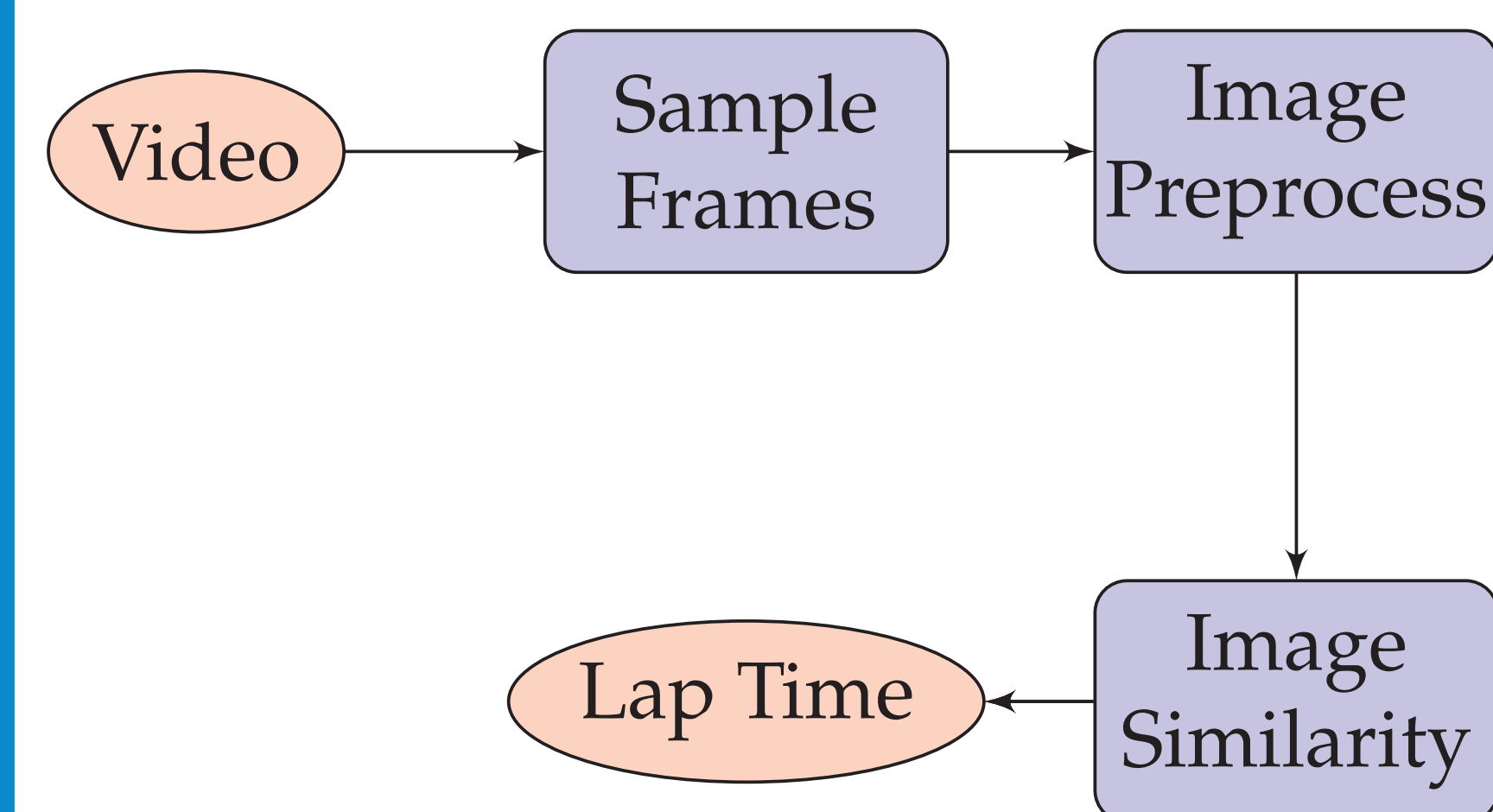


ABSTRACT

Today there are dashboard cameras in many cars providing a video log of our drives. The recordings of work commutes and other trips could be useful for many purposes, for example, identifying unusual incidents in trips, assisting in insurance claims for accidents, etc. Our goal is to build automatic tools for analyzing these logs and annotate the video stream with relevant information. We start by studying freely available video streams of sports cars on the race tracks. In particular we first focus on estimating the lap times of these cars based purely on the video footage. Here we present our preliminary results using a number of methods and algorithms, and discuss our future work.

