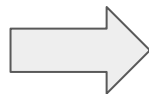
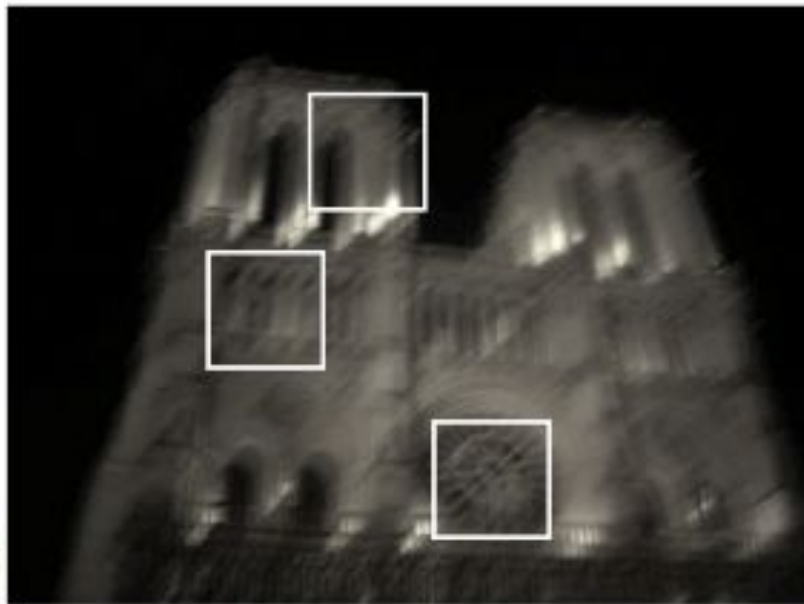


