remain}
          \mathcal{T}, \mathcal{F}_{trk} \leftarrow \mathcal{T} \cup C_{remain}, \mathcal{F}_{trk} \cup \mathcal{F}_{remain}
24 end
```



Tracking 결과 출력 🔻

후보 필터링

후보 x에 대한 Rol 분류확률
$$p(y|\mathbf{z},\mathbf{x}) = \sigma(\frac{1}{wh}\sum_{i=1}^{k^2}\sum_{(x,y)\in bin_i}\mathbf{z}_i(x,y)),$$
 (1)

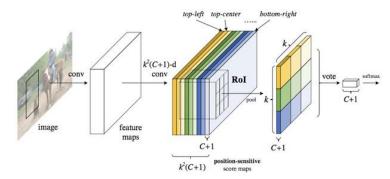


Figure 1: Key idea of R-FCN for object detection. In this illustration, there are $k \times k = 3 \times 3$ position-sensitive score maps generated by a fully convolutional network. For each of the $k \times k$ bins in an RoI, pooling is only performed on one of the k^2 maps (marked by different colors).

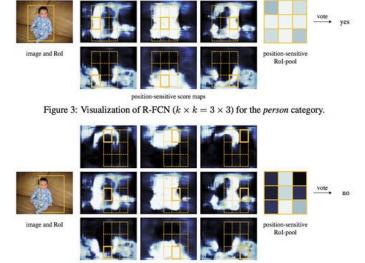


Figure 4: Visualization when an RoI does not correctly overlap the object.

position-sensitive score maps

후보 필터링

Tracklet 신뢰도

$$s_{trk} = \max(1 - \log(1 + \alpha \cdot L_{trk}), 0) \cdot \mathbb{1}(L_{det} \ge 2), \quad (2)$$

Ltrk : 최종적으로 트래킹한 결과의 수 Ldet : 최종적으로 탐지한 결과의 수

적어도 탐지된 결과가 2개 이상이고, 최종 트래킹 수가 적을수록 신뢰도가 높다



후보가 많을 수록 신뢰도가 낮음



후보가 적을 수록 신뢰도가 높음

후보 필터링

후보 x에 대한 score 계산

$$s = p(y|\mathbf{z}, \mathbf{x}) \cdot (\mathbb{1}(\mathbf{x} \in C_{det})) + s_{trk} \mathbb{1}(\mathbf{x} \in C_{trk})). \tag{3}$$

X : 후보

P(y|z, x) : 식 1에서 계산된 신뢰도

Strk: 식 2에서 계산된 신뢰도

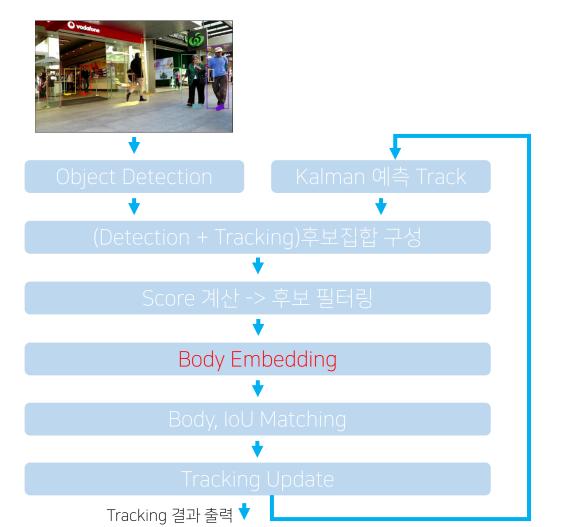
R-FCN으로 계산한 점수 + Tracklet(후보) 신뢰도

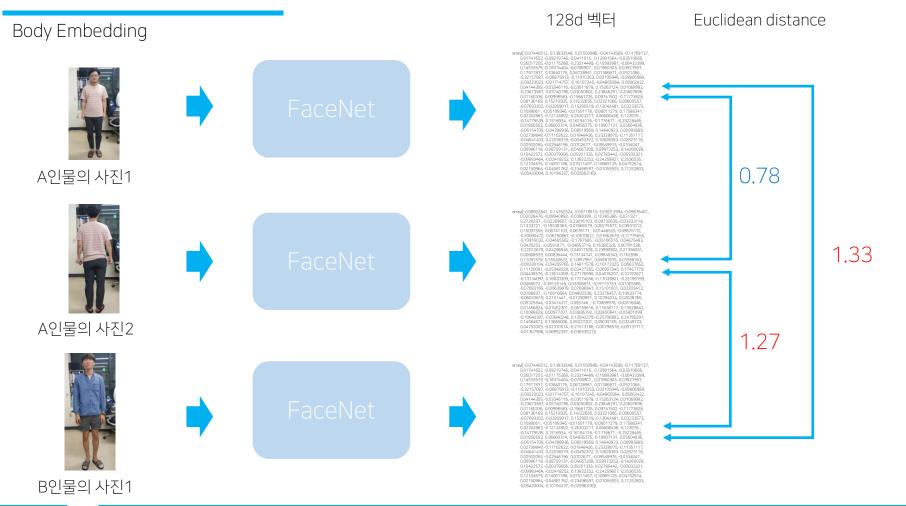
만약 최종 신뢰도 s가 0.4 이하라면 후보를 버린다.

