Track an Object in 3D Space ReadMe

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FP.0 Final Report

Provide a Writeup / README that includes all the rubric points and how you addressed each one. You can submit your writeup as markdown or pdf.

The document at hand represents the readme file.

FP.1 Match 3D Objects

Implement the method "matchBoundingBoxes", which takes as input both the previous and the current data frames and provides as output the ids of the matched regions of interest (i.e. the boxID property). Matches must be the ones with the highest number of keypoint correspondences.

As a first step, I changed the references to be `const` whenever possible. That is nothing functional, but makes the code a bit safer.

In order to address the matching of the box identifiers, I decided to implement a greedy algorithm. As a foundation, I set up a matrix which contains a row for every box ID in the previous frame, and a column for every box ID in the current frame. Every element of this matrix corresponds therefore represents a concatenation between two box identifiers and therefore objects (vehicles). The keypoint matches are now filled into this matrix. Once the matrix is complete, I greedily select the elements with the largest number of keypoint matches. The position in the matrix (row and column) then connects the box identifiers between the previous and the current frame. Once a connection is established, the entire row and column is set to zero, as this identifier pair has now been dealt with.

In order to get a better feeling for what is going on, I created some visual debug output in the form of images, see Figure 1.

FP.2 Compute Lidar-based TTC

Compute the time-to-collision in second for all matched 3D objects using only Lidar measurements from the matched bounding boxes between current and previous frame.

Figure 1: Simultaneous visualization of the 3D top view from the previous and current frame, along with the keypoint descriptor matching, the latter being augmented by the 2D bounding boxes. In this specific scene, the identifier of the leading vehicle changes from 5 to 3.

According to lesson 2, the time-to-collision (TTC) based on a constant velocity model is

$$t_{\text{ttc}} = \frac{d_1}{v_0} = \frac{d_1 \Delta t}{d_0 - d_1} \tag{1}$$

with d_0 being the distance from our vehicle to the lead vehicle in the previous frame (index 0), and d_1 being the distance from our vehicle to the lead vehicle in the current frame (index 1). v_0 is the velocity. As it is a constant velocity model, $v_0 = v_1$. Δt is the step size, i.e., the difference between the time stamps of the individual measurements. Δt is the reciprocal of the frame rate.

The current model for the vehicle extent consists of axis-aligned bounding boxes. In other words, any (non-zero) orientation of the vehicles as well as curvature on their boundary is neglected. For this reason, it is valid to assume that the tail of the vehicles can be represented by a plane with a normal vector which is pointing along the ego vehicle's x-axis (x pointing forward in accordance with ISO 8855 and as used throughout this course). This in turn allows us to use the plane fitting RANSAC from the Lidar course in order to robustly estimate the tail of the lead vehicle, thereby removing outliers, as can be seen in Figure 2. I included my Lidar code into the project, slightly adapted for the Camera course data types, in order to compute the RANSAC. The point cloud library is not needed.

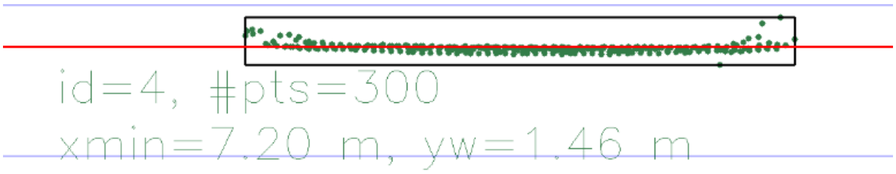


Figure 2: Estimation of the tail of the lead vehicle by means of plane fitting using RANSAC. The plane is constrained to have a normal vector which is pointing along the x-axis. In the top view, the red line represents the plane. Note how the outlier in the bottom right region enlarges the bounding box, but is rejected by the plane fit.

FP.3 Associate Keypoint Correspondences with Bounding Boxes

Prepare the TTC computation based on camera measurements by associating keypoint correspondences to the bounding boxes which enclose them. All matches which satisfy this condition must be added to a vector in the respective bounding box.

First of all, as before, const correctness is established (not related to the function though).

As has been recommended by Andreas Haja, I looped over all keypoint matches and checked if the associated current keypoint is within the region of interest. This is a necessary requirement. It is however not sufficient for a valid keypoint match, as there might be outliers. Therefore, as has also been recommended, I computed the Euclidean distance d for every keypoint match (in the region of interest). Based on those distances, I computed the mean μ and the standard deviation σ. A keypoint match is then declared to be valid if

$$|d - \mu| < 2\sigma. \tag{2}$$

This means that it must not be too far off.

FP.4 Compute Camera-based TTC

Compute the time-to-collision in second for all matched 3D objects using only keypoint correspondences from the matched bounding boxes between current and previous frame.

In order to solve this task, I used the formulas which have been provided in Lesson 3 (Engineering a Collision Detection System), Concept 3 (Estimating TTC with a Camera). I used the keypoints in order to compute an average distance ratio instead of using the heights, as has been explained towards the end of that concept. The TTC formula is

$$t_{\text{ttc}} = \frac{-\Delta t}{1 - \rho} \tag{3}$$

with ρ being the average distance ratio between the keypoints of the current frame and the keypoints of the previous frame.

FP.5 Performance Evaluation 1

Find examples where the TTC estimate of the Lidar sensor does not seem plausible. Describe your observations and provide a sound argumentation why you think this happened.

In order to address this task, I extended my performance evaluation class from the midterm project so that I can export the Lidar-based distance, velocity, and TTC estimates. The values are depicted in Table 1 and visualized in Figures 3 to 5.

It can be seen in Figure 3 that the distances are located approximately on a straight line.

