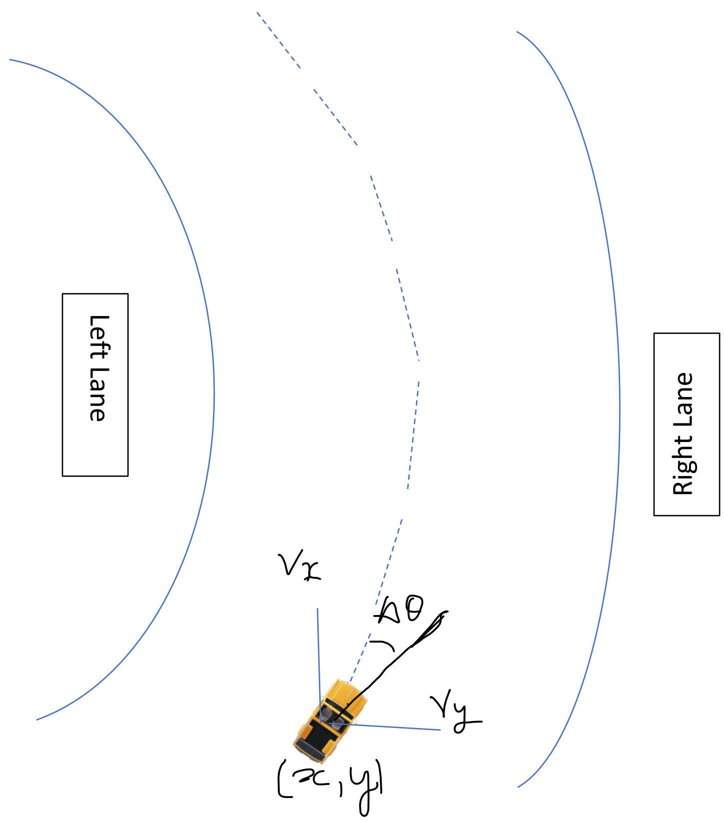
Prediction of trajectory of Autonomous vehicle using Long Short-Term Memory

Over the past few years, automated driving technology has garnered considerable interest from academics and in business. A human being could perfectly drive a vehicle in a different lane in the real world. As a result, the aim of this approach is to develop an autonomous driving strategy that is close to that of human drivers in terms of maintaining a steady drive.

First an expectation line should be computed so that the vehicle should keep tracking the expectation line. The lane includes right lane and left plan. The expectation line (EL) is used to determine the autonomous vehicle's appreciate route.



The AV is depicted in two dimensional plane where (x,y) is the coordinates of centroid of vehicle. Vx and Vy refers to longitudinal and lateral velocity at the center of mass and θ is the angle between tangent of EL line and vector of longitudinal velocity which represents orientation of vehicle.

The state of the vehicle at time Δt is given as follows

1. $x(t+1) = x(t) + v_{x(t)}\Delta t$
2. $y(t+1) = y(t) + v_y(t)\Delta(t)$
3. $v(t+1) = v_t + a(t)\Delta t$

Generally, the trajectory would not shift substantially or frequently when driving comfortably. As a result, previous trajectory data may be utilized to forecast the trajectory's future state. Assuming the past trajectory data is accurate.

Past Trajectory Data = {P1, P2, P3……..Pn} at time T, where pi(1 < i < n) is the passed position of the vehicle. The trajectory prediction model will be used to estimate the vehicle's future locations ahead of time. The following function might be used to define the set of future locations Past Trajectory Data .

$$\Delta \text{ PTD} = \text{f(PTD, } \Delta\text{D)}$$

That is, f should be constructed in such a way that it can learn patterns from past data. Additionally, future ΔD location data might be forecasted.

The observation of autonomous vehicle at present time t could be computed by

Ot = $\left(x_t, y_t, v_{xt}, v_{yt,} \theta t\right)$.

First, create the expectation line ELt using Lt which is computed by CNN. The fully connected (FC) layer is followed by the rectified linear unit (ReLU) activation function in the LSTM component. The Fully connected layer could convert the five-dimensional input data Ot into the same dimensional feature that the LSTM cell required. Furthermore, it increases network capacity so that the complicated structure of the trajectory data can be handled. The Fully Connected layer output is routed into the LSTM stack, which is built with 512-dimensional cell memory. The LSTM output is routed to another FC layer, which is then followed by a Softmax layer. The output of the FC layers is sent into the Softmax function, which predicts the future trajectory.

The Loss function can be computed as follows

$$L(w) = \sum_{i=1}^{n} \left(\left| x_{t+\Delta t} - z_{t,x} \right|^2 + \left| y_{t+\Delta t} - z_{t,y} \right|^2 + \lambda R(w) \right)$$

Where $Z_{t,x}$ and $Z_{t,y}$ are the predicted value of LSTM network and R(w) is the regularization term with parameter λ.