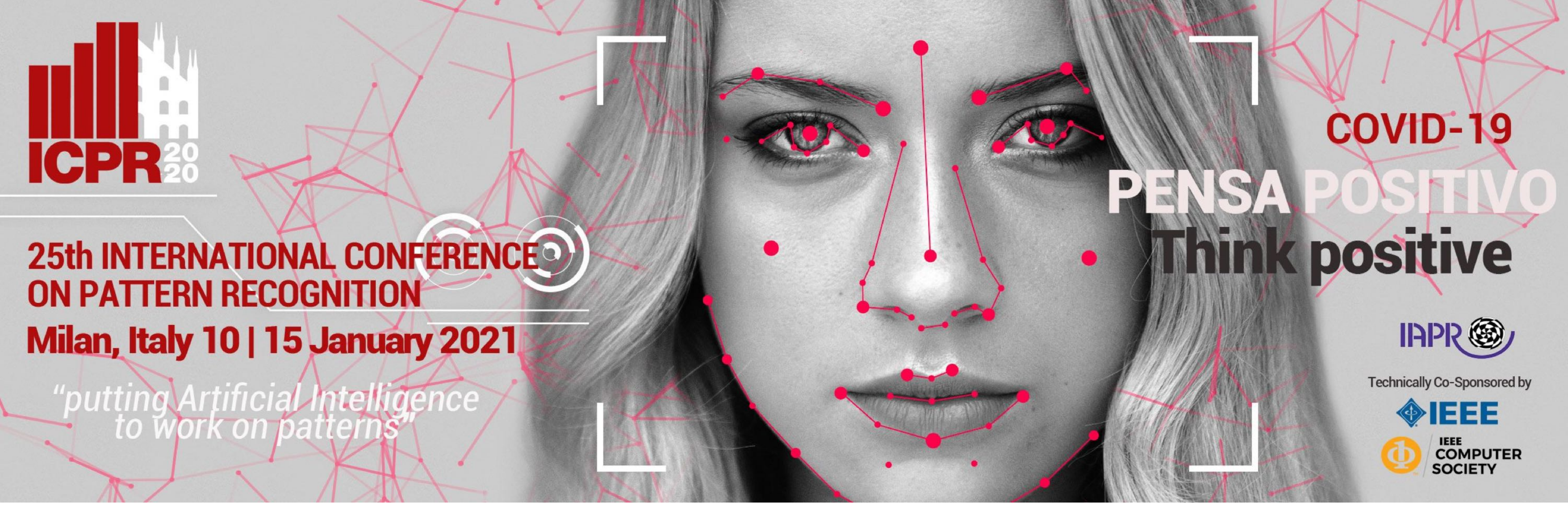

Unsupervised Moving Object Detection through Background Models for PTZ Camera

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Overview: Moving Object Detection in PTZ camera

