



北京交通大学

Deep Learning Based Motion Planning For Autonomous Vehicle Using Spatiotemporal LSTM Network

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Self Introduction



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Project Intro.

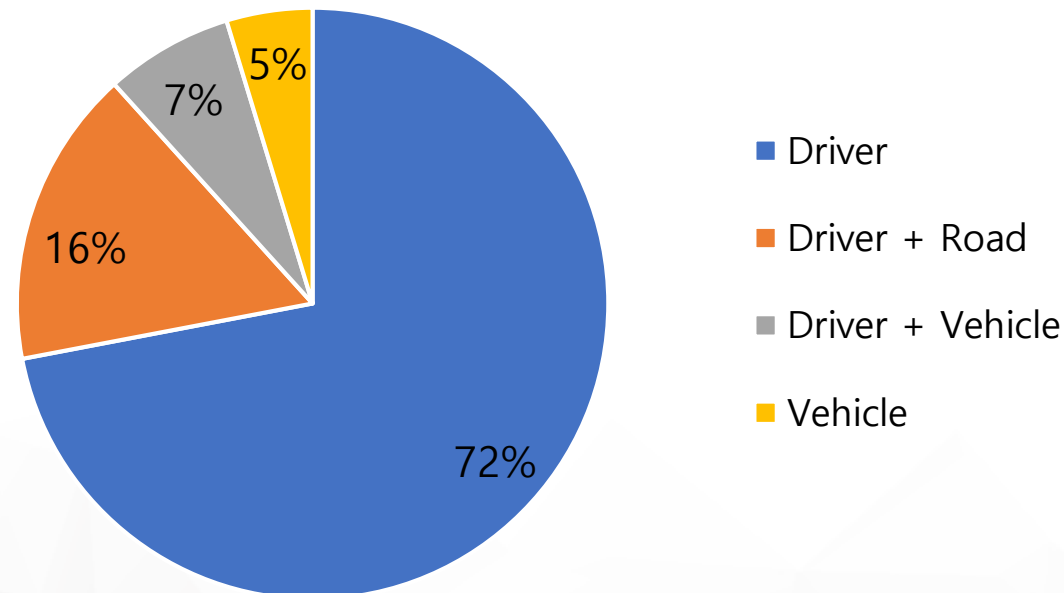


Motivation



- About 1.25 million people die each year as a result of road traffic crashes
- Without sustained action, road traffic crashes are predicted to become the seventh leading cause of death by 2030

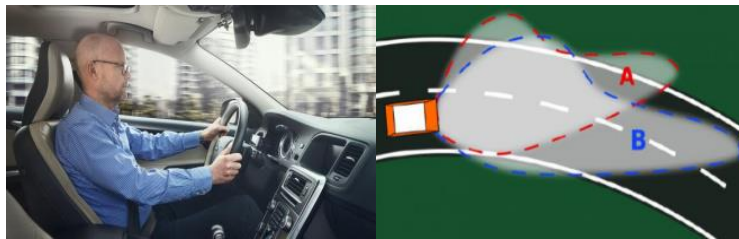
Cause of Traffic Crashes



Background

ITS is essentially a multi-variable complex system with **human-vehicle coupling**

Human2Vehicle



Driving Behavior

Path Planning

Vehicle2Vehicle



Car-following

Lane change

Vehicle2Road

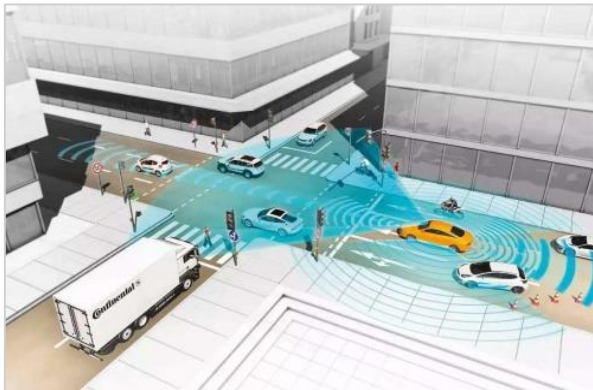


Interwoven road

Intersection

H-V-R Coupling

Human
↕
Vehicle
↕
Road



Extrinsic Features of Traffic System

- ◆ Path planning
- ◆ Motion planning
- ◆ Motion control
- ◆ Road Capacity
- ◆ Service Level

.....

