3D-ZeF: A 3D Zebrafish Tracking Benchmark Dataset Supplementary Material

Malte Pedersen*, Joakim Bruslund Haurum*, Stefan Hein Bengtson, Thomas B. Moeslund Visual Analysis of People (VAP) Laboratory, Aalborg University, Denmark

mape@create.aau.dk, joha@create.aau.dk, shbe@create.aau.dk, tbm@create.aau.dk

A. Content

In these supplementary materials we provide: examples of the visual difference between the fish in the three splits, a more detailed explanation of the detectors, details on the benchmark pipeline parameters, a more detailed presentation of the relation between the proposed dataset complexity measures and tracking metrics, and the full set of tracking metrics for each step in the proposed benchmark pipeline.

B. Fish Examples

The visual appearance of the fish varies both within and between the splits as unique groups of fish have been used for each split. However, the two groups of fish used in the train and validation sets are from the same cohort, whereas the zebrafish in the test split are from a cohort of younger and smaller fish. We present a fish from each of the three splits in Figure 1 captured at the approximately same position in the water tank. The resolution of the zebrafish from the test split is significantly smaller compared to the fish in the training and validation splits, mainly due to the physical size of the fish.

C. Naive Object Detection

The Naive object detection algorithms presented briefly in the paper are described in more details in this section. The methods are inspired by Qian *et al.* [1] and their work on tracking zebrafish in 2D.

C.1. Pre-Processing

Initially the background image, without any fish, is estimated by taking the median of N images sampled uniformly across the video. In the tests presented in the paper a set of 80 images were used to create the background image for each recording. All further processing is restricted within a defined region of interest based on the boundaries of the water tank and the level of water, in order to limit the processing time. The video is downsampled by a factor of 2, in order to further decrease the processing time. Background subtraction is applied by calculating the absolute difference image, |im - bg|, choosing the max value across all color channels, and normalizing the image into the range [0; 255]. The resulting image is filtered with a 5 × 5 median filter to reduce noise.

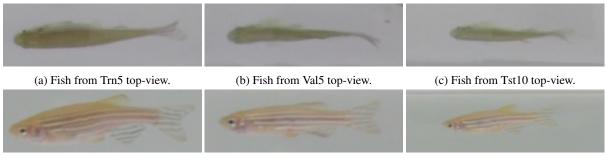
C.2. Top-View Detection

The top-view is thresholded based on the assumption of the image histogram being bimodal, due to a near uniform bright background, and darker zebrafish. Therefore the intermodal approach of Prewitt *et al.* [2] can be utilized. The threshold is set to the middle point between the two modes in the image histogram. If the histogram is not bimodal, the frame is filtered with a 3×3 mean filter, until its histogram is bimodal.

The fish are detected by applying a skeletonization based approach. BLOBs are initially detected and filled, and the skeletonization approach of Zhang and Suen [3] is applied. The skeleton is analyzed in order to find the skeleton keypoints: head, tail, and junctions. This is done by convolving the frame with the kernel in Equation (1). All end points of the skeleton have a value of 116, 117, 118, or 131, while junctions have a value of 148, 149, 150, or 151. Values, like 132, that can represent both an end point or an arbitrary point on the skeleton are not considered.

Each keypoint is assigned a weight, w, consisting of the smallest eigenvalue of the covariance matrix of the BLOB coordinates extracted from a 20×20 window around the keypoint. The smallest eigenvalue is used, as it is assumed the variance will be smallest along the width of the head. This way the head keypoints will be assigned a larger w than the tail keypoints, as the width of the zebrafish head is

^{*}Equal contribution



(d) Fish from Trn5 front-view.

(e) Fish from Val5 front-view.

(f) Fish from Tst10 front-view.

Figure 1: Examples of zebrafish from the train, validation, and test split captured from the approximately same position in the water tank. The top- and front-view pairs show the same fish. Notice the variation in size of the zebrafish.

Parameter	c	δ_T	δ_F	$ au_k$	α	$ au_p$	β
Value	95	15	0.5/15	10	10	25	0.02

Table 1: Pipeline parameters used for testing.

usually larger than the width of the zebrafish tail. The w of the junction points are reduced by a factor of 2.5, as they are usually larger than endpoint keypoints.

Keypoints too close to each other are removed by applying non-maximal suppression (NMS). Each keypoint is assigned a bounding box of size $w \times w$, and kept if the bounding box does not overlap with any other keypoint by more than NMS_{thresh}% of the area of the keypoint in focus. In case there is an overlap, only the keypoint with the largest w is kept. NMS_{thresh} was set to 50 in the conducted tests.

Finally, all keypoints with w < 1 are discarded. Per skeleton, the two keypoints furthest apart are determined, and the keypoint with largest w is kept. Furthermore, half of the additional extra keypoints with the largest w values are also kept in order to handle crossings and occlusions. Every keypoint ideally represent a zebrafish head and they are all kept as individual detections.

