視覚皮質の計算論的モデル
--- 面の知覚から形の知覚へ

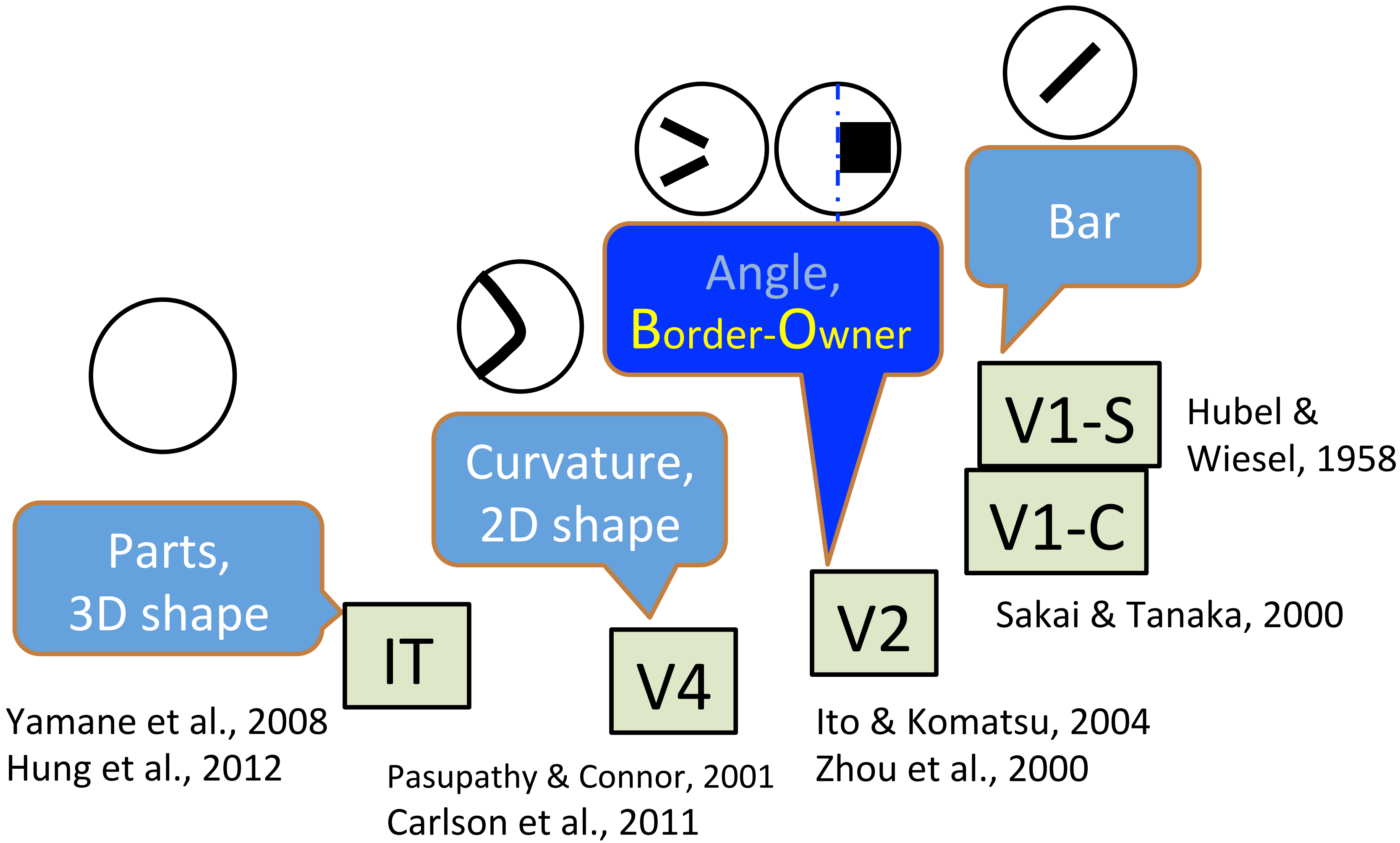
酒 井　宏

筑波大学

University of Tsukuba

Computational Vision Science Lab.

Sakai@CVS


Parts,
3D shape
IT
Yamane et al., 2008
Hung et al., 2012
Curvature,
2D shape
V4
Pasupathy & Connor, 2001
Carlson et al., 2011
Angle,
Border-Owner
V2
Ito & Komatsu, 2004
Zhou et al., 2000
Bar
V1-S
V1-C
Hubel &
Wiesel, 1958
Sakai & Tanaka, 2000

Border Ownership

Physiology: Natural Images and Latency $\boxed{\text{65\% consistency}}$ ✔

Computational Model:

1. Surround Modulation Model
2. Latency Analysis
3. Population Coding: Theoretical Limit

Towards Shape Coding

Curvature Selectivity

BO constraint

The Aim of the Study

What is the neural mechanism underlying

Border Ownership

How the neurons in V2 compute BO?

歌川国芳

Border Ownership

Physiology: Natural Images and Latency

Computational Model:

1. **Surround Modulation Model**
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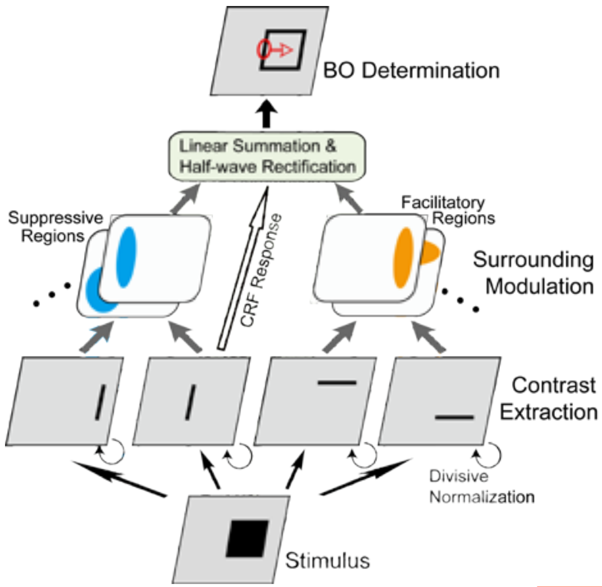
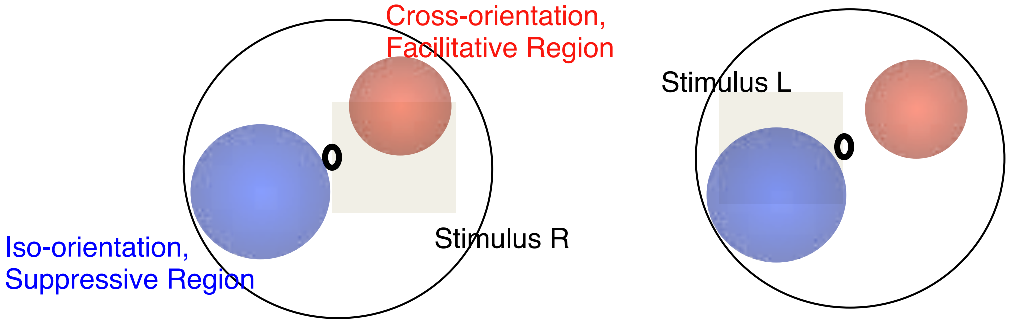
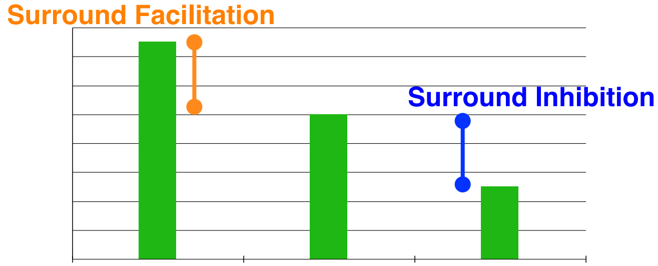
Surround Modulation Model for BO selectivity



Localized, Asymmetric Surrounding Suppression/Facilitation





Our Hypothesis

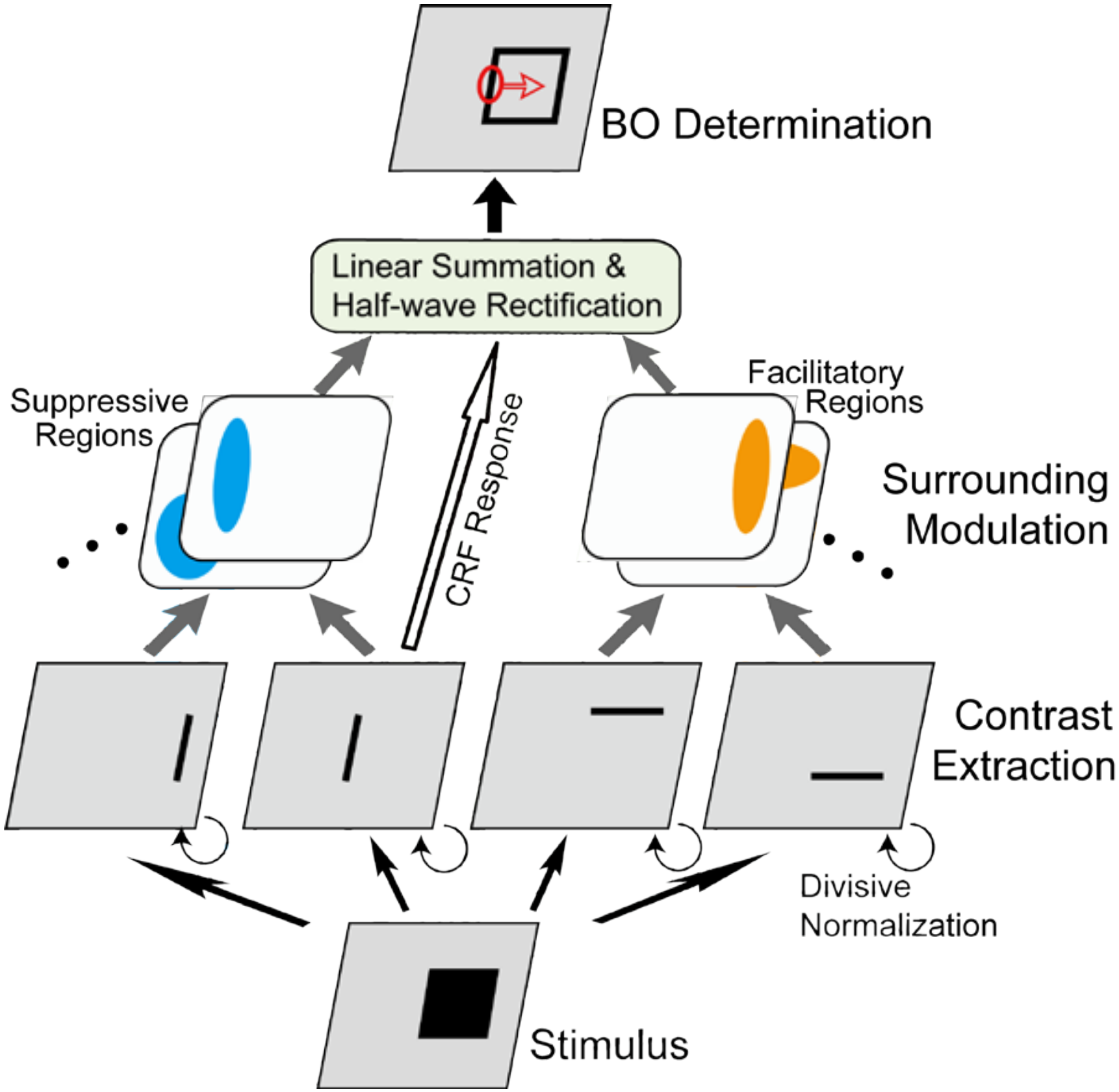
周辺変調でBOが生起

特定の空間内の線分をpoolすると
図の方向が判る！

Sakai & Nishimura, *Journal of Cognitive Neuroscience*, 2006

Wagatsuma, Oki & Sakai., *Frontiers in Comp. Neurosci.*, 2013

The Model with linear modulation



Simple mechanism.