# DL Methods for Motion Deblurring

# Objective of Motion Deblurring

Notre Dame

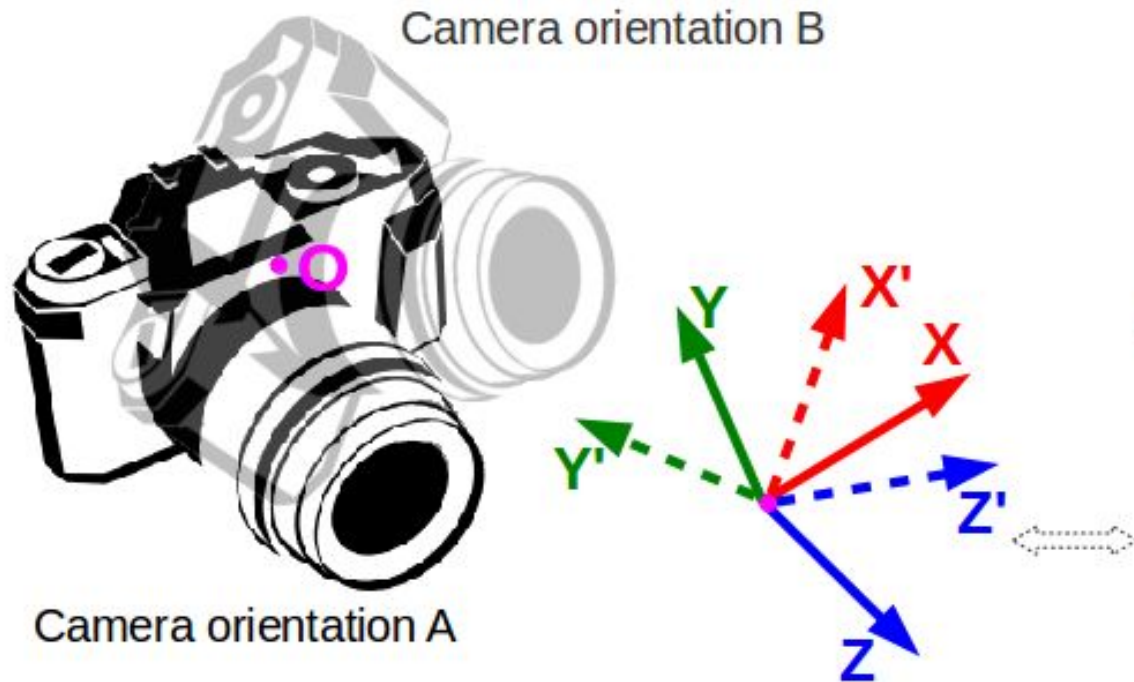


Blurred Image



Clean Image

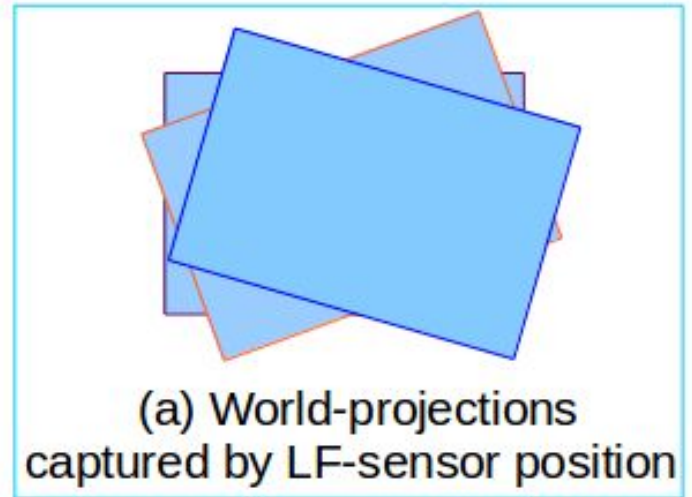
# Motion blur Model



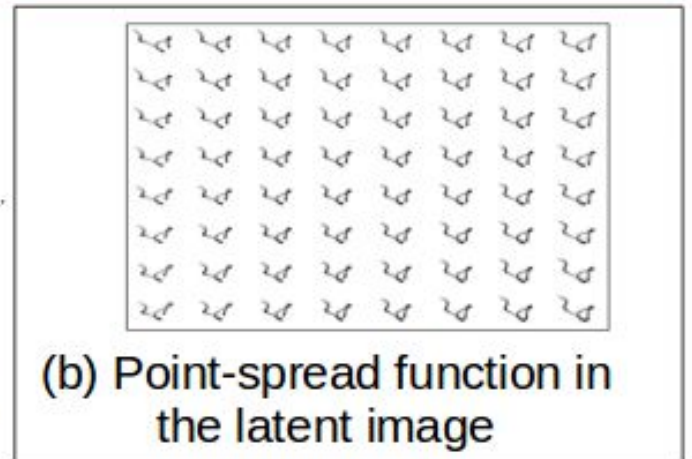
Camera orientation A

Camera orientation B

$(X, Y, Z)$  – World system for A  
 $(X', Y', Z')$  – World system for B

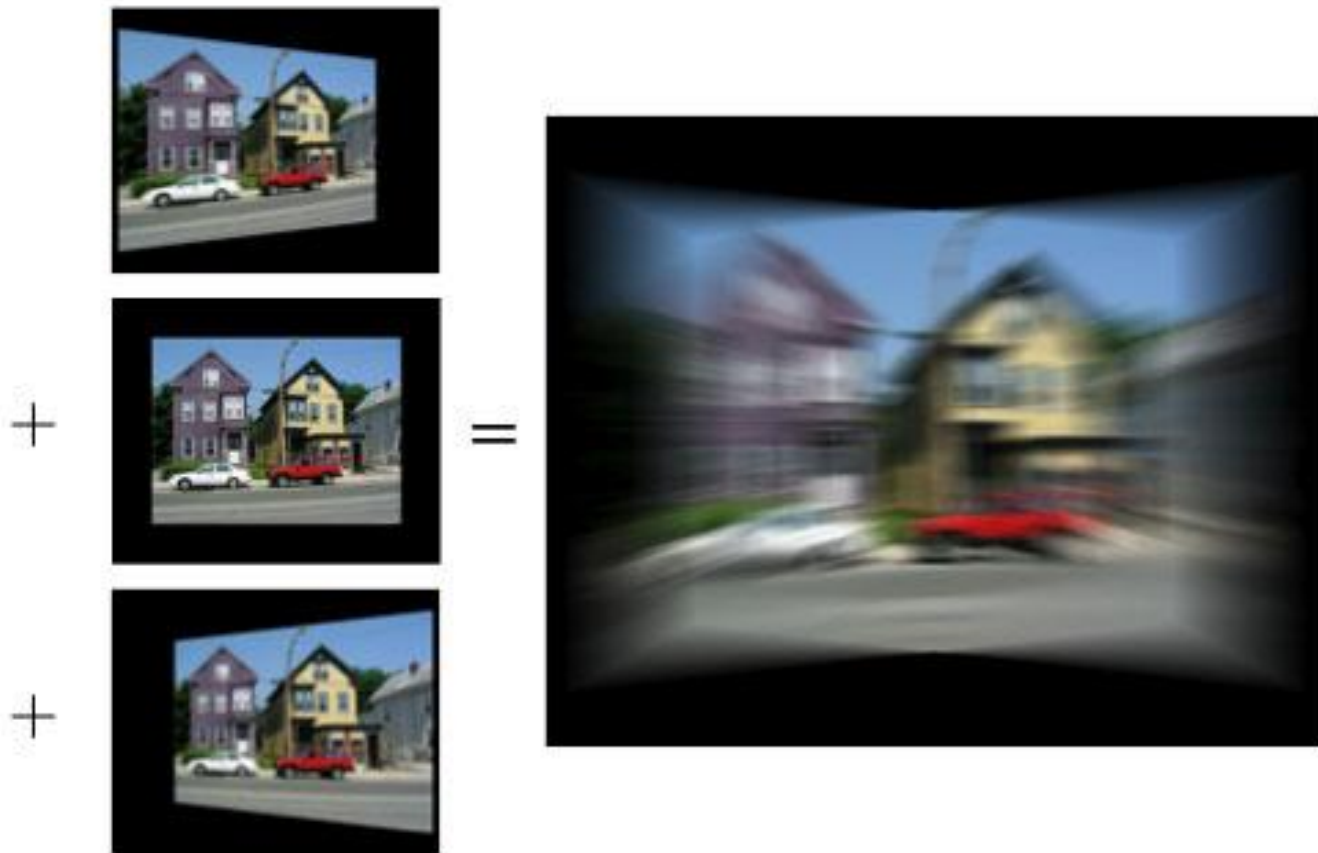


(a) World-projections captured by LF-sensor position