C.3. Front-View Detection

The front frame cannot be thresholded based on the assumption of a bimodal distribution of the image histogram, as the stripes of the zebrafish results in a non-uniform appearance. Instead the frame is thresholded by finding the point maximizing the total entropy of the image [4]. The entropy is modeled as *background* and *foreground* entropy for each non-zero bin.

For bin k the background entropy, b_k , is calculated by

$$b_{k} = |\sum_{i=0}^{k} \frac{h(i)}{h_{c}(i)} \log(\frac{h(i)}{h_{c}(i)})|, \qquad (2)$$

where h is the normalized image histogram and h_c is the cumulative histogram of h. The foreground entropy, w_k , is

calculated by

$$w_k = |\sum_{i=k+1}^{255} \frac{h(i)}{1 - h_c(i)} \log(\frac{h(i)}{1 - h_c(i)})|, \qquad (3)$$

resulting in the two entropy sets $B = \{b_0, b_1, ..., b_{255}\}$ and $W = \{w_0, w_1, ..., w_{255}\}$ which are combined into

$$E = B + W, \tag{4}$$

and the threshold, t, is then finally determined by

$$t = \operatorname*{argmax}_{r} E(x). \tag{5}$$

The BLOBs in the thresholded image are found through simple Connected Component Analysis (CCA). Only the $2N_{\text{fish}}$ largest BLOBs are kept, as long as the area of the BLOBs are larger than a predefined threshold. This allows for potential reflections being detected alongside the true detection of the fish. Otherwise, if only the N_{fish} largest BLOBs are considered for further analysis, it is possible that reflections are considered at the expense of real fish.

As it is not known where the head of the fish is, two points are saved as proxies for the head, together with the center-of-mass. If the width of the BLOB bounding box is larger than the height, the proxy points are $(\min(x), \mu(y))$ and $(\max(x), \mu(y))$, where x and y are the coordinates of the BLOB pixels, and μ is the arithmetic mean function. Otherwise, the proxy points are $(\mu(x), \min(y))$ and $(\mu(x), \max(y))$. The center-of-mass is further used for constructing 2D tracklets, as it is the most stable of the three proxy points.

D. FRCNN-H Object Detection

Two Faster R-CNN networks were trained to detect the zebrafish heads in each view, respectively. The official Py-Torch implementation of Faster R-CNN with a ResNet50

	Property	Mean	Std. Dev.	Median
ц	Reproj. Error $[px]$	8.03	5.26	7.59
Trn	Speed $[cm/s^2]$	2.13	2.32	1.54
al	Reproj. Error $[px]$	6.22	4.50	5.43
Val	Speed $[cm/s^2]$	2.02	2.37	1.41
st	Reproj. Error $[px]$	4.36	3.27	3.69
É	Speed $[cm/s^2]$	2.11	1.93	1.58

Table 2: Statistics of the reprojection error and speed of the zebrafish, for each split, based on the ground truth annotations.

based Feature Pyramid Network [5] backbone was utilized in both cases. The model was pretrained on the COCO train2017 dataset. The network was fine-tuned for 30 epochs, using stochastic gradient descent with momentum. A learning rate of 0.005, momentum of 0.9, weight decay of 0.0005, and batch size of 8 was used. The learning rate was "warmed up" during the first epoch, linearly interpolating the learning rate from 0.001 to 0.005. Each model was trained on an RTX 2080TI.

E. Pipeline Parameters

The full system pipeline has a set of parameters, which needs to be manually set. The parameters were chosen based on empirical investigation on the training data and they are shown in Table 1. The front-view distance threshold, δ_F , has two different values, depending on the method applied. For the Naive method it is set to 0.5, as the distance is measured in standard deviations, whereas for the FRCNN-H method it is set to 15, where the distance is measured in pixels.

Furthermore, during the association of 2D tracklets between views, a set of exponential distributions are utilized. These distributions are parameterized using the mean of the reprojection error of the ground truth training annotations and the average speed of the zebrafish in the training split. This builds on the assumption that these parameters generalize across the different splits. As shown in Table 2, the average speed of the zebrafish for each split are within $0.1\frac{cm}{c^2}$, which can be seen as a negligible difference, whereas the mean reprojection error is 2-4 pixels larger in the training and validation splits than in the testing split. The cause of this difference is hypothesized to be the larger amount and duration of occlusions in the training and validation splits, which can introduce some uncertainty during the annotation phase. The training split has the largest reprojection error, which means the utilized exponential distribution penalize larger reprojection errors less harshly. However, as the mean training reprojection error is still low, it is still deemed fitting for the task.

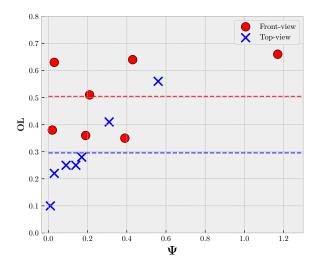


Figure 2: Ψ is the proposed complexity measure based on the front- and top-view recordings. OL is the average length of occlusion events and the dashed lines show the mean OL for the two views. Tst1 is not included.