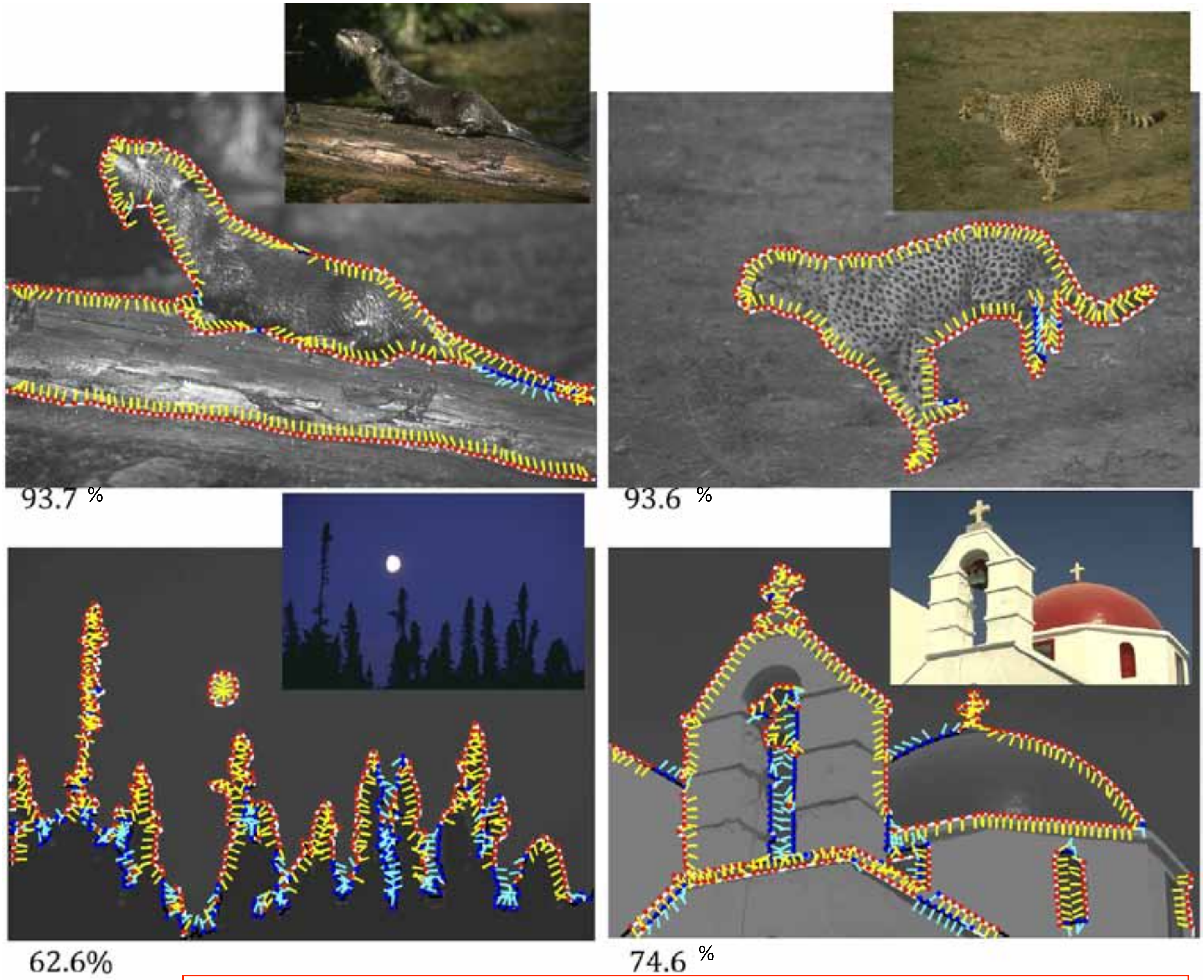
Consistency among stimuli?

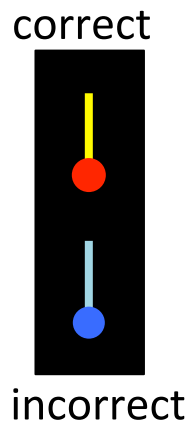
Need to test consistency !!

「注目する位置(CRF)の周りに,
輪郭がどう分布しているか」
をみるモデル

J. Cognit. Neurosci., Sakai & Nishimura, 2006
Sakai, et al, *Neural Networks*, 2012

Surround modulation model applied for natural images





67% correct on average from grey, natural surrounds

Original Images from Berkeley Segmentation Dataset

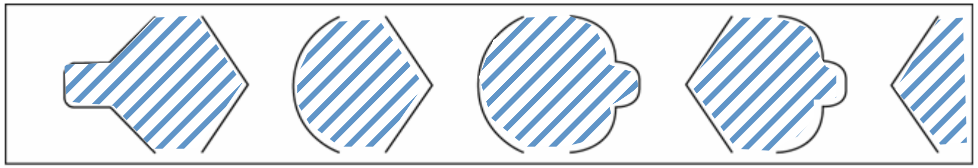
Sakai, et al, *Neural Networks*, 2012

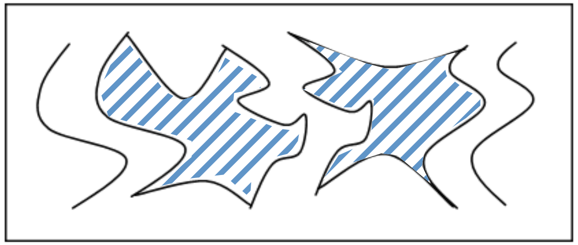
Gestalt Factors that evoke Figure/Ground

なぜ，この簡単なメカニズムでうまくいくのか？

In local contour of natural images,
each of these factors promote BO perception.

- Convexity
- Closure
- Parallel
- Size of region
- Lying below ground region
- .....



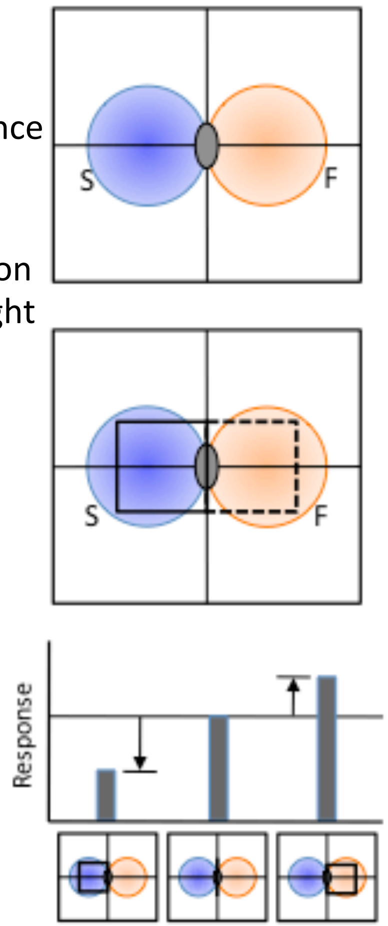


Fowlkes, Martin, Malik (JoV, 2007), Shimizu, Aono, Sakai (VISION, 2009)

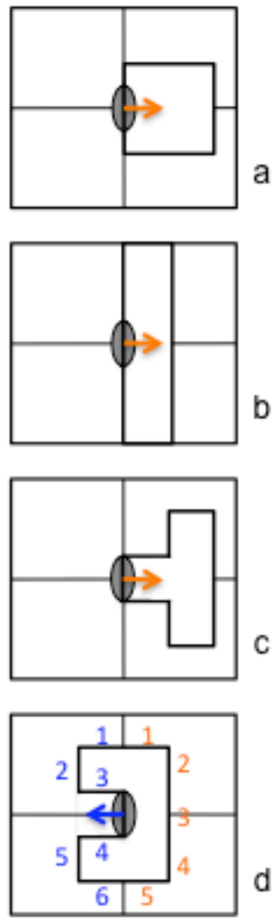
Intuitive illustration of Gestalt factors & surround regions

It detects imbalance of contrast.