Traffic Efficiency



Autonomous Vehicle : a Crucial part of ITS

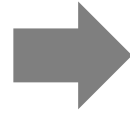
Related Works

Model Based : Pre-defined control strategies

Model Free : DL based Learning Process



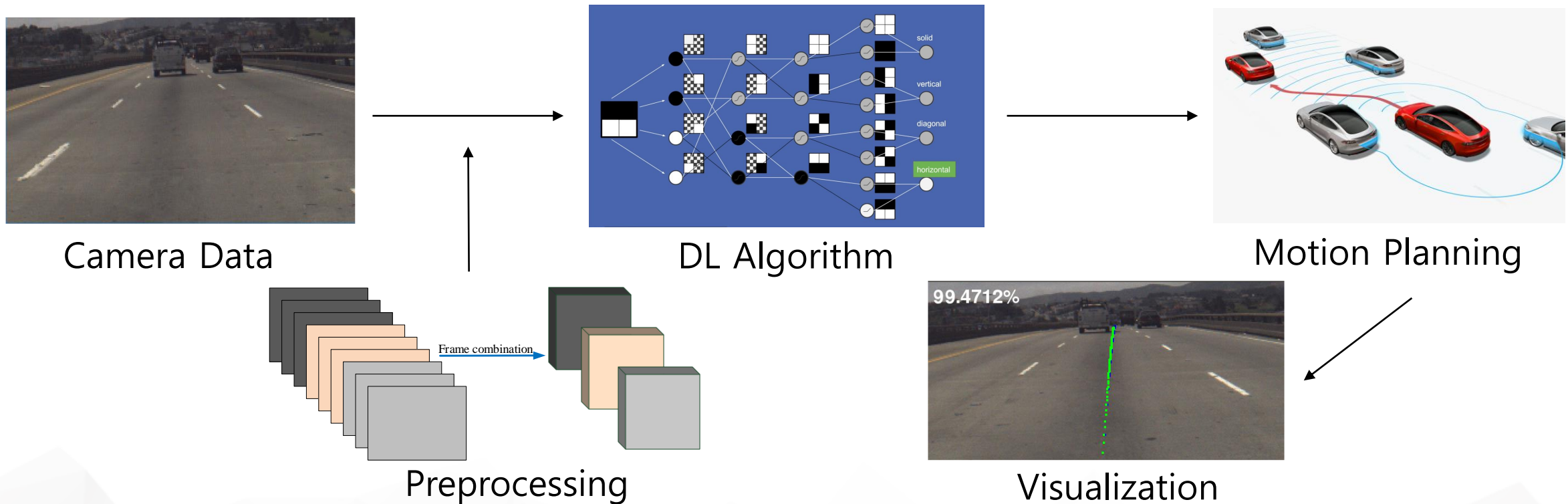
Imagination



