

# Parking Space Status Inference upon a Deep CNN and Multi-task Contrastive Network with Spatial Transform



- Hoang Tran Vu and Ching-Chun Huang

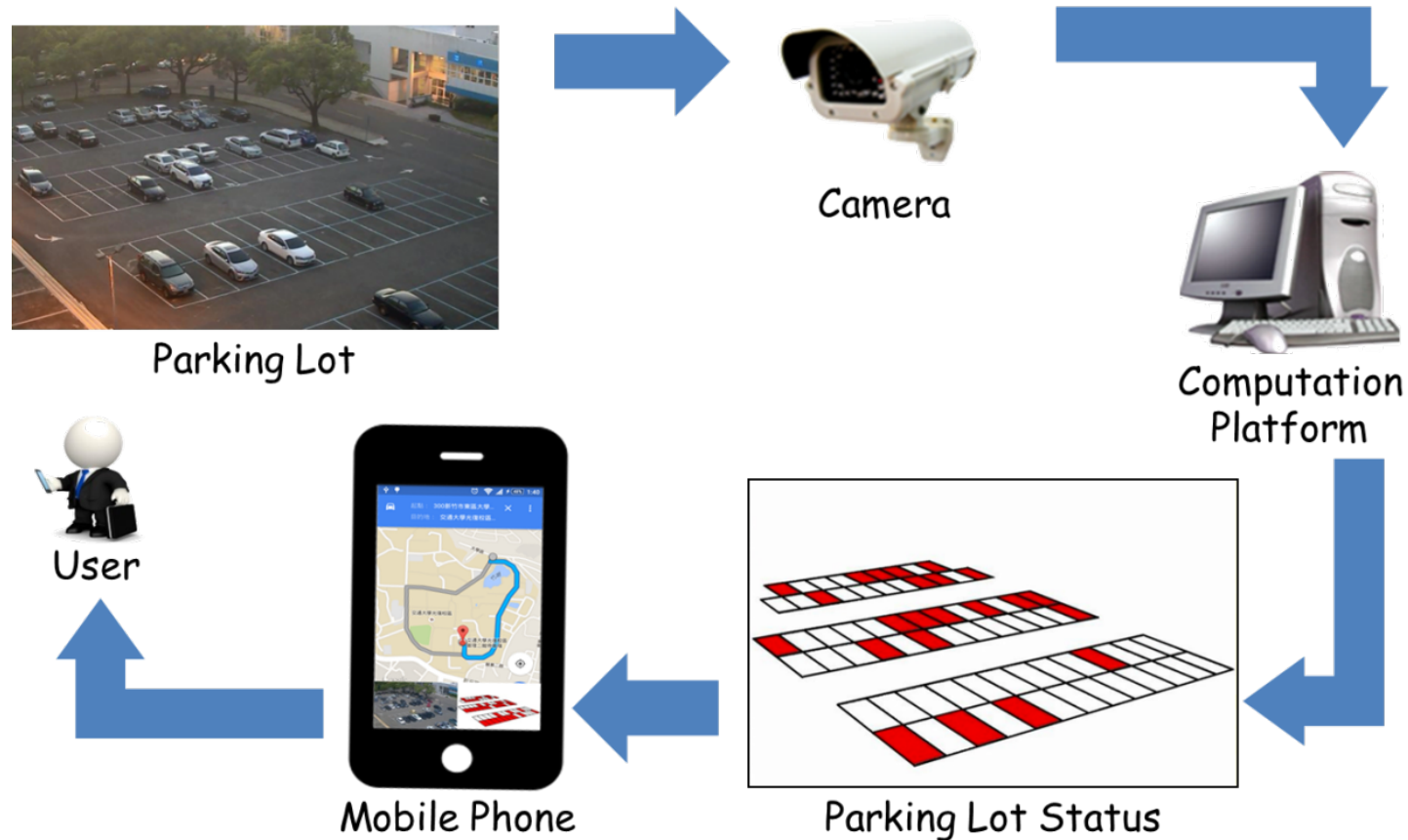
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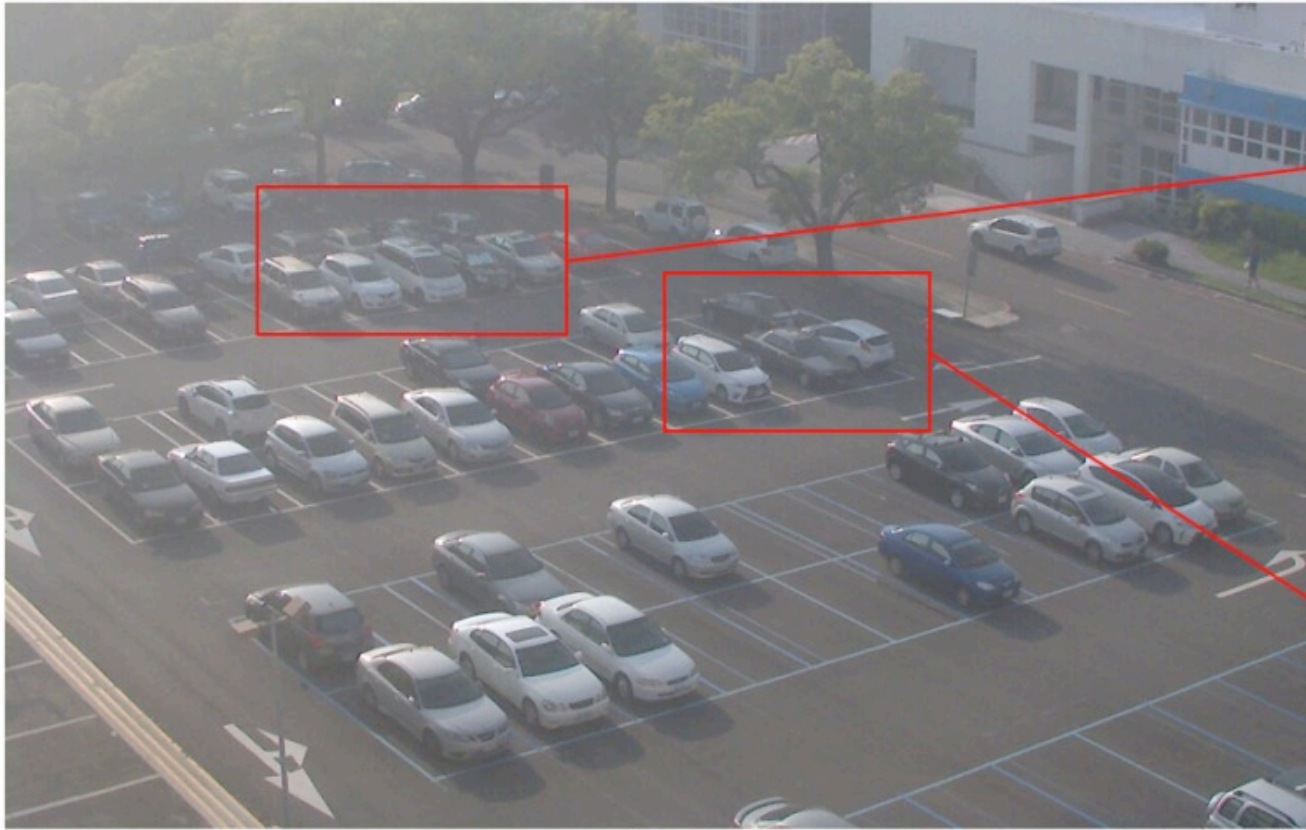
# Goal

