# Real-time End-to-End Lane ID Estimation Using Recurrent Networks


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## I. Introduction:

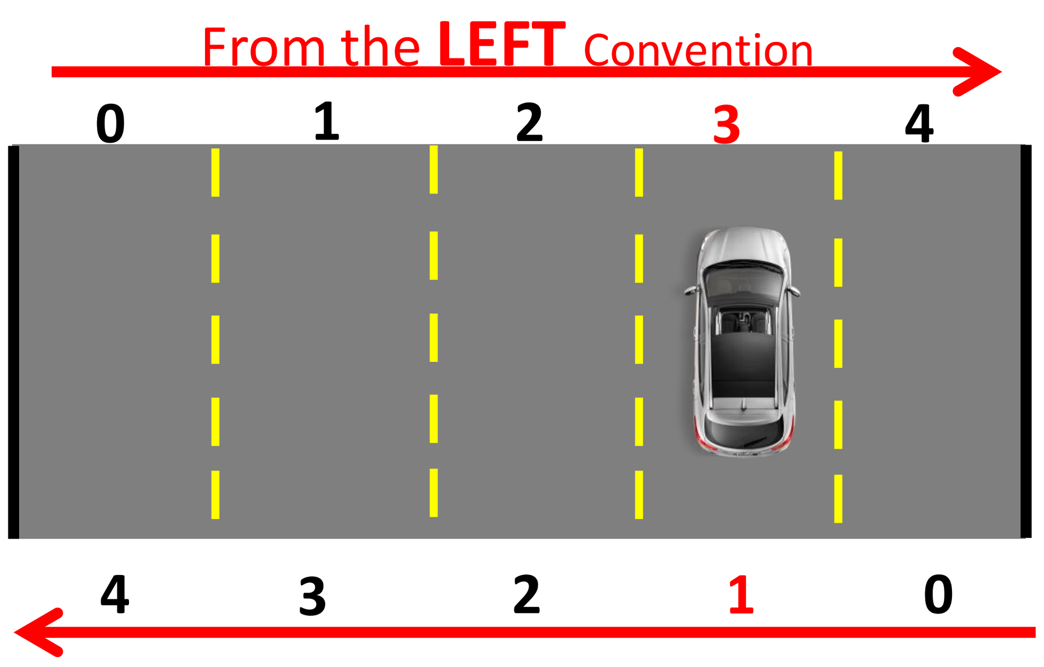
- **Task description**: Given a visual representation of a driving scene (image), **the car should be able to identify which lane it is driving on.**
- The identification is defined by a number/Identifier of the lane (Lane ID estimation).

Input Image → DNN Model → Lane ID Estimate

## II. Method:

### *1. Dual Convention:*

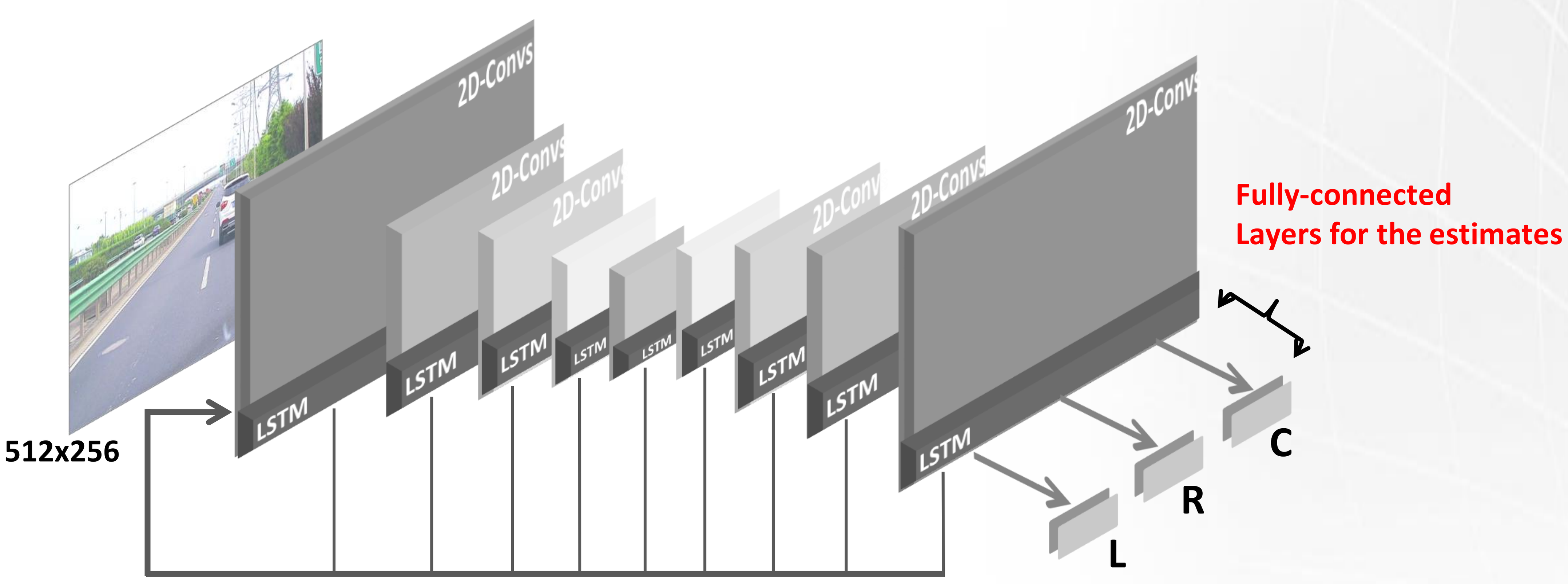
- For our end-to-end approach, we are using a **Dual ID Convention:**




$$\delta l + \delta r + 1 = C$$

In this case, the car is on:
- $\delta l = 3$ from **left**.
- $\delta r = 1$ from **right**.
- **C** = 5 is **total lane count**.

### *2. Model:*




Closed-Loop Design using LSTMs (Long-Short-Time-Memory)

An Encoder-decoder Model with interposed Conv-LSTM cells between the layers to get profit from temporal dimension → Moka-convLSTM

### *3. Pre-processing:*

- we track the average perceived brightness of the driving sequence given as input.
- If the perceived brightness of the current frame is below the tracked average ➔ Adjust the brightness of the frame.
- The brightness adjustment can be done via a **linear transformation of the pixel intensities** (with a corresponding alpha parameter).

$$R'(x,y) = \min(255, \alpha \,.\, R(x,y))$$

$$G'(x,y) = \min(255, \alpha \,.\, G(x,y))$$

$$B'(x,y) = \min(255, \alpha \,.\, B(x,y))$$

### *4. Loss Function:*

Classification task N = 8 with a proposed cost function is composed of 3 parts:

– Cross Entropy Loss

– Adaptive Penalty

– Triangular Regularization

- **L_gt: Ground Truth LEFT Lane ID**
- **R_gt: Ground Truth RIGHT lane ID**
- **C_gt: Ground Truth LANE count**

- *L: Estimated LEFT Lane ID*
- *R: Estimated RIGHT lane ID*
- *C: Estimated LANE count*

$L_{gt}$ $R_{gt}$ $C_{gt}$ $L$ $R$ $C$ → Cross-Entropy Loss

$$L_{cross-entropy}(x,y) = -\sum_i y_i \log(x_i)$$

More Weights to smaller estimates.

$1 + \exp(-5 * L)$

$1 + \exp(-5 * R)$

Adaptive Penalty

Triangular Regularization

Additional penalty term based on R + L + 1 = C

Final Loss Term

## III. Results: