Bird's eye view trajectory reconstruction of the SHRP2 NDS

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ABSTRACT

This document outlines methods for reconstructing bird's eye view trajectories from the Second Strategic Highway Research Program's (SHRP2) Naturalistic Driving Study (NDS). Utilising extended Kalman filters (EKFs), trajectories for subject vehicles and surrounding objects are reconstructed from recorded sensor data. In total 10,919 safe baseline trips and 8,111 trips involving safety-critical events (crashes and near-crashes) are reconstructed, where the accuracy of reconstruction is also evaluated. Further, a dataset of 4,875 safety-critical events is refined for future safety research. For these events, environmental conditions, event timing, and scenario types are included in addition to trajectories for more detailed analyses.

1 Overview

This document describes the methods used to reconstruct bird's eye view trajectories of the trips in the Second Strategic Highway Research Program's (SHRP2) Naturalistic Driving Study (NDS) [1]. The SHRP2 NDS is a large-scale research initiative aimed at understanding driver behaviour and performance. Between 2010 and 2013, it collected extensive data using instrumented vehicles in six states in the United States. More than 3,300 participant vehicles were equipped with data acquisition systems that recorded video footage, vehicle network data (e.g., speed, brake, and accelerator positions), and signals from additional sensors such as forward radar and accelerometers. A significant strength of SHRP2 NDS is its comprehensive set of manually annotated traffic safety events, including crashes and near-crashes that are collectively termed "safety-critical events", along with "safe baselines" selected through stratified random sampling. Table 1 outlines the operational definitions of these events as described in [2], where further details of the SHRP2 NDS are also referred to.

2 Trajectory reconstruction

The reconstruction uses two existing databases, [3, 4], which were derived from SHRP2 NDS. The accessible motion dynamics data do not contain positional information of the subject (participant) vehicles to protect driver privacy. In addition, the other road users are detected by forward radars as surrounding objects in a moving local coordinate system. To align these data with the mainstream bird's eye view datasets, we reconstruct the trajectories for both subject vehicles and surrounding objects using extended Kalman filters (EKFs). First, we linearly interpolate all time-series signals to a uniform frequency of 0.1 seconds. Next, we reassign the indices of surrounding objects when necessary. Due to detection limitations, an object may be temporarily lost and re-detected later with a new index. If a newly detected object is within a specified distance threshold of a previously tracked object, the new object is assigned the previous index. We define the distance threshold as the object's position displacement relative to the subject over 0.3 seconds, constrained to a minimum of 0.5 m and a maximum of 2.5 m. Then we reconstruct trajectories for each event in two steps.

Table 1. Operational definitions of traffic safety events in the SHRP2 NDS.

Event	Operational definition
Crash	"Any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated is considered a crash. This also includes non-premeditated departures of the roadway where at least one tire leaves the paved or intended travel surface of the road, as well as instances where the subject vehicle strikes another vehicle, roadside barrier, pedestrian, cyclist, animal, or object on or off the roadway."
Near-crash	"Any circumstance that requires a rapid evasive manoeuvrer by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal, to avoid a crash is considered a near-crash. A rapid evasive manoeuvrer is defined as steering, braking, accelerating, or any combination of control inputs."
Safe baseline (Non-conflict)	"Normal driving behaviours and scenarios where the driver may react to situational conditions and events, but the reaction is not evasive and the situation does not place the subject or others at elevated risk."

2.1 Subject vehicle's trajectory reconstruction

We apply an EKF assuming constant yaw rate and acceleration. The motion dynamics are updated according to Equations (1) and (2), where (x_i, y_i) denotes the vehicle's position, ψ_i the heading angle relative to the x-axis, v_i the longitudinal speed, ω_i the yaw rate, a_i the longitudinal acceleration, and ϵ is a threshold to use longitudinal updates when near-zero yaw rates induce numerical instability. The update interval $\Delta t = 0.1$ seconds. We place the subject vehicle initially at $(x_i, y_i) = (0, 0)$ with its heading $\psi_i = 0$ along the x-axis, and set the initial states of speed, yaw rate, and acceleration from original data. The data of yaw rates and accelerations are stably recorded, but speed measurements are not always consistent. We thus consider two orders of time sequence depending on whether the earliest or latest 0.5-second speed states are missing. If the latest states are missing, we let the EKF propagate forward from the earliest available measurement; if the earliest states are missing, we let the EKF propagate backward. When both earliest and latest speed states exist, we run two EKFs from both ends and then select the reconstructed trajectory that deviates less in speed and yaw rate from the original sensor data.