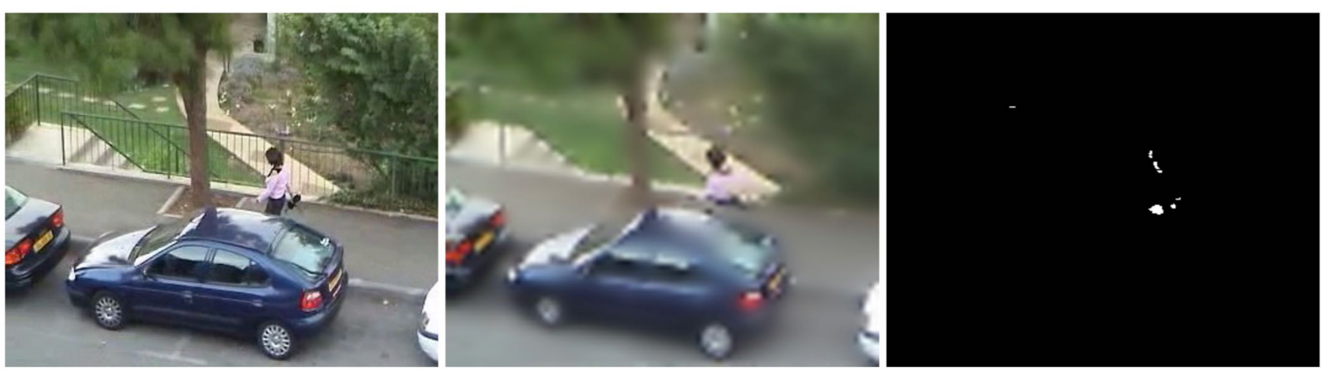
- Related research area

  ≈ video object detection / segmentation
  - supervised method / human intervention for first frame
- Ours: Background-Centric approach
  - Visual surveillance and monitoring
  - Strength: Unsupervised method / Real-time operation without GPU

Overview

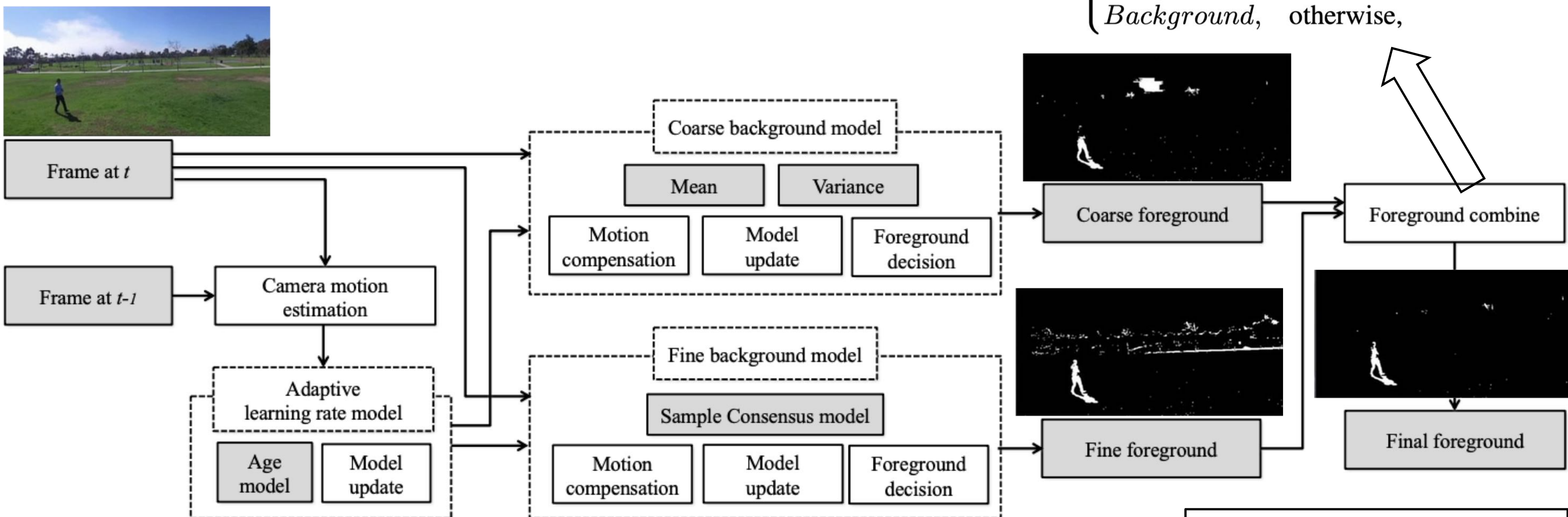
- Naive approach
  - Background modeling with Gaussians (mean, variance)
  - Apply the affine/projective transform for Moving Camera
  - Problem: Too many false positives

- Conventional approach
  - Reduce the false positives
  - Apply the Spatio-Temporal background modeling
  - Problem: Foreground loss caused by background contamination



Proposed method

$$l_{init}(i) = \begin{cases} Foreground, & \text{if } l_c(i) \wedge l_f(i) = True, \\ Candidate, & \text{if } l_c(i) \vee l_f(i) = True, \\ Background, & \text{otherwise,} \end{cases}$$



white: function block

gray: memory block

- The overall framework of the proposed method
  - Build the fine background models by extending ViBe*
    - spatio-temporal update is applied
    - model initialization and update rule is changed by camera movement
  - Combine the coarse and fine foreground using Watershed segmentation

[1] ViBe: O. Barnich and M. Van Droogenbroeck, "ViBe: A Universal Background Subtraction Algorithm for Video Sequences." IEEE Trans Image Process, vol. 20, no. 6, pp. 1709–1724, 2011.