As we are approaching the leading vehicle, we can expect the TTC to decrease. I therefore decided to introduce yet another metric: the expected collision time (ECT). This makes it easier to spot outliers, as the trend has been removed, and the ECT can be assumed to be constant based on a constant-velocity model. The ECT is the TTC plus the current time that has passed since the start of the program. As the frame rate is 10 Hz, we are adding 0.1 s for every frame that has passed. The resulting ECT is depicted in Figure 6, along with the mean value and the 1-sigma band. It can be seen that there are 3 points over the 1-sigma band to the top, and 3 points below the 1-sigma band to the bottom. I decided to analyze the one at $t = 8$ and $t = 14$ in detail, as those seem to be the largest "outliers" to the top and bottom respectively. In can also be seen that the velocity, which is an essential part for computing the TTC according to Equation 1, has "outliers" at time steps $t = 8$ and $t = 14$. The velocity in turn is computed based on the distance change, so I have a look at the distances, as is also recommended to do in the course: *"The assertion that the TTC is off should be based on manually estimating the distance to the rear of the preceding vehicle from a top view perspective of the Lidar points."*

The bird's eye view for the time stamps 7 and 8 is shown in Figure 7. It can be seen that the RANSAC-based distance estimation is shifted a bit towards the head of the leading vehicle, therefore decreasing the distance delta and the velocity estimate, and at the same time increasing the TTC.

The bird's eye view for the time stamps 13 and 14 is shown in Figure 8. To be honest, I cannot see a geometric reason caused by the Lidar point cloud which would cause the RANSAC-based distance estimate to be "way off". The RANSAC-fitted line is actually moving quite well with the Lidar point cloud.

Summarizing the task, I did not find any TTC which deserves to be labelled as "way off". Only the TTC at time stamp $t = 8$ is outside the 2-sigma domain and therefore a real outlier. The other points are within the 2-sigma band of the associated Gaussian distribution and therefore should not be called outliers, but rather noise.

However, as required, I want to give a sound argumentation and name several reasons why the TTC seems noisy, and point out avenues how to improve the TTC estimate:

Table 1: Lidar-based distance, velocity, and TTC estimates.

Time index	Distance (m)	Velocity (m/s)	TTC (s)
0	8.015	0.549994	14.5729
1	7.945	0.709996	11.1902
2	7.900	0.489998	16.1225
3	7.843	0.590000	13.2932
4	7.774	0.689998	11.2667
5	7.724	0.660000	11.7030
6	7.653	0.730000	10.4836
7	7.606	0.469999	16.1830
8	7.565	0.419998	18.0120
9	7.510	0.579996	12.9484
10	7.436	0.710001	10.4732
11	7.370	0.660000	11.1667
12	7.290	0.809999	9.00002
13	7.229	0.619998	11.6597
14	7.140	0.890002	8.02245
15	7.062	0.730004	9.67392
16	6.974	0.869999	8.01610
17	6.910	0.500002	13.8199

1. The constant velocity model does not adequately describe the relative velocity between the leading vehicle and our vehicle. Especially as we are heading towards an intersection and therefore decelerating, a constant velocity model might be an oversimplification. I propose to use a constant acceleration model.

2. We compute the velocity directly by evaluating the delta between the distance d_1 of the previous frame and the distance d_0 of the current frame. That makes the velocity highly susceptible to noise. A better approach would be to use some kind of low-pass filter (realized as IIR or FIR filter) in order to smoothen the velocity and TTC signals, or alternatively to use a Kalman filter on top of our constant velocity (or constant acceleration) motion model.

3. A geometric reasoning: Neither a bounding box nor a line fit (as done using RANSAC here) is a perfect model for the shape of the leading vehicle, as its tail is not flat. It might prove beneficial to fit an ellipse segment instead, as this better describes the shape of the leading vehicle's tail.

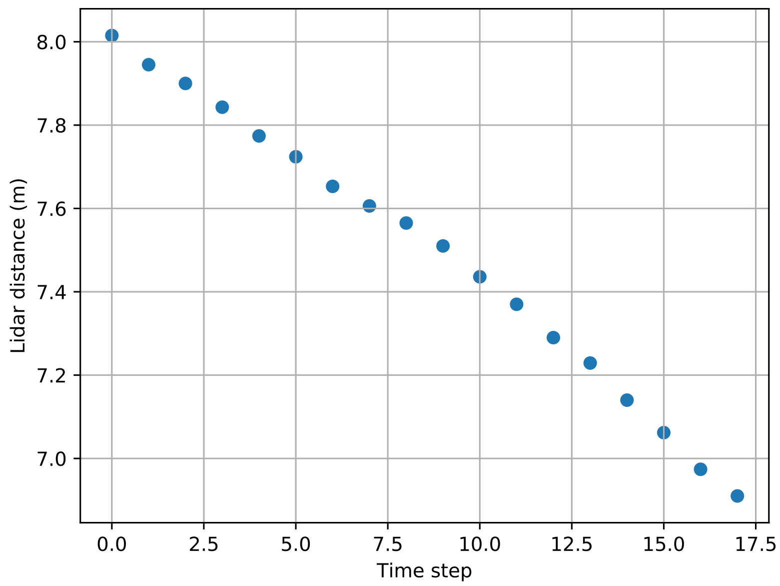


Figure 3: Lidar distance over time. The time is given in time steps (not in seconds).