F. Tracking Metrics and Results

When evaluating tracking tasks, a wide suite of metrics are often used, each expressing different properties of the task. Commonly, the MOTA metric is used as a representative metric for the overall performance of the tracker, as it incorporates false positives and negatives, as well as the amount of identity swaps. However, as shown by Carr and Collins [6] the MOTA metric is not guaranteed to be robust at all times. We evaluate the generated tracks using the collection of metrics from the MOT challenge, consisting of the CLEAR MOT [7], mostly tracked/lost metric [8], and identity based metrics of Ristani et al. [9], as well as using the MTBF metric proposed by Carr and Collins [6]. A description of each of the used metrics are presented in Table 3. Each step of the pipeline has been evaluated according to the previous mentioned metrics. Specifically the following steps have been evaluated:

- 2D tracklets after 2D Tracklet Construction (for topview see Table 4 and for front-view see Table 5)
- 2D tracklets after 2D Tracklet Association Between Views (for top-view see Table 6 and for front-view see Table 7)
- 3D tracklets after 2D Tracklet Association Between Views (see Table 8)
- 3D tracks after 3D Tracklet Association (see Table 9)

For the 2D tracklets, a distance threshold of 20 px is used.

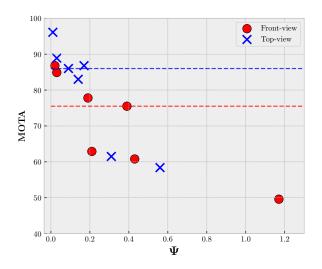


Figure 3: Ψ is the proposed complexity measure based on the front- and top-view recordings. MOTA is based on the oracle tracker and the dashed lines show the mean MOTA for the two views. Tst1 is not included.

G. Occlusions

The two views are not equal when it comes to occlusions. Due to the social behavior of zebrafish they tend to swim in the same horizontal layer of the water column. This is indicated by the graph in Figure 2, where the occlusion lengths are displayed with respect to the proposed complexity measure, Ψ . It should be noted that Ψ is calculated per view and not as a mean between the two, as in the main article. Data points are presented for all the recordings from both views, except Tst1 as it only contains a single fish and therefore has a complexity measure of zero. The dashed lines illustrate the mean occlusion lengths and shows that there is a significant difference between the two views. In general, the occlusion events seems longer in the front-view recordings.

The MOTA of the hypothetical oracle tracker is plotted against the proposed complexity measure in Figure 3. MOTA is calculated for the top- and front-view 2D tracklets as presented in Table 4 and Table 5, respectively. The tracking performance of the oracle tracker correlates well with the complexity in both views. Notice the significant difference in performance of the tracker in the two views; the mean scores are MOTA_{top} = 86.0% and MOTA_{front} = 75.5% as illustrated by the two dashed lines.

References

 Z.-M. Qian, S. H. Wang, X. E. Cheng, and Y. Q. Chen, "An effective and robust method for tracking multiple fish in video image based on fish head detection," *BMC Bioinformatics*, vol. 17, p. 251, June 2016.

- [2] J. M. S. Prewitt and M. L. Mendelsohn, "The analysis of cell images*," *Annals of the New York Academy of Sciences*, vol. 128, no. 3, pp. 1035–1053, 1966.
- [3] T. Y. Zhang and C. Y. Suen, "A Fast Parallel Algorithm for Thinning Digital Patterns," *Commun. ACM*, vol. 27, pp. 236– 239, Mar. 1984.
- [4] P. Sahoo, S. Soltani, and A. Wong, "A survey of thresholding techniques," *Computer Vision, Graphics, and Image Processing*, vol. 41, no. 2, pp. 233 – 260, 1988.
- [5] T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- [6] P. Carr and R. T. Collins, "Assessing tracking performance in complex scenarios using mean time between failures," in 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1–10, March 2016.
- [7] K. Bernardin and R. Stiefelhagen, "Evaluating multiple object tracking performance: The CLEAR MOT metrics," *EURASIP Journal on Image and Video Processing*, vol. 2008, p. 246309, May 2008.
- [8] Bo Wu and R. Nevatia, "Tracking of multiple, partially occluded humans based on static body part detection," in 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06), vol. 1, pp. 951–958, June 2006.
- [9] E. Ristani, F. Solera, R. Zou, R. Cucchiara, and C. Tomasi, "Performance measures and a data set for multi-target, multicamera tracking," in *Computer Vision – ECCV 2016 Workshops* (G. Hua and H. Jégou, eds.), (Cham), pp. 17–35, Springer International Publishing, 2016.
- [10] Y. Li, C. Huang, and R. Nevatia, "Learning to associate: HybridBoosted multi-target tracker for crowded scene," in 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 2953–2960, June 2009.