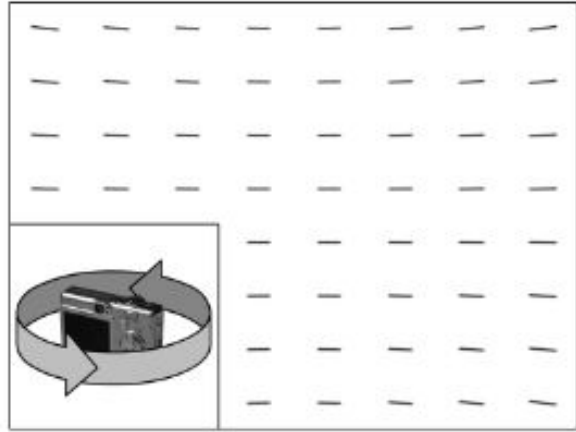


(b) Point-spread function in the latent image

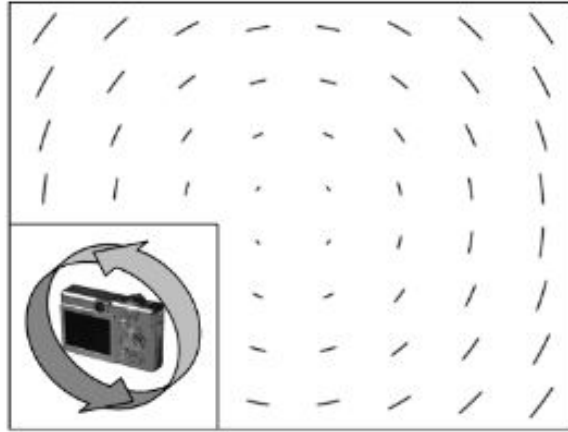
# Interpretation 1: As a Sum of Warped Images



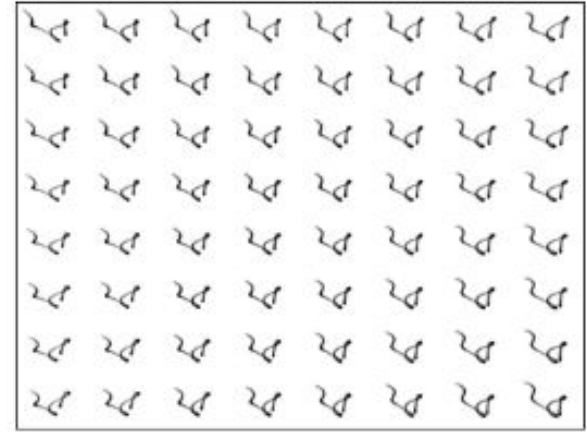
# Interpretation 2: As Space-variant Convolution



Y-axis rotation of the camera



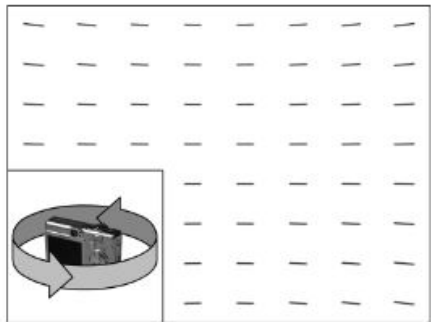
Z-axis rotation of the camera



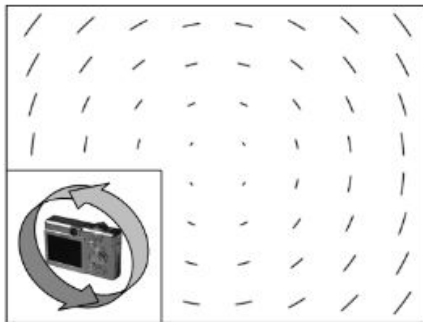
Arbitrary sequence of rotations

Formation of Point Spread Function (PSF)