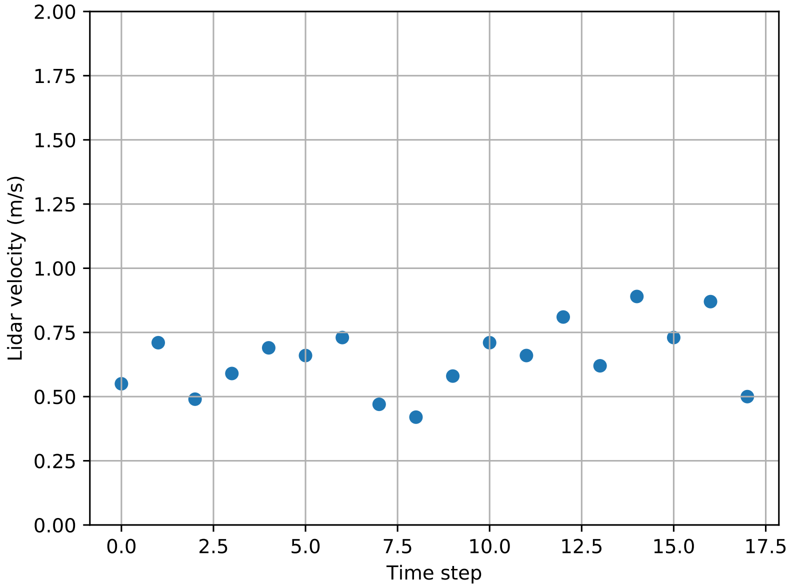


Figure 4: Lidar velocity over time. The time is given in time steps (not in seconds).

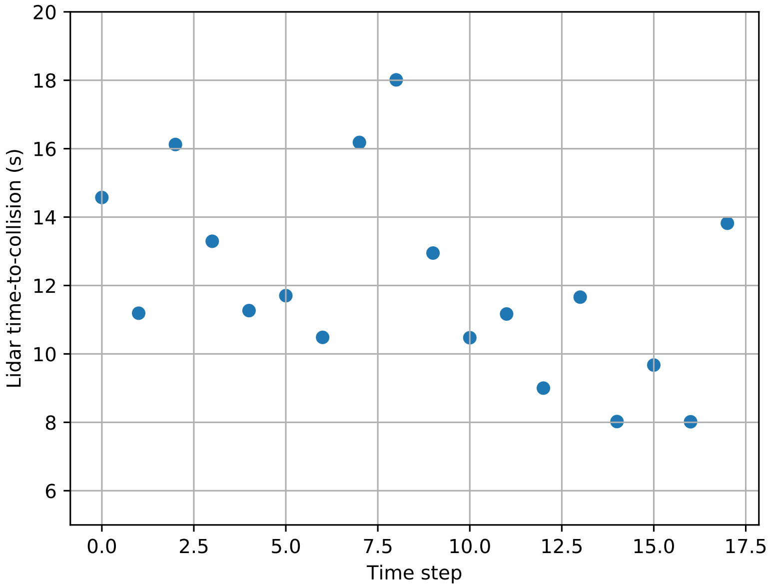


Figure 5: Lidar-based time-to-collision. The time is given in time steps (not in seconds).

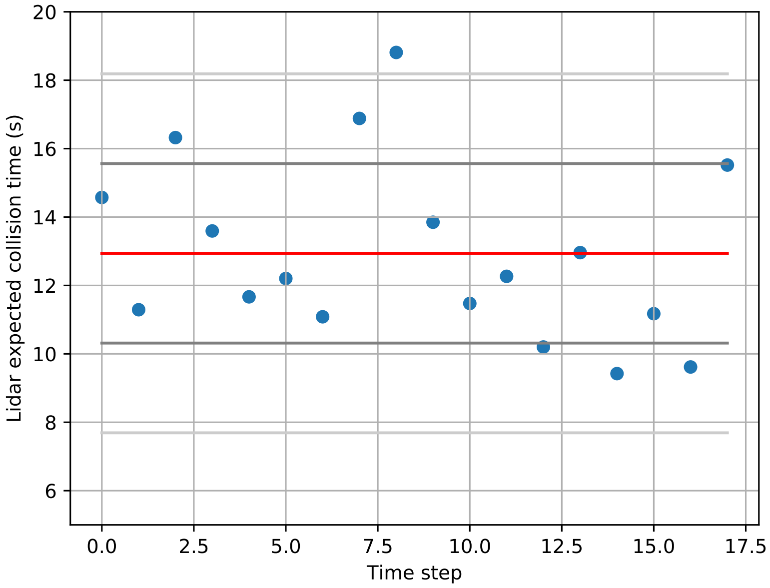
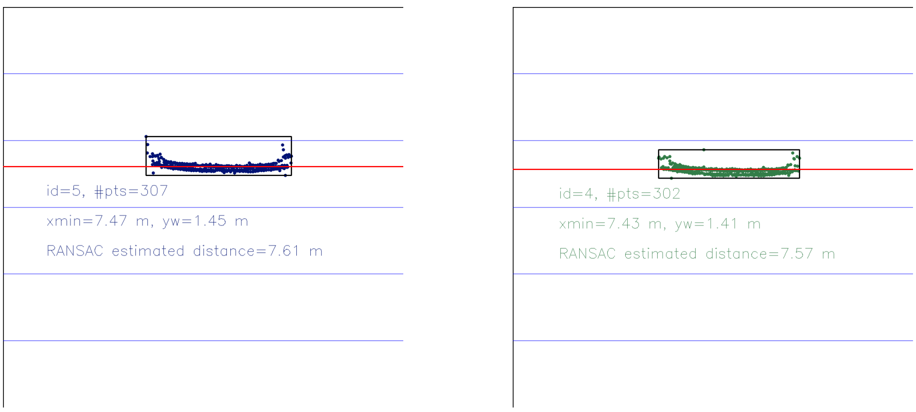


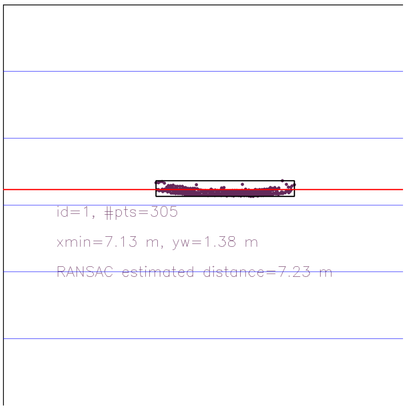
Figure 6: Lidar-based expected collision time. The time is given in time steps (not in seconds). The red line shows the mean value, and the gray lines show the plus/minus one (dark gray) or two (light gray) σ (standard deviation) boundaries.