Metric	Better	Range	Description
MOTA	Higher	$] - \infty, 100]$	Overall tracking accuracy based on ID-swaps, and false negatives/positives [7]
MOTP	Lower	$[0,\infty[$	Distance between predicted position and ground truth [7]
Prc.	Higher	[0, 100]	Precision: The percentage of correctly predicted positions
Rcll.	Higher	[0, 100]	Recall: The percentage of ground truth positions detected
ID-Prc.	Higher	[0, 100]	ID-Precision: The percentage of correctly identified predicted positions [9]
ID-Rcll.	Higher	[0, 100]	ID-Recall: The percentage of correctly identified ground truth positions [9]
ID-F1	Higher	[0, 100]	F1-score of the predicted identities [9]
FP	Lower	$[0,\infty[$	Amount of incorrectly predicted positions
FN	Lower	$[0,\infty[$	Amount of ground truth positions missed
MT	Higher	[0, 100]	Amount of ground truth tracks which are 80% or more correctly tracked [8]
ML	Lower	[0, 100]	Amount of ground truth tracks which are 20% or less correctly tracked [8]
ID Sw.	Lower	$[0,\infty[$	Total amount of identity switches [10]
Frag.	Lower	$[0,\infty[$	Total amount of track fragmentations
$MTBF_s$	Higher	$[0,\infty[$	Mean time between ID-switches or false negatives/positives [6]
$MTBF_m$	Higher	$[0,\infty[$	Monotonic version of MTBF _s [6]

Table 3: Description of the full collection of utilized tracking metrics.

	Method	MOTA ↑	MOTP \downarrow	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	FP↓	FN↓	MT ↑	ML↓	ID Sw.↓	Frag. ↓	MTBF _s ↑	$MTBF_m \uparrow$
	Naive	21.9%	3.309	57.2	91.0	10.7	6.7	8.2	9798	1301	2	0	136	428	26.316	14.109
Trn2	FRCNN-H	91.3%	2.128	98.8	92.8	12.4	13.2	12.8	156	1030	2	0	72	140	87.829	45.408
E	Oracle	61.5%	0.000	100.0	63.0	6.7	10.6	8.2	0	5314	0	0	216	216	41.587	20.699
	Naive	38.2%	3.196	64.1	90.1	31.5	22.4	26.2	2274	447	5	0	58	124	27.020	14.792
Trn5	FRCNN-H	90.2%	2.038	99.1	91.6	31.9	34.5	33.2	39	378	5	0	24	50	73.607	38.523
Г	Oracle	58.4%	0.000	100.0	59.6	19.1	32.0	23.9	0	1819	0	0	52	52	47.035	23.726
	Naive	59.8%	3.050	72.6	96.7	57.1	42.8	48.9	1315	118	2	0	13	44	68.275	36.653
Val2	FRCNN-H	96.8%	2.165	99.2	97.9	75.9	76.8	76.3	30	76	2	0	10	17	167.810	92.737
-	Oracle	88.9%	0.000	100.0	89.7	25.8	28.8	27.2	0	372	2	0	28	28	107.600	55.655
	Naive	89.4%	3.552	93.1	97.0	51.7	49.6	50.6	330	135	5	0	19	36	92.083	52.619
Val5	FRCNN-H	96.4%	2.782	99.5	97.2	48.3	49.4	48.8	22	128	5	0	15	23	147.567	83.528
_	Oracle	86.0%	0.000	100.0	86.9	37.2	42.8	39.8	0	598	4	0	40	40	87.933	46.553
	Naive	83.1%	4.095	85.6	100.0	100.0	85.6	92.2	152	0	1	0	0	0	900.000	900.000
Tst1	FRCNN-H	85.1%	2.513	100.0	85.7	49.7	58.0	53.5	0	129	1	0	5	34	22.029	11.174
L	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
	Naive	98.6%	3.771	99.6	99.1	99.1	99.6	99.3	8	17	2	0	0	10	148.583	81.045
Tst2	FRCNN-H	72.6%	2.443	100.0	74.1	39.0	52.7	44.8	0	467	1	0	26	93	14.032	7.053
	Oracle	96.1%	0.000	100.0	96.7	32.6	33.7	33.1	0	60	2	0	10	10	145.000	79.091
	Naive	82.8%	3.801	89.3	94.7	49.7	46.8	48.2	512	237	5	0	24	82	45.839	24.222
Tst5	FRCNN-H	70.5%	2.685	99.9	71.8	25.6	35.6	29.7	4	1271	0	0	52	145	21.384	10.836
	Oracle	83.0%	0.000	100.0	84.0	44.7	53.2	48.6	0	721	3	0	44	44	77.122	39.779
0	Naive	83.4%	3.752	89.3	95.4	59.0	55.2	57.0	1026	418	10	0	49	138	52.329	28.323
Tst1	FRCNN-H	70.8%	2.803	99.8	72.4	26.4	36.4	30.6	13	2483	4	0	130	417	14.879	7.543
H	Oracle	86.8%	0.000	100.0	87.5	42.1	48.1	44.9	0	1128	10	0	64	64	106.378	56.229

Table 4: Full metric evaluation of the 2D tracking in the top-view, on all sequences.