Proposed method

- Fine background model
  - reduce the background contamination

Input | coarse background | fine background

Algorithm 1: Updating the fine background model

for *Each pixel i on current frame $I^{(t)}$* **do**
  if $t = 0$ **then**
    $\mathbf{M}_i$ is initialized to $\{I_i^{(0)}, I_i^{(0)}, ..., I_i^{(0)}\}$
  else
    Motion compensation is applied to $\mathbf{M}_i$.
    if $t < N$ **then**
      $\tilde{v_i}^{(t)}$ is removed from $\mathbf{M}_i$
      $I_i^{(t)}$ is inserted to $\mathbf{M}_i$
    Compute C_i in equation (8)
    if $C_i \geqslant \#_{min}$ **then**
      $P \leftarrow \min(\alpha_i, \phi)$
      $p \sim Uniform(0, P-1)$
      if $p = 0$ **then** ▷ update for pixel i
        $n \sim Uniform(0, N-1)$
        $\tilde{v_i}^{(n)}$ is removed from $\mathbf{M}_i$
        $I_i^{(t)}$ is inserted to $\mathbf{M}_i$
      $p_2 \sim Uniform(0, P-1)$
      if $p_2 = 0$ **then** ▷ update for neighbor pixel j
        $k \sim Uniform(0, K)$
        $j \leftarrow S_i(k)$
        $n \sim Uniform(0, N-1)$
        $\tilde{v_j}^{(n)}$ is removed from $\mathbf{M}_j$
        $I_i^{(t)}$ is inserted to $\mathbf{M}_j$

camera movement handling

model initialize update

modified model update rule

$$C_i = \sum_{j \in S_i} \sum_{n=1}^{N} \mathbb{1}(D(I_i, \tilde{v_j}^{(n)}) < R), \quad (8)$$

spatio-temporal update rule

Experiments

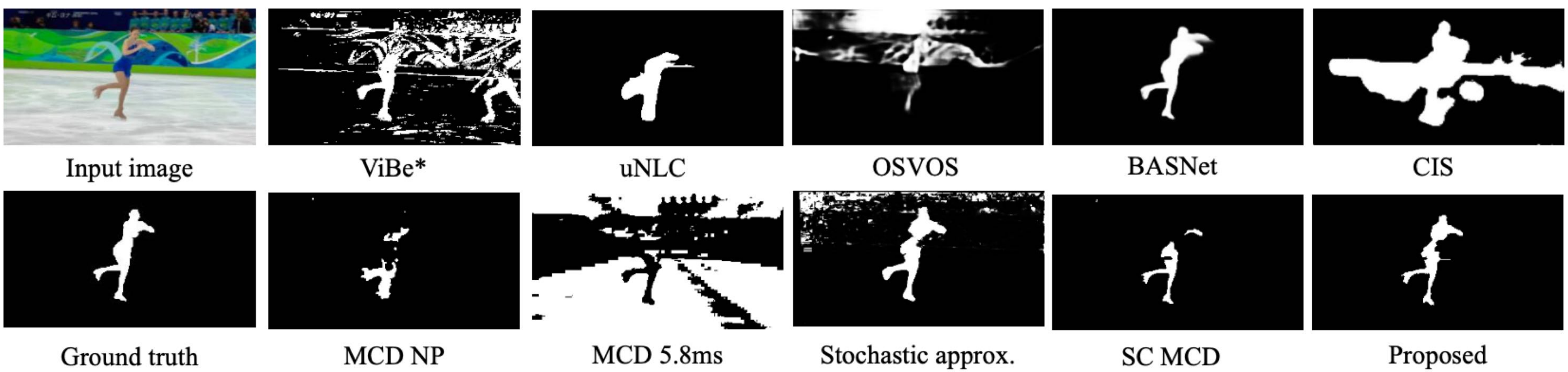
- Compared methods
  - Object-centric methods
    - uNLC (unsupervised version of NLC)
    - OSVOS (video object segmentation without finetuning)
    - CIS
    - BASNet (Salient object detector)
  - Background-centric methods
    - Background modeling + Naive extension (ViBe*, FIC*, BMRI-ViBe*)
    - Conventional methods: MCD NP, MCD 5.8ms, Stochastic approx, FP Sampling, , SC MCD
- Dataset
  - Moving camera dataset from SC MCD