If more contours on the right, BO is right



(A)



Closure

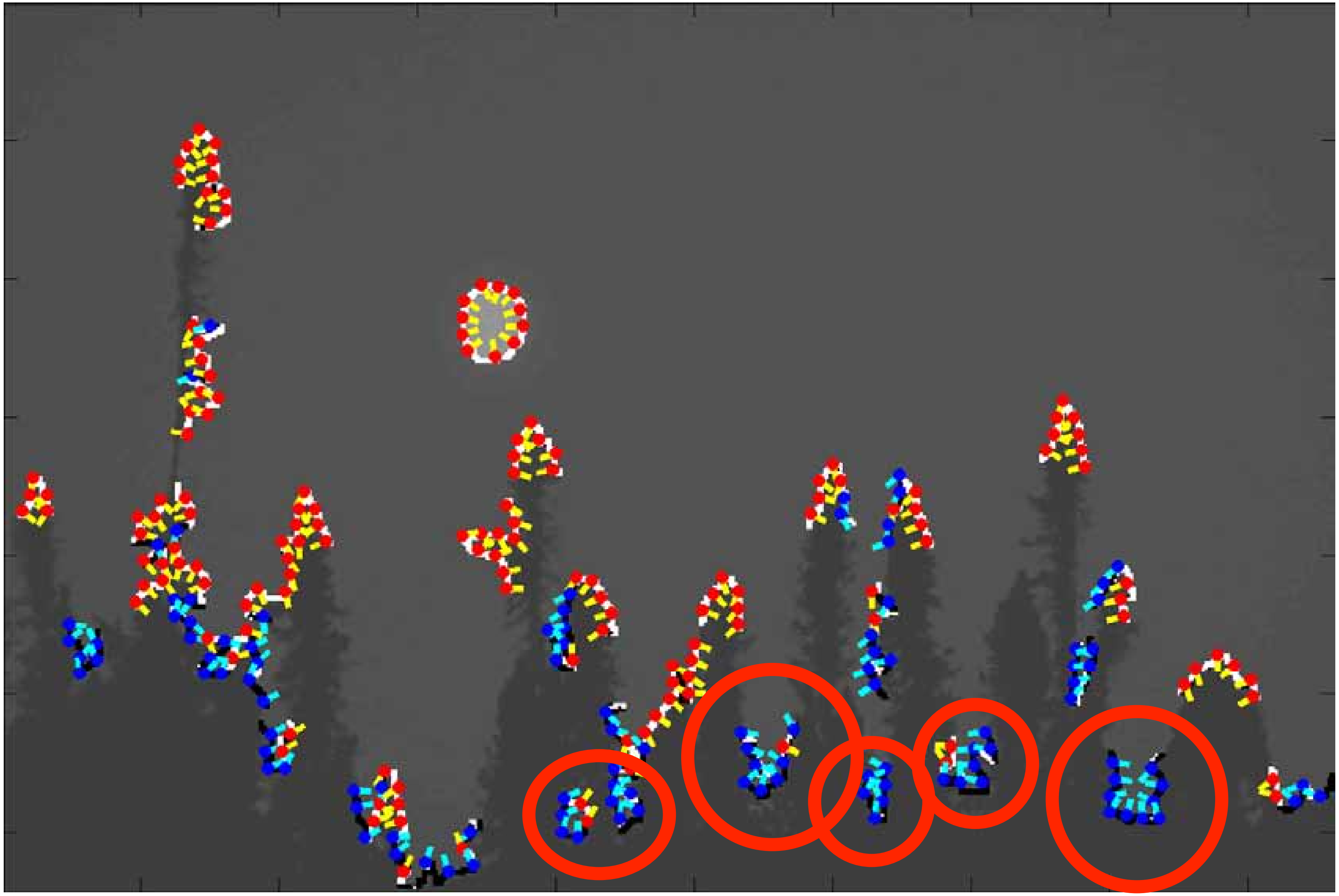
Parallel

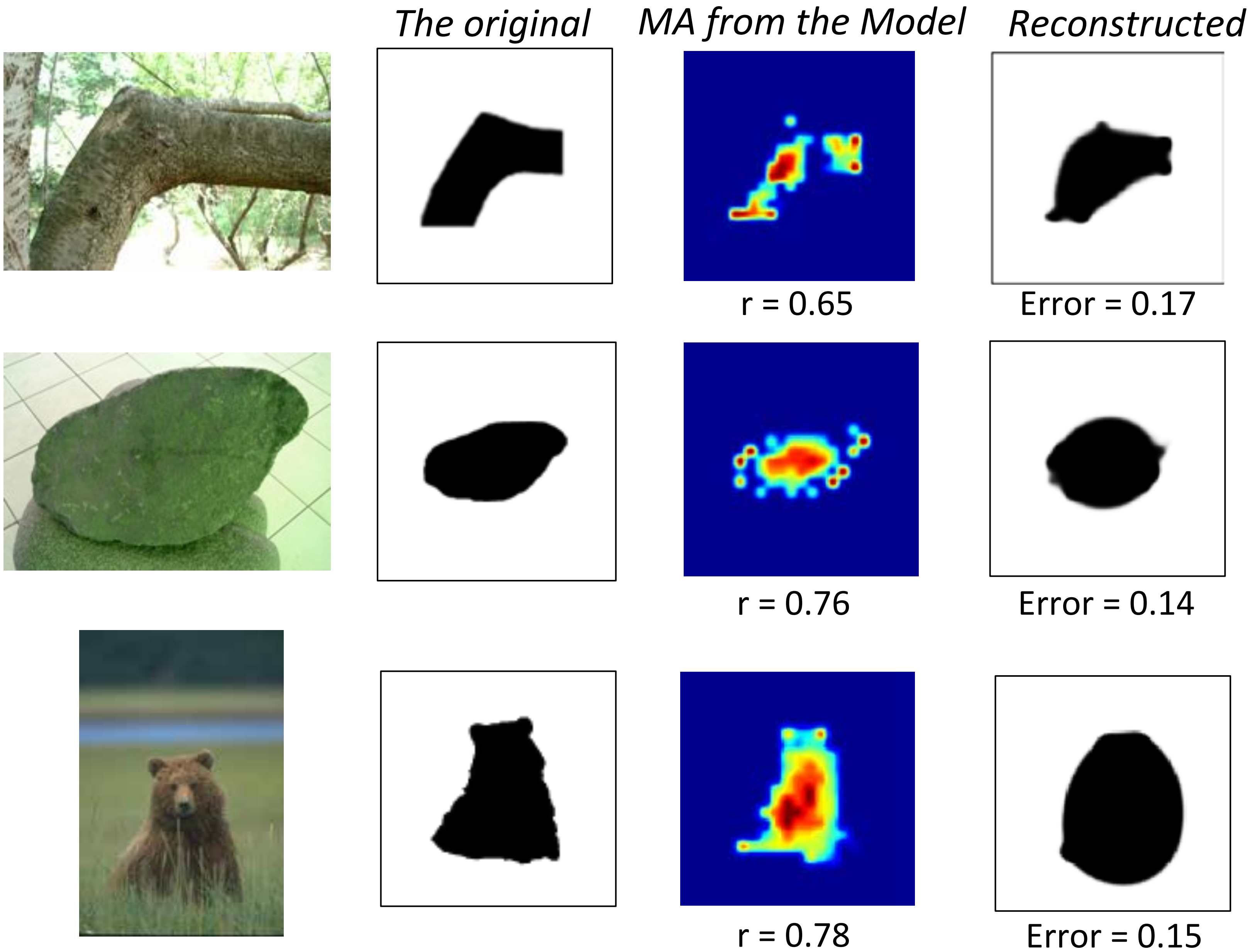
Convex

Concave

(C)

Recall natural images!





Hatori & Sakai, Journal of Optical Society of America, A, 2014

Border Ownership

Physiology: Natural Images and Latency

線分を,
特定の空間領域内だけ
pool する

Computational Model:

1. **Surround Modulation Model** ✔
2. Latency Analysis
3. Population Coding: Theoretical Limit

・Simple model.
・High consistency
・Agreement w/ physiology & human perception

Towards Shape Coding

Curvature Selectivity

BO constraint

Border Ownership

Physiology: Natural Images and Latency

Computational Model:

Spatial Character.

1. Surround Modulation Model
2. **Latency Analysis** ← Temporal Character.
3. Population Coding: Theoretical Limit

New physiology!

Towards Shape Coding

Curvature Selectivity

BO constraint

Border Ownership

Physiology: Natural Images and Latency

Computational Model:

Single cell model

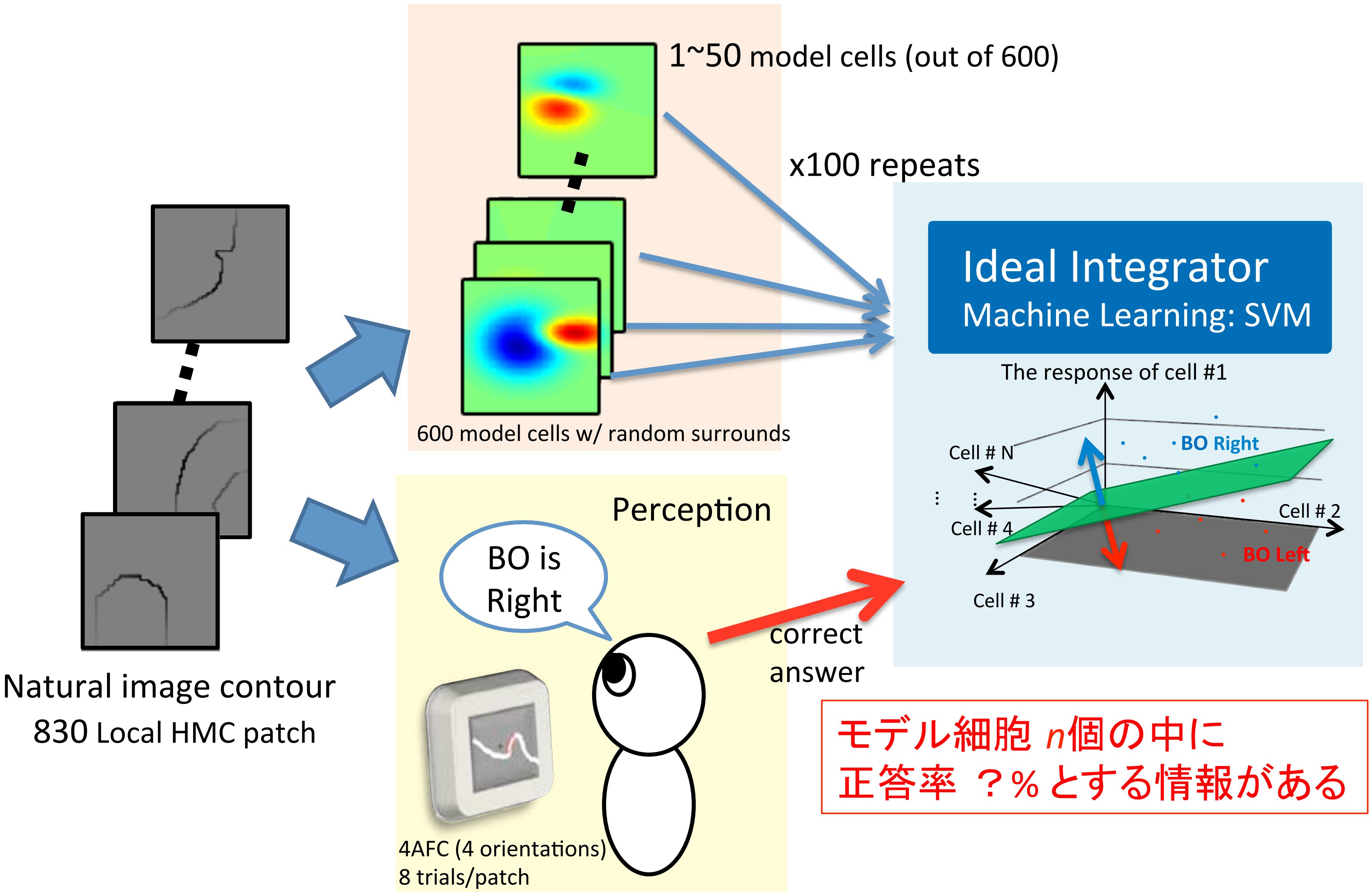
1. Surround Modulation Model
2. Latency Analysis
3. **Population Coding: Theoretical Limit**