Deep Learning: More adaptive to the complexity in real traffic scenarios

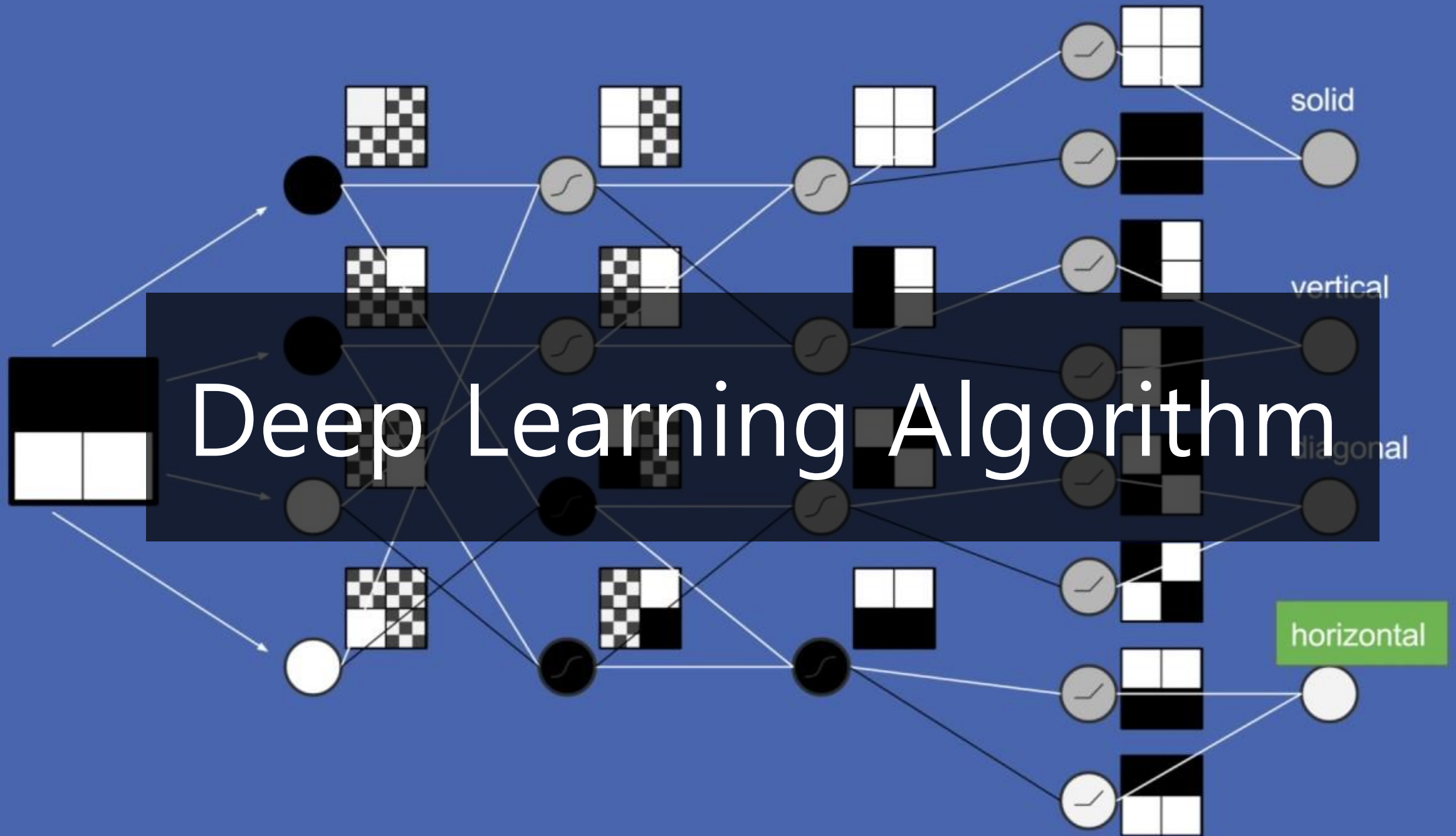
Project Overview

- **Input:** Human-level Control Through Deep Reinforcement Learning (Nature)
- **Algorithm:** Convolutional LSTM + 3D-CNN + FCNN
- **Output:** Motion planning (Steering angle)

