Long range horizontal connectivity : **Cost-effective circuit for natural image perception**

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Results

Local

Global

Local+

Globa

Introduction

Visual cortex and deep neural network (DNN) both excel 0 in natural image perception



• LRCs dramatically improve natural image classification performance









(DNN1: Alexnet Krizhevesky et al 2012) (DNN2: VGG Simonyan et al 2014) (DNN3: Resnet He et al 2015)

By adding only a small number of LRCs to the FF network, the performance of the network dramatically increased

The combination of a few LRC with local convergent connections maximize the cost-effectiveness of connections

• Visual cortex consists of fewer layers than DNNs, presumably due to the limited volume of the brain



• LRCs contribute particularly to encoding global structure of input image



Q. What is the structure of the brain to recognize natural image efficiently ?

Hypothesis

Long-range horizontal connections may allow cost-effective perception for natural image by integrating global information efficiently

Long rage connection (LRC)

Spatial structure of natural image : local + global

OLRC can be spontaneously evolved on the model network when total connection length is limited







→ The combination of long-range horizontal connections and local convergent connections enables efficient coding of the natural image



Starting from random initial connectivity, network was changed toward the direction that **minimizing the total length** while **recognizing** image correctly

Development of lateral connection



Most initial connections were pruned through learning, but a few long connections survived until the end of learning, even with length penalty

Total length decreased as the accuracy increased with length penalty

Optimized lateral connections

Disconnect random conn.

600

of deleted connection

(Two-sampled t-test : * p < 0.001)

800

200

400

important than other connections



(Two-sampled t-test : * p < 0.001)

LRC distribution was not formed if the training data was not a natural image

Methods

• Model network of visual pathway

-Basic structure : 3 layer MLP

• LRCs are applicable to conventional deep neural network for natural image perception

Implementation of LRCs on CNN

Conv

ReLU

Pool

Conv

Summary

Layer 1

Layer 2

[32 x 32 x 32



Layer 1

[32 x 32 x 32]

Layer 2

Cost effectiveness : LRC vs Layer









[15 x 15 x 32] [15 x 15 x 32] ReLU ReLU Pool Pool ReLU Layer 3 Conv Layer 3 Conv [7 x 7 x 64] [7 x 7 x 64] ReLU ReLU Pool Pool Cifar10 Layer 4 [3 x 3 x 64] Layer 4 [3 x 3 x 64] -ReLU ReLU LRC Layer 5 [1 x 1 x 64] Layer 5 Softmax [1 x 1 x 64] Softmax Output Output Classify Classify [1 x 1 x 10] [1 x 1 x 10] Receptive LRC

> LRCs were implemented as skip connections covering RF non-overlapping range via dilated convolution layer

ReLU 🌶

Pool

Conv

• Task : image classification

- Dataset: Cifar-10 (Natural image) Plane Cat

- **Training**: minimizing error of network's prediction by updating weights

field(RF)

> The combination of LRCs and local connections dramatically enhances visual perception

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- > LRCs contribute to image perception by integrating low-frequency global information
- LRCs can be spontaneously evolved when total connection length is limited
- LRCs can be applied to conventional DNN for cost-efficient perception of natural images



conv L +LRC 0.71 Accuracy RF non overlapping Adding LRCs is more efficient to resource usage than adding a layer 5 layer 4 lave 0.68 0.6 4.5 5 5.5 6 6.5 7 7.5

of parameters

 $\times 10^{\circ}$