- Introducing a CNN-based deep learning framework for parking space detection system



# Challenges

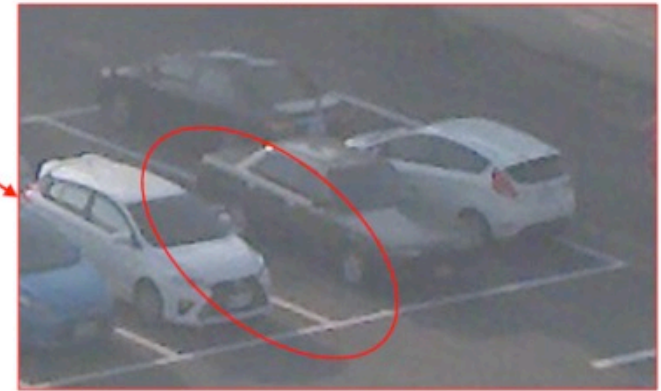
Lighting variation & perspective distortion



Occlusion effects & Vehicle size problems



Parking displacement





# Challenges

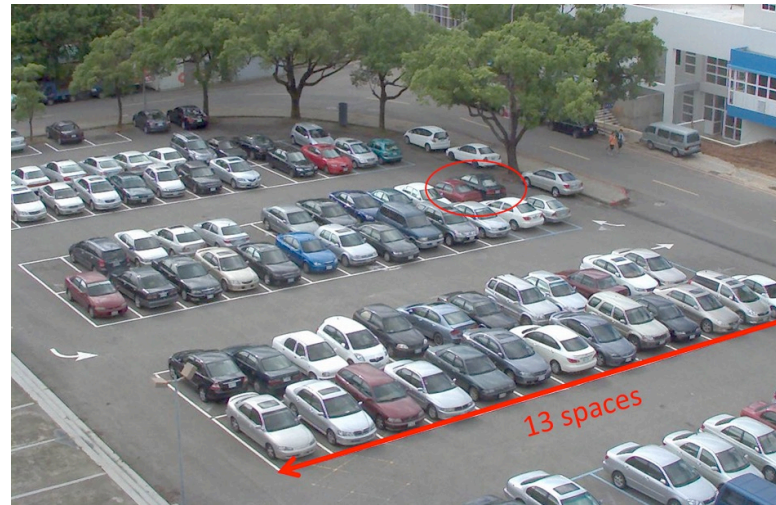
- Difference of space size

Occlusion problem becomes severer

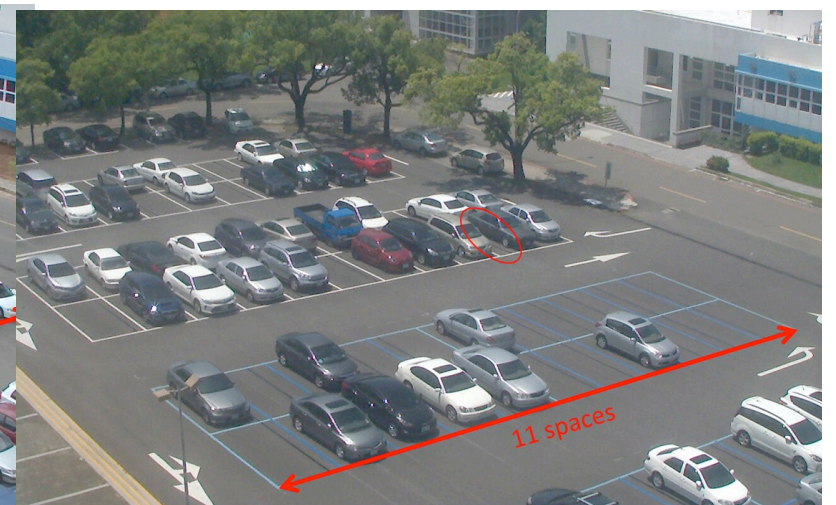
Parking displacement becomes uncontrollable