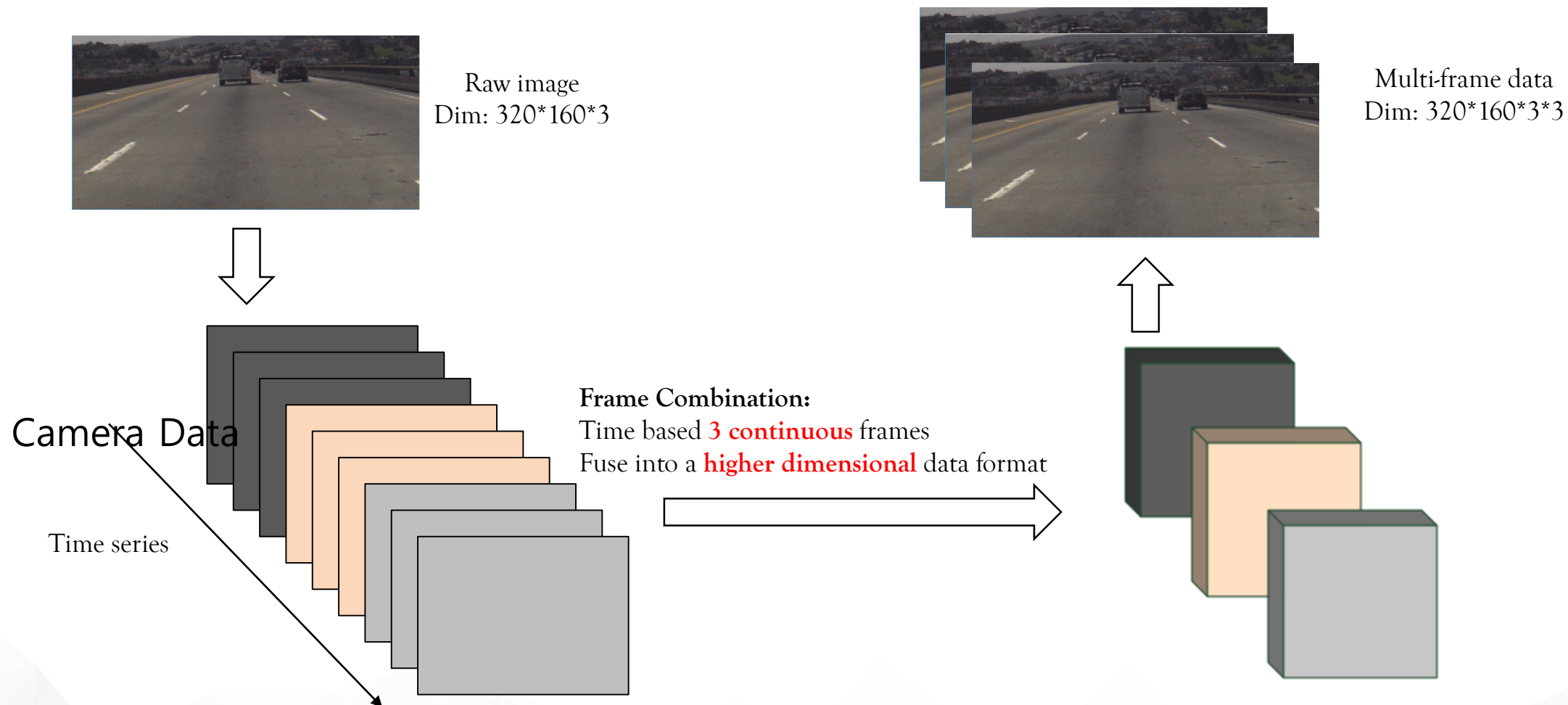


Raw image → Steering angle

Deep Learning Algorithm



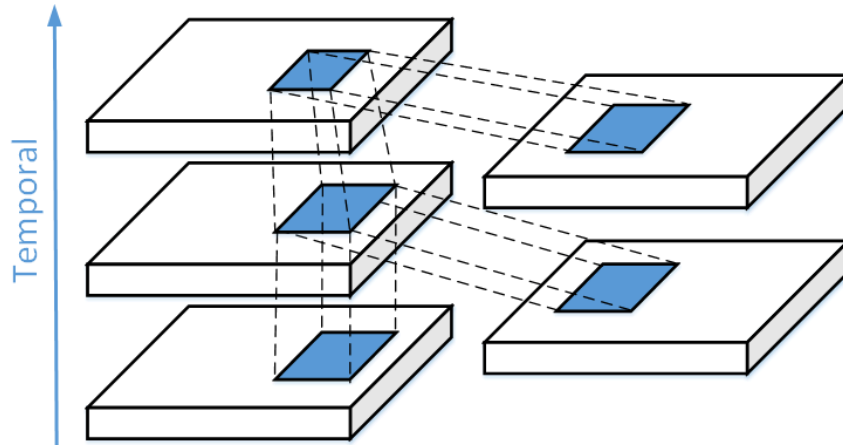
Data Preprocessing



Single frame image → Time based visual data

Convolutional LSTM

- Conv-LSTM :
 - Based on **multi-frame** picture segments
 - Use **batch normalization** between two layers



