PRINCETON VISION GROUP Tracking Revisited using RGBD Camera: Unified Benchmark and Baselines

Motivation

1.Traking is difficult but depth may help

- Popularity of depth sensors made it possible to obtain reliable depth easily
- Game changer for tracking?
- Prevent model drift & handle occlusion?

2. A Good benchmark is important



- Small
- Inconsistently labeled
- No depth

Contribution

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• We construct a unified benchmark dataset of 100 RGBD videos with high diversity

• We propose various kinds of RGBD tracking algorithms in both 2D and 3D, and present a quantitative comparison

Data + Code: http://tracking.cs.princeton.edu



 $RGB \rightarrow HOG \rightarrow iHOG$ Depth $\rightarrow HOG \rightarrow iHOG$ Point Cloud $\rightarrow 3D$









Occlusion Handling



The depth histogram of all pixels inside a bounding box can be approximated as a Gaussian distribution:

$$h_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$$

The likelihood of occlusion:

$$O_i = \sum_{d=0}^{\mu_i - \sigma_i} \frac{h_i(d)}{\sum_d h_i(d)}$$

Red Gaussians: the target model Green Gaussian: the occluder model





Shuran Song

Princeton Tracking Benchmark



100 RGBD videos, including deformable objects, various occlusion conditions, moving camera, and different scenes.

RGBD tracking algorithm based on 2D image patch

Results

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$$r_i = \begin{cases} \frac{\operatorname{area}(\operatorname{ROI}_{T_i} \cap \operatorname{ROI}}{\operatorname{area}(\operatorname{ROI}_{T_i} \cup \operatorname{ROI}} \\ 1 \\ -1 \end{cases}$$

 ROI_{T_i} : tracking bounding box,

$$R = \frac{1}{N} \sum_{i=1}^{N} u_i, \quad \mathbf{w}$$

RGB tracking Algorithms

[Struck] S. Hare, A. Saffari, and P. H. S. Torr. Struck: Structured output tracking with kernels. In ICCV, 2011 [VTD] J. Kwon and K. M. Lee. Visual tracking decomposition. In CVPR, 2010. [CT] K. Zhang, L. Zhang, and M.-H. Yang. Real-time compressive tracking. In ECCV, 2012 [MIL] B. Babenko, M.-H. Yang, and S. Belongie. Visual Tracking with Online Multiple Instance Learning. In CVPR, 2009 [TLD] Z. Kalal, K. Mikolajczyk, and J. Matas. Trackinglearning-detection. PAMI, 2012. [SemiB] H. Grabner, C. Leistner, and H. Bischof. Semisupervised on-line boosting for robust tracking. In ECCV,



Evaluation

Successful Rate

 $\frac{\partial I_{G_i}}{\partial I_{G_i}}$ if both ROI_{T_i} and ROI_{G_i} exist if neither ROI_{T_i} and ROI_{G_i} exist otherwise

 ROI_{G_i} is the ground truth bounding box. By setting a minimum overlapping area r_t , we can calculate the average success rate R:

. I if $r_i > r_t$

Error Type

Type I : $\operatorname{ROI}_{T_i} \neq null$ and $\operatorname{ROI}_{G_i} \neq null$ and $r_i < r_t$ Type II : $\operatorname{ROI}_{T_i} \neq null$ and $\operatorname{ROI}_{G_i} = null$ Type III : $\operatorname{ROI}_{T_i} = null$ and $\operatorname{ROI}_{G_i} \neq null$



Ranking

Our Baseline Algorithms

Table 1: Strong RGBD baseline algorithms	
OF	Uses only optical flow tracking.
Ddet	Uses Depth HOG detection tracking.
RGBdet	Uses RGB HOG detection tracking.
RGB +OF	Uses RGB HOG detection with optical flow.
RGBD + OF	Uses RGBD HOG detection with optical flow.
RGBDOcc	Uses RGBD HOG detection and optical flow with occlusion
+ OF	handling.
PCflow	Uses 3D point tracker.
PCdet	Uses point cloud detection.
PC(det+flow)	Uses point cloud detection and 3D point tracking with occlu-
	sion handling.

 Table 2: Performance upper-bounds (GT:ground truth)

GTfirstSize Uses the GT location and first frame box size.

GTbestsize	Uses the GT location and fixed box size that optimize the
	successful rate.
GTfirstRatio	Uses the GT location and first frame box aspect ratio.
GTbestRatio	Uses the GT location and fixed box aspect ratio that optimize
	the successful rate.
GTnoOcc	Outputs the GT box, if exists, and a random box otherwise.
	Table 3: Performance lower-bound algorithms
IIDfirstBB	Always outputs the first frame bounding box for all frames.
IIDcenterBB	Always outputs the box locate at center of image, with first
	frame box size.
IIDrandSize	Outputs bounding boxes with the first frame box location and
	a random size based on dataset statistics.
IIDrandLoc	Outputs bounding boxes with the first frame box size and a
	random location based on dataset statistics
IIDrandLoc	Outputs bounding boxes with random location and size based
Size	on dataset statistics
IIDrand With-	Outputs bounding boxes with random location and size with-
outPrior	out any prior knowledge of dataset