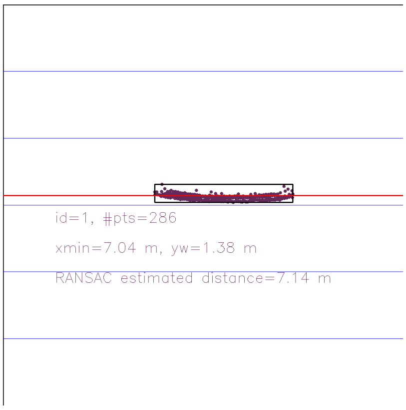
(a) Time step 7.

(b) Time step 8.

Figure 7: Lidar distances bird's eye view. The distance between the blue horizontal lines corresponds to one meter. The world view starts at $x = 4\,\mathrm{m}$ and ends at $x = 10\,\mathrm{m}$.



(a) Time step 13.



(b) Time step 14.

Figure 8: Lidar distances bird's eye view. The distance between the blue horizontal lines corresponds to one meter. The world view starts at $x = 4\,\mathrm{m}$ and ends at $x = 10\,\mathrm{m}$.

FP.6 Performance Evaluation 2

Run several detector / descriptor combinations and look at the differences in TTC estimation. Find out which methods perform best and also include several examples where camera-based TTC estimation is way off. As with Lidar, describe your observations again and also look into potential reasons.

In order to address this task, I create plots for the TTC and for the ECT (expected collision time) for all detector and descriptor combinations. As in the previous section, the ECT is used because it does not contain the decreasing trend that we see in the TTC due to us approaching the leading vehicle, but rather should be a constant value.

The TTC plots are shown in Figures 9 to 15.

I also compute the expected collision time mean and the standard deviation for every keypoint detector and descriptor combination. The smaller the standard deviation the better. The results are shown in Table 2.

It can be seen that –opposed to Lidar– there are now really some TTC estimates which deserve to be called "way off". One example would be the combination of the Shi-Tomasi detector with the BRIEF descriptor at time step 6. It can be seen that the TTC is even estimated to be negative. An example where the TTC is estimated way too large is the Harris detector in combination with the BRISK descriptor at time step 12.

In order to figure out what went wrong, I had a detailed look into the setting with keypoint detector Shi-Tomasi and descriptor BRIEF. The terminal output is shown in Figure 16. It can be seen that my outlier checking condition in camFusion_Student.cpp:286 `(std::abs(euclidean_diff - euclidean_diff_mean) < 2.0 * euclidean_diff_std)` does not capture all outliers. Therefore, some keypoints are mismatched, resulting in the outlier TTC.

Based on the ECT standard deviation as given in Table 2, I would recommend to use for instance

- Shi-Tomasi detector with BRISK descriptor,
- Shi-Tomasi detector with BRIEF descriptor,
- Shi-Tomasi detector with SIFT descriptor, or
- AKAZE detector with SIFT descriptor.

However, even then, the use of some low-pass filter or (model-based) Kalman filter would be recommended.