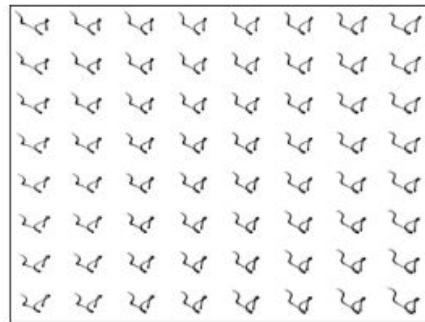
# Interpretation 2: As Space-variant Convolution



Y-axis rotation of the camera



Z-axis rotation of the camera



Arbitrary sequence of rotations



Clean Image

\*



PSF

=

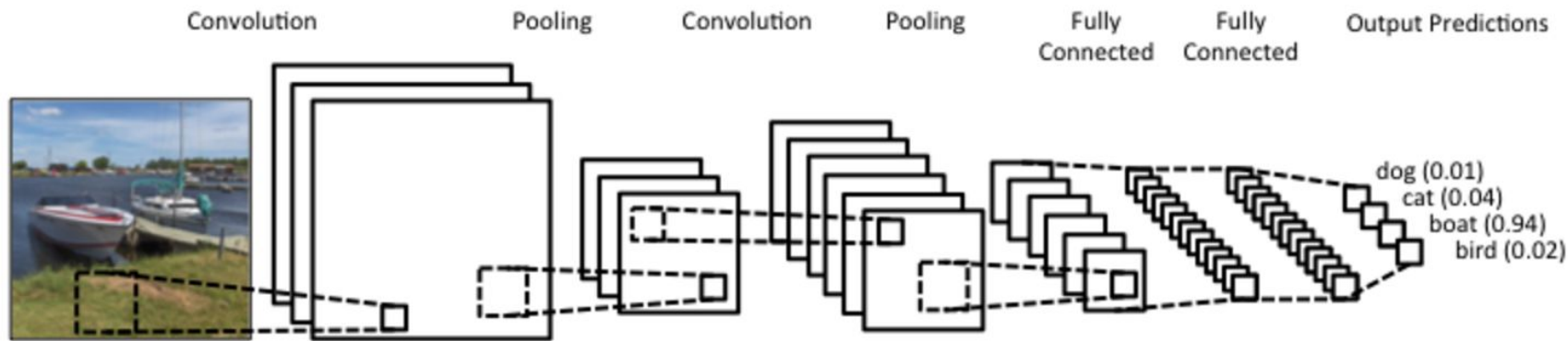


Blurred Image

# **Approach 1**



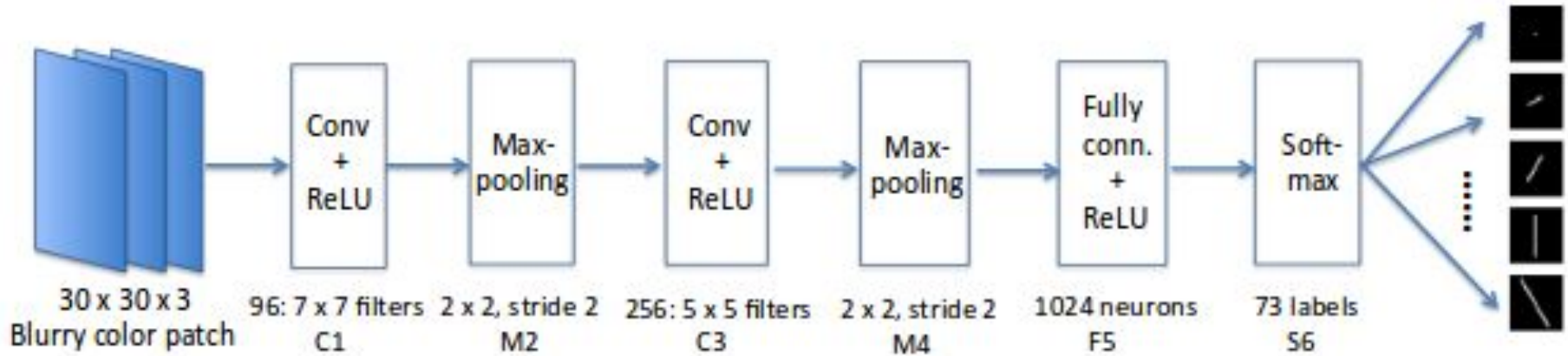
# Kernel classification using CNN.