	Method	MOTA \uparrow	MOTP \downarrow	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	$FP\downarrow$	$FN\downarrow$	MT ↑	$\mathrm{ML}\downarrow$	ID Sw. \downarrow	Frag.↓	$MTBF_s \uparrow$	$MTBF_m \uparrow$
2	Naive	-69.5%	12.666	7.6	6.2	0.6	0.7	0.6	10756	13490	0	2	134	159	4.709	2.528
Tm	FRCNN-H	92.8%	3.521	99.8	95.0	6.4	6.8	6.6	26	723	2	0	288	126	43.218	30.898
Г	Oracle	62.9%	0.000	100.0	64.1	2.4	3.8	3.0	0	5168	0	0	170	170	53.558	26.936
10	Naive	-73.5%	12.768	5.2	4.2	3.1	3.8	3.4	3478	4310	0	5	19	22	5.758	2.923
Trn5	FRCNN-H	90.7%	3.634	99.9	92.4	23.2	25.1	24.1	6	341	5	0	72	47	45.207	29.496
Г	Oracle	60.8%	0.000	100.0	61.7	20.1	32.6	24.9	0	1724	1	0	41	41	60.348	29.849
	Naive	-93.1%	12.918	3.7	3.6	0.8	0.8	0.8	3444	3469	0	2	37	28	3.119	1.795
Val2	FRCNN-H	93.6%	4.113	100.0	97.4	12.9	13.3	13.1	0	95	2	0	136	24	25.036	21.372
-	Oracle	84.9%	0.000	100.0	85.3	16.3	19.1	17.6	0	530	2	0	14	14	191.875	102.333
	Naive	-68.8%	12.419	10.0	8.5	2.9	3.4	3.1	3480	4162	0	5	37	44	6.690	3.464
Val5	FRCNN-H	79.0%	4.224	99.6	81.8	16.2	19.7	17.8	14	826	3	0	117	72	26.791	17.402
-	Oracle	49.6%	0.000	100.0	50.8	16.5	32.4	21.8	0	2240	0	0	54	54	39.153	19.914
_	Naive	-44.8%	14.682	27.5	26.2	5.2	5.5	5.4	621	664	0	0	18	28	6.378	3.522
Tst1	FRCNN-H	41.4%	7.031	99.0	44.4	15.0	33.4	20.7	4	500	0	0	23	17	13.333	8.163
Г	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
	Naive	-38.3%	13.201	30.0	27.0	5.1	5.6	5.3	1135	1314	0	1	41	41	7.967	4.673
Tst2	FRCNN-H	16.4%	7.828	100.0	18.7	6.6	35.4	11.1	0	1464	0	1	40	57	5.695	2.824
	Oracle	86.8%	0.000	100.0	87.3	45.8	52.4	48.9	0	228	2	0	10	10	131.000	71.455
	Naive	-39.2%	12.703	28.5	24.3	4.6	5.4	4.9	2734	3408	0	3	124	138	5.717	3.250
st5	FRCNN-H	53.5%	5.601	98.7	56.4	15.4	27.0	19.7	33	1962	0	0	99	147	15.962	8.161
Г	Oracle	77.8%	0.000	100.0	78.7	32.6	41.4	36.5	0	957	2	0	42	42	75.383	38.934
0	Naive	-54.1%	13.667	19.6	16.9	3.8	4.4	4.1	6219	7482	0	5	171	195	5.816	3.209
Tst10	FRCNN-H	47.4%	5.604	99.4	50.3	13.0	25.6	17.2	27	4474	0	0	229	277	14.368	7.518
E -	Oracle	75.5%	0.000	100.0	76.5	25.7	33.6	29.2	0	2115	4	0	94	94	66.202	33.261

Table 5: Full metric evaluation of the 2D tracking in the front-view, on all sequences.