METHODS

We propose a framework as follows.



First, given an initial frame index, we randomly sample N frames around initial frame to construct a sample set.

Then, for each image in the sample set, we mask out the irrelevant part and noise (cars in this case).

Next, we try to find similar images for each image in the sample set using the following algorithms.

- Mean Square Error (MSE)
- Oriented FAST and Rotated BRIEF (ORB)
- Perceptual Hashing (pHash)

For each image in the sample set, the lap time is estimated by

$$\hat{T} = \frac{\text{Similar Frame Index} - \text{Initial Frame Index}}{\text{Frame Per Second (FPS)}}$$

Last, the final lap time is calculated by averaging the results of all sample frames.

For multiple laps, given initial frame index for first lap, we update initial frame index for next lap by the similar frame index of the last lap.

DATA

We test our framework on a dash cam video (16m44s) with 9 completed laps. The FPS of this video is 29.9393. For each frame, we mask out irrelevant part and noise (cars here) in the image. To capture cars, we use **ImageAI**, which provides pre-trained deep neural networks for object detection, like RetinaNet. Some examples are shown in Figure 1.

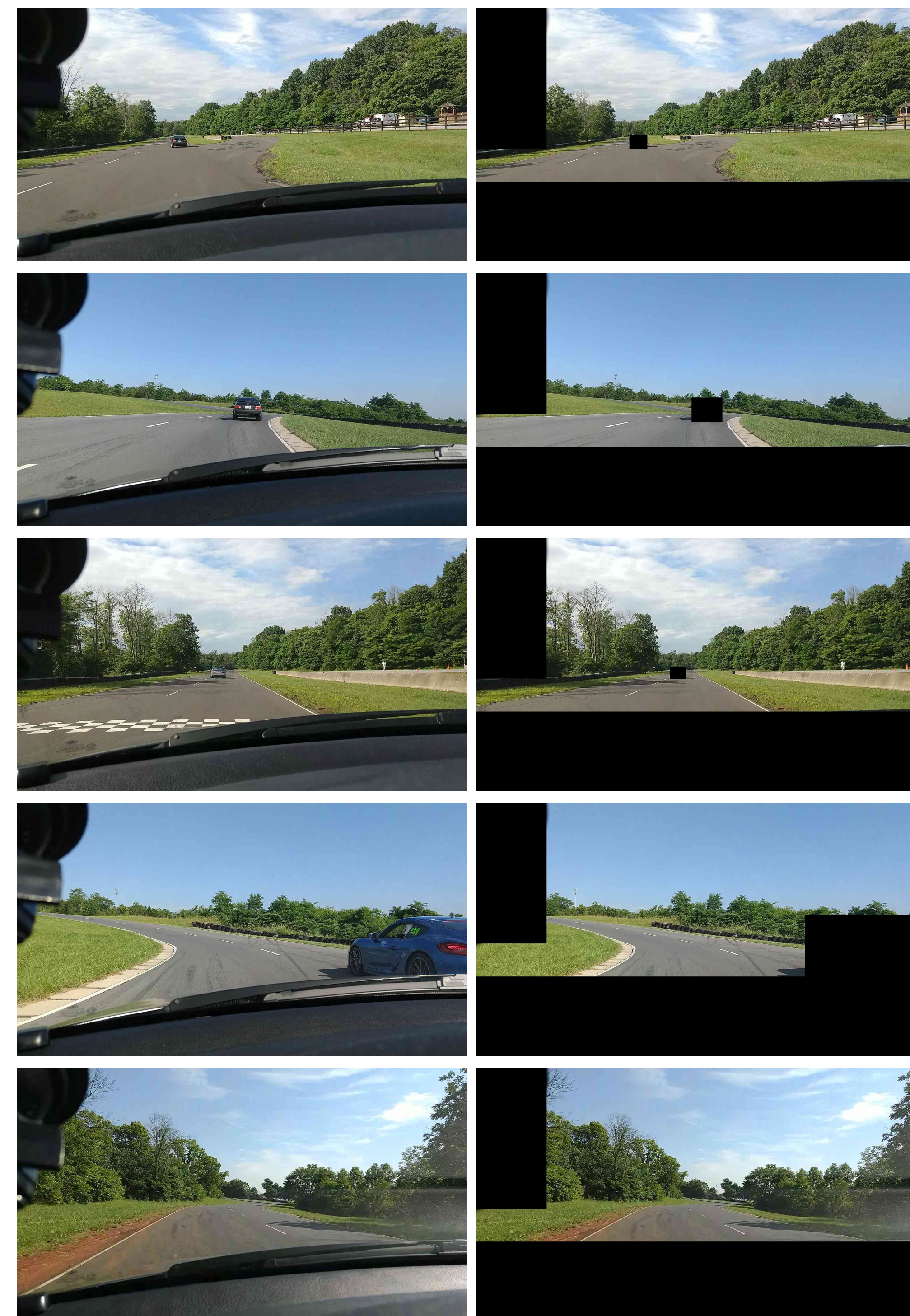


Figure 1: Original (left) and Masked (right) Frames

RESULTS

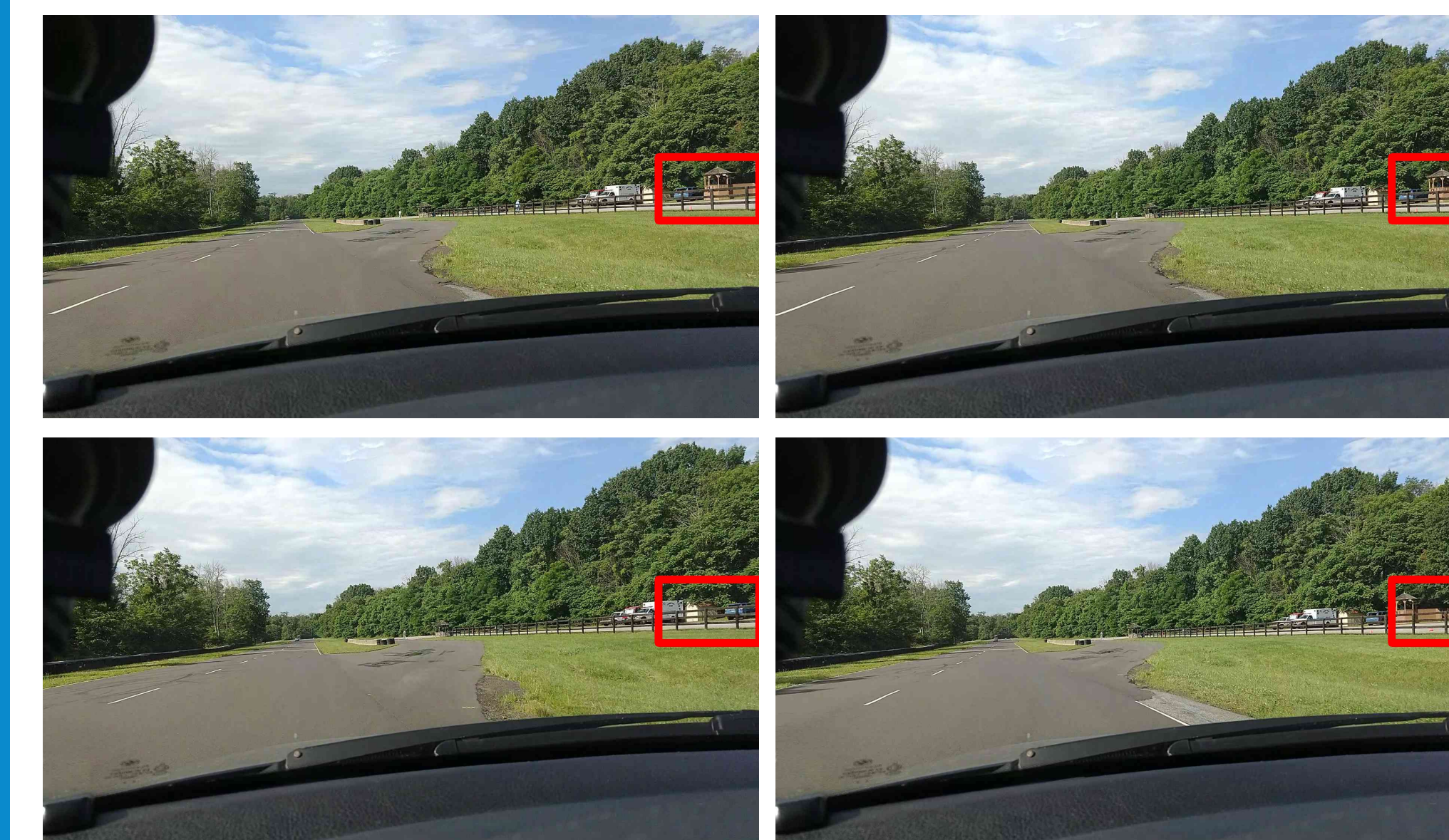


Figure 2: Similar Frames (Left top: initial; right top: by MSE; left bottom: by ORB; right bottom: by pHash)

Figure 2 shows the initial frame and similar frames detected by different algorithms for lap 3. Note that they are almost the same perceptually. An example of the tiny difference could be found in the red rectangle. Figure 3 shows the difference between initial frame and similar frames in pixel. Colorful parts suggest some difference between two images. Again it indicates that the algorithms could find the right frame.

Lap	Video	MSE	ORB	pHash
1	92.1865	+0.0044	-0.1114	+0.0445
2	92.1197	+0.0712	+0.0846	+0.0779
3	90.7502	+0.0635	+0.0279	+0.0802
4	90.0488	+0.0256	-0.0935	-1.0132
5	89.6814	0.0000	+0.1069	+0.0111
6	89.9152	-0.0802	-0.0557	+0.0534
7	89.0802	+0.0568	-0.0167	+0.1213
8	90.0822	-0.0067	+0.0690	-0.9185
9	89.5812	-0.0312	-0.0969	+0.1959
Mean Error		0.0377	0.0736	0.2795