Towards Shape Coding

Curvature Selectivity

BO constraint

モデル細胞が集まると自然画像のBO判断がより良くできるか？
その時、モデル細胞は幾ついるか？



モデル細胞 *n*個の中に
正答率 ？％とする情報がある

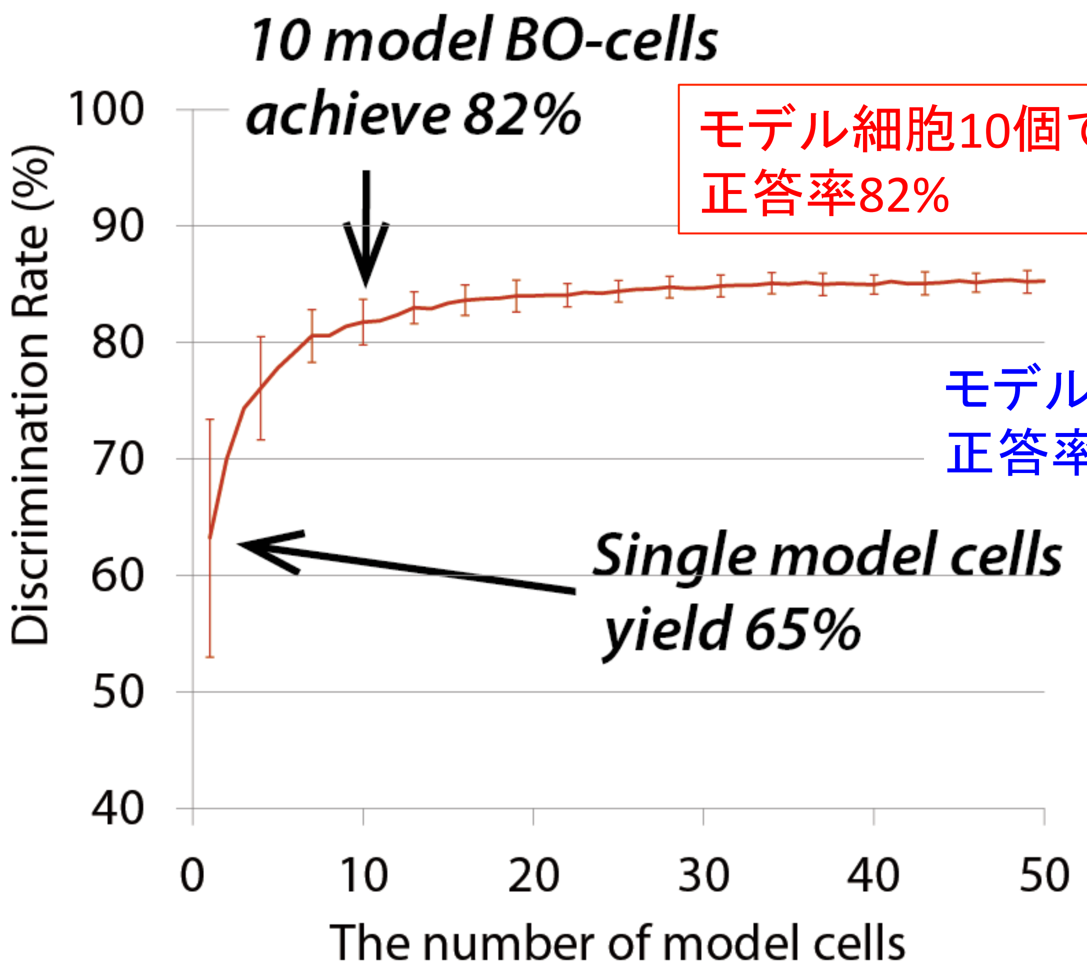
$$Confidence = \frac{|Left - Right| + |Up - Down|}{8}$$

Nakata & Sakai, LNCS, 2012
JNSS 2012

Exp.1 *How many BO cells are required?*

We applied SVM to the outputs of individual model-cells, so as to maximize the discrimination rate.

About 10 !!



モデル細胞10個で
正答率82%

モデル細胞 10個の中に
正答率82% とする情報がある

Border Ownership

Physiology: Natural Images and Latency

Computational Model:

1. Surround Modulation Model
2. Latency Analysis
3. **Population Coding: Theoretical Limit**

$\boxed{\text{10 BO-cells yields 82\% correct}}$ ✔

Towards Shape Coding

Curvature Selectivity

BO constraint

Border Ownership

Physiology: Natural Images and Latency

Computational Model:

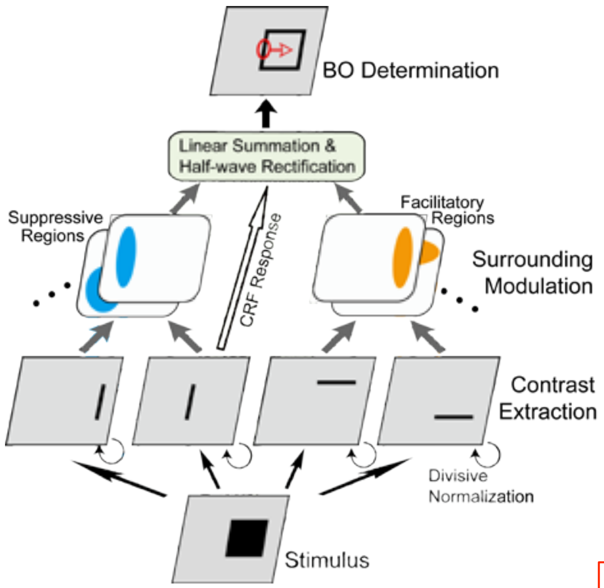
1. Surround Modulation Model
2. Latency Analysis
3. Population Coding: Theoretical Limit

Towards Shape Coding

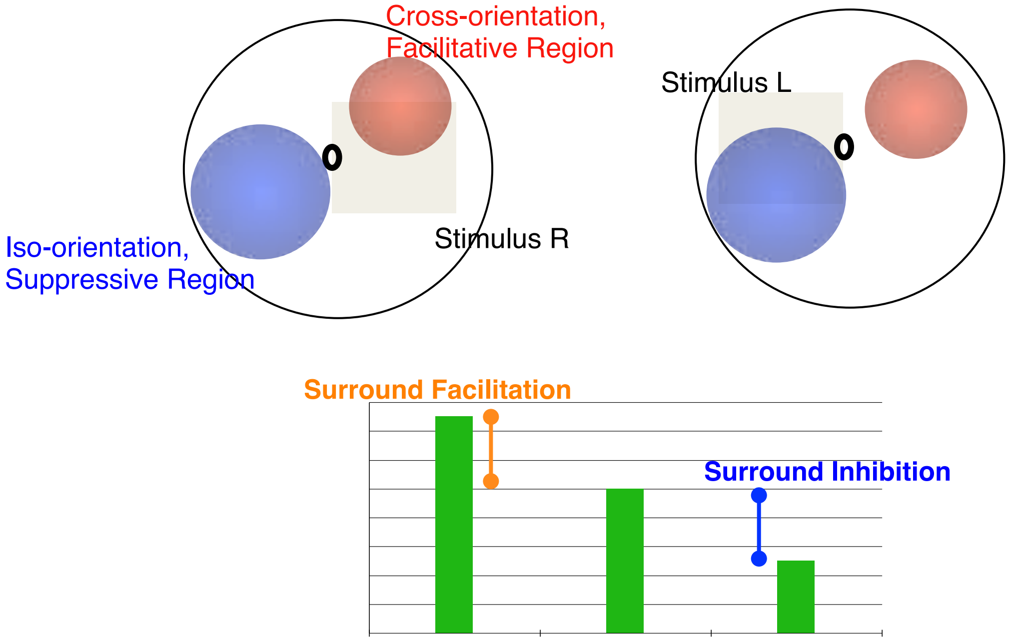
Curvature Selectivity

BO constraint

Selective Spatial Pooling of Bars generates BO selectivity



Localized, Asymmetric Surrounding Suppression/Facilitation



まとめ

特定の空間にある 線分を poolすると
図方向を決められる

Sakai & Nishimura, *Journal of Cognitive Neuroscience*, 2006

Wagatsuma, Oki & Sakai., *Frontiers in Comp. Neurosci.*, 2013

Border Ownership

V2

Physiology: Natural Images and Latency

Computational Model:

1. Surround Modulation Model
2. Latency Analysis
3. Population Coding: Theoretical Limit

Towards Shape Coding

Curvature Selectivity

V4

Computational Model:

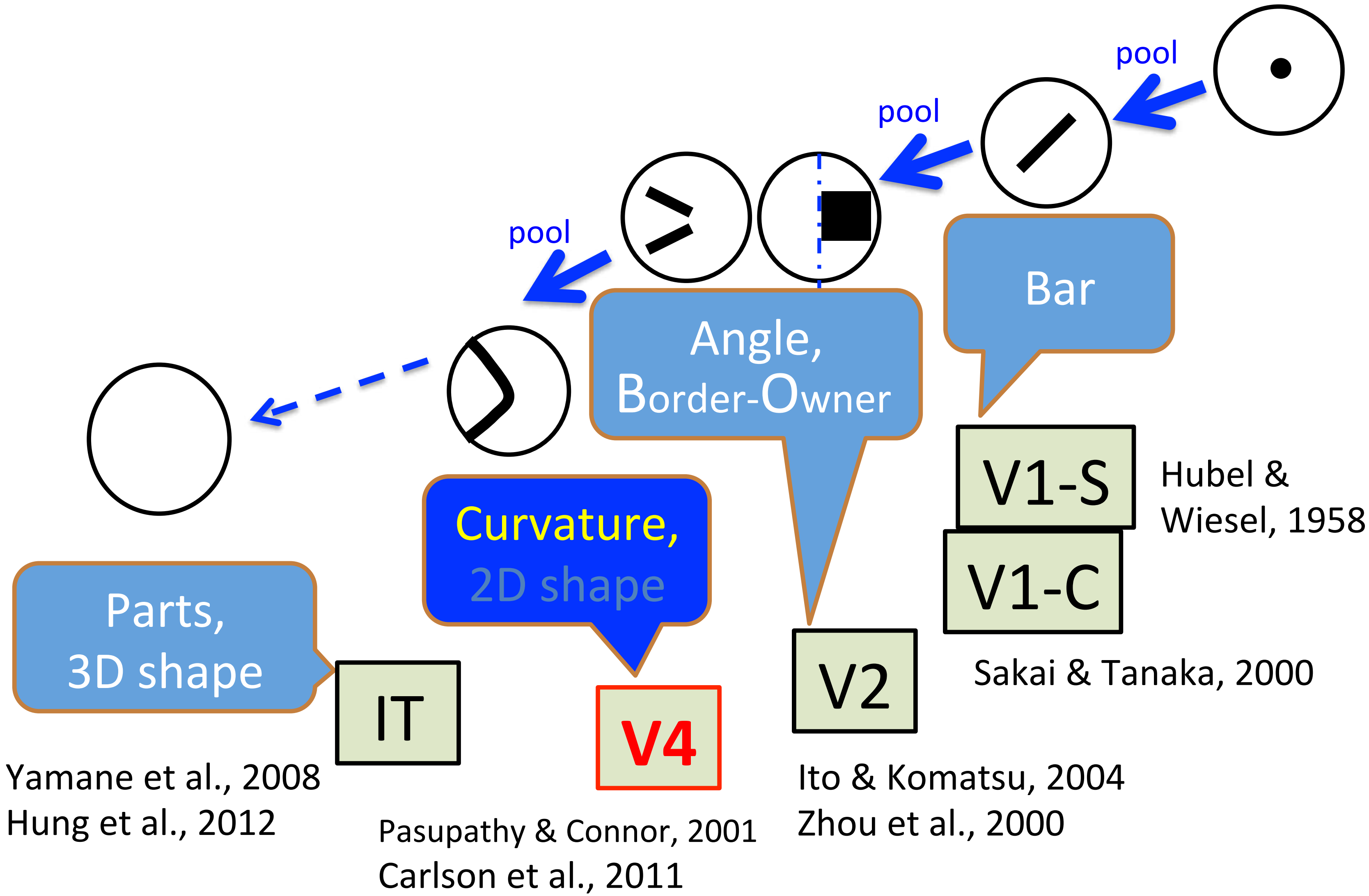
1. Pooling Model
2. Sparse Coding Model

Curvature Selectivity

Physiology: Selective to a specific curvature & its direction

Computational Models:

1. Pooling Model
2. Sparse Coding Model


pool
pool
pool
Bar
Angle,
Border-Owner
Curvature,
2D shape
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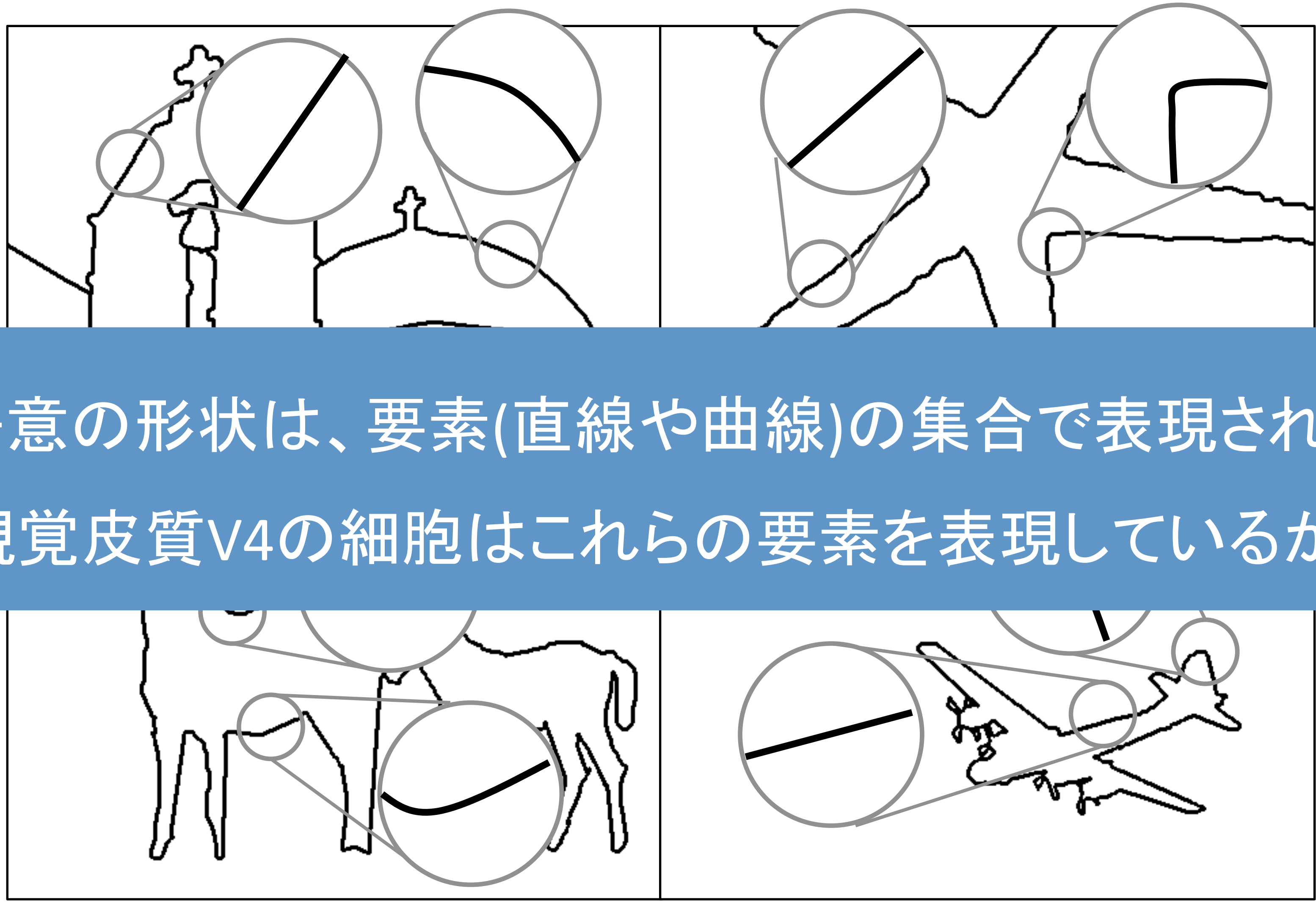
Hubel &
Wiesel, 1958
Sakai & Tanaka, 2000
V2
Ito & Komatsu, 2004
Zhou et al., 2000
V4
Pasupathy & Connor, 2001
Carlson et al., 2011
IT
Yamane et al., 2008
Hung et al., 2012

任意の形状は、要素(直線や曲線)の集合で表現される。

視覚皮質V4の細胞はこれらの要素を表現しているか?



Images from The Berkeley Segmentation Dataset

Curvature Selectivity

Physiology: Selective to a specific curvature & its direction ✔

Computational Models:

1. Pooling Model
2. Sparse Coding Model

<u>Curvature Selectivity</u>

Physiology: Selective to a specific curvature & its direction

Computational Models:

1. Pooling Model
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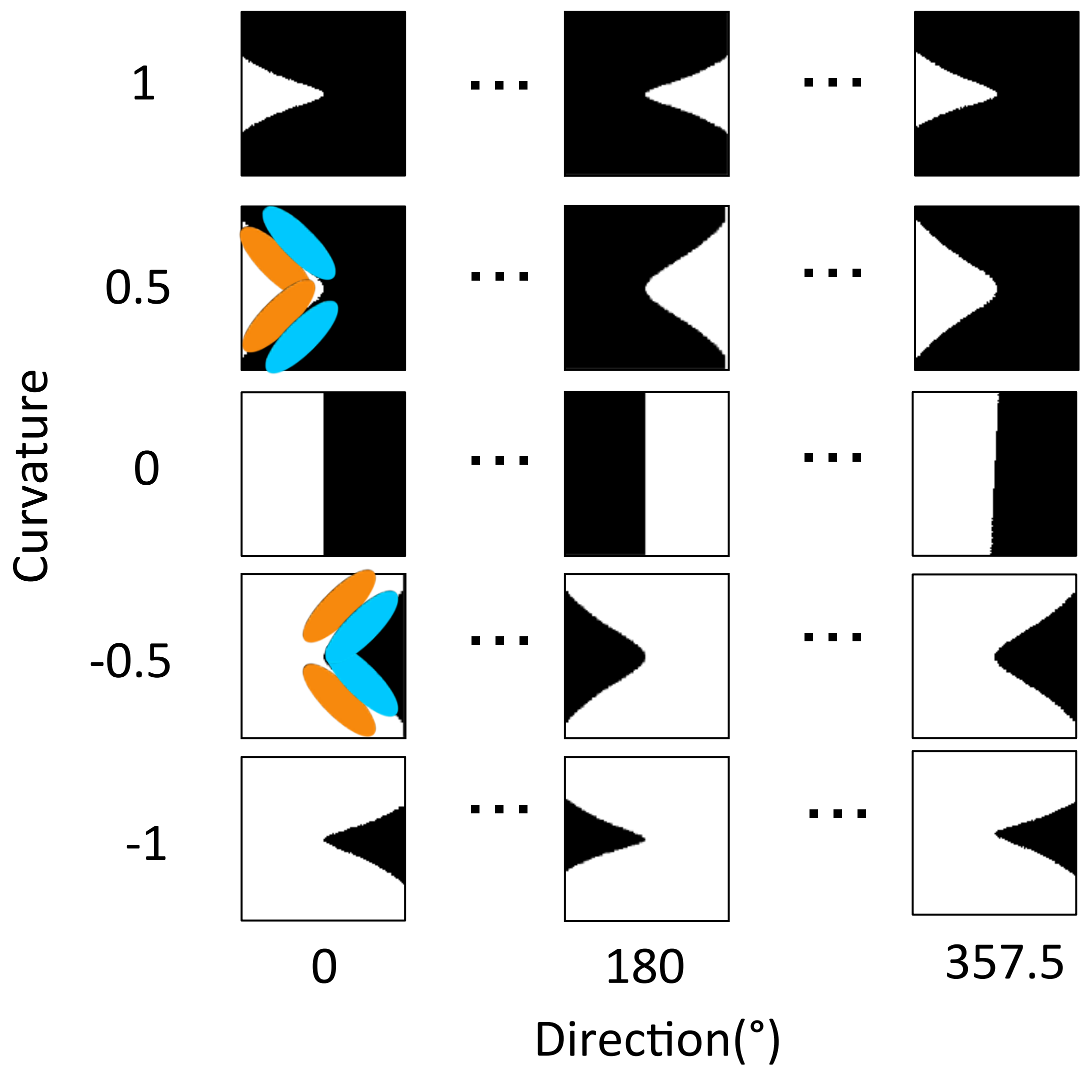

1
0.5
0
-0.5
-1
Curvature
0
180
357.5
Direction(°)