1	Method	MOTA \uparrow	MOTP \downarrow	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	$FP\downarrow$	$FN\downarrow$	MT ↑	$ML\downarrow$	ID Sw. \downarrow	Frag. \downarrow	$\text{MTBF}_s \uparrow$	$MTBF_m \uparrow$
	Naive	82.6%	3.247	96.2	86.5	13.2	14.6	13.9	497	1939	2	0	73	403	28.732	14.846
Trn2	FRCNN-H	90.9%	2.113	100.0	91.1	22.1	24.2	23.1	1	1273	2	0	41	144	85.667	43.836
F (Oracle	44.8%	0.000	100.0	46.2	2.4	5.3	3.3	0	7742	0	0	202	202	32.539	16.190
	Naive	79.3%	3.151	95.9	83.4	37.5	43.2	40.1	159	748	3	0	23	119	29.543	15.129
Tm5	FRCNN-H	90.2%	2.028	100.0	90.5	45.6	50.4	47.8	0	427	5	0	13	44	81.460	42.874
г (Oracle	36.6%	0.000	100.0	37.8	10.9	28.9	15.9	0	2799	0	0	53	53	29.328	14.175
	Naive	89.0%	3.047	99.4	89.8	63.3	70.1	66.6	20	369	2	0	8	52	57.696	29.642
Val2	FRCNN-H	96.1%	2.163	100.0	96.3	78.4	81.4	79.8	0	133	2	0	7	20	157.591	82.548
	Oracle	73.9%	0.000	100.0	74.9	12.7	17.0	14.5	0	902	0	0	36	36	71.000	35.500
	Naive	92.1%	3.524	99.8	92.5	53.3	57.4	55.3	9	341	4	0	9	57	67.968	34.826
Val5	FRCNN-H	90.9%	2.765	100.0	91.1	51.8	56.8	54.2	0	404	4	0	10	24	143.138	76.870
	Oracle	42.2%	0.000	100.0	43.6	13.2	30.3	18.4	0	2567	0	0	64	64	28.812	14.406
	Naive	99.6%	4.102	100.0	99.6	99.6	100.0	99.8	0	4	1	0	0	2	298.667	179.200
Tst1	FRCNN-H	69.8%	2.477	100.0	69.8	69.8	100.0	82.2	0	272	0	0	0	31	19.625	9.812
- ·	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
	Naive	98.1%	3.782	99.9	98.1	98.1	99.9	99.0	1	34	2	0	0	18	88.300	46.474
Tst2	FRCNN-H	40.8%	2.514	100.0	40.9	32.8	80.1	46.5	0	1063	0	1	2	35	19.919	9.827
- ·	Oracle	82.2%	0.000	100.0	83.2	24.3	29.2	26.6	0	302	2	0	18	18	74.900	37.450
	Naive	86.1%	3.737	98.3	87.9	52.8	59.1	55.8	67	546	4	0	13	69	51.351	26.716
Tst5	FRCNN-H	65.8%	2.666	100.0	66.2	34.0	51.3	40.9	0	1519	0	0	21	110	25.698	13.075
- ·	Oracle	65.7%	0.000	100.0	66.8	26.8	40.1	32.2	0	1492	1	0	50	50	54.691	26.857
0	Naive	87.0%	3.757	98.4	88.6	68.1	75.7	71.7	126	1023	9	0	23	151	48.054	24.697
	FRCNN-H	62.4%	2.797	100.0	62.9	31.4	49.9	38.6	2	3341	2	0	39	293	18.677	9.323
	Oracle	64.7%	0.000	100.0	66.0	20.0	30.3	24.1	0	3059	1	0	119	119	46.054	22.676

Table 6: Full metric evaluation of the 2D tracking in the top-view, after 3D tracklet association, on all sequences.

	Method	MOTA \uparrow	$\text{MOTP} \downarrow$	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	$FP\downarrow$	$\mathrm{FN}\downarrow$	$\mathbf{MT}\uparrow$	$ML\downarrow$	ID Sw. \downarrow	Frag. \downarrow	$\text{MTBF}_s \uparrow$	$MTBF_m \uparrow$
	Naive	-5.5%	14.688	46.6	33.4	6.6	9.2	7.7	5513	9577	0	0	82	772	6.174	3.091
Trn2	FRCNN-H	85.3%	3.482	99.9	85.6	19.5	22.8	21.0	10	2074	2	0	37	141	82.040	42.289
Г	Oracle	44.8%	0.000	100.0	46.2	2.4	5.3	3.3	0	7742	0	0	202	202	32.539	16.190
5	Naive	2.2%	13.648	51.9	37.8	19.1	26.2	22.1	1577	2800	0	2	22	168	9.770	4.843
Ľ,	FRCNN-H	81.5%	3.540	99.9	82.0	41.4	50.5	45.5	3	812	3	0	16	47	68.296	35.124
Г	Oracle	36.6%	0.000	100.0	37.8	10.9	28.9	15.9	0	2799	0	0	53	53	29.328	14.058
~	Naive	-7.9%	14.061	45.5	39.0	30.7	35.8	33.0	1678	2197	0	0	11	165	8.401	4.201
Val2	FRCNN-H	82.1%	4.095	100.0	82.3	63.6	77.2	69.7	0	638	1	0	7	36	75.949	39.493
-	Oracle	73.9%	0.000	100.0	74.9	12.7	17.0	14.5	0	902	0	0	36	36	71.000	35.500
	Naive	-6.9%	11.925	43.9	24.0	13.9	25.5	18.0	1391	3460	0	2	15	108	9.646	4.781
Val5	FRCNN-H	69.3%	4.068	99.9	69.7	35.0	50.1	41.2	4	1379	0	0	15	55	51.984	26.207
-	Oracle	42.3%	0.000	100.0	43.7	13.3	30.3	18.4	0	2562	0	0	64	64	28.812	14.099
	Naive	72.1%	8.828	92.8	78.2	78.2	92.8	84.9	55	196	0	0	0	35	19.556	9.778
Cst1	FRCNN-H	37.8%	6.992	100.0	37.8	37.8	100.0	54.8	0	560	0	0	0	7	42.500	20.000
Г	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
	Naive	75.7%	6.560	95.6	79.4	79.4	95.6	86.7	66	371	1	0	0	38	35.725	18.089
Tst2	FRCNN-H	7.8%	6.187	100.0	7.9	4.8	61.3	9.0	0	1658	0	2	2	10	11.833	5.462
	Oracle	82.2%	0.000	100.0	83.2	24.3	29.2	26.6	0	302	2	0	18	18	74.900	37.450
	Naive	39.7%	9.665	77.9	56.1	38.6	53.6	44.9	717	1977	0	0	21	229	10.736	5.403
Tst5	FRCNN-H	50.1%	5.460	99.4	50.9	27.2	53.2	36.0	13	2209	0	0	23	91	23.619	11.749
ſ	Oracle	65.7%	0.000	100.0	66.8	26.8	40.1	32.2	0	1492	1	0	50	50	54.691	27.345
0	Naive	42.1%	10.218	78.3	59.0	45.4	60.3	51.8	1467	3693	0	0	47	339	15.034	7.506
Tst10	FRCNN-H	39.8%	5.488	99.9	40.3	19.6	48.8	28.0	3	5377	0	0	37	120	27.656	13.620
Ē	Oracle	64.7%	0.000	100.0	66.0	20.0	30.3	24.1	0	3059	1	0	119	119	46.054	22.589