$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f)$$

$$C_t = f_t + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c)$$

$$o_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o)$$

$$H_t = o_t \circ \tanh(C_t)$$

i_t : Input gate at time t

o_t : Out put gate at time t

f_t : Forget gate at time t

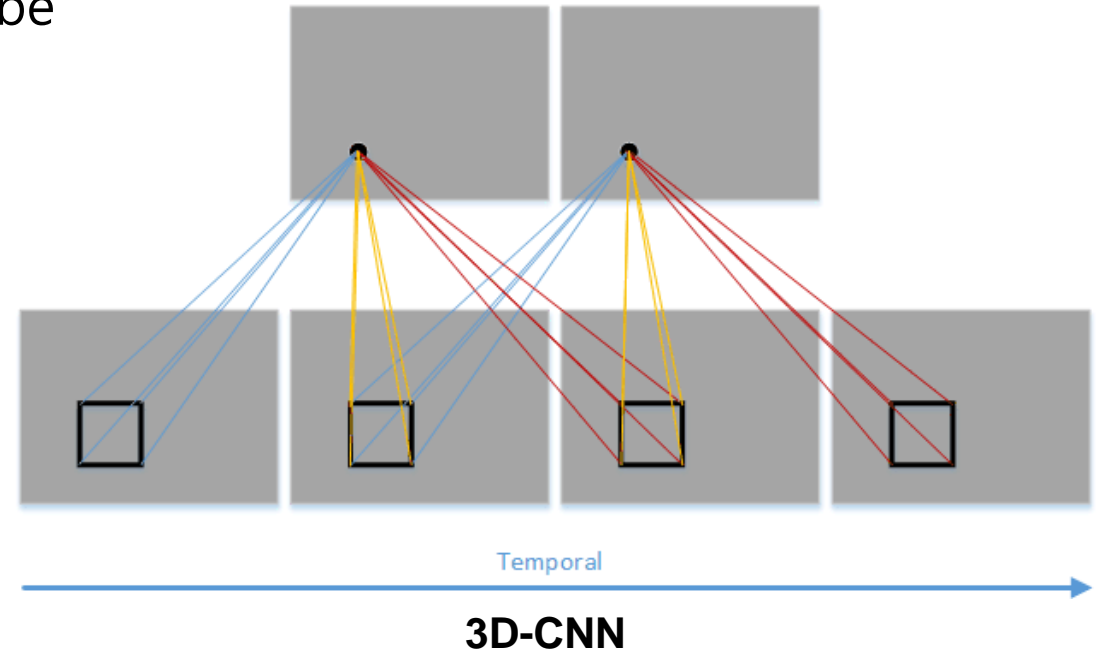
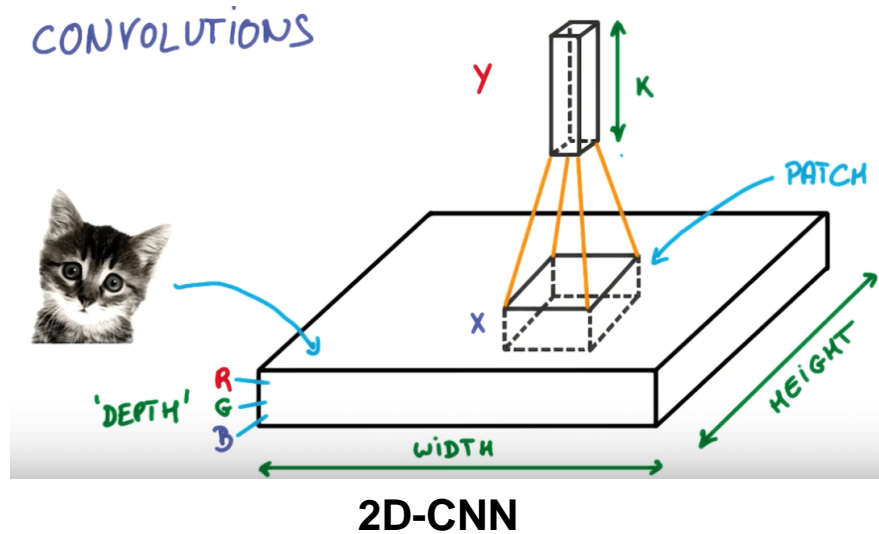
H_t : Hidden gate at time t

