Collision Avoidance Detour for Multi-Agent Trajectory Forecasting: A Solution for 2023 Waymo Open Dataset Challenge - Sim Agents

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Abstract

We present our approach, Collision Avoidance Detour (CAD), which won the 3rd place award in the 2023 Waymo Open Dataset Challenge - Sim Agents, held at the 2023 CVPR Workshop on Autonomous Driving. To satisfy the motion prediction factorization requirement, we partition all the valid objects into three mutually exclusive sets: Autonomous Driving Vehicle (ADV), World-tracks-to-predict, and World-others. We use different motion models to forecast their future trajectories independently. Furthermore, we also apply collision avoidance detour resampling, additive Gaussian noise, and velocity-based heading estimation to improve the realism of our simulation result.

1. Introduction

In the 2023 Waymo Open Dataset Challenge - Sim Agents [3], the predicted future trajectories of the ADV agent and other agents, denoted as World agents, need to be conditionally independent given the context information about the scene, such as the static map and agents' past trajectories. More specifically, the joint conditional probability of future trajectories of the ADV agent and the World agents needs to satisfy the following factorization equation:

$$p(S_{1:T}^{ADV}, S_{1:T}^{World}|c) = \Pi_{t=1}^{T}(\pi_{ADV}(S_t^{ADV}|s_{<t}^{ADV}, s_{<t}^{World}, c)p(S_t^{World}|s_{<t}^{ADV}, s_{<t}^{World}, c)), \quad (1)$$

where the time step T is the prediction time horizon, $S_{1:T}^{ADV}$ represents the predicted future trajectory of the ADV agent, $S_{1:T}^{World}$ represents the predicted future trajectories of the World agents, c represents the context information about the static map and agents' past trajectories, and π_{ADV} represents the driving policy of the ADV.

2. Method

Our architecture diagram can be seen in Figure 1.

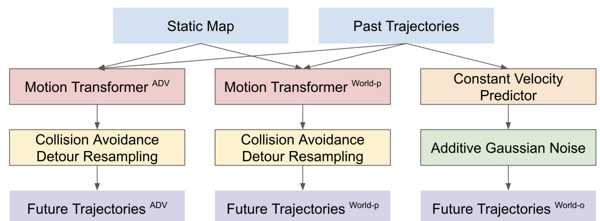

Figure 1: Architecture Diagram.

2.1. Object Partition

We first partition all valid objects in each scenario into three mutually exclusive groups: ADV, World-tracks-to-predict ($World-p$), and World-others ($World-o$). The ADV group contains the single autonomous driving vehicle in each scenario of the dataset. The $World-p$ group contains other objects with the **tracks_to_predict** flags. The $World-o$ group contains all other valid objects.

2.2. Motion Models

We first train the Motion Transformer (MTR) [1, 2] model using the setting of Waymo Open Dataset Challenge - Motion Prediction. An MTR model takes the context information c as the input and predicts 6 future trajectories and the corresponding probability distribution for each object as the output. To satisfy the conditional independence requirement, we select the model checkpoints after training for 29 epochs and 30 epochs to generate the final sampled future trajectories of the object in the ADV group and the objects in the $World-p$ group separately as follows:

$$p^{ADV}(S_{1:T}^{ADV}, S_{1:T}^{World-p}|c) = MTR^{ADV}(c), \quad (2)$$
$$p^{World-p}(S_{1:T}^{World-p}, S_{1:T}^{ADV}|c) = MTR^{World-p}(c), \quad (3)$$

where MTR^{ADV} and $MTR^{World-p}$ are two separate motion prediction models. Note that both models will predict preliminary future trajectories for objects in both ADV and $World-p$ groups, but we will only keep the result $S_{1:T}^{ADV}$ from MTR^{ADV}, keep the result $S_{1:T}^{World-p}$ from

$MTR^{World-p}$, and disregard other results in the end. Due to limited development time before the challenge submission deadline, we only train the motion transformer model using 20% of training data and follow the default hyperparameter and configuration settings in [1, 2].