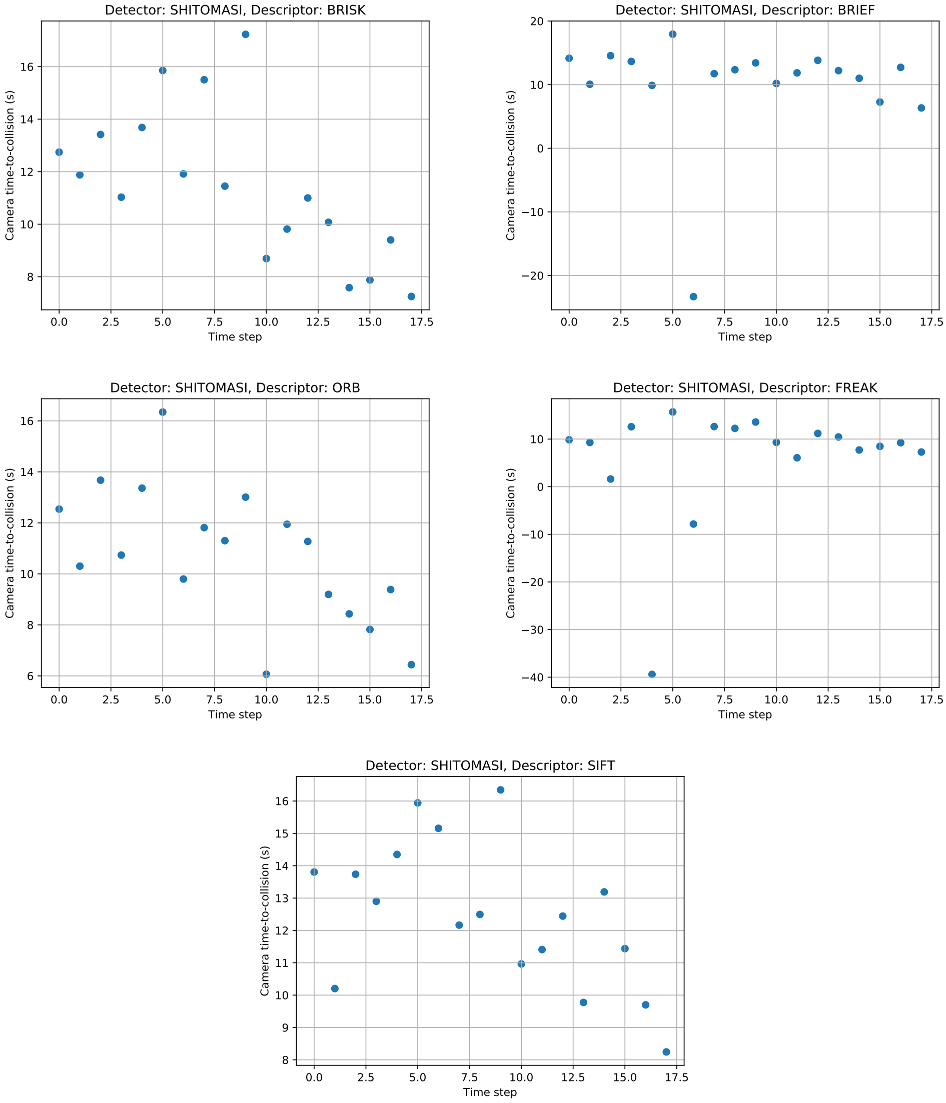


Figure 9: Camera TTC for the Shi-Tomasi detector.

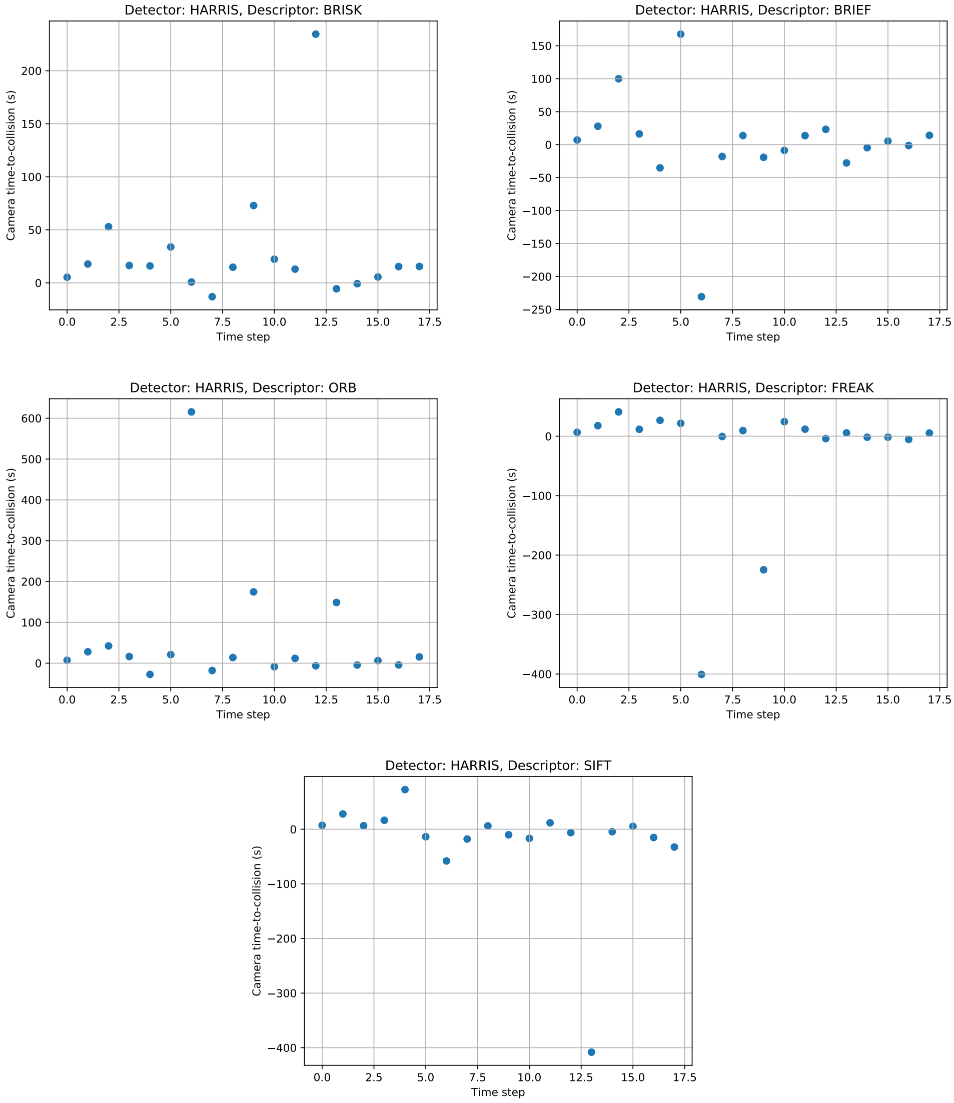


Figure 10: Camera TTC for the Harris detector.