Central Idea : Harnesses classification capabilities of CNN

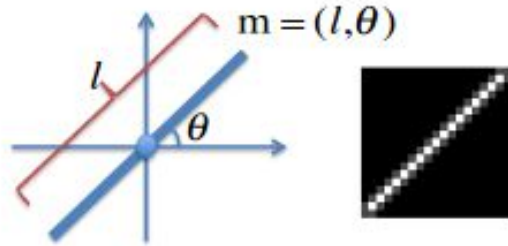


# Kernel classification using CNN.

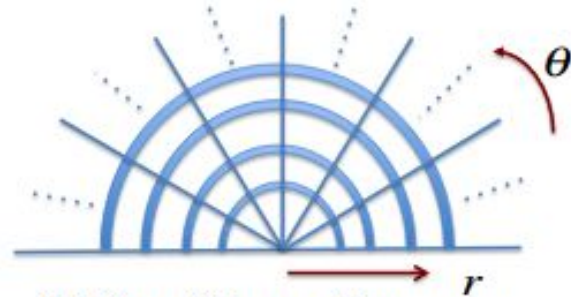


Central Idea : Harnesses classification capabilities of CNN

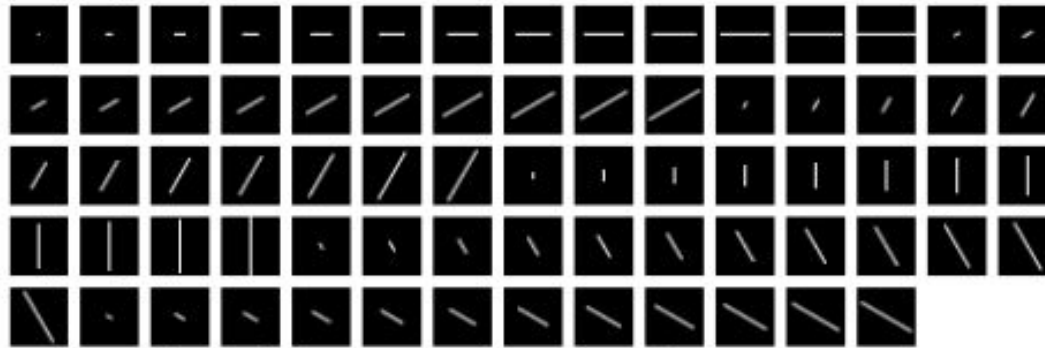
# Kernel classification using CNN.