Small size



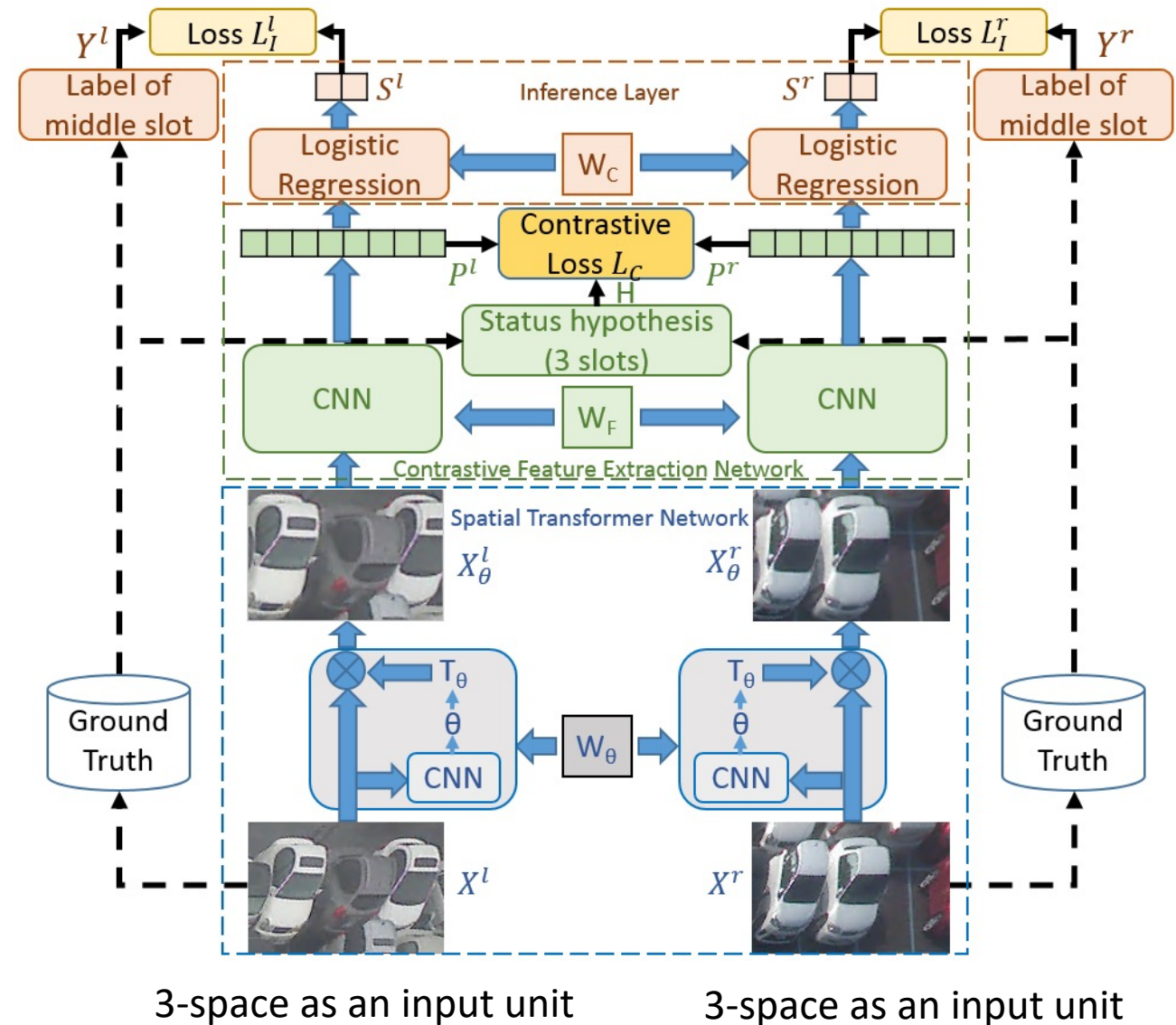
Medium size



Large size

# Proposed method

- Three main parts:
  - Spatial Transformer network (STN)
  - Contrastive Feature Extraction Network (CFEN)
  - Status Inference Layer



# Spatial Transformer network

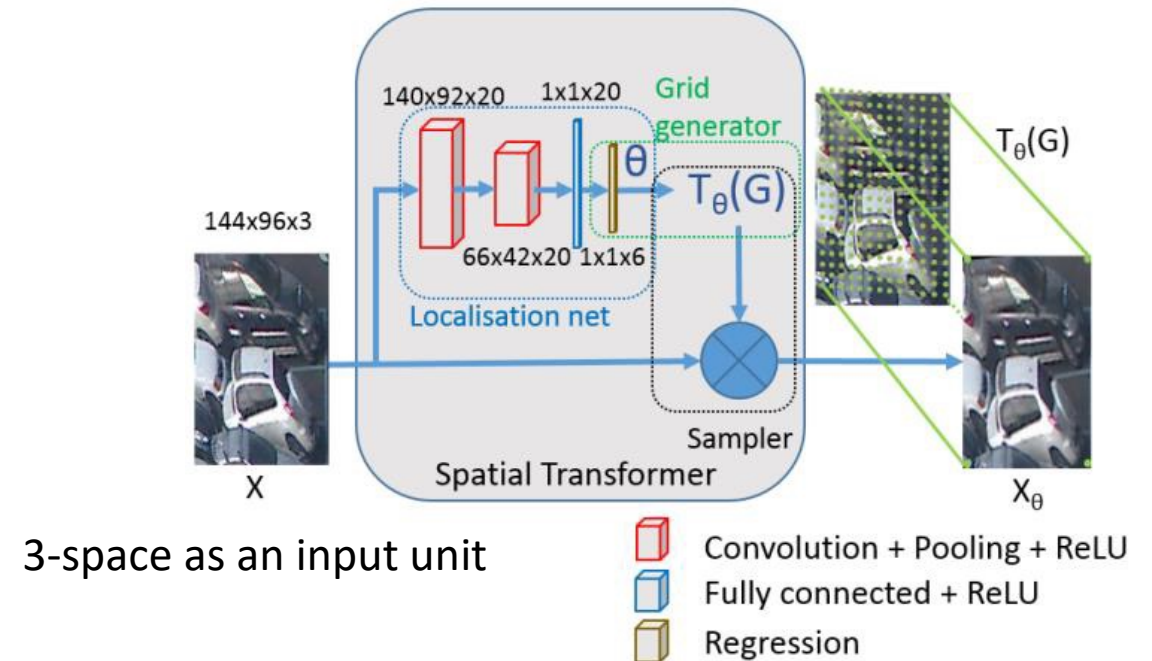
- Reducing the variations from perspective distortion, parking displacement, and vehicle size.
  - Using a spatial transformer network (STN) [25]

$$\begin{pmatrix} x_i^s \\ y_i^s \end{pmatrix} = T_\theta(G_i) = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \end{bmatrix} \begin{pmatrix} x_i^t \\ y_i^t \\ 1 \end{pmatrix}$$