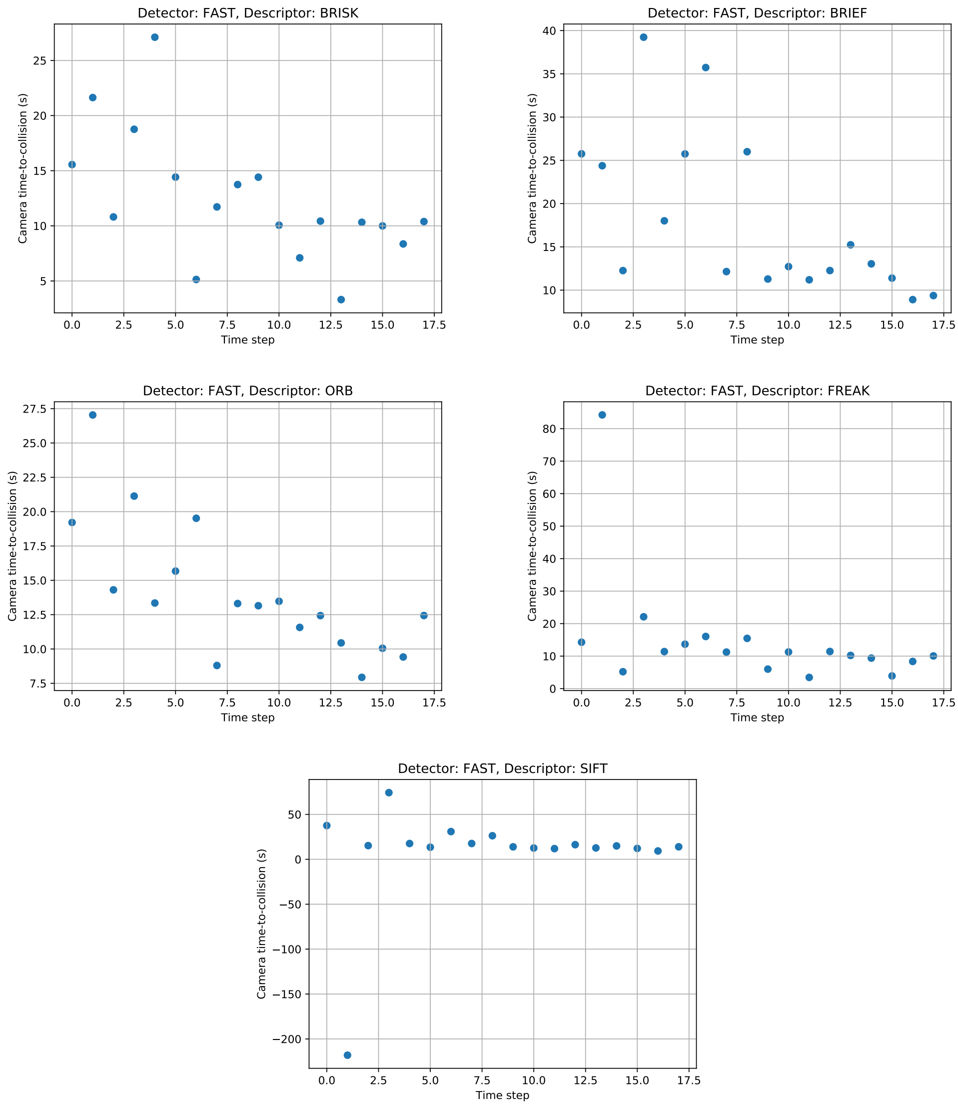


Figure 11: Camera TTC for the FAST detector.

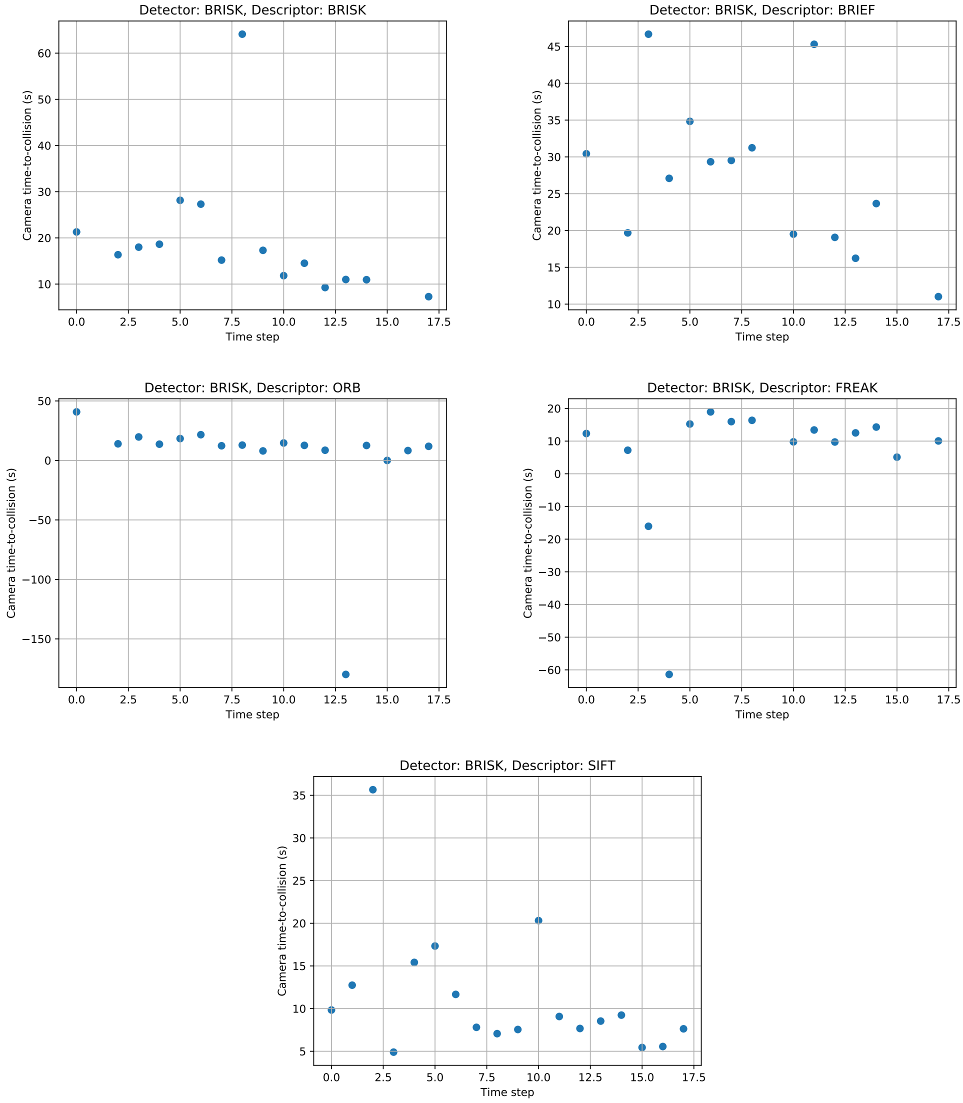


Figure 12: Camera TTC for the BRISK detector.