Curvature Selectivity

Physiology: Selective to a specific curvature & its direction

Computational Models:

1. Pooling Model

どうやって適当な組み合わせを選ぶのか？
どのような原理で作られるのか？

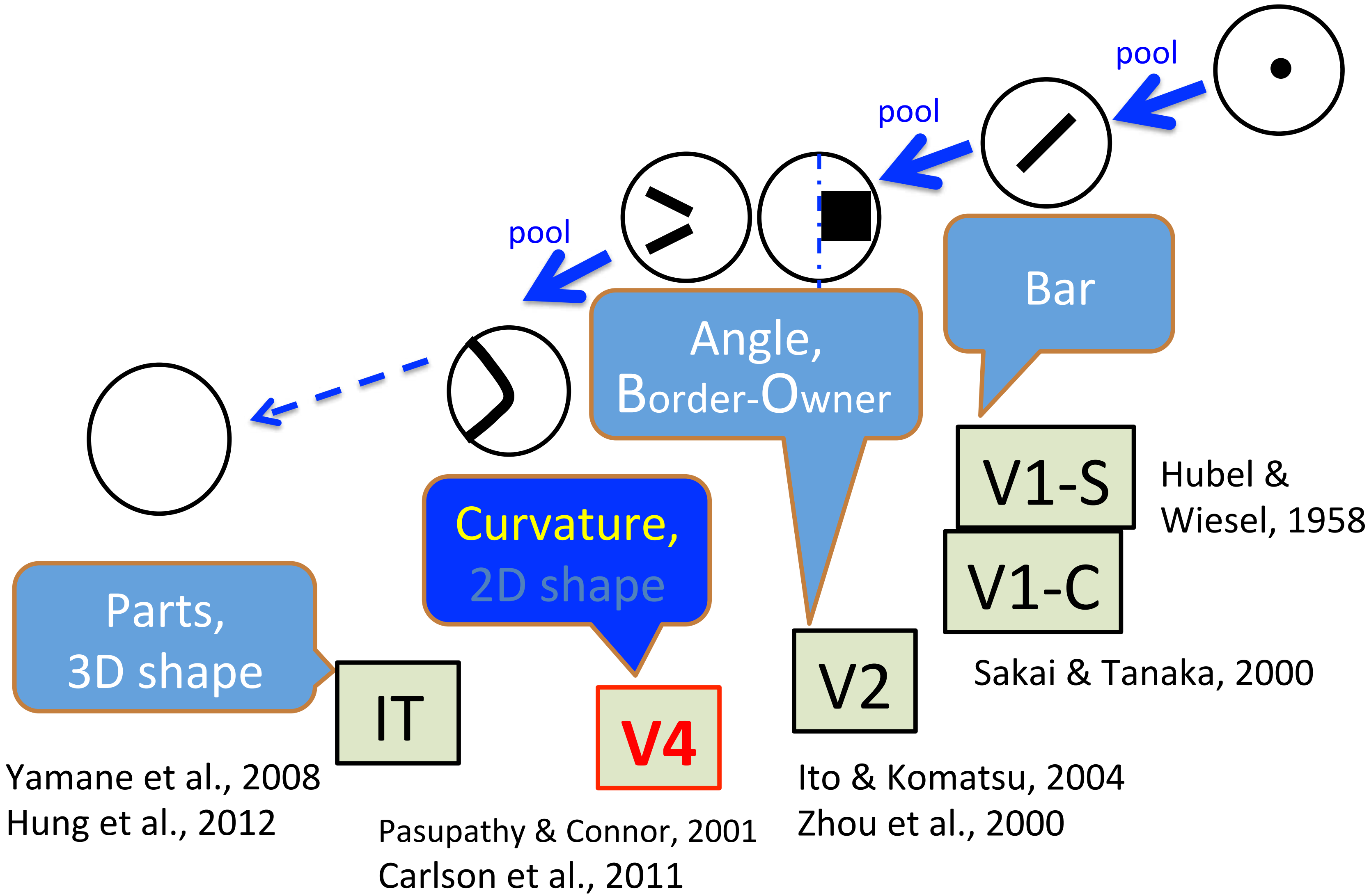
2. Sparse Coding Model

Hypothesis

SparsenessがV4の曲率選択性の生成をコントロールする。

⬇

- 様々なsparsenessを持つ基底関数を求め、生理実験の曲率選択性と比較を行う。


pool
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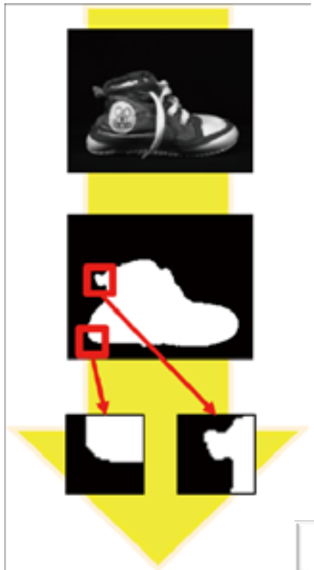
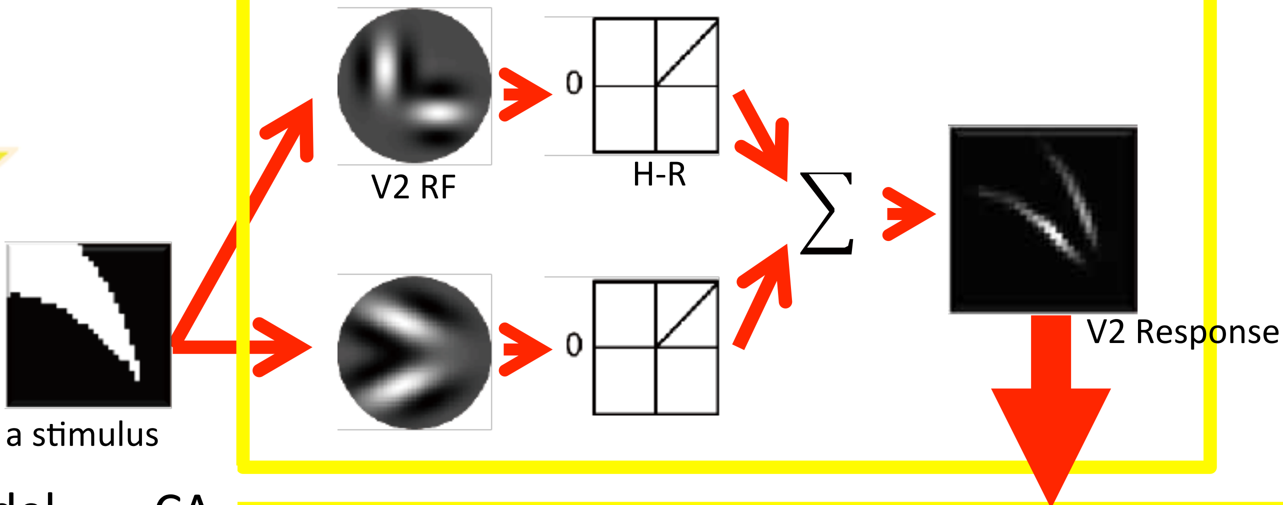
Sakai & Tanaka, 2000
Ito & Komatsu, 2004
Zhou et al., 2000
Pasupathy & Connor, 2001
Carlson et al., 2011
Yamane et al., 2008
Hung et al., 2012

Component Analysis to Construct V4 RF

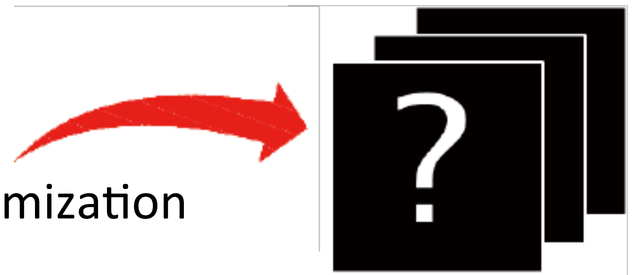


V2 Model ---Hardwired



V4 Model --- CA

Constraints
1. Sparse Coding
2. Reconstruction Error Minimization



V4 Bases?

Cost Function:

$$[reconstruction\ error] +\ \lambda[sparseness\ of\ s_i]$$

$$= \sum_{x,y}\left[X_{batch}(x,y) - \sum_i s_i a_i(x,y)\right]^2 + \lambda \sum_i S(s_i)$$