$$\begin{bmatrix} x_i \\ y_i \\ \psi_i \\ v_i \\ \omega_i \\ a_i \end{bmatrix}_{t+\Delta t} = \begin{bmatrix} x_i \\ y_i \\ \psi_i \\ v_i \\ \omega_i \\ a_i \end{bmatrix}_{t} + \begin{bmatrix} \Delta x_i \\ \Delta y_i \\ \omega_i \Delta t \\ a_i \Delta t \\ 0 \\ 0 \end{bmatrix}, \text{ where} \tag{1}$$

$$\Delta x_i = \begin{cases} \cos(\psi_i)(v_i \Delta t + \frac{1}{2} a_i \Delta t^2), & \text{if } |\omega_i| \leq \epsilon, \\ \dfrac{v_i \omega_i [\sin(\psi_i + \omega_i \Delta t) - \sin(\psi_i)] + a_i [\cos(\psi_i + \omega_i \Delta t) - \cos(\psi_i)] + a_i \omega_i \sin(\psi_i + \omega_i \Delta t) \Delta t}{\omega_i^2}, & \text{otherwise;} \end{cases}$$
$$\Delta y_i = \begin{cases} \sin(\psi_i)(v_i \Delta t + \frac{1}{2} a_i \Delta t^2), & \text{if } |\omega_i| \leq \epsilon, \\ \dfrac{v_i \omega_i [\cos(\psi_i) - \cos(\psi_i + \omega_i \Delta t)] + a_i [\sin(\psi_i + \omega_i \Delta t) - \sin(\psi_i)] - a_i \omega_i \cos(\psi_i + \omega_i \Delta t) \Delta t}{\omega_i^2}, & \text{otherwise.} \end{cases} \tag{2}$$

2.2 Surrounding objects' trajectory reconstruction

We then reconstruct the trajectories of the surrounding objects. This reconstruction has the forward field of view only because only forward radar data are available. During an event, the subject vehicle may detect multiple objects (e.g., vehicles, cyclists, pedestrians, or animals), of which the edge nearest to the subject vehicle is detected. For each object, we first convert its local radar coordinates into the subject vehicle's reconstructed global coordinate system. Then we determine the object's centroid based on its dimensions and whether the detected edge corresponds to its front or rear, inferred from its heading direction. Since only relative positions and speeds are available for these detected objects, we use an EKF under the assumption of constant heading and speed. The update equations are given in Equation (3).

$$\begin{bmatrix} x_j \\ y_j \\ \psi_j \\ v_j \end{bmatrix}_{t+\Delta t} = \begin{bmatrix} x_j \\ y_j \\ \psi_j \\ v_j \end{bmatrix}_t + \begin{bmatrix} \cos(\psi_j)v_j\Delta t \\ \sin(\psi_j)v_j\Delta t \\ \psi_j \\ v_j \end{bmatrix} \tag{3}$$

3 Reconstruction evaluation

We optimise the EKF parameters of uncertainties and motion ranges by minimising the root mean squared reconstruction error in subject speed, subject yaw rate, subject acceleration, and object speed, as well as the mean displacement error of objects. The distributions of eventual reconstruction errors are presented in Figure 1. These include the root mean squared error (RMSE) in subject speed, subject yaw rate, subject acceleration, and object speed, as well as the mean absolute error (MAE) of object displacement. The errors are evaluated for each event in the categories of crashes, near-crashes, and safe baselines.