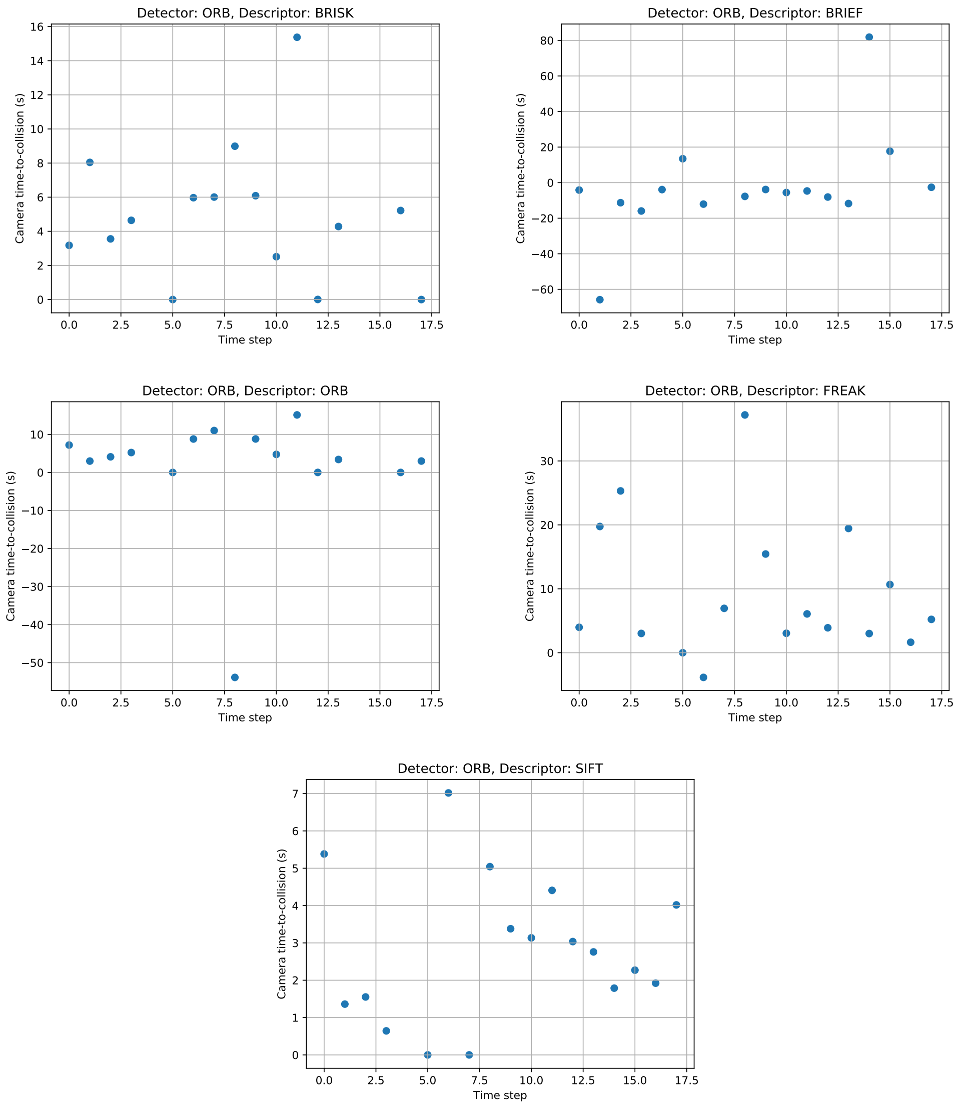


Figure 13: Camera TTC for the ORB detector.