選択性が出現するか？
その時のSparsenessは？

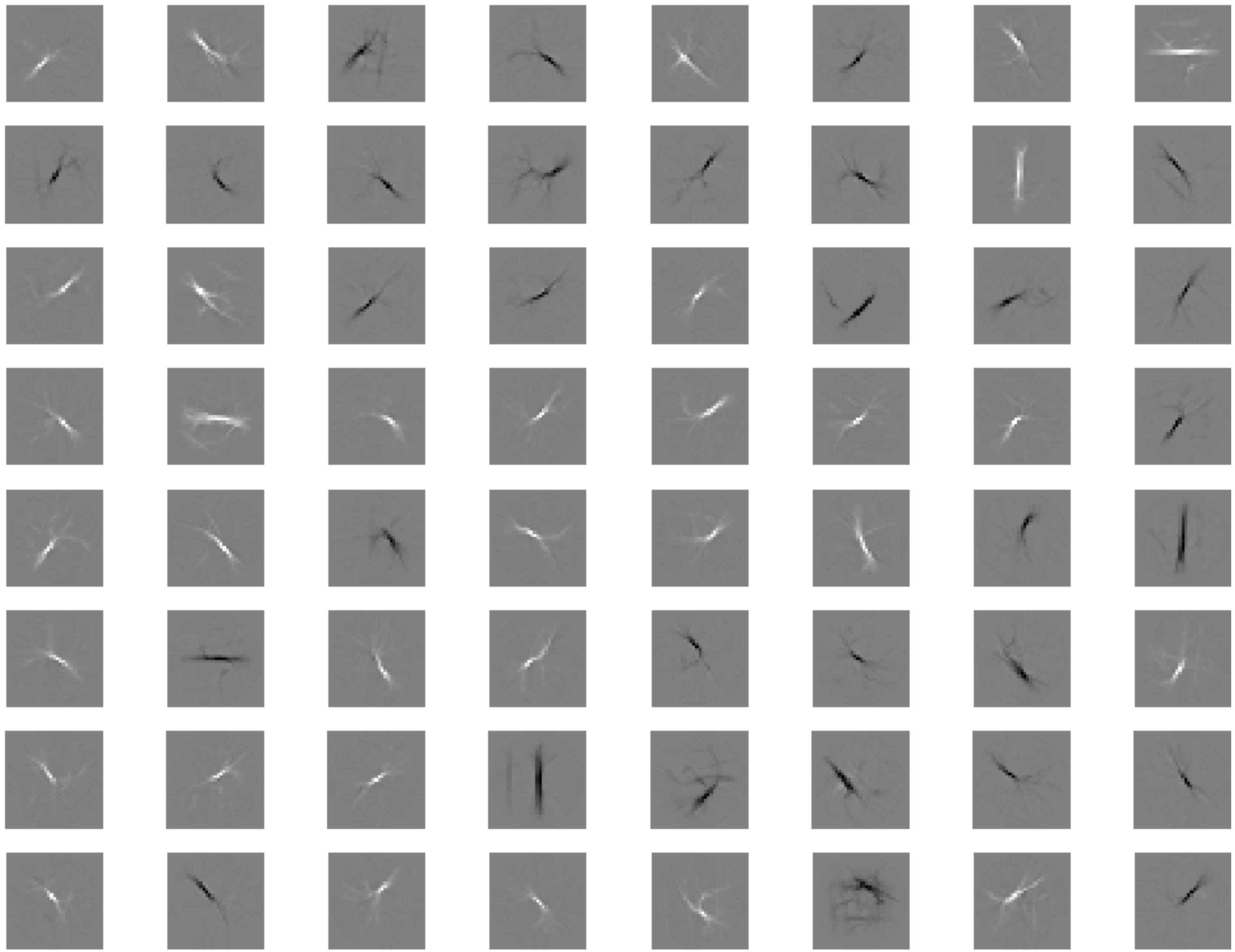
$$S(x) = log(1 + x^2)$$

Olshausen & Field, Nature 1996

Results: Example basis functions
sparseness = 0.81

$i = 64$

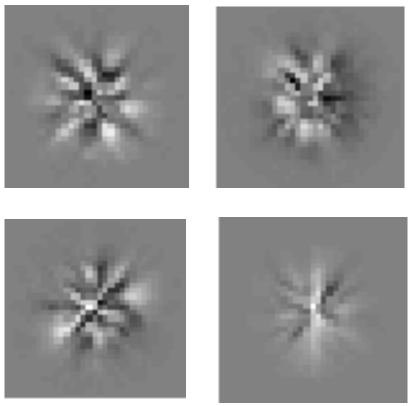
$\lambda=2.2, \quad \sigma=0.316$



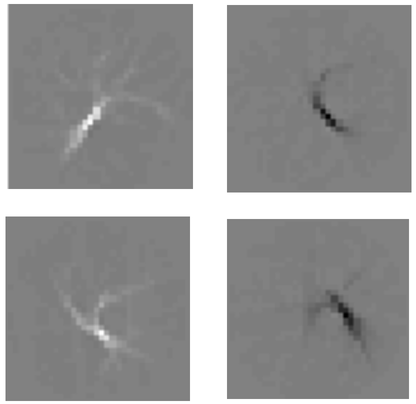
Hatori & Sakai, LNCS 2013

Results: Selectivity of basis functions

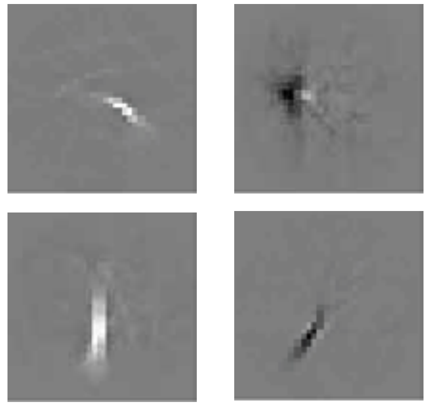
Sparseness = 0.38



Sparseness = 0.81

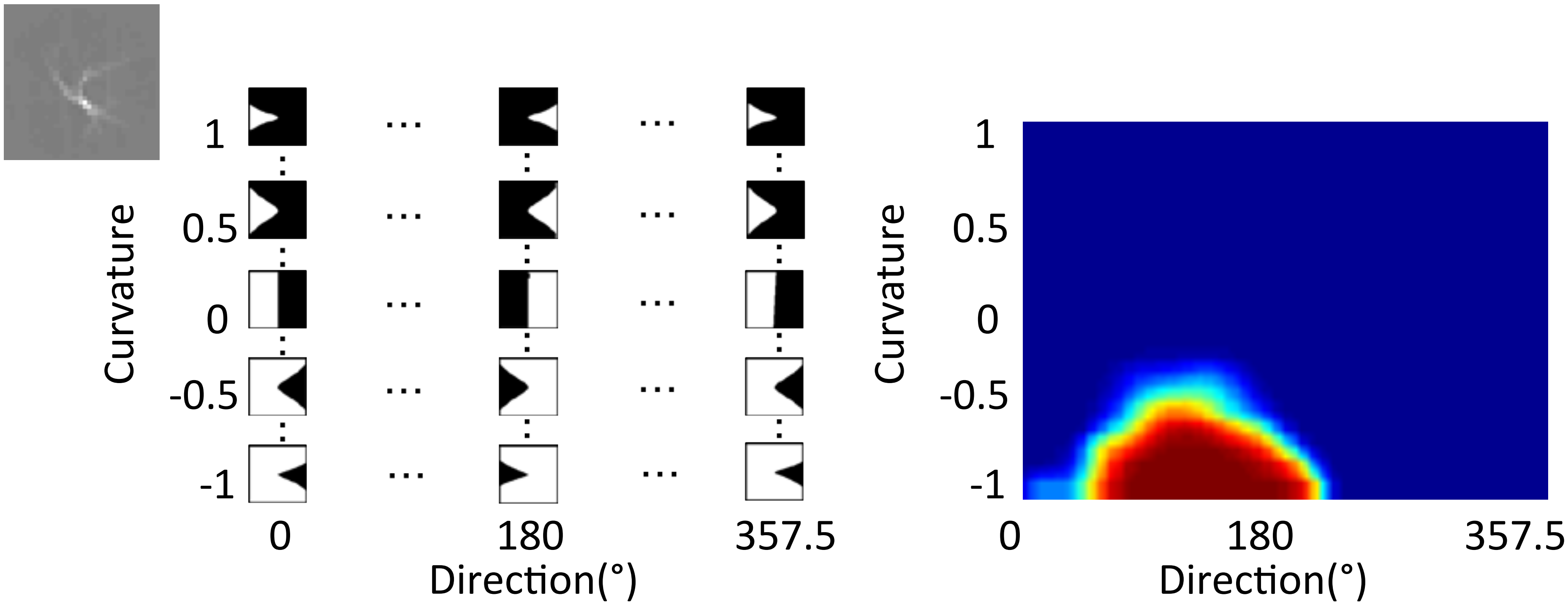


Sparseness = 0.87



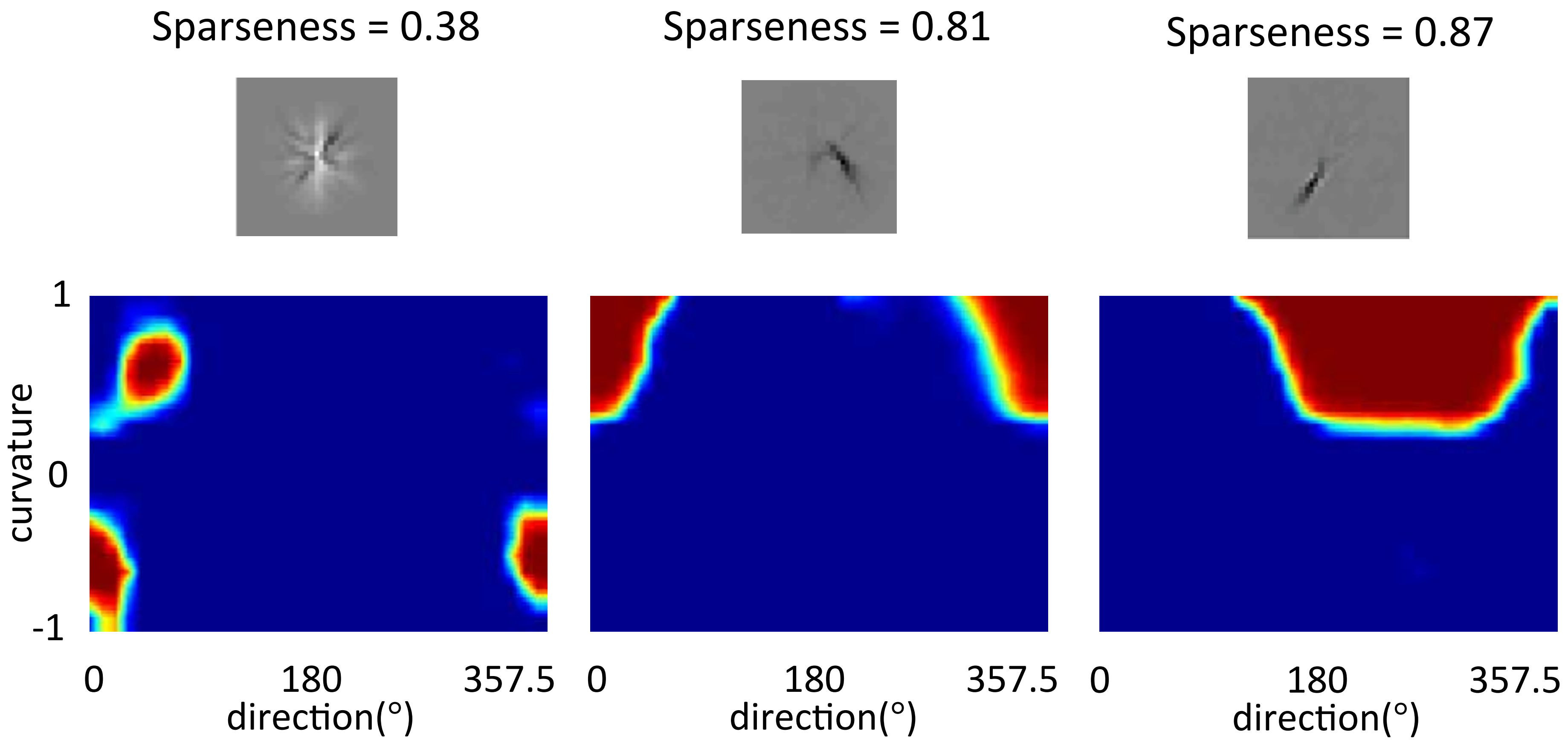
Hatori & Sakai, LNCS 2013

Computation of curvature selectivity



基底と各刺激の畳み込み積分により算出

Results: Selectivity of basis functions



Sparsenessが高い場合、単一細胞レベルの曲率選択性が再現された。

- Sparsenessは曲率選択性の生成をコントロールするか?
  - 単一基底関数の評価
    - 単一基底関数の曲率選択性はsparsenessが高い場合に生成される
  - 基底関数集団の特性の評価