$(x^s, y^s)$ : the source coordinate in the input image

$T_\theta$ : 2D affine transformation (6 parameters)

$(x^t, y^t)$ : the target coordinate in the transformed image



3-space as an input unit

- Convolution + Pooling + ReLU
- Fully connected + ReLU
- Regression



# Results and Discussions

Transformed Patches based on Different Network Structures:

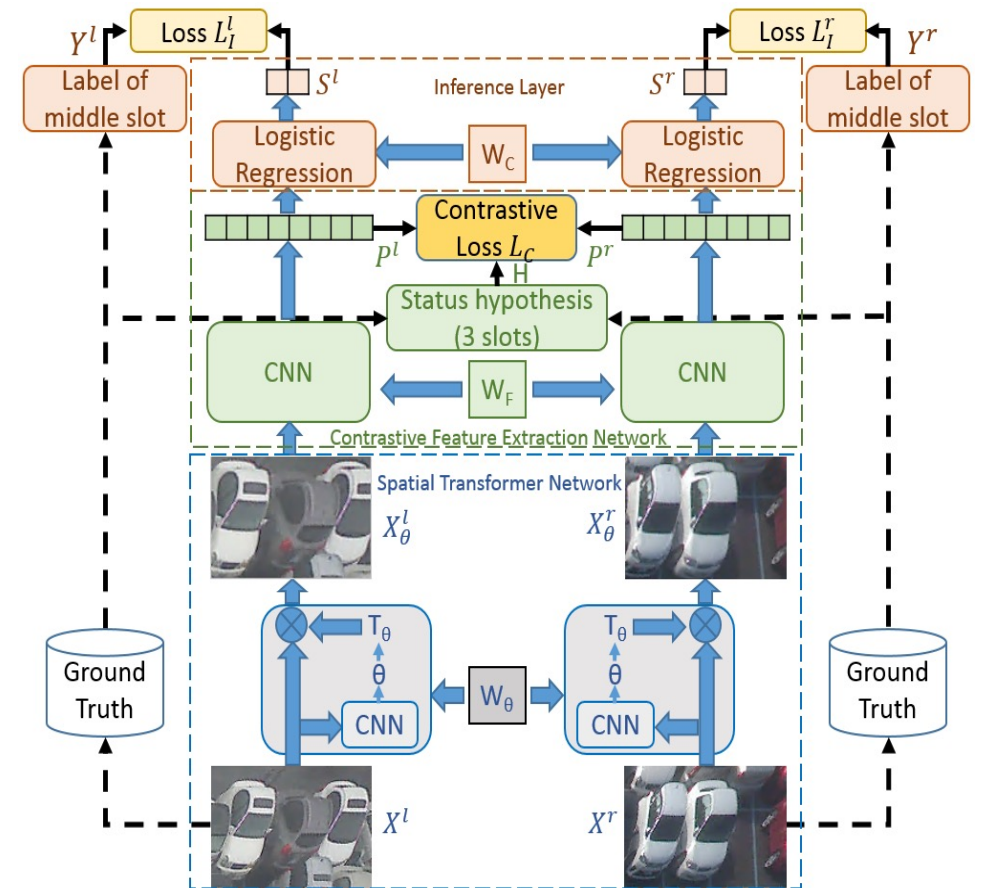
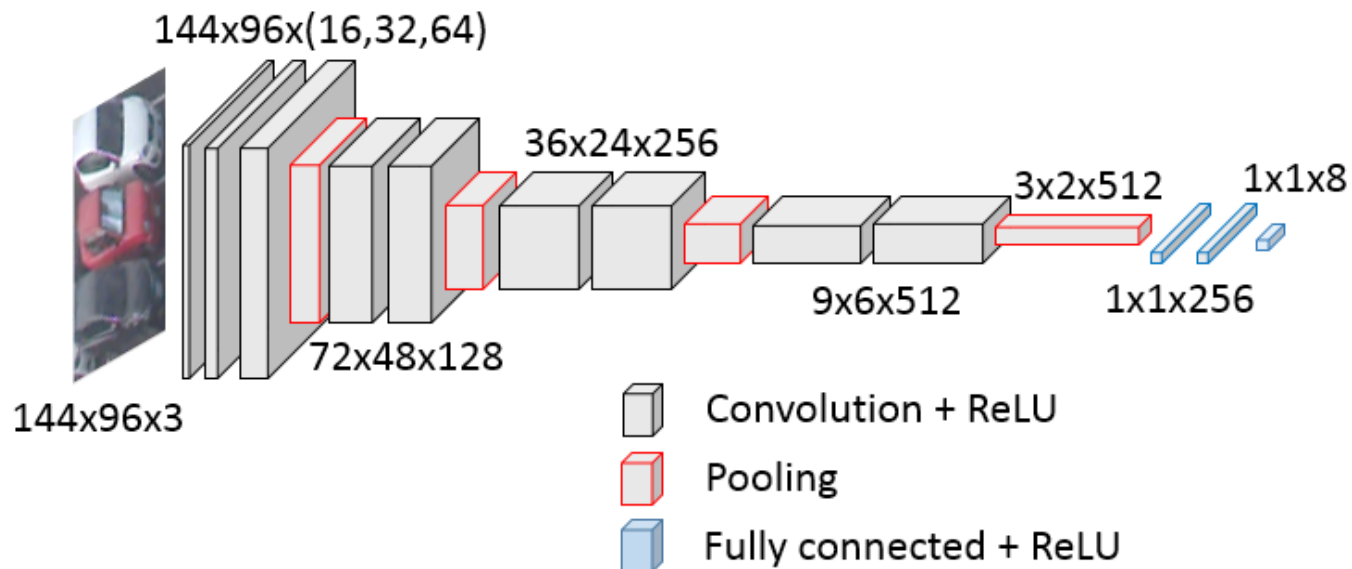
- Red boxes: false detection
- Green boxes: correct detection
- The true status of the target space: “V” is vacant and “O” is occupied.