C_t : LSTM cell at time t

Extracting the **temporal hidden feature** information

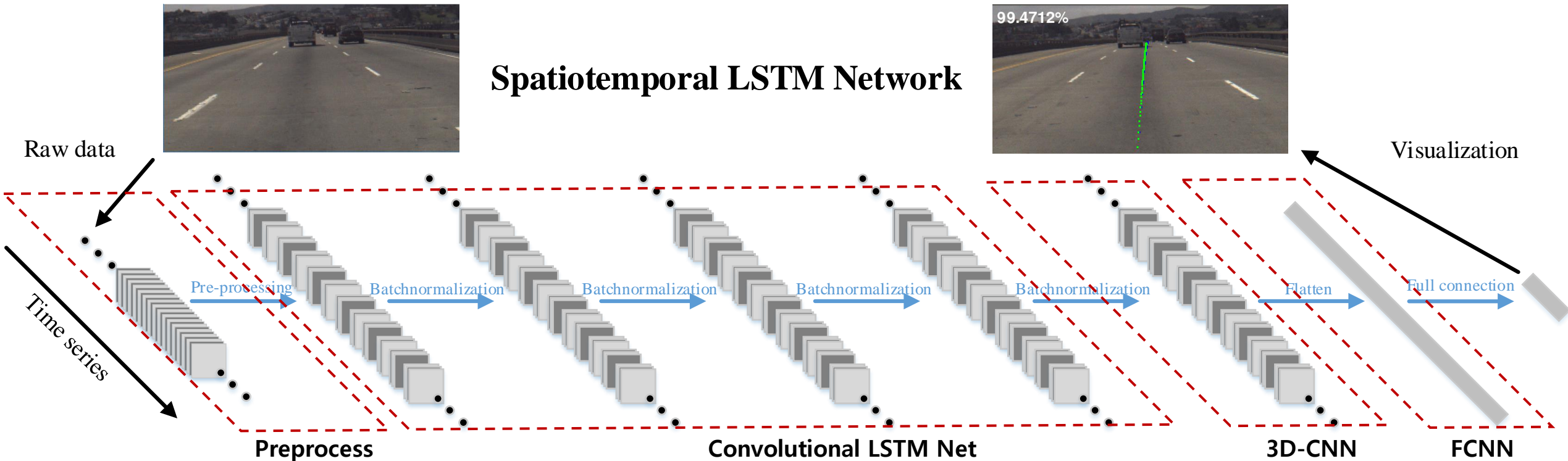
3D-CNN

- 3D-CNN :
 - Build a cube by **stacking multiple consecutive frames**
 - Use the **3D convolution kernel** in the cube



Capturing the **temporal** and **spatial** features of time based image **stream**

Final DL Model



Activation Function

$$\text{LeakyReLU} = \begin{cases} -0.2 * x, & x < 0 \\ x, & x \geq 0 \end{cases}$$

Loss Function

$$\text{MSE}(x, y) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} (x_i - y_i)^2$$