Results: Sparseness is crucial for the curvature selectivity

- Sparsenessは曲率選択性の生成をコントロールするか?
  - 単一基底関数の評価
    - 単一基底関数の曲率選択性は sparsenessが高い場合に生成される
  - 基底関数集団の特性の評価
    - Sparsenessが適切である場合、population activityにおける高い曲率に対するbiasが再現される

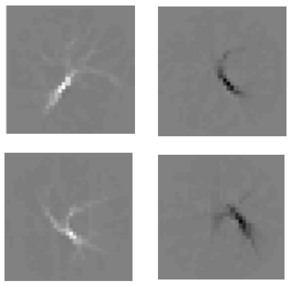
曲率選択性は sparseness から導かれる選択性である。

Prediction: Curvature selectivity needs the appropriate sparseness

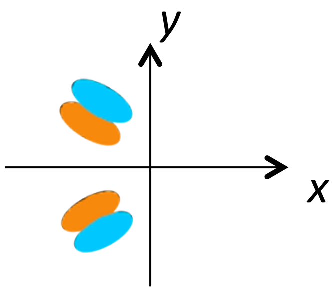
適切なsparsenessが
実現される　⇒　曲率選択性が生成される

- 曲率選択性を示したモデルV4細胞(hard-wired)の反応は，sparseになることが予想される。

- モデルV4細胞と基底関数のlifetime sparsenessを比較する。



⇄



sparseness を制約とした kernel model　　　機能を実現する hard-wire model

Lifetime sparseness

- Lifetime sparseness は以下の式で定義。

$$S_L(R) = \frac{1-a}{1-\frac{1}{n}},$$

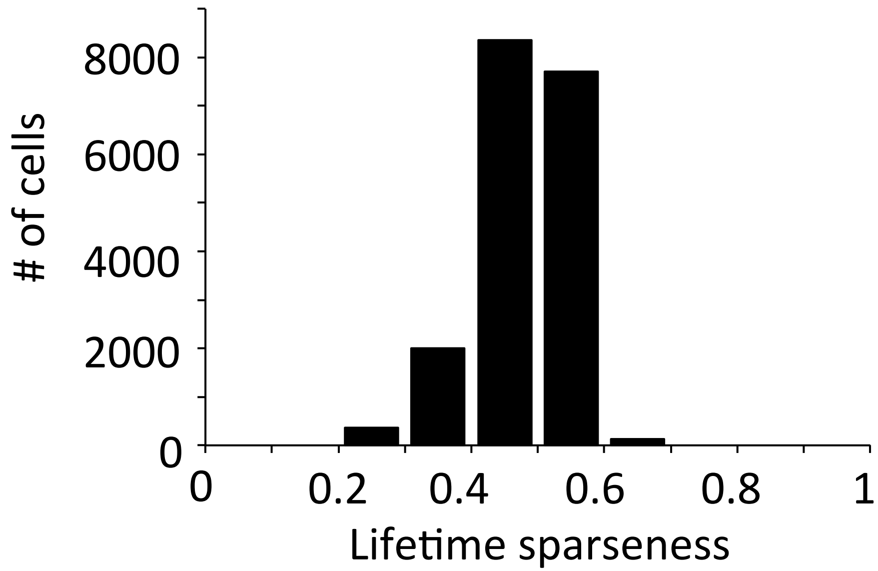
$$a = \frac{1}{n}\left(\frac{(\sum_i r_i)^2}{\sum_i r_i^2}\right),$$

r_i : response to *i*th stimulus

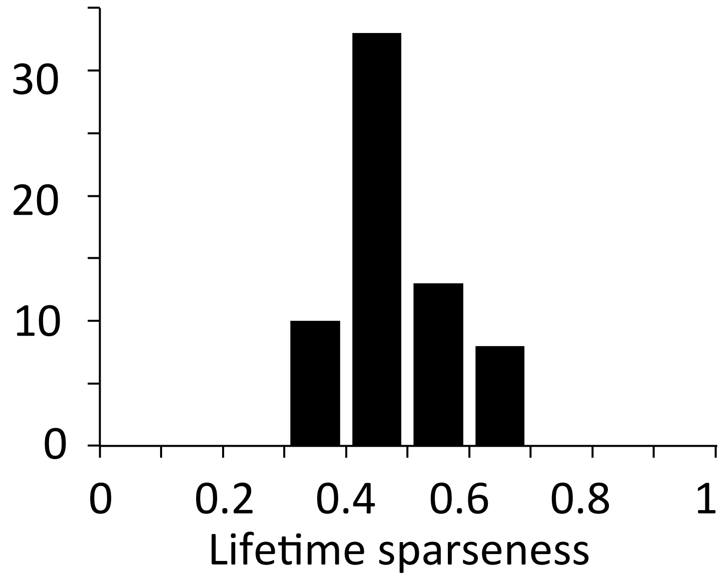
- 選択性の鋭さを評価する指標。
  - 指標が1であれば、その細胞は一つの刺激のみに反応することを意味する

Results: Distributions of lifetime sparseness

Physiological (pooling) model



Sparse coding model



- sparsenessの分布は一致した。
  - Statistically insignificant (t-test, $p > 0.70$)

Hard-wired 機能モデル と CA モデル のsparseness は一致している。
適当な Sparseness で符号化すると，曲率選択性が生起できる。

Hatori & Sakai, Journal of Optical Society of America, A (to appear)

Curvature Selectivity

Physiology: Selective to a specific curvature & its direction

Computational Models:

1. Pooling Model
2. Sparse Coding Model ✔

Curvature Selectivity

Physiology: Selective to a specific curvature & its direction

Computational Models:

1. Pooling Model
2. Sparse Coding Model

SparsenessはV4における曲率選択性を
生成する上で重要な役割を果たす

面表現に基づく局所方位の統合により、
曲率選択性が生成される

Border Ownership in V2

Physiology: **Natural Images** and Latency

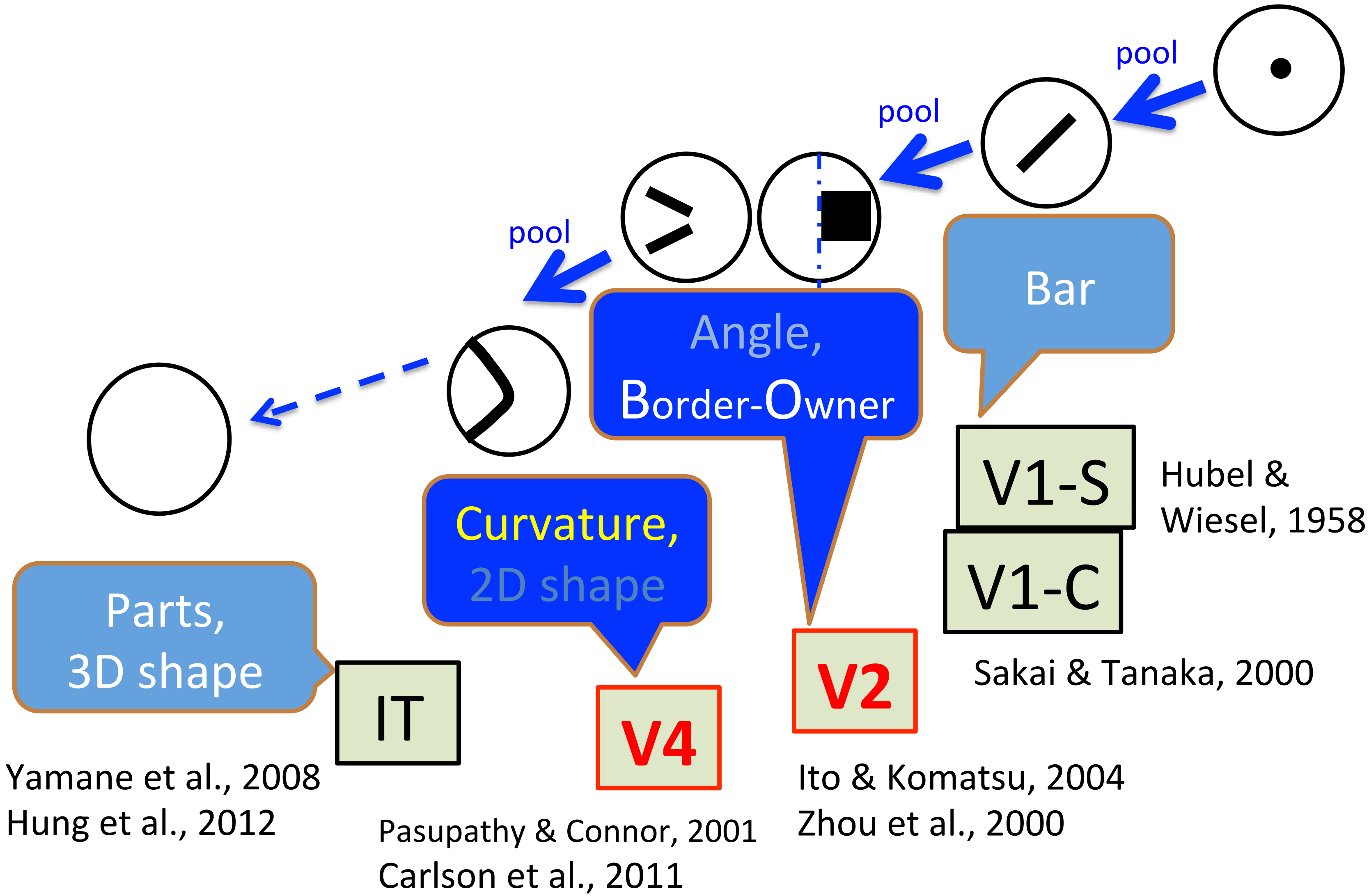
Computational Model:

- **Surround Modulation** Model — H. Nishimura
- Latency & Segment Analysis **Feedforward** — S. Michii
- **Population Coding**: Theoretical Limit — Y. Nakata

Towards Shape Coding

Curvature Selectivity in V4

- **Pooling** Model — Y. Hatori
- **Sparse** Coding Model — T. Mashita



Feature Extraction + Poolingと、Sparsenessが
皮質における情報処理において重要である。

Computational Vision Science Lab.