3D Part-Based Sparse Tracker with Automatic Synchronization and Registration

Adel Bibi , Tianzhu Zhang , Bernard Ghanem

King Abdullah University of Science and Technology (KAUST)

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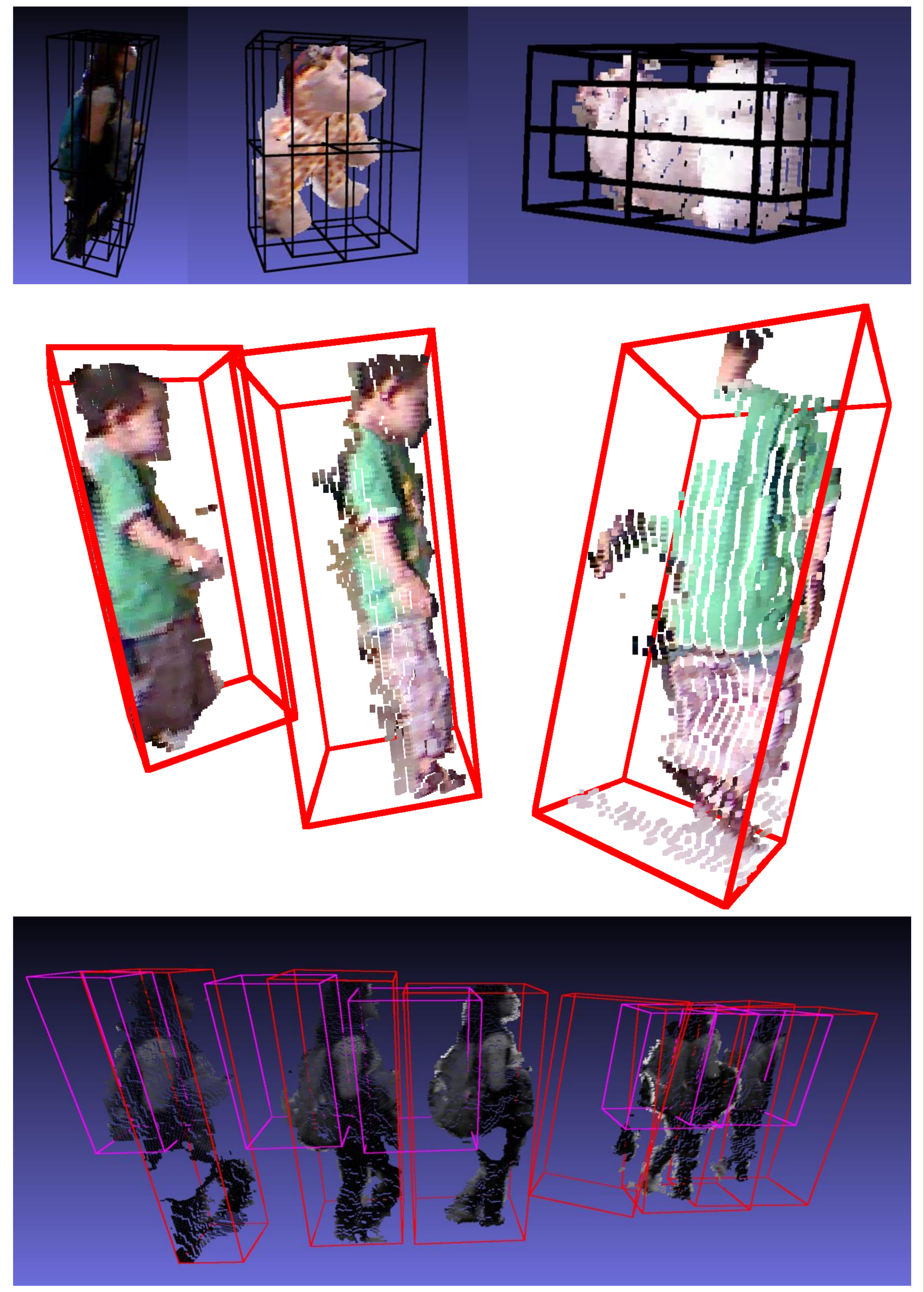
Abstract

- We propose a part-based sparse tracker in a particle filter framework, where both motion and appearance models are formulated in 3D. The motion model is adaptive and directed according to a simple yet powerful occlusion handling paradigm.
- We propose an automated method to correct for nuisances in both synchronization and registration that may occur between RGB(D) pairs.
- Extensive experiments are conducted on a popular RGBD tracking benchmark. At the time of publication, our tracker ranks 1st among all other state-of-the-art RGBD trackers.



