

IPT: A Dataset for Identity Preserved Tracking in Closed Domains

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Motivation

- The IPT dataset aims to facilitate the application of state-of-the-art computer vision methods to privacy-critical applications such as:
 - Ambient Assisted Living (AAL)
 - Security

 Privacy is protected by using a depth sensor as an anonymizing imaging method. In many cases behavior analysis does not need to know who is acting but rather what they are doing.





Contribution

 A new public dataset for identity preserved human detection and tracking with flexible labelling for use in either 2d or 3d space.

• Baseline results for person detection and tracking.





Dataset Overview



• 10 sequences featuring:

- Indoor environments
- Both scripted and natural behavior
- Frequent person-person and person-object occlusions
- 72k frames in total, static depth sensor at 640×480 resolution and 30 fps.
- Split by sequence into training (70%), validation (20%) and test sets (10%).



Dataset Labeling

- 3d location of actors
 - Consistent actor ID across all sequences
- 2d bounding boxes
 - Inferred from 3d locations
- Semantic room layout layers
 - Exterior space (walls, outside space)
 - Obstructed space (furniture, appliances, ...)
 - Semi-obstructed space (chairs, beds, ...)
- Sensor pose
- Tracking ground truth in the MOT Challenge format

Inferred 2d bounding boxes



Semantic room layout labeling (birds eye view)





Baseline Object Detection

- 2d detection baseline using a YOLOv3 [1] model modified for single *person* class output.
- Model performance is improved using an efficient background model [2].
 - Three channel input (x_t, μ_t, σ_t) with depth frames x_t and geometrically weighted mean μ_t and standard deviation σ_t .
 - Updated once per second.
 - During training an approximation of the background model is computed using a ten second window preceding each sample.



J. Redmon, S. Divvala, R. Girshick, and A. Farhadi. "You only look once: Unified, real-time object detection." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788. 2016.
C. R. Wren, A. Azarbayejani, T. Darrell, and A. P. Pentland. "Pfinder: Real-time tracking of the human body." IEEE Transactions on pattern analysis and machine intelligence 19, no. 7 (1997): 780-785.



Object Detection Results

Model	Average Precision	
	Validation	Test
YOLOv3	77.2%	89.2%
YOLOv3 + BG Model	85.2%	89.6%
YOLOv3 Tiny	71.9%	82.0%

- Results show significant variation in model performance across sequences due to different room layouts, sizes and occlusion profiles.
- Comparison of validation set and test set performance suggests non-representative test set, addressed in upcoming work.
- YOLOv3 Tiny included for potential use in target applications with inference on embedded devices.



Baseline Tracking

- 2d tracking baseline using the SORT [3] and DeepSORT [4] tracking algorithm.
- Evaluation using full MOT Challenge metrics (CVPR19 benchmark).

Mode	MOT Accuracy	Identity F1
SORT	76.6%	14.5%
DeepSORT	77.2%	17.5%
DeepSORT Short Tracks	77.3%	58.8%

- Results suggest utility of deep features for reidentification even for pure depth data.
- "Short Tracks" change track ID whenever subjects leave the sensors' field of view.

[3] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft. "Simple online and realtime tracking." In 2016 IEEE International Conference on Image Processing (ICIP), pp. 3464-3468. IEEE, 2016.
[4] N. Wojke, A. Bewley, and D. Paulus. "Simple online and realtime tracking with a deep association metric." In 2017 IEEE international conference on image processing (ICIP), pp. 3645-3649. IEEE, 2017







Thank you