Learning the data from both **spatial** and **temporal** dimensions

Experiment

- Experimental platform : ubuntu16.04LTS + Tensorflow + Keras



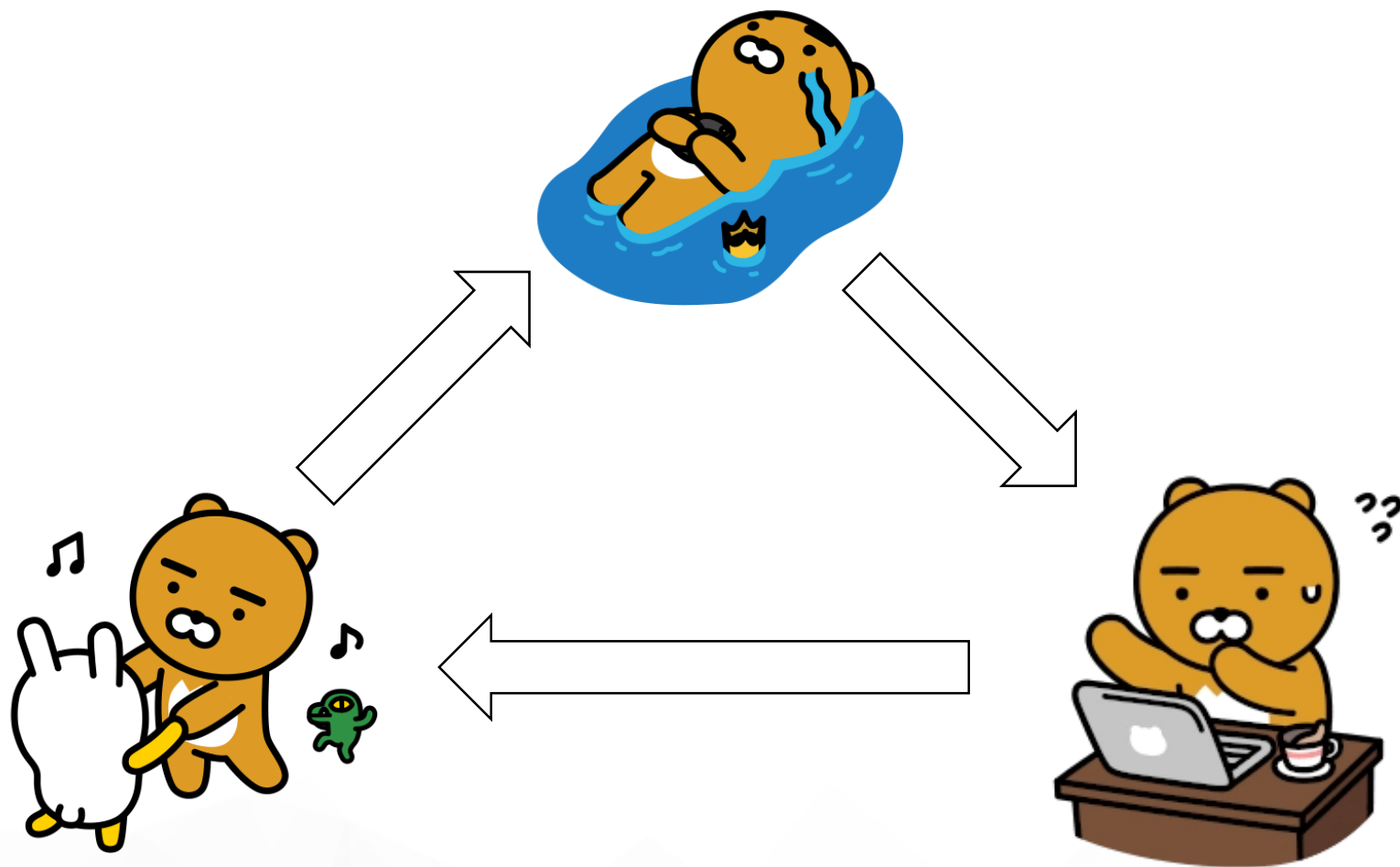
- Database : Comma-ai Dataset



Dataset content:

- **80GB** data
- Raw **image** data and vehicle **actual state** data
- Collected from the **vehicle-based sensors** respectively

Progress of Experiment Making

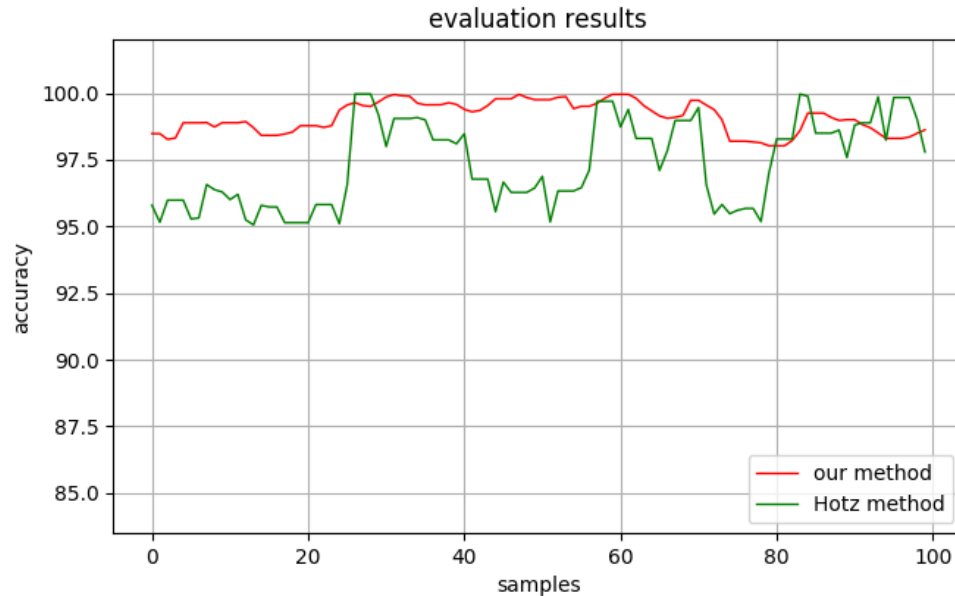


A yellow Ford Mustang race car, featuring 'DINOCO' branding and the number '51', is shown from a rear three-quarter view, driving on a paved road. In the background, a checkered flag is visible, and the scene is set against a backdrop of trees with autumn foliage under a blue sky.