Table 7: Full metric evaluation of the 2D tracking in the front-view, after 3D tracklet association, on all sequences.

	Method	MOTA ↑	MOTP ↓	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	FP ↓	FN ↓	MT ↑	ML↓	ID Sw.↓	Frag.↓	$MTBF_s \uparrow$	$MTBF_m \uparrow$
	Naive	41.1%	0.198	85.0	50.5	9.1	15.3	11.4	1285	7118	0	0	60	586	12.344	6.172
Trn2	FRCNN-H	73.7%	0.066	96.9	76.3	18.8	23.8	21.0	352	3407	0	0	29	215	50.548	25.333
Г	Oracle	44.8%	0.000	100.0	46.2	2.4	5.3	3.4	0	7738	0	0	202	202	32.539	16.190
	Naive	40.3%	0.169	83.5	50.5	25.5	42.1	31.8	448	2218	0	0	12	134	16.309	8.039
Trn5	FRCNN-H	63.5%	0.064	92.1	69.7	37.1	49.1	42.3	269	1358	1	0	9	67	43.431	21.867
Г	Oracle	36.7%	0.000	100.0	37.9	11.0	28.9	15.9	0	2784	0	0	53	53	29.328	14.175
	Naive	59.7%	0.163	92.2	65.4	48.5	68.3	56.7	200	1244	0	0	5	86	26.682	13.341
Val2	FRCNN-H	71.4%	0.062	96.3	74.4	61.4	79.5	69.3	103	919	0	0	4	36	70.342	36.122
	Oracle	74.1%	0.000	100.0	75.1	12.8	17.0	14.6	0	894	0	0	36	36	71.000	36.459
10	Naive	28.4%	0.204	78.8	39.1	23.2	46.8	31.1	477	2764	0	0	8	93	18.122	9.015
Val5	FRCNN-H	61.3%	0.070	95.4	64.6	33.7	49.7	40.2	143	1607	1	0	9	60	45.123	22.562
-	Oracle	42.4%	0.000	100.0	43.8	13.3	30.3	18.5	0	2552	0	0	64	64	28.812	14.618
	Naive	77.6%	0.152	96.0	80.9	80.9	96.0	87.8	30	171	1	0	0	28	25.000	12.500
Tst1	FRCNN-H	30.2%	0.105	100.0	30.2	30.2	100.0	46.4	0	625	0	0	0	15	16.938	8.212
Г	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
-	Naive	77.6%	0.138	96.9	80.2	80.2	96.9	87.7	46	353	1	0	0	44	31.022	15.856
Tst2	FRCNN-H	5.7%	0.133	100.0	5.8	3.5	60.2	6.6	0	1677	0	2	2	17	5.421	2.641
Г	Oracle	80.6%	0.000	100.0	81.6	23.9	29.3	26.3	0	328	2	0	18	25	53.778	27.396
	Naive	39.7%	0.168	80.0	53.1	38.0	57.3	45.7	589	2078	0	0	9	186	12.340	6.219
Tst5	FRCNN-H	40.0%	0.099	98.0	41.3	23.2	55.1	32.6	37	2605	0	0	17	117	15.000	7.469
L	Oracle	66.7%	0.000	100.0	67.8	27.2	40.1	32.4	0	1427	1	0	50	50	54.691	28.112
0	Naive	48.2%	0.153	86.7	57.1	46.3	70.3	55.8	780	3824	0	0	16	273	18.007	8.925
st1	FRCNN-H	25.2%	0.099	97.0	26.3	14.1	52.0	22.2	72	6571	0	3	32	225	9.996	4.904
H	Oracle	65.2%	0.000	100.0	66.6	20.2	30.3	24.3	0	2982	1	0	119	119	46.031	23.105

Table 8: Full metric evaluation of the 3D tracklets generated from the 3D tracklet association, on all sequences.