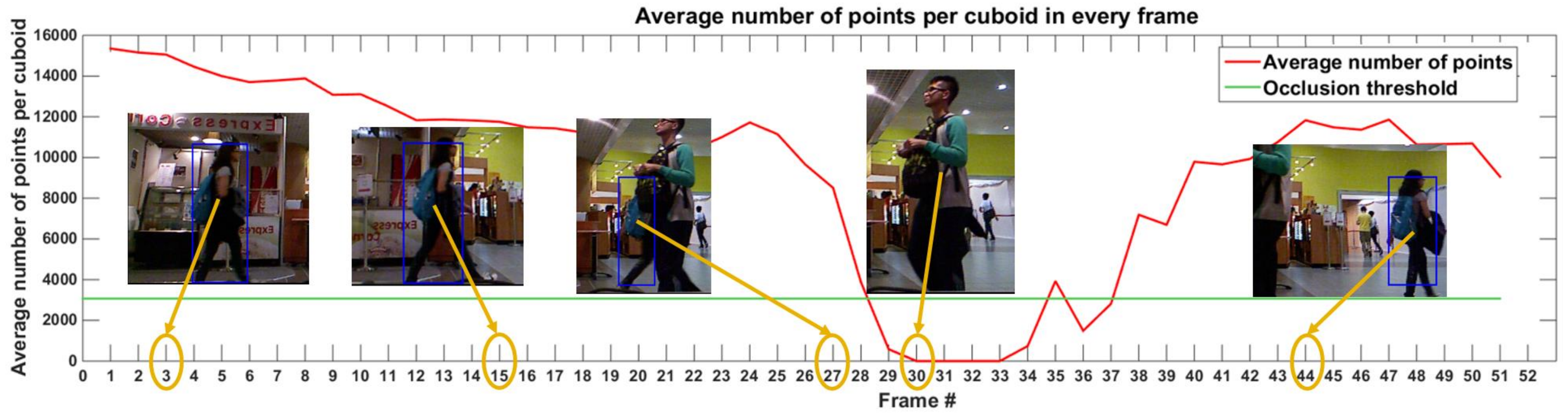
GT   Ours   DS-KCF   Prin-RGBD

Problem Formulation

- **3D-Tracker:** We learn K dictionaries using KSVD for each part and solve the following decomposable Lasso problem on the set of particles that do not violate the coherence structure between consecutive frames:

$$\underset{\mathbf{X}_k;\forall k}{\text{minimize}} \sum_{k}^{K} \|\mathbf{D}_k\mathbf{X}_k - \mathbf{Y}_k\|_F^2 + \lambda\|\mathbf{X}_k\|_{1,1} \;\; ; \;\; \mathbf{D}_k = [\hat{\mathbf{D}}_{1k}|\hat{\mathbf{D}}_{2k}|...|\hat{\mathbf{D}}_{Nk}|\mathbf{I}_{m_k}]$$

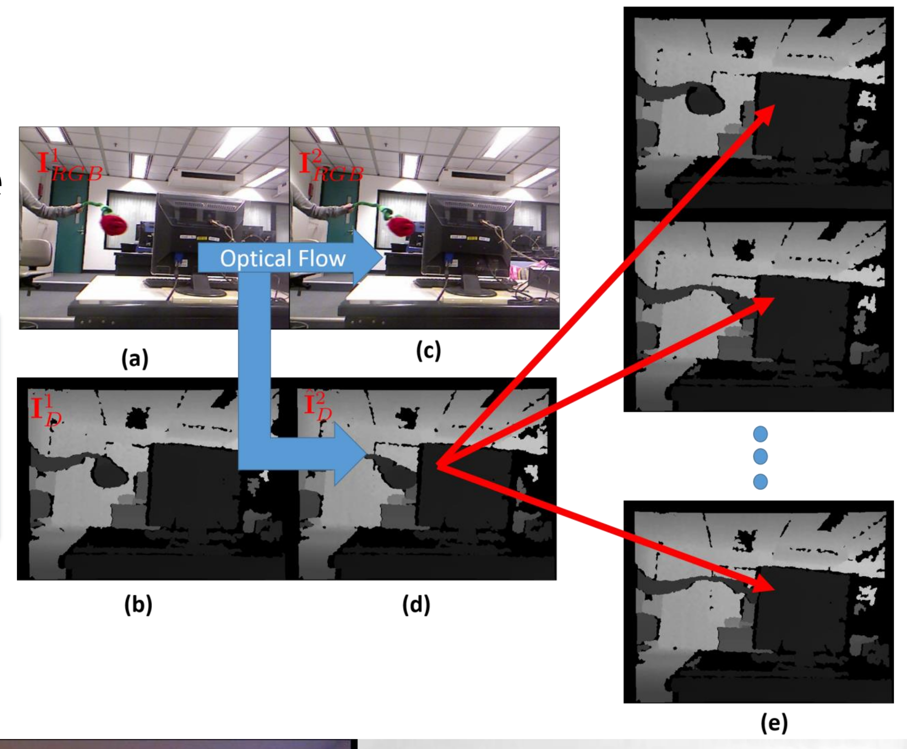
- **Occlusion Handling**



- **Correcting Synchronization Errors:**

Only point correspondences with a large $\{(\mathbf{x}_i^1, \mathbf{y}_i^2)\}_{i=1}^p$ optical flow are considered.