< Reference >
NLC – A. Faktor and M. Irani, "Video Segmentation by Non-Local Consensus voting,," in *BMVC*, 2014.
OSVOS – S.Caelles et al., "One-Shot video object segmentation," in *CVPR*, 2017.
CIS – Y. Yang et al., "Unsupervised moving object detection via contextual information separation," in *CVPR*, 2019.
BASNet – X. Qin et al., "BASNet: Boundary-Aware Salient Object Detection," in *CVPR*, 2019.
ViBe – O. Barnich and M. Van Droogenbroeck, "ViBe: A Universal Background Subtraction Algorithm for Video Sequences." *IEEE Trans Image Process*, 2011.
FIC – J. Choi et al., "Robust moving object detection against fast illumination change," *Comput Vis Image Und*, 2012.
BMRI-Vibe – F. C. Cheng et al., "A background model re-initialization method based on sudden luminance change detection," *Eng Appl Artif Intell*, 2015.
MCD NP – Kim et al., "Detection of moving objects with a moving camera using non-panoramic background model," *Mach Vis Appl*, 2012.
MCD5.8ms – Yi et al., "Detection of Moving Objects with Non-stationary Cameras in 5.8ms: Bringing Motion Detection to Your Mobile Device," in *CVPR Workshop*, 2013.
Stochastic approx – F. J. Lo ́pez-Rubio and E. Lo ́pez-Rubio, "Foreground detection for moving cameras with stochastic approximation," *Pattern Recognit Lett*, 2015.
FP Sampling – K. Yun and J. Y. Choi, "Robust and fast moving object detection in a non-stationary camera via foreground probability based sampling." in *ICIP*, 2015.
SC MCD – K. Yun et al., "Scene conditional background update for moving object detection in a moving camera," *Pattern Recognit Lett*, 2017.