	Method	MOTA \uparrow	MOTP \downarrow	Prc. ↑	Rcll. ↑	ID-Rcll. ↑	ID-Prc. ↑	ID-F1↑	$\text{FP}\downarrow$	$FN\downarrow$	MT ↑	$ML\downarrow$	ID Sw. \downarrow	Frag. ↓	$MTBF_s \uparrow$	$MTBF_m \uparrow$
	Naive	41.4%	0.198	85.3	50.4	28.5	48.3	35.9	1250	7133	0	0	40	573	12.597	6.298
Trn2	FRCNN-H	73.8%	0.066	96.9	76.3	44.0	55.9	49.2	352	3407	0	0	14	216	50.317	25.216
Г	Oracle	46.2%	0.000	100.0	46.2	46.2	100.0	63.2	0	7738	0	0	0	202	32.539	16.190
5	Naive	40.4%	0.170	83.8	50.3	32.5	54.2	40.7	436	2228	0	0	7	135	16.121	7.947
Ĕ	FRCNN-H	63.5%	0.064	92.1	69.7	40.9	54.1	46.6	269	1359	1	0	7	66	44.028	22.170
Г	Oracle	37.9%	0.000	100.0	37.9	37.9	100.0	55.0	0	2784	0	0	0	53	29.328	14.175
	Naive	59.6%	0.163	92.2	65.3	50.8	71.7	59.4	199	1248	0	0	3	82	27.905	13.870
Val2	FRCNN-H	71.5%	0.062	96.3	74.4	71.7	92.8	80.9	103	920	0	0	2	35	72.216	37.111
-	Oracle	75.1%	0.000	100.0	75.1	75.1	100.0	85.8	0	894	0	0	0	36	71.000	36.459
	Naive	28.5%	0.204	78.9	39.1	23.2	46.8	31.1	476	2764	0	0	7	93	18.122	9.015
Val5	FRCNN-H	61.3%	0.070	95.4	64.6	40.2	59.4	48.0	143	1607	1	0	5	60	45.123	22.562
-	Oracle	43.8%	0.000	100.0	43.8	43.8	100.0	60.9	0	2552	0	0	0	64	28.812	14.618
	Naive	77.6%	0.152	96.0	80.9	80.9	96.0	87.8	30	171	1	0	0	28	25.000	12.500
[st]	FRCNN-H	30.2%	0.105	100.0	30.2	30.2	100.0	46.4	0	625	0	0	0	15	16.938	8.212
Г	Oracle	100.0%	0.000	100.0	100.0	100.0	100.0	100.0	0	0	1	0	0	0	900.000	900.000
	Naive	77.6%	0.138	96.9	80.2	80.2	96.9	87.7	46	353	1	0	0	44	31.022	15.856
St2	FRCNN-H*	5.7%	0.133	100.0	5.8	3.5	60.2	6.6	0	1677	0	2	2	17	5.421	2.641
Г	Oracle	81.6%	0.000	100.0	81.6	81.6	100.0	89.9	0	328	2	0	0	25	53.778	27.396
	Naive	39.7%	0.168	80.0	53.1	43.4	65.4	52.2	588	2079	0	0	7	185	12.400	6.249
Tst5	FRCNN-H	40.2%	0.099	98.0	41.2	29.8	70.9	41.9	37	2609	0	0	7	115	15.217	7.577
-	Oracle	67.8%	0.000	100.0	67.8	67.8	100.0	80.8	0	1427	1	0	0	50	54.691	28.112
0	Naive	48.3%	0.153	86.9	57.1	48.5	73.8	58.5	768	3829	0	0	11	268	18.313	9.075
st1	FRCNN-H*	25.2%	0.099	97.0	26.3	14.1	52.0	22.2	72	6571	0	3	32	225	9.996	4.904
F	Oracle	66.6%	0.000	100.0	66.6	66.6	100.0	79.9	0	2982	1	0	0	119	46.031	23.105

Table 9: Full metric evaluation of the final 3D tracks generated from the 3D track association, on all sequences. An * indicates that the method did not complete the 3D Tracklet Association step for the sequence, as there were not enough concurrent 3D tracklets at any one point in the sequence. In this case, the 3D tracklet results are reported.