$$j^* = \underset{j\in\mathcal{C}}{\text{argmin}} \sum_{i=1}^{p} \left(\hat{\mathbf{I}}_D^2(\mathbf{y}_i^2) - \mathbf{I}_D^j(\mathbf{y}_i^2)\right)^2$$

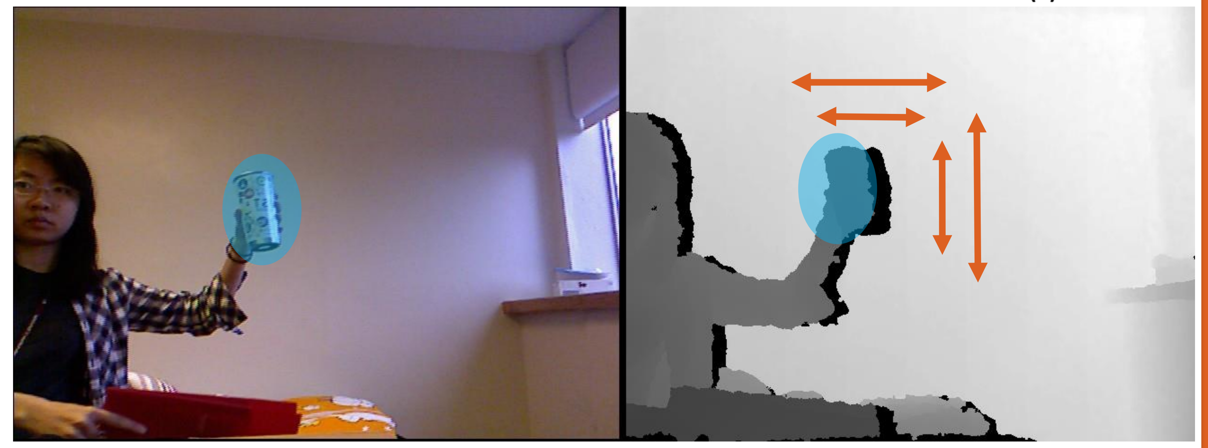


- **Correcting Registration Errors:**

$$\min_{\mathbf{z}_i\forall i} \frac{1}{p}\sum_{i}^{p}(d_1^i - \mathbf{d}_2^{i\,T}\mathbf{z}_i)^2$$

$$s.t \quad \mathbf{z}_i \in \{0,1\}^N \; \forall i,$$

$$\mathbf{1}^T\mathbf{z}_i = 1 \; \forall i, \;\; \text{rank}(\mathbf{Z}) \le r$$