(a) Motion kernel represented by motion vector

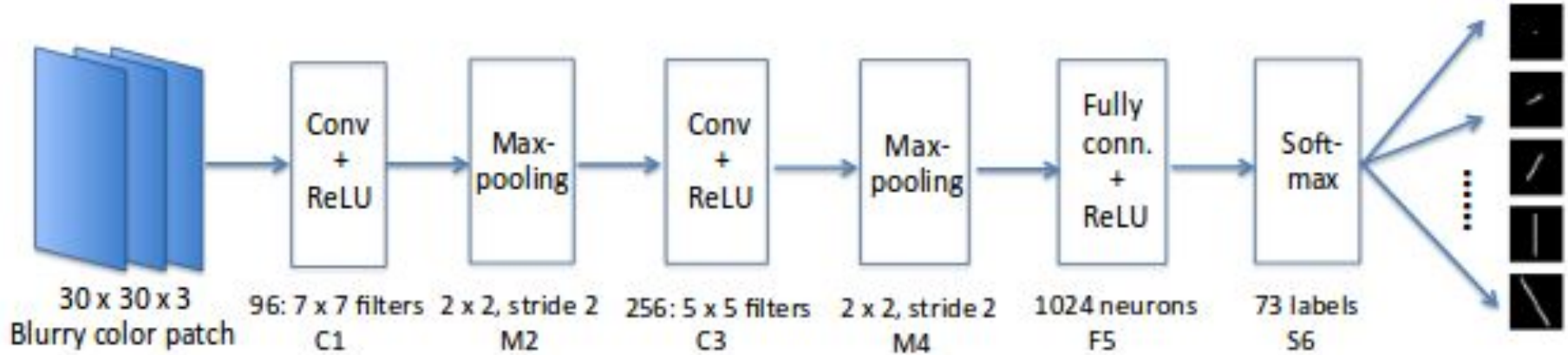


(b) Discretizing motion vector



(c) Candidate motion kernel set for learning CNN

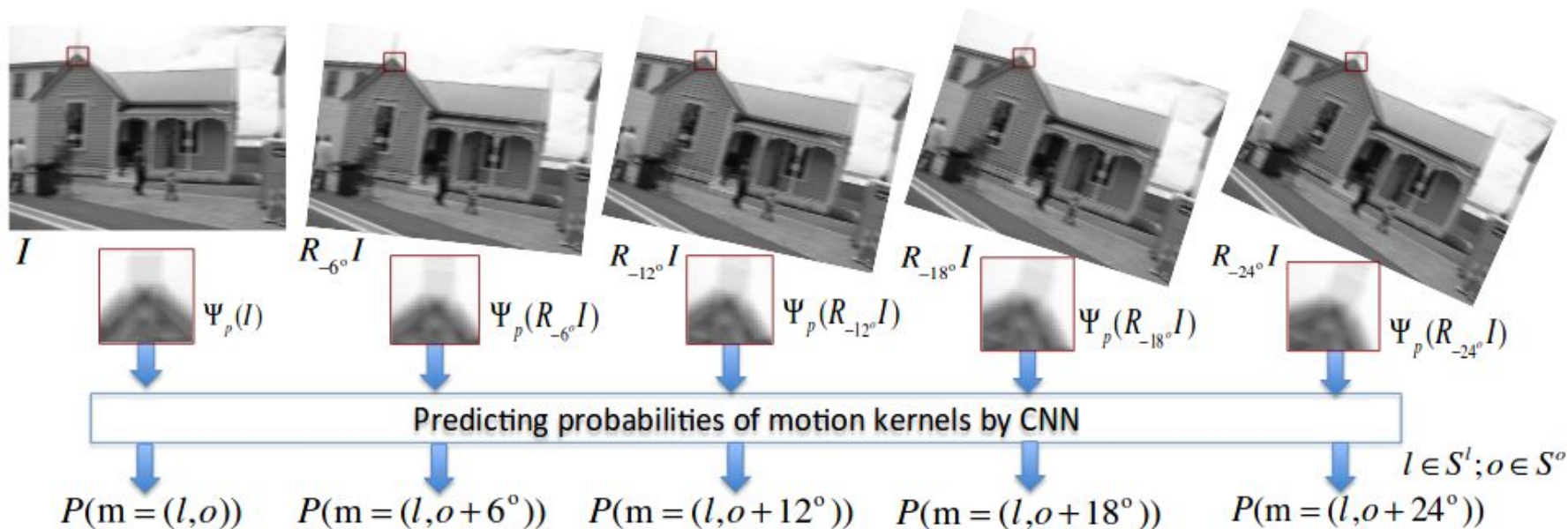
# Kernel classification using CNN.



**Problem 1:** Only 36 classes of Kernels (too small).

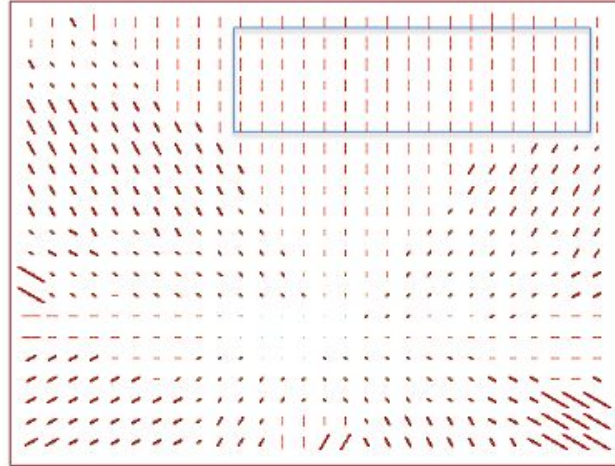
# Kernel classification using CNN.

**Solution:** Only 36 classes of Kernels (too small).

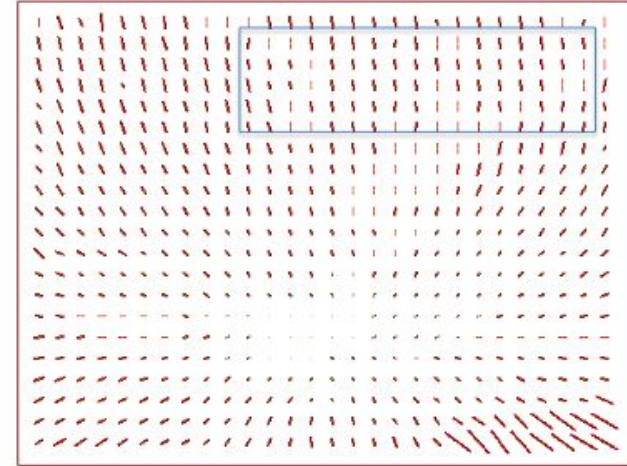


# Kernel classification using CNN.

## Analysis of Kernel Extension:



Approximation with **36** Kernels



Approximation with **361** Kernels



# Kernel classification using CNN.

Results:



## **Approach 2**



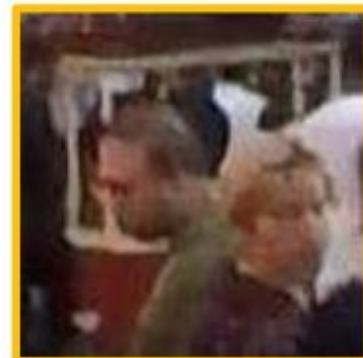
# End-to-end training using CNN with Multi-scale Loss



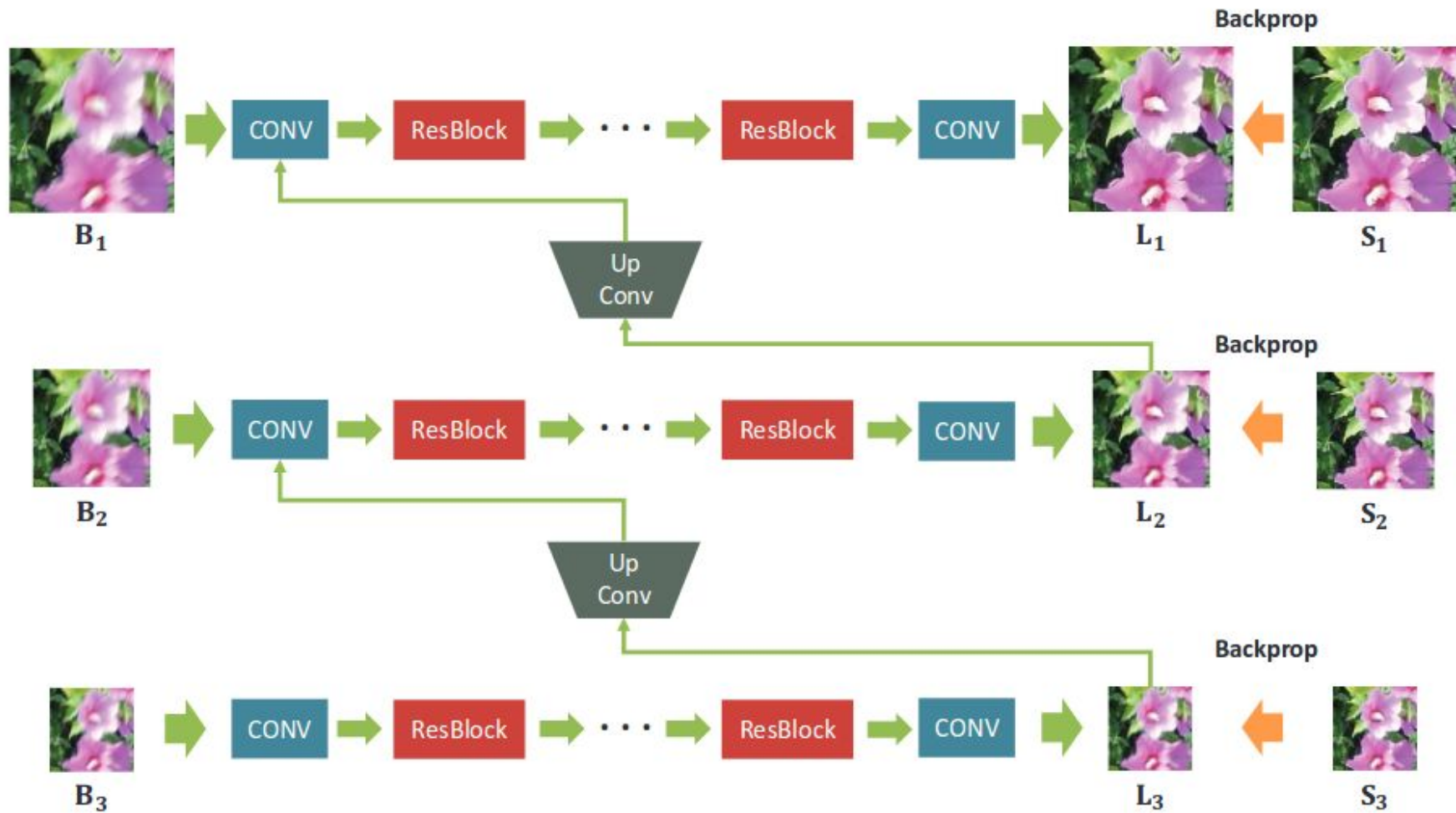
Blurry image

Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring  
Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee, CVPR 2017

# End-to-end training using CNN with Multi-scale Loss

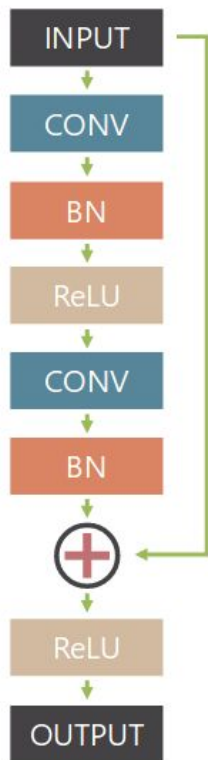


Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring  
Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee, CVPR 2017