	Input Patch	CNN-STN <sub>2</sub>	CNN-STN <sub>8</sub>	Our method
(a) “O”				
(b) “O”				
(c) “V”				

(d) “V”				
(e) “V”				
(f) “O”				
(g) “O”				

# Contrastive Feature Extraction Network

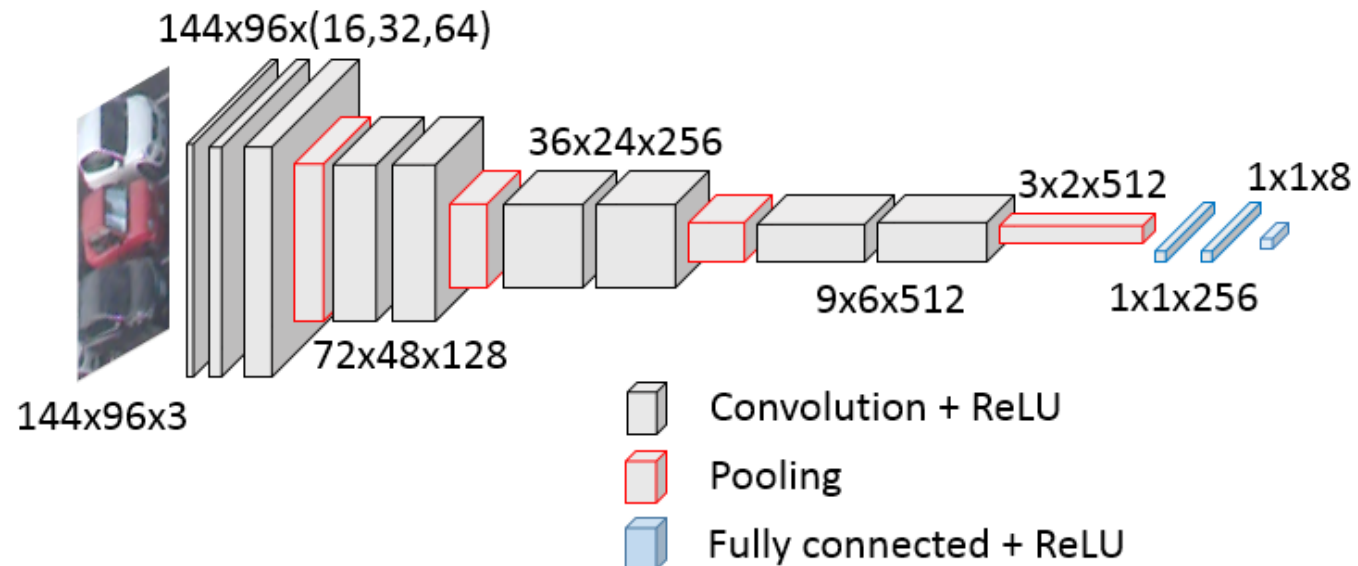
- Solving the inter-occlusion/lighting problem.
  - Designing a CNN-based deep learning network to **learn the occlusion pattern** within the transformed patch.





# Contrastive Feature Extraction Network

- This network is designed with the following properties.
  - Being determined by **many stages** separated by a pooling layer.
  - **down-sampling** the input image to a small size before applying fully connected layers for classification.
  - **Increasing the number of kernels** in the later layers
  - Applying FC layers to **reduce the feature dimension**



# Inference layer

- Inferring the status of the considered space.
  - Building a 2- class logistic regression model on the top of CFEN.

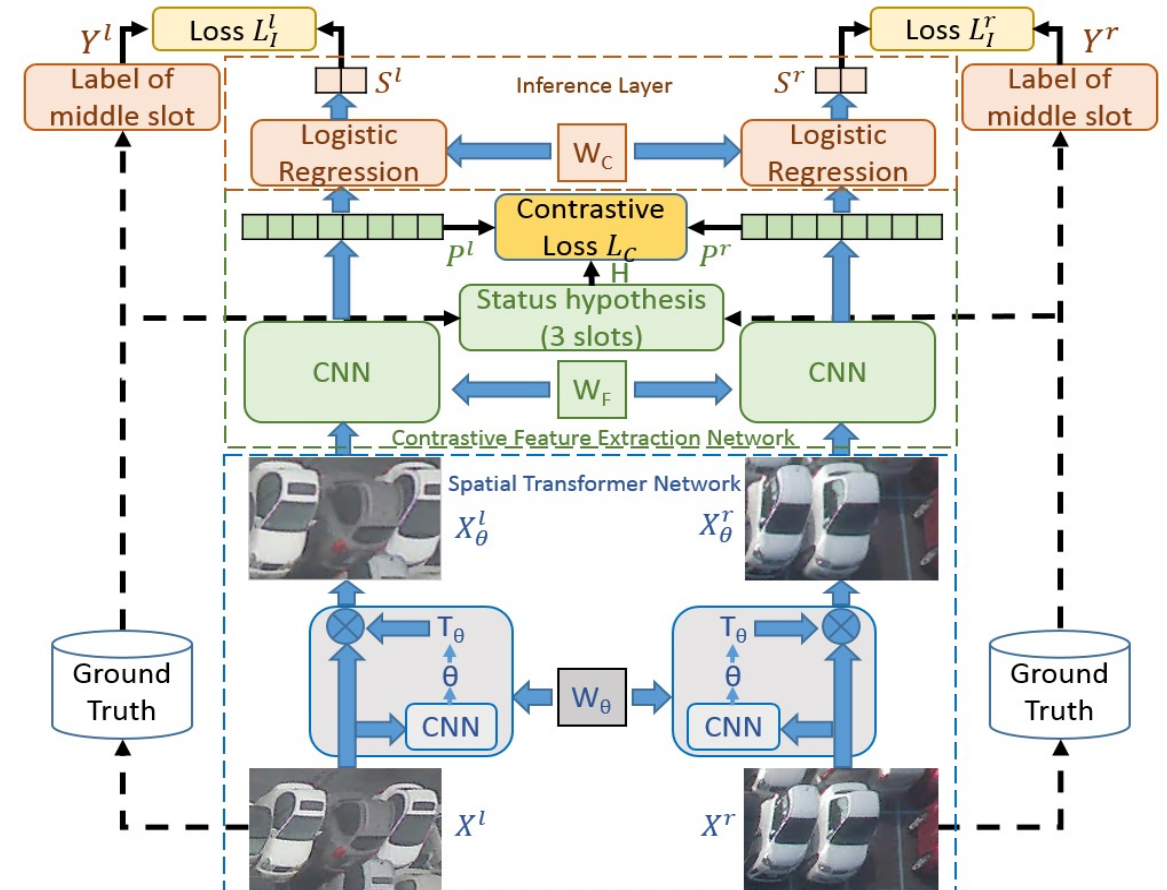
$$L_S(W_F, W_\theta, W_C | \{X_t, H\}) = -\frac{1}{N} \sum_{n=1}^N [y_n \log(S_n^1) + (1 - y_n) \log(S_n^0)].$$

$W_C$  : inference layer parameters.

$N$  : sample number.

$y_n$  : the label of the middle space of the  $n^{th}$  3-space unit.

$S_n^1$  and  $S_n^0$  : the occupied and vacant probabilities of the middle space.



# Results and Discussions

- Evaluation under **Different Parking Space Sizes**

**Table VI. The Performance of Status Inference under Different Space Sizes**

Space Size	ACC (%)			FPR (%)			FNR (%)		
	S	M	L	S	M	L	S	M	L
Huang's work [17]	98.44	99.61	99.69	1.28	0.5	0.40	1.73	0.31	0.25
CNN <sub>2</sub>	96.78	98.26	99.00	6.66	1.7	1.12	1.36	1.78	0.91
CNN <sub>8</sub>	98.71	99.53	99.82	1.29	0.64	0.17	1.29	0.28	0.20
Our method	<b>99.68</b>	<b>99.74</b>	<b>99.87</b>	<b>0.24</b>	<b>0.39</b>	<b>0.14</b>	<b>0.37</b>	<b>0.12</b>	<b>0.13</b>

Huang's work [17]: IEEE TCSVT 2016

CNN<sub>2</sub> : CNN(considered space) +  $L_2(\cdot)$

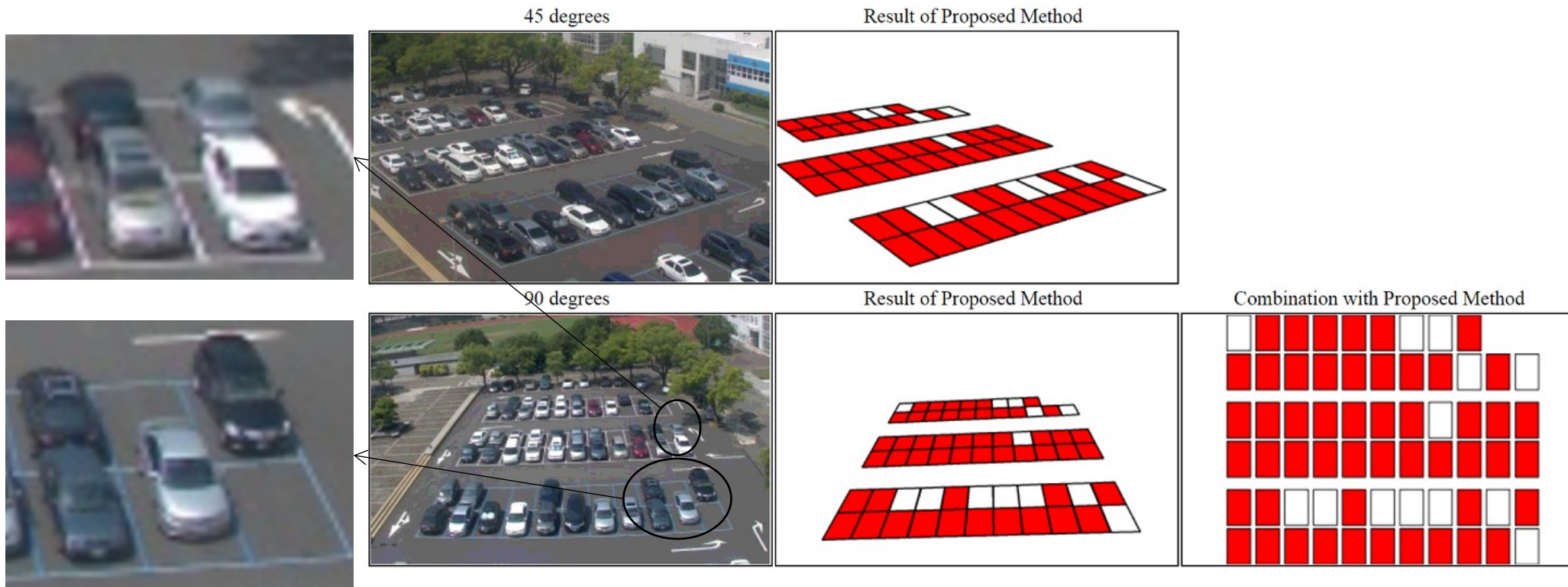
CNN<sub>8</sub> : CNN(three spaces) +  $L_2(\cdot)$



# Results and Discussions

- The real-time camera view and detection results.

Real Time Parking System Demo



Demo Time : 08:00 ~ 17:15 【GMT+0800 (Taipei Standard Time)】

Wed Sep 20 2017 11:14:33 GMT+0800 (Taipei Standard Time)