Experiment results

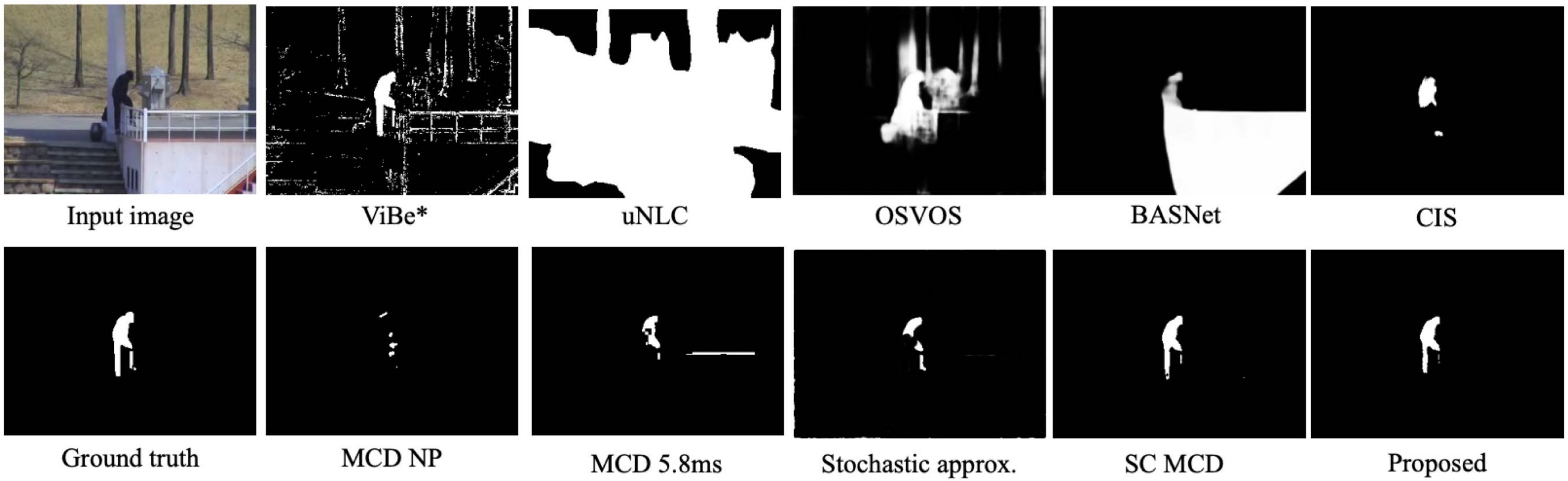
- F-score measure

Method	walking	skating	woman	woman2	fence	ground1	ground2	ground3	ground4	ground5	average
ViBe* [6]	0.0375	0.2229	0.0375	0.0929	0.1042	0.5656	0.4733	0.4118	0.0299	0.1309	0.2107
FIC* [8]	0.0613	0.2373	0.0361	0.1345	0.0954	0.4543	0.4108	0.1538	0.0453	0.1319	0.1761
BMRI-ViBe* [9]	0.0438	0.2402	0.0400	0.0921	0.1104	0.4249	0.3868	0.2161	0.0383	0.1377	0.1730
MCD NP [25]	0.4351	0.4164	0.4935	0.5791	0.2691	0.2773	0.3750	0.1222	0.1969	0.3540	0.3519
MCD 5.8ms [26]	0.7349	0.2447	0.3395	0.3448	0.7357	0.6573	0.7177	0.1531	0.5274	0.0678	0.4523
Stochastic approx [28]	**0.8335**	0.6543	0.3986	**0.8783**	**0.8788**	0.2221	0.2792	0.0181	0.0111	0.2181	0.4392
FP Sampling [27]	0.7058	0.8539	0.7268	0.5828	0.7654	0.7977	0.8306	0.1396	0.4226	0.8212	0.6646
SC MCD [29]	0.7496	0.8560	0.6650	0.6311	0.7637	0.8965	**0.9118**	0.8843	0.8824	0.9326	0.8173
uNLC [32]	0.0158	0.1419	0.0178	0.0487	0.0346	0.0570	0.0342	0.0216	0.0031	0.0143	0.0389
OSVOS [1]	0.3397	0.5344	0.0121	0.1260	0.7033	0.7697	0.5447	**0.9696**	0.0050	0.1224	0.4127
CIS [33]	0.0538	0.3036	0.1522	0.4681	0.1180	0.1545	0.0862	0.0581	0.0046	0.0184	0.1418
BASNet [34]	0.3433	0.9379	0.0205	0.2289	0.2119	0.6039	0.9564	0.9586	**0.9439**	**0.9829**	0.6188
Proposed method	0.7809	**0.9600**	**0.7269**	0.7065	0.8081	**0.9037**	0.9032	0.8700	0.9080	0.9793	**0.8546**