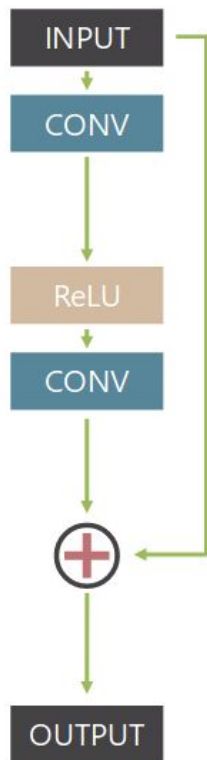


# End-to-end training using CNN with Multi-scale Loss

## More Details



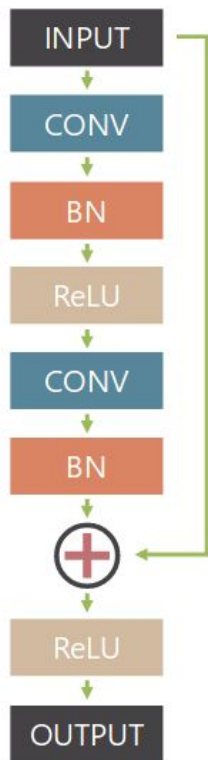
Resblock



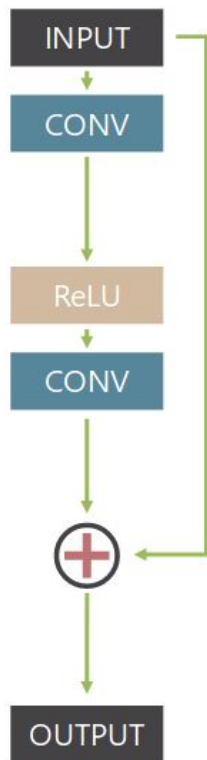
Modified Resblock

# End-to-end training using CNN with Multi-scale Loss

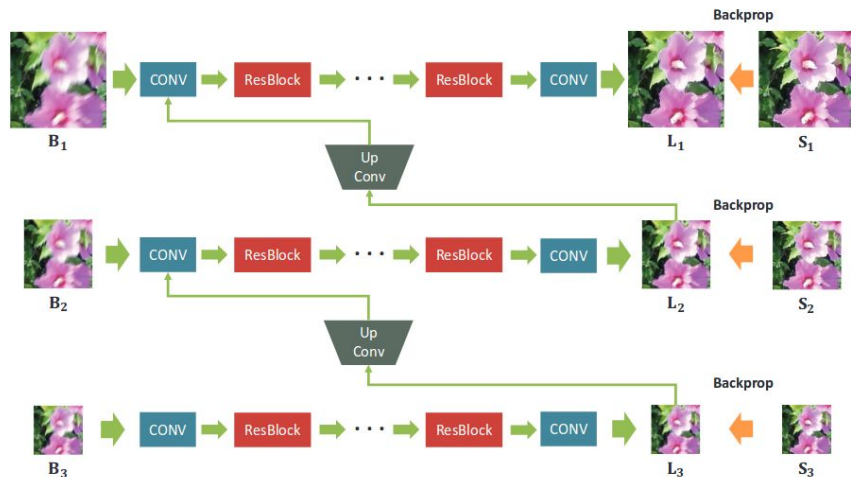
## More Details



Resblock



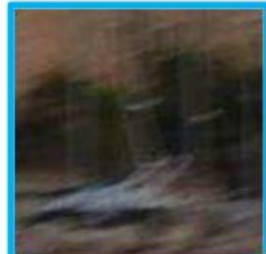
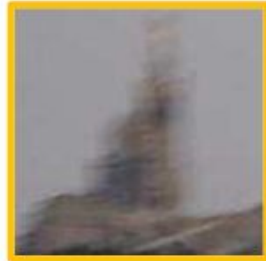
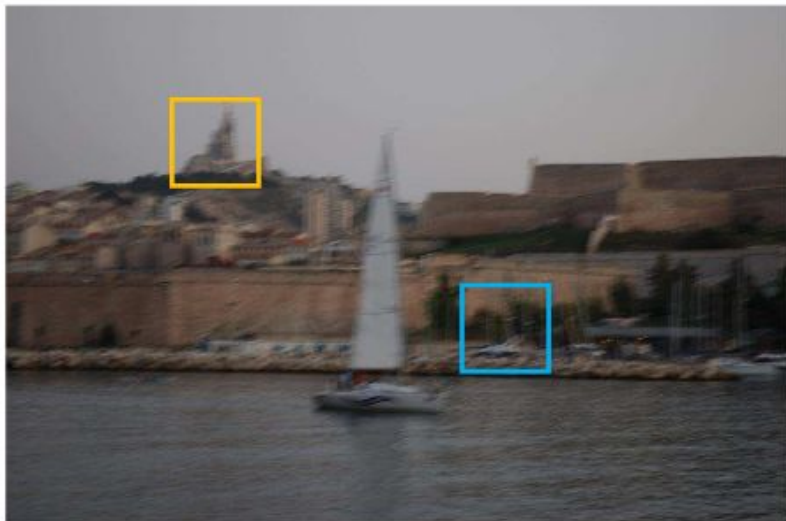
Modified Resblock



1. Coarsest level operates on 64X64 image patches
2. MSE Loss in all scales
3. Training data obtained using GoPro cameras.



Input



Output