For objects in the $World-o$ group, we use a constant velocity model with additive Gaussian noise to predict their future trajectories, the same approach as the one used in the Sim Agents challenge's tutorial:

$$p^{World-o}(S_{1:T}^{World-o}|c) = \\ ConstantVelocityPredictor(c) + k\,\mathcal{N}(0,1), \tag{4}$$

where $k = 0.01$ is the noise scale constant factor applied on the Gaussian noise $\mathcal{N}$ with zero mean and unit variance.

2.3. Simulation

During simulation, we sample future trajectories of objects in different groups independently. For objects in the $World-o$ group, we simply sample as follows:

$$s_{1:T}^{World-o} \sim p^{World-o}(S_{1:T}^{World-o}|c). \tag{5}$$

For objects in the ADV and $World-p$ group, we apply the collision avoidance detour resampling algorithm independently on the respective motion transformer outputs from equations 2 and 3 without any information exchange between the two groups, which will be described in the following subsection.

2.3.1 Collision Avoidance Detour Resampling

The algorithm of performing collision avoidance detour resampling for a set of predicted future trajectories and the corresponding probability distribution can be seen in Algorithm 1. The inputs include each object i's 6 predicted future trajectories in an object set O: $S_{1:T}^i \in \mathbb{R}^{6\times T\times 3}\ \forall\, i \in O$, and the corresponding probability distribution $p^i \in [0,1]^6\ \forall\, i \in O$. The output are the sampled predicted future trajectories: $s_{1:T}^i \in \mathbb{R}^{T\times 3}\ \forall\, i \in O$.

We first sample every object's future trajectory based on the input probability distribution and then perform collision detection. If a collision happens, we simply resample all objects' future trajectories until we find collision-free joint future trajectories or we reach the maximum number of sampling trials. In our experiment, we set the maximum number of sampling trials to 10. We use the object center distance threshold 0.1 meters to determine whether two objects collide with each other.

Note that we apply the collision avoidance detour resampling on the ADV and the $World-p$ group independently without exchanging any information between the two groups. More specifically, to generate the final sampled future trajectory for the ADV, the MTR^{ADV} model predicts preliminary future trajectories and probability distribution $p^{ADV}(S_{1:T}^{ADV}, S_{1:T}^{World-p}|c)$ for objects in ADV groups and $World-p$ group, as shown in equation 2. Such model output is used as the input of the collision avoidance detour resampling algorithm $(S_{1:T}^i, p^i)$. And we only keep the sampled ADV trajectory of this collision avoidance detour resampling process as the final sampled future trajectory of ADV and disregard other objects' collision avoidance detour resampling results. All the collision detection and simulation sampling are only based on the anticipated future from the context information c and the MTR^{ADV} model, without using any information from the $MTR^{World-p}$ model, any predicted trajectory from the $MTR^{World-p}$ model, or any final sampled future trajectory of any object in the $World-p$ or $World-o$ groups.

Similarly, for the $World-p$ groups, the output of $MTR^{World-p}$ model $p^{World-p}(S_{1:T}^{World-p}, S_{1:T}^{ADV}|c)$, as shown in equation 3, is used as the input of a separate collision avoidance detour resampling process. And we only keep the sampled trajectories of objects in $World-p$ from this collision avoidance detour resampling result as the final result and disregard ADV's result in this collision avoidance detour resampling process. Therefore, all the collision detection and simulation sampling in this process are only based on the anticipated future from the context information c and the $MTR^{World-p}$ model, without using any information from the MTR^{ADV} model, any predicted trajectory from the MTR^{ADV} model, or any final sampled future trajectory of ADV or $World-o$ groups.

2.4. Heading Estimation

The aforementioned algorithm is mainly used to predict future object center positions. To predict the future heading of each object, we use the velocity-based estimation as follows:

$$h_t = arctan(\frac{y_t - y_{t-1}}{x_t - x_{t-1}}), \tag{6}$$

where h_t is the predicted object heading at time step t, (x_t, y_t) is the predicted object center position at time step t, and (x_{t-1}, y_{t-1}) is the predicted object center position at time step $t-1$.

2.5. Result Aggregation

Once we finish sampling the future trajectory of each object in each group, we simply aggregate them as one final simulation rollout. And we repeat the same procedure 32 times to generate 32 different simulation rollouts.