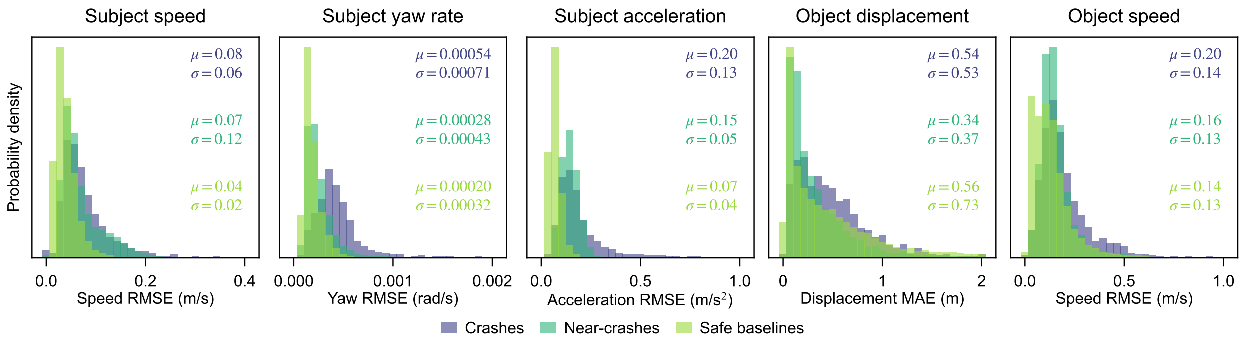

Figure 1. Reconstruction error distributions of crashes, near crashes, and safe baselines in the SHRP2 NDS. The mean values (μ and standard deviations σ are marked in each plot.

Note that due to the absence of ground truth, the very small errors we achieved do not indicate an accurate capture of reality. Instead, the errors quantify reconstruction deviations from the sensor measurements. On average, the standard deviation is smallest for safe baselines, and larger for near-crashes and crashes. But the difference is rather small, with 0.03-0.04 m/s of subject speed, 0.08-0.13 m/s^2 of subject acceleration, and 0.02-0.06 m/s of object speed.

4 Safety-critical test set

For future research, we further derive a test set of crashes and near-crashes, with the reconstructed trajectories alongside additional information relevant to these safety-critical events. Not all of the 8,895 events could be reconstructed due to missing values, sensor inaccuracies, and the absence of ground-truth data. There are 6,664 events where the trajectories of both the subject vehicle and at least one surrounding object are reconstructed. From these, we extract a useful test set by excluding invalid events that meet any of the following criteria:

- no object is detected for more than 5 seconds (too short to observe risk evolution),
- the crash or near-crash is with an object behind the subject vehicle (given the lack of rearward radar data),
- the crash or near-crash involves a "shapeless" obstacle (e.g., roadside pavement).

Eventually, we obtain 4,875 events in the test set. Figure 2(a) illustrates the numbers of originally recorded events in the SHRP2 NDS, the subset with both subject and object trajectories reconstructed, and the final filtered subset. The distributions of event types are further displayed in Figure 2(b), where the difference is primarily a result of the fact that rear-end events are more likely to be continuously detected by the forward radar.

The resulting dataset constitutes the largest known trajectory database of traffic crashes and near-crashes. In addition to the reconstructed trajectories, we attach other information of the safety-critical events. To consider a broader range of factors leading to potential collisions, the environment conditions, including weather, lighting, road surface, and traffic density, are incorporated. To evaluate whether and when a potential collision is successfully detected, the annotations

Figure 2. Statistics of original and processed events in the SHRP2 NDS.

of time when an event starts and ends, when the driver reacts (if applicable), and when the impact occurs (a physical contact for crashes or the closest proximity in near-crashes) are also included. Further, the specific type (e.g., with a leading object, during crossing or turning) of an event is included to evaluate the detection of potential collisions in different scenarios. Lastly, when necessary, each event's narrative is referred to for further verification.

* Note on conflicting object

The specific "conflicting object", i.e., the object involved in a crash or near-crash, is not explicitly labelled in the SHRP2 data, and it's possible the conflicting object's trajectory cannot be reconstructed. We hereby remind users of this.

In the paper we publish along with the release of this database, we propose a method to identify a conflicting object in each event. It is not the only way, but please feel free to refer to it.

References

[1] Federal Highway Administration. *Strategic Highway Research Program (SHRP2)*. 2018. URL: https://highways.dot.gov/safety/data-analysis-tools/rsdp/rsdp-tools/strategic-highway-research-program-shrp2 (visited on 03/28/2025).

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