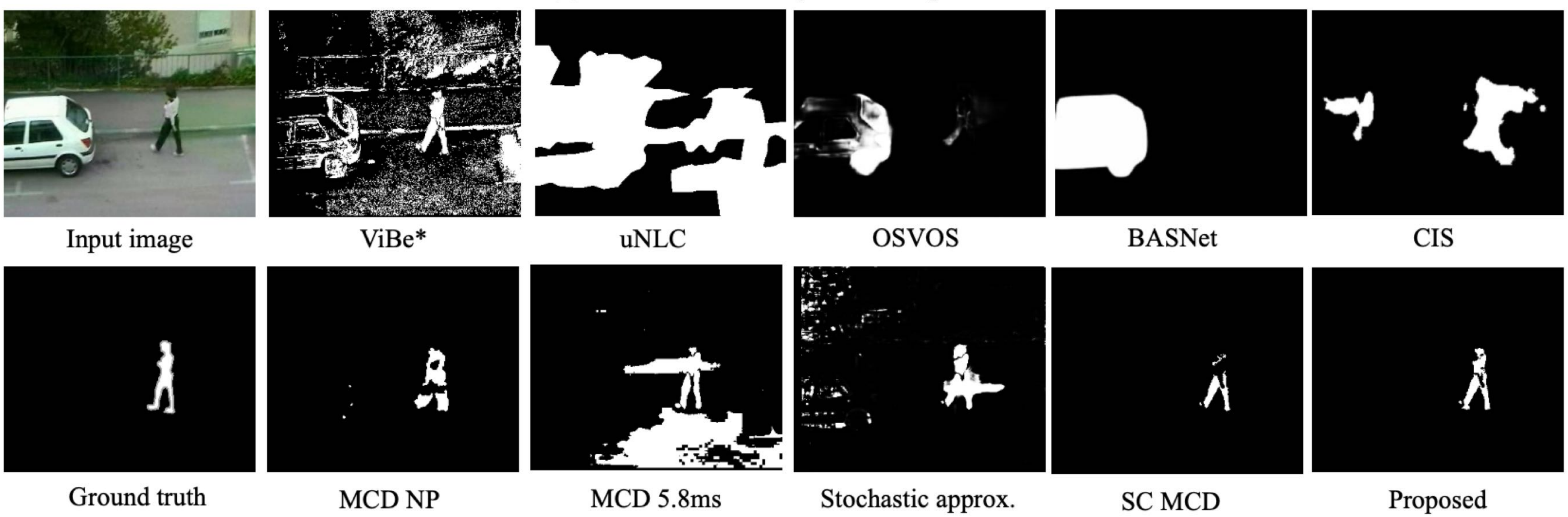


(a) Results of the *skating* sequence.

Experiment results



(a) Results of the *fence* sequence.



(b) Results of the *woman* sequence.

Experiment results

- Measure from video object segmentation

Measure	Mean $\mathcal{J}$	Recall $\mathcal{J}$	Mean $\mathcal{F}$	Recall $\mathcal{F}$
ViBe* [6]	0.2095	0.1364	0.1717	0.0773
FIC* [8]	0.1701	0.0607	0.2256	0.1337
BMRI-ViBe* [9]	0.1640	0.0553	0.1703	0.0817
MCD NP [25]	0.2634	0.0580	0.5569	0.7090
MCD 5.8ms [26]	0.3736	0.3756	0.5427	0.6100
Stochastic approx [28]	0.3398	0.3789	0.4003	0.4245
FP Sampling [27]	0.4294	0.5009	0.6031	0.7156
SC MCD [29]	0.5213	0.5952	0.7021	0.8200
uNLC [32]	0.1073	0.1002	0.1416	0.1181
OSVOS [1]	0.2547	0.2259	0.4129	0.3068
CIS [33]	0.1583	0.0591	0.2356	0.1253
BASNet [34]	0.5540	0.6204	0.6696	0.6880
Proposed method	**0.5603**	**0.6541**	**0.7214**	**0.8378**

$\mathcal{J}$: region-based segmentation similarity
$\mathcal{F}$: contour-based accuracy

- Synergy effect of two backgrounds

Method	*precision*	*recall*	F-measure
coarse BG model	0.9084	0.7655	0.8248
fine BG model	0.5669	0.7833	0.6095
combined model	0.9286	0.8041	0.8546

