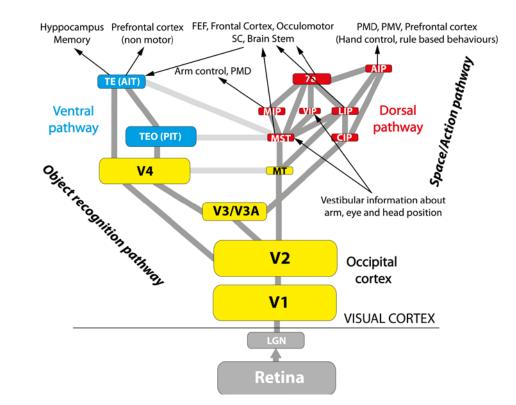


# Deep Hierarchies in Human and Computer Vision

Norbert Kruger University of Southern Denmark Cognitive and Applied Robotics Group

# Overview

- Some annoying prior remarks
- The primate's vision system: A deep Hierarchy
- SotA and Problems of research on deep hierarchical systems
- Reflections



#### IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, DOI: 10.1109/TPAMI.2012.272, AUTHOR FINAL DRAFT

## Deep Hierarchies in the Primate Visual Cortex: What Can We Learn For Computer Vision?

Norbert Krüger, Peter Janssen, Sinan Kalkan, Markus Lappe, Aleš Leonardis, Justus Piater, Antonio J. Rodríguez-Sánchez, Laurenz Wiskott

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Index Terms—Computer Vision, Deep Hierarchies, Biological Modeling

#### 1 INTRODUCTION

The history of computer vision now spans more than half a century. However, general, robust, complete satisfactory solutions to the major problems such as large-scale object, scene and activity recognition and categorization, as well as visionbased manipulation are still beyond reach of current machine vision systems. Biological visual systems, in particular those of primates, seem to accomplish these tasks almost effortlessly and have been, therefore, often used as an inspiration for computer vision researchers.

Interactions between the disciplines of "biological vision" and "computer vision" have varied in intensity throughout

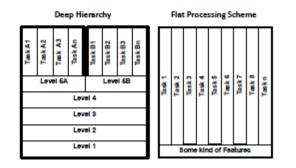
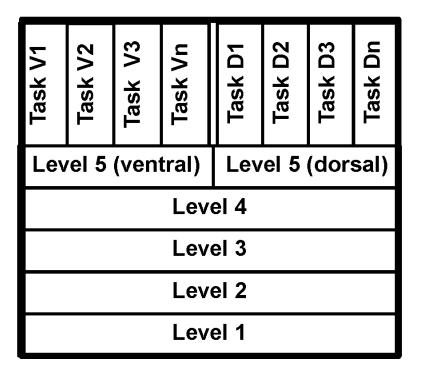


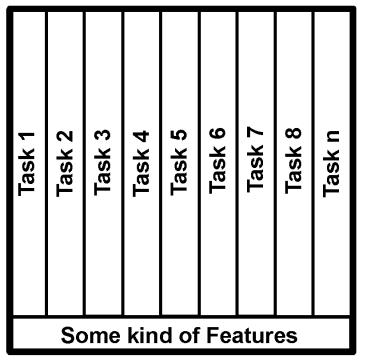
Fig. 1. Deep hierarchies and flat processing schemes