Experiments

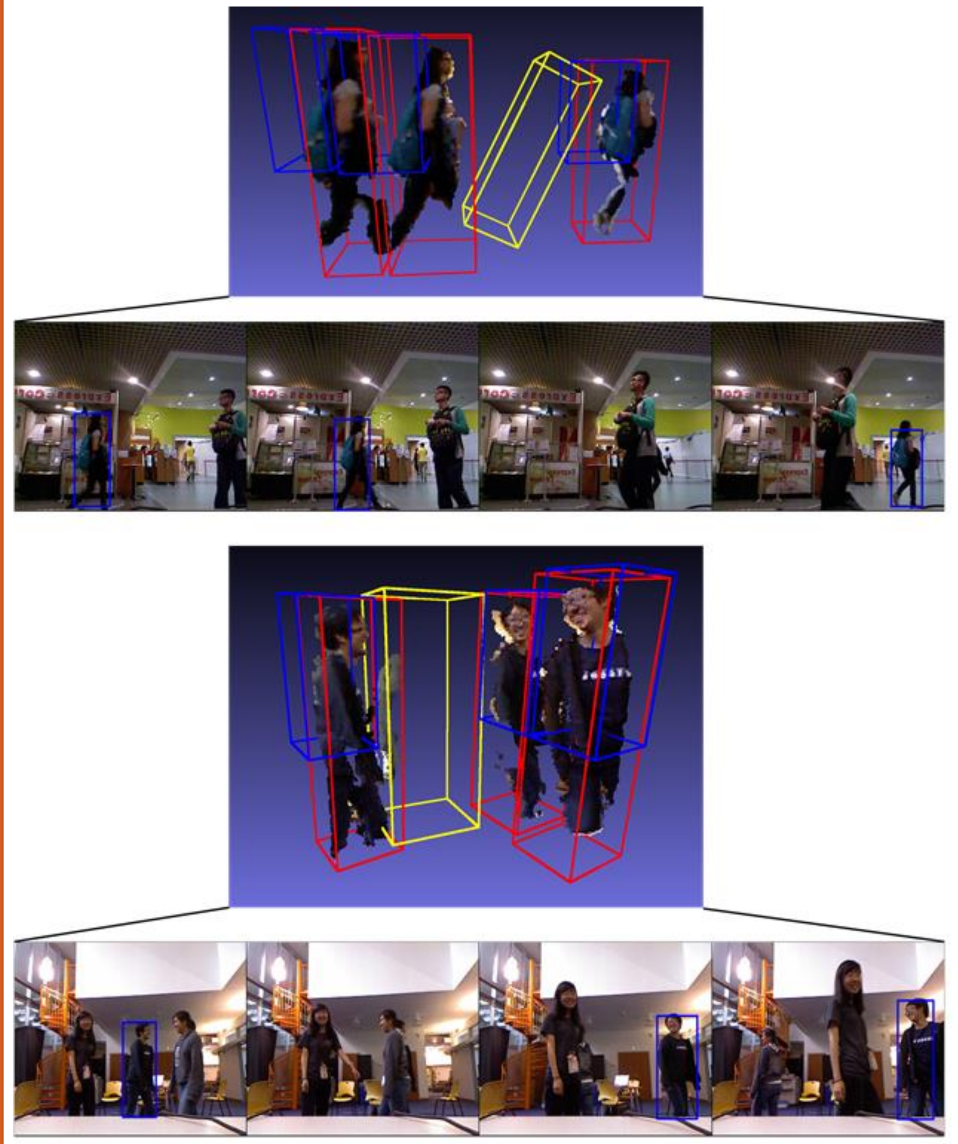
Quantitative Results and Evaluation of Design Choices: We compare our method (and its variants) with state-of-the-art methods on Princeton RGBD benchmark [2].

Algorithm	Target type			Target Size		Movement		Occlusion		Motion Type	
	Human	Animal	Rigid	Large	Small	Slow	Fast	Yes	No	Passive	Active
Ours_Manual	0.81	0.64	0.73	0.80	0.71	0.75	0.75	0.73	0.78	0.79	0.73
Ours_Sync_Reg	0.74	0.66	0.70	0.77	0.65	0.76	0.68	0.67	0.76	0.75	0.69
Ours_Sync_Raw_Reg	0.68	0.58	0.71	0.76	0.61	0.74	0.64	0.62	0.74	0.75	0.64
Ours_Raw_Sync_Raw_Reg	0.64	0.57	0.67	0.71	0.58	0.73	0.60	0.57	0.73	0.72	0.61
Ours_One_Part_Manual	0.60	0.56	0.46	0.58	0.50	0.58	0.52	0.48	0.62	0.54	0.54

Table1: Comparison between different variants of our proposed tracker

Algorithm	Avg. Rank	Target Type			Target Size		Movement		Occlusion		Motion Type	
		Human	Animal	Rigid	Large	Small	Slow	Fast	Yes	No	Passive	Active
Ours_Manual	2.27	0.81	0.64	0.73	0.80	0.71	0.75	0.75	0.73	0.78	0.79	0.73
OAPF[1]	2.63	0.64	0.85	0.77	0.73	0.73	0.85	0.68	0.64	0.85	0.78	0.71
RGBDOcc+OF[2]	2.81	0.74	0.63	0.78	0.78	0.70	0.76	0.72	0.72	0.75	0.82	0.70
Ours_Sync_Reg	3.72	0.74	0.66	0.70	0.77	0.65	0.76	0.68	0.67	0.76	0.75	0.69
DS-KCF[3]	4.54	0.67	0.61	0.76	0.69	0.70	0.75	0.67	0.63	0.78	0.79	0.66
RGBD+OF[2]	5.27	0.64	0.65	0.75	0.72	0.65	0.73	0.66	0.60	0.79	0.74	0.66
PCdet_flow[2]	7.27	0.51	0.52	0.73	0.63	0.56	0.74	0.53	0.55	0.64	0.75	0.53

Table2: Tracking results from the online evaluation for our tracker on both the manually and automatically synchronized and registered data compared with the top 5 trackers.



References:

[1] K. Meshgi, "Occlusion Aware Particle Filter tracker to Handle Complex and persistent occlusions", CVIU.

[2] S. Song, "Tracking revisited using rgbd camera: Unified benchmark and baselines", ICCV2013.

[3] M. Camplani, "Real-time rgb-d tracking with depth scaling kernelised correlation filters and occlusion handleing", BMVC2015.

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