- Computations

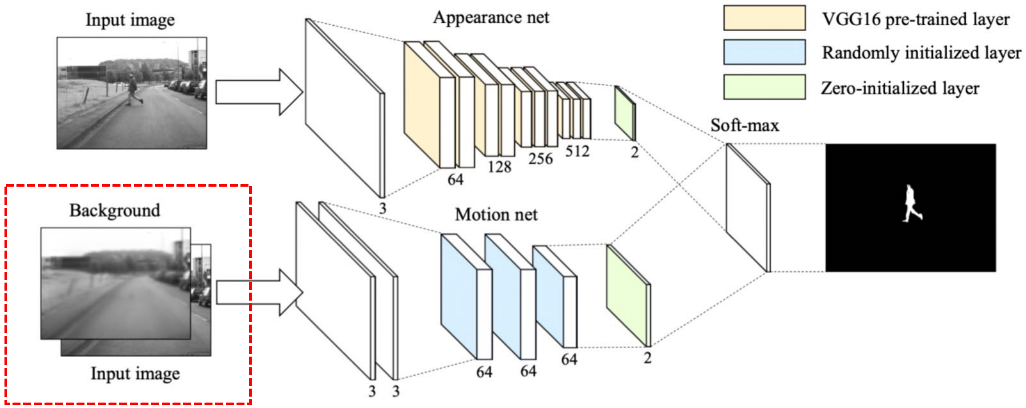
Module	Time (millisecond)
Motion estimation	2.207
Motion compensation	5.117
Age map update	0.595
Background model update	13.902
Foreground combining	0.671
Total	22.492

CPU only, 320 x 240, 45.5fps

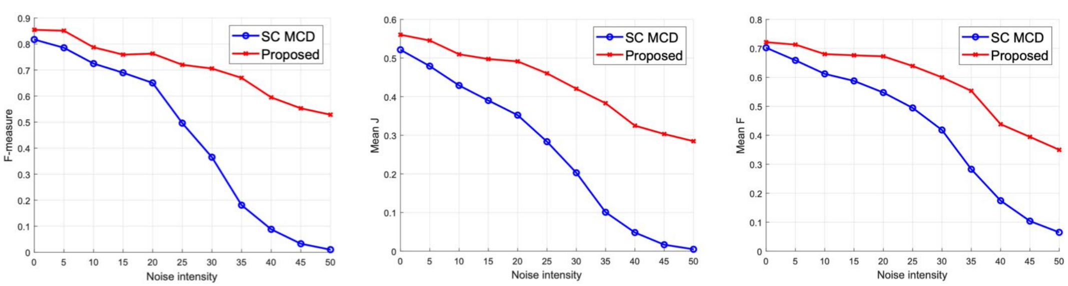
Experiment results

- Combined with supervised method (AMNet*)

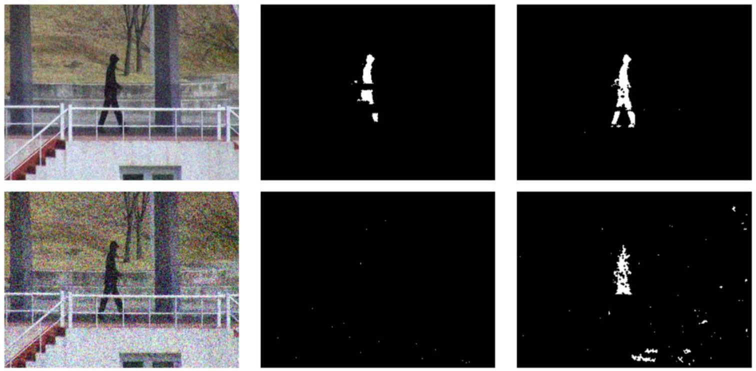
Method	F-measure
AMNet [37] using MCD 5.8ms [26]	0.8789
AMNet [37] using SC MCD [29]	0.9175
AMNet [37] using Proposed BG	0.9529



- Robustness test to image noise



Performance change according to image noise intensity: F-measure, Mean J, Mean F



(a) Input (b) SC MCD (c) Proposed

Fig. 7. Example results for the noisy images. Each row shows the experimental results when the noise mean of image is 25 and 50, respectively.

AMNet – Heo et al., "Appearance and motion based deep learning architecture for moving object detection in moving camera," in ICIP, 2017.

Conclusion

- Moving Object detection in PTZ Camera
  - Find moving object region in an unsupervised manner
  - Combine the characteristics of two background models
  - Fine background: reduce foreground loss
  - Robust to image noise and can combine the supervised method
  - Real-Time operation without GPU
  - Suitable for pre-processing and surveillance application

- Future work
  - Combine the powerful appearance model such as salient object detector
  - Extend the method to video object segmentation or video inpainting