Experiment & Result

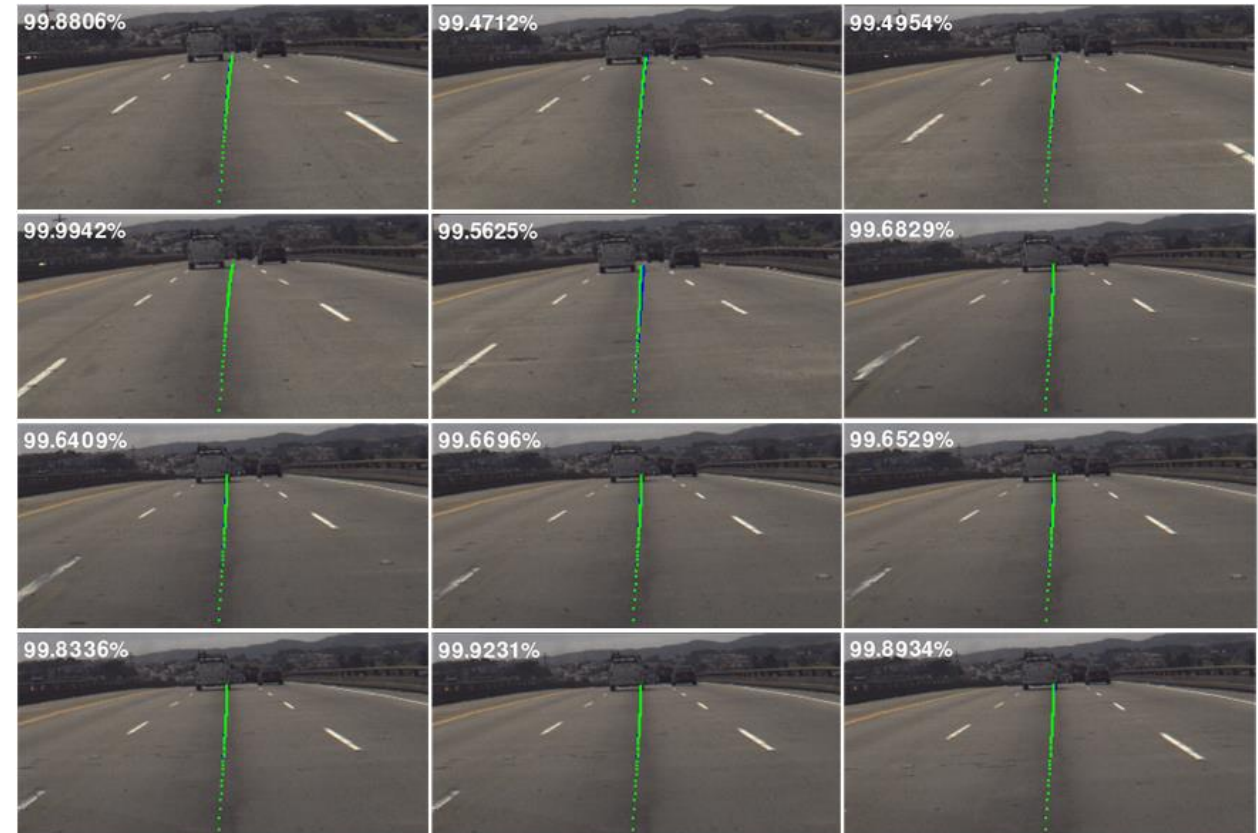
Result & Visualization

Contrast experimental results



- **Our method:** high accurate and stable
- **Hotz's method:** Can achieve the high accuracy sometime but with higher fluctuation

Visualization Results



Spatiotemporal LSTM Network : Get more **accurate and **stable** results**

Result Video



- It can drive vehicle!! But not smart at all scenario
- The Spatiotemporal LSTM Network has the ability to learn the data from both spatial and temporal dimensions.
 - Spatial: more **precise** results in motion output
 - Temporal: more **stable** motion in complex scenario
- Changing layers and parameters can cause much better result
 - Need more **3D-CNN** layer, more **FCNN** layer!
 - More **training time**!!

After This Project...

- Training the algorithm with a better computer in lab!
- Read and implement more papers to reinforce my DL algorithm
- Training and testing algorithms with more dataset
- Compare the results in different sensor data
 - Lidar + Image
 - Only Image
 - Only Lidar
- Implement in a real vehicle?





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THANK YOU !



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