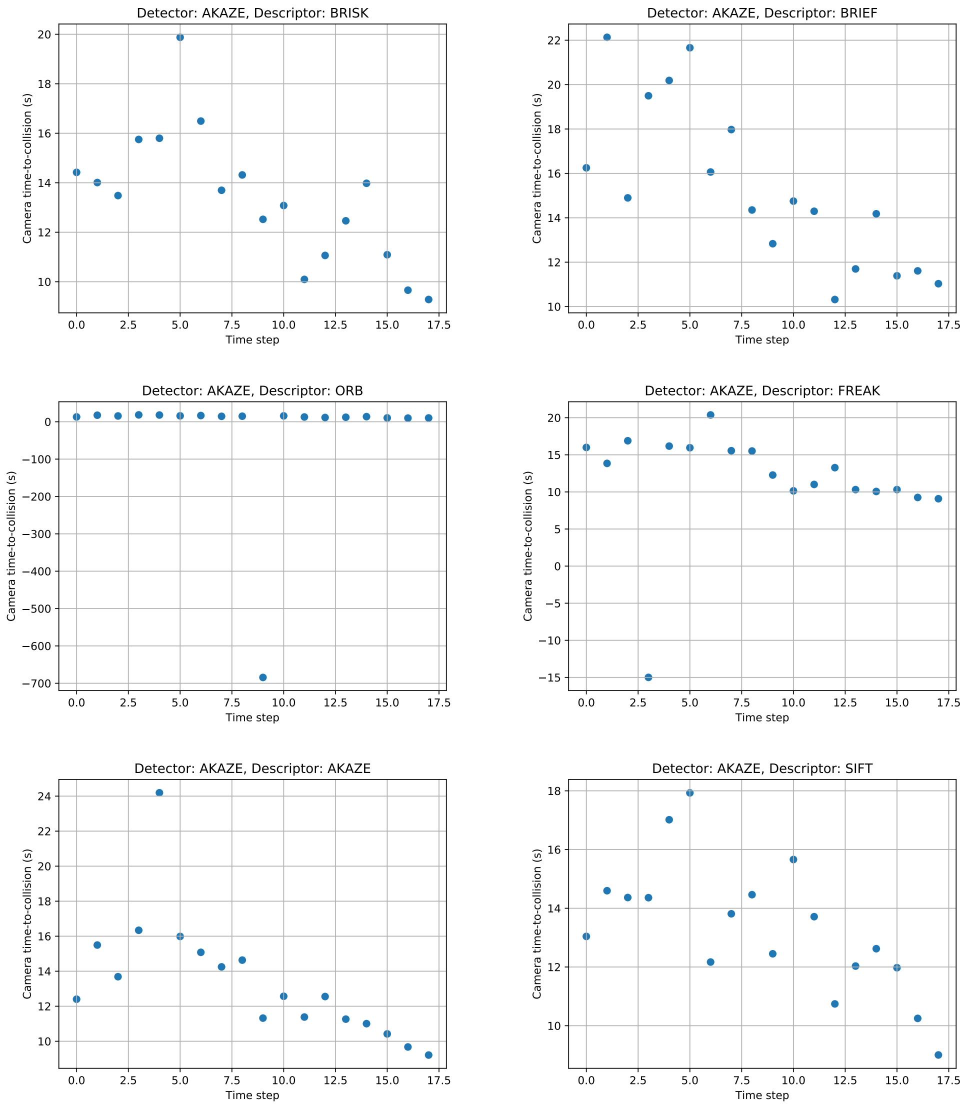


Figure 14: Camera TTC for the AKAZE detector.

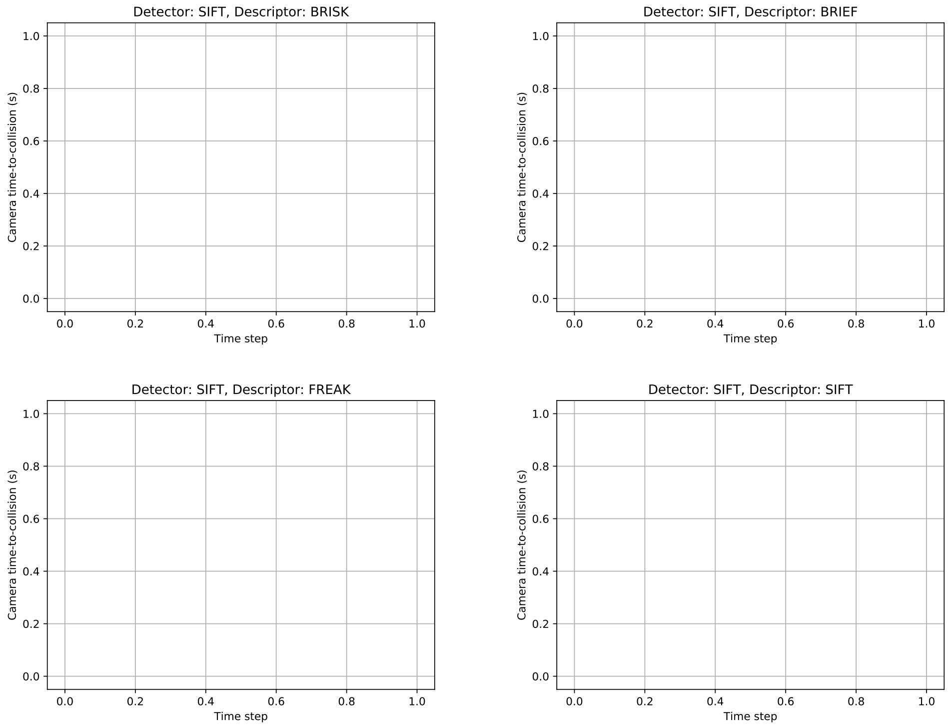


Figure 15: Camera TTC for the SIFT detector.

Table 2: Mean values and standard deviation for the ECT in seconds. The rows are the detectors, and the columns are the descriptors.

		BRISK	BRIEF	ORB	FREAK	AKAZE	SIFT
SHITOMASI	μ	12.3164	10.8412	11.5964	6.95721	N/A	13.3082
	σ	2.5886	8.73406	2.34092	12.6196	N/A	1.99947
HARRIS	μ	29.5739	3.29687	58.1579	-24.507	N/A	-23.0387
	σ	55.2819	75.1791	148.966	109.502	N/A	99.4211
FAST	μ	13.2524	18.8866	14.9198	15.7288	N/A	8.19293
	σ	5.48023	8.88155	4.51431	17.6802	N/A	58.3958
BRISK	μ	NaN	NaN	NaN	NaN	N/A	12.1515
	σ	NaN	NaN	NaN	NaN	N/A	7.1678
ORB	μ	NaN	NaN	NaN	NaN	N/A	NaN
	σ	NaN	NaN	NaN	NaN	N/A	NaN
AKAZE	μ	14.2429	16.1344	-23.8059	12.5731	14.2648	14.1947
	σ	2.32234	3.29111	164.653	7.36428	3.13008	1.95166
SIFT	μ	NaN	NaN	N/A	NaN	N/A	NaN
	σ	NaN	NaN	N/A	NaN	N/A	NaN

Figure 16: Detailed analysis of a camera TTC outlier. Not all keypoint mismatch outliers are caught.