Body Embedding

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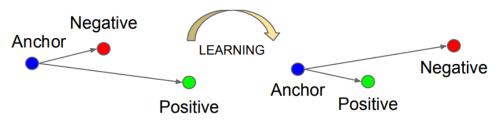


Body Embedding - Triplet

$$l_{triplet} = \frac{1}{N} \sum_{\langle \mathbf{I}_i, \mathbf{I}_j, \mathbf{I}_k \rangle \in \mathbf{T}} \max(d_{ij} - d_{ik} + m, 0), \quad (4)$$

Triplet:세개의데이터

- Anchor (x_i^a) : 기준 인물의 벡터
- Positive(x_i^p): 기준과 같은 인물의 벡터
- Negative(x_i^n): 기준과 다른 인물의 벡터



기준 인물과 같은 인물은 가깝도록, 기준 인물과 다른 인물은 멀도록

Person Re-Identification 평균 거리 11.24(0제외) Jiseong iseong 0, gunhee0 28.64 gunhee 27.87 iseong 3, gunhee3 : 23.1914684226621 장균거리 : 28.6442521100325 supil iseong 3, supil1 : 23.8073005976364 iseong 3, supil2 : 27.0416266409934 iseong 3, supil3 : 20.8900794862151 물균거리 : 27.871751142991

jiseong

iiseong

gunhee2

jiseong 2

: 13.1192839922723

iseong O iiseong 2

Matching

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Matching

1. 후보와 Active tracklet을 Body Feture를 이용하여 매칭

이전 프레임



- Active Tracklet
- 그 후보

Body Feature Threshold: 0.64

IoU Threshold: 0.4

현재 프레임



Matching

2. 후보와 Lost Tracklet과 Body Feature를 이용하여 매칭

이전 프레임 1



이전 프레임 2



Tracking Object를 잃어버림

현재 프레임



- Active Tracklet
- Lost Tracklet
- 그 후보

Body Feature Threshold: 0.64

IoU Threshold: 0.4

Matching

3. 후보와 Active tracklet을 IoU를 이용하여 매칭

이전 프레임



- Active Tracklet
- 그 후보

IoU Threshold: 0.7

현재 프레임



Matching

4. 후보와 Lost Tracklet과 IoU를 이용하여 매칭

이전 프레임 1



이전 프레임 2



Tracking Object를 잃어버림

현재 프레임



Active Tracklet

■ Lost Tracklet

고 후보

IoU Threshold: 0.7

MOTA



Ground Truth와 관심영역의 IOU가 0.5 이상일 때 True로 판단

MOTA: tracker 성능지표로 적합

$$MOTA = 1 - \frac{\sum_{t} (FN_t + FP_t + IDSW_t)}{\sum_{t} GT_t},$$
 (1)

t: 프레임 인덱스

FN : 잘못탐지

FP : 놓친 객체

IDSW: id가 바뀐 횟수

GT: Ground Truth의 수

IDF1

IDF1: 얼마나 지속적으로 객체를 동일하게 판단하는가

TP: 가장 많이 나온 ID의 개수 = 12

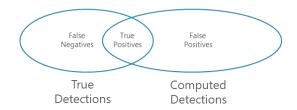
FP: 나머지 ID의 개수 = 2

FN: True - TP = 4

• ID Precision
$$P = \frac{TP}{TP + FP} = \frac{TP}{C}$$

• ID Recall
$$R = \frac{TP}{TP + FN} = \frac{TP}{T}$$

• F₁-score $F_1=2\frac{PR}{P+R}=\frac{TP}{\frac{T+C}{T+C}}$



Vision Module

MOT Challenge

Method	C	T	A	MOTA↑	IDF1↑	IDS↓	FAF↓
Baseline				28.4	32.8	628	0.85
	✓			33.0	37.6	445	0.77
	✓	✓		33.7	37.3	475	0.63
			\checkmark	30.6	42.4	234	1.01
Proposed	✓	✓	✓	35.7	45.3	184	0.58

Method	Length	MOTA ↑	IDF1↑	IDS↓	FAF↓
None	-	33.7	37.3	475	0.63
Color histogram	750	34.9	38.6	250	0.73
HOG	1152	34.6	38.5	317	0.70
Color + HOG	1902	34.7	39.3	307	0.68
ReID feature	512	35.7	45.3	184	0.58

Tracker	Method	MOTA (%)↑	IDF1(%) ↑	IDR (%)↑	MT (%)↑	ML(%)↓	FP↓	FN↓	IDS↓	FPS↑
LINF1 [2]	batch	41.0	45.7	34.2	11.6	51.3	7,896	99,224	430	4.2
MHT_DAM [5]	batch	45.8	46.1	35.3	16.2	43.2	6,412	91,758	590	0.8
JMC [11]	batch	46.3	46.3	35.6	15.5	39.7	6,373	90,914	657	0.8
LMP [6]	batch	48.8	51.3	40.1	18.2	40.1	6,654	86,245	481	0.5
EAMTT [7]	online	38.8	42.4	31.5	7.9	49.1	8,114	102,452	965	11.8
CDA_DDAL [1]	online	43.9	45.1	34.1	10.7	44.4	6,450	95,175	676	0.5
STAM [8]	online	46.0	50.0	38.5	14.6	43.6	6,895	91,117	473	0.2
AMIR [3]	online	47.2	46.3	34.8	14.0	41.6	2,681	92,856	774	1.0
MOTDT (Ours)	online	47.6	50.9	40.3	15.2	38.3	9,253	85,431	792	20.6

감사합니다.