2.6. Justification

To show that our proposed algorithm satisfies the conditional independence requirement, we present the following justification. Given the context information c, our algorithm

Algorithm 1 Collision Avoidance Detour Resampling

Input: An object set O. Each object i's 6 predicted future trajectories: $S^i_{1:T} \in \mathbb{R}^{6\times T\times 3}\ \forall\ i \in O$, and the corresponding probability distribution $p^i \in [0,1]^6\ \forall\, i \in O$.

Output: Final sampled predicted future trajectories : $s^i_{1:T} \in \mathbb{R}^{T\times 3}\ \forall\, i \in O$.

```
N ← |O|
for number_of_trials ← 1 ... 10 do
    for i ← 1...N do
        ŝ^i_{1:T} ∼ (S^i_{1:T}, p^i)
    end for
    collision ← False
    for t ← 1...T do
        for q ← 1...N do
            for r ← 1...N do
                if q ≠ r and |ŝ^q_t − ŝ^r_t|_2 < 0.1 then
                    collision ← True
                end if
            end for
        end for
    end for
    if collision is False or number_of_trials = 10 then
        for i ← 1...N do
            s^i_{1:T} ← ŝ^i_{1:T}
        end for
        return
    end if
end for
```

performs sampling and simulation for the objects in the three groups independently by using three independent motion models described in this section. Therefore, our algorithm satisfies the following equation:

$$\begin{aligned} p(S^{ADV}_{1:T}, S^{World}_{1:T}|c) &= p(S^{ADV}_{1:T}, S^{World-p}_{1:T}, S^{World-o}_{1:T}|c) \\ &= p(S^{ADV}_{1:T}|c)p(S^{World-p}_{1:T}|c)p(S^{World-o}_{1:T}|c) \end{aligned} \tag{7}$$

Purely based on the formal definition of joint probability and conditional probability, we can continue to derive that:

$$\begin{aligned} &p(S^{ADV}_{1:T}, S^{World}_{1:T}|c) = \\ &p(S^{ADV}_{1:T}|c)p(S^{World-p}_{1:T}|c)p(S^{World-o}_{1:T}|c) = \\ &\Pi^T_{t=1}(p(S^{ADV}_t|s^{ADV}_{<t}, c)p(S^{World-p}_t|s^{World-p}_{<t}, c) \\ &p(S^{World-o}_t|s^{World-o}_{<t}, c)) \end{aligned} \tag{8}$$

Compared with the factorization equation 1, we can see that we further factor the World agents into two groups, which is allowed based on the challenge guideline. Another difference is that our algorithm's prediction about ADV's future trajectory does not use the earlier predicted World agents' trajectories, and vice versa. And that means that our algorithm uses less available information. Similar to the algorithm used in the tutorial, using less or no information from the past predicted trajectories of agents in different groups could result in worse performance. But the result is still considered a valid submission satisfying the factorization requirement.

3. Experiment Result

Our algorithm's performance on the test set is shown in Table 1. Please refer to the official website of Waymo Open Dataset Challenge - Sim Agents[3] for details about the formal definition of each evaluation metric.

Table 1: Evaluation results on the test set of Waymo Open Dataset - Sim Agents.

Metric Name	Value
Realism meta-metric	0.4321
Linear Speed Likelihood	0.3464
Linear Acceleration Likelihood	0.2526
Angular Speed Likelihood	0.4327
Angular Acceleration Likelihood	0.3110
Distance To Nearest Object Likelihood	0.3300
Collision Likelihood	0.3114
Time To Collision Likelihood	0.7893
Distance To Road Edge Likelihood	0.6376
Offroad Likelihood	0.5397
minADE	2.3146

References

[1] S. Shi, L. Jiang, D. Dai, and B. Schiele. Motion transformer with global intention localization and local movement refinement. *Advances in Neural Information Processing Systems*, 2022.

[2] S. Shi, L. Jiang, D. Dai, and B. Schiele. Mtr-a: 1st place solution for 2022 waymo open dataset challenge–motion prediction. *arXiv preprint arXiv:2209.10033*, 2022.

[3] Waymo. 2023 Waymo Open Dataset Challenge - Sim Agents. https://waymo.com/open/challenges/2023/sim-agents/, 2023.