Table 1: Estimated Lap Time

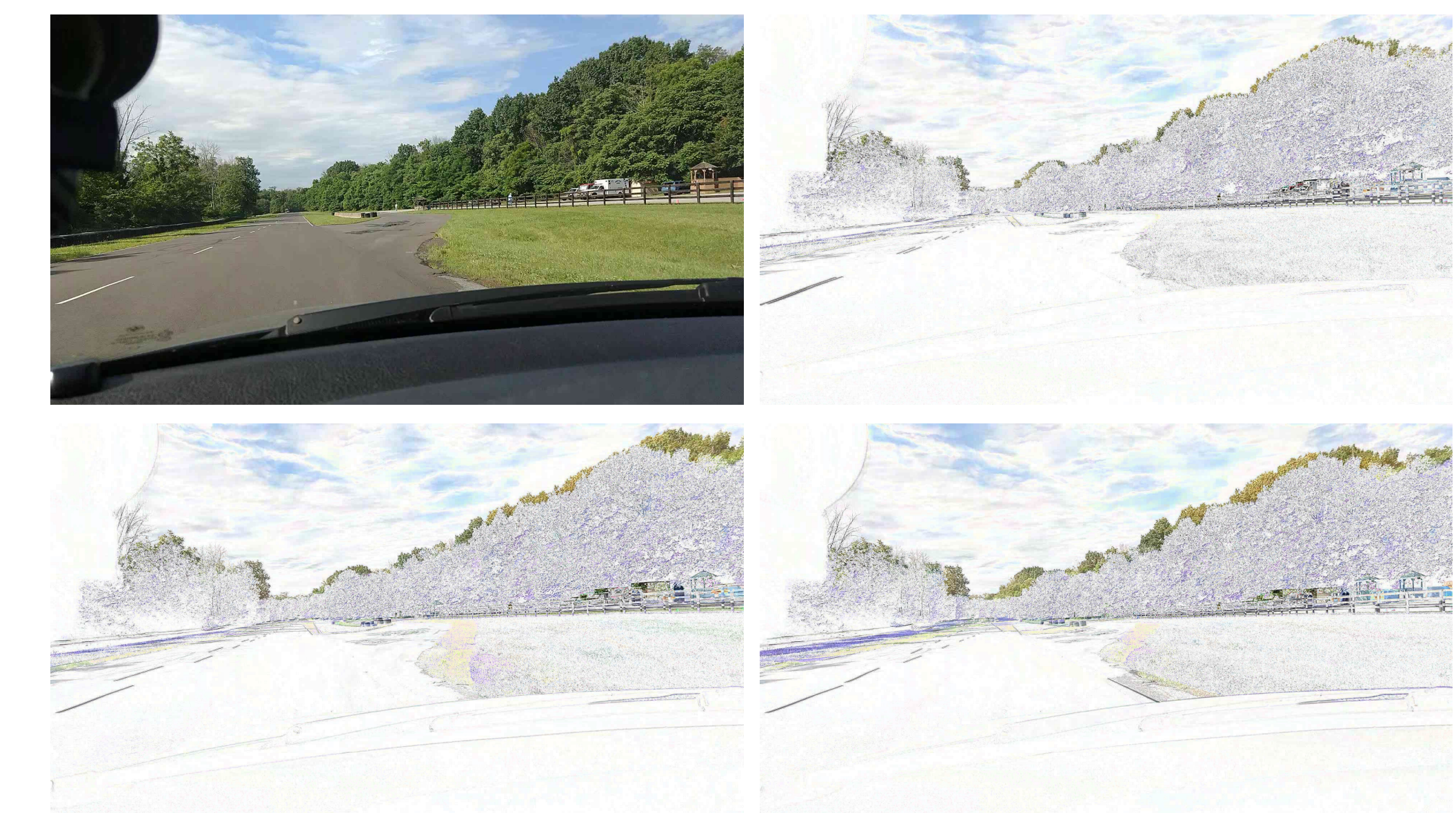


Figure 3: Difference between Initial and Similar Frames (Same Layout as Figure 2)

The full results of 9 laps are summarized in Table 1. Here **Video** columns indicates the lap times observed from video while **MSE**, **ORB** and **pHash** columns are deviation between estimated lap times and **Video**. The observed and estimated lap times are shown in Figure 4. We could note that MSE (pixel-wise distance), ORB (feature based similarity) and pHash (image hashing) all could have accurate estimation of lap times.

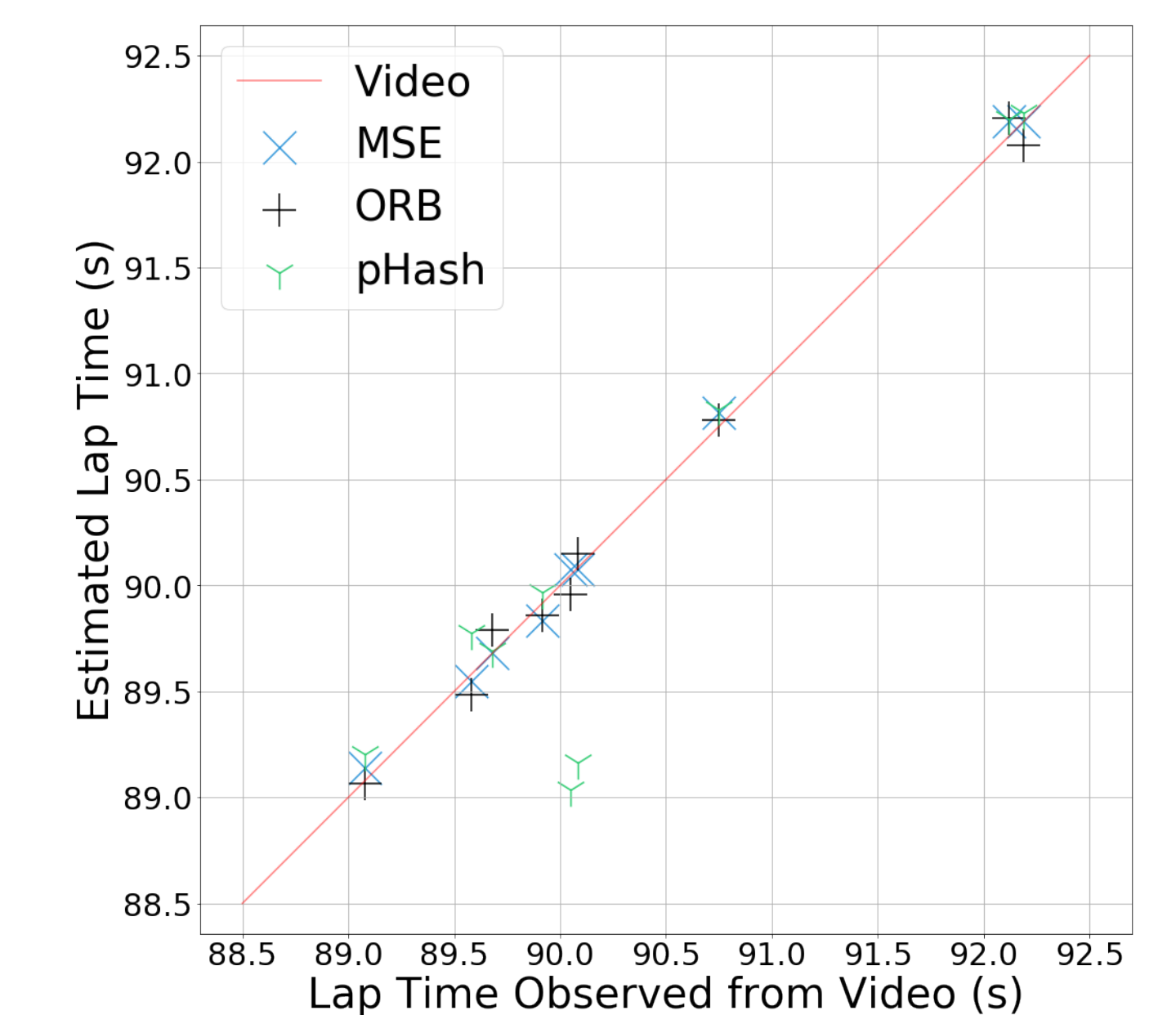


Figure 4: Estimated Lap Time

CONCLUSION & FUTURE WORK

To improve our framework, we could focus on **(1) The size of sample set** and **(2) Image similarity measure**. Furthermore, this framework could be the first step to build automatic tools for analyzing dash cam videos, which could be used in identifying unusual incidents in trips, assisting in insurance claims for accidents, etc.

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