# **Flat versus deep Hierarchies**

**Deep Hierarchy** 

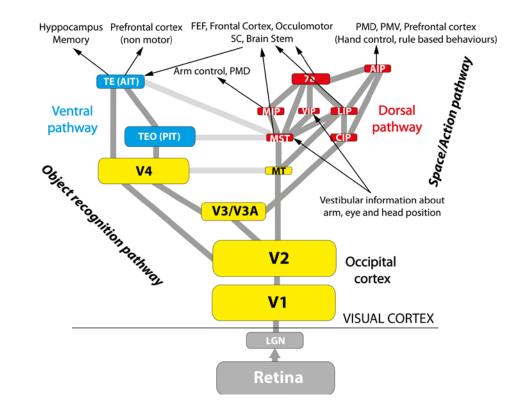
**Flat Hierarchy** 



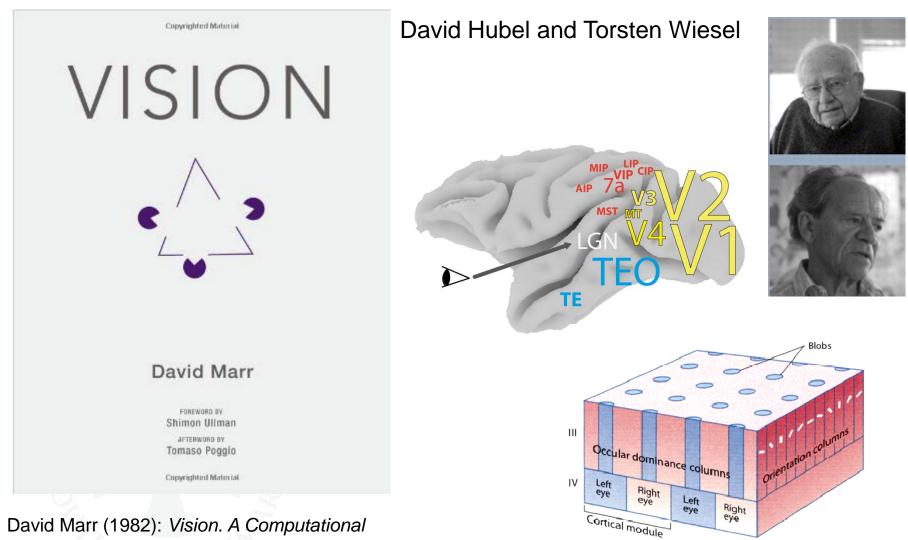


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Investigation into the Human Representation and Processing of Visual Information.

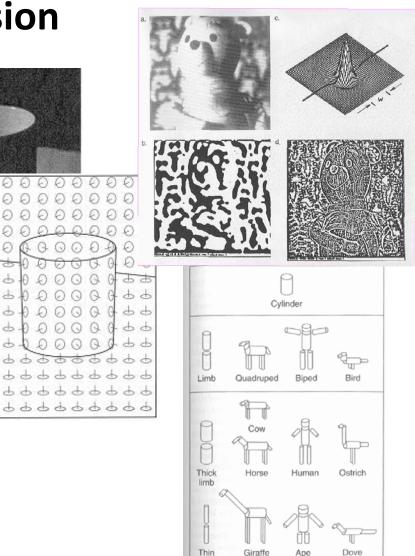
#### The Nobel Prize in Medicine 1981

(Aus Gazzaniga et al., 1998)

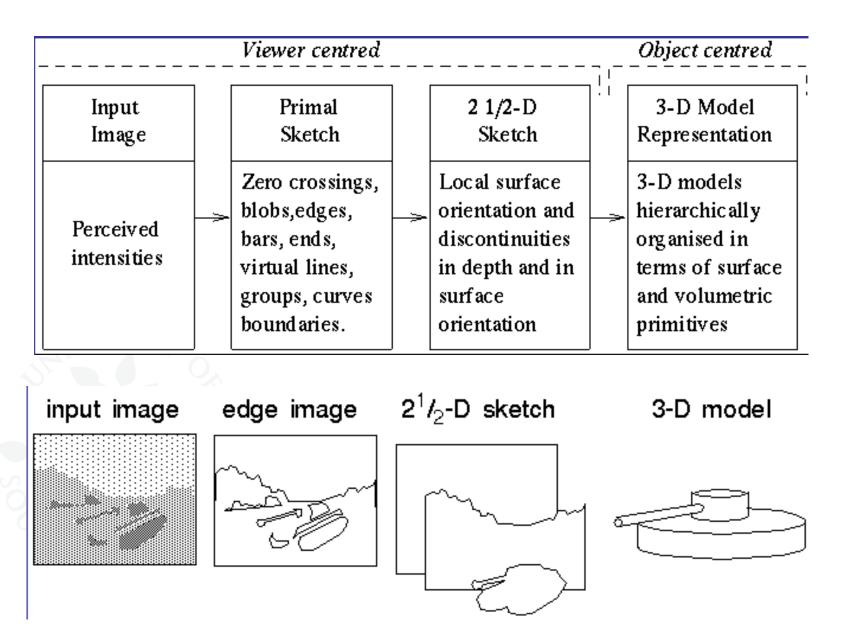
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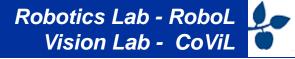
# Some remarks on the interaction of human vision research and computer vision

- David Marr 1982: Vision: A computational investigation into the human representation and processing of visual information
- 3 Stages
  - Primal Sketch: Multi-scale
     Edge Detection
  - 2.5D Sketch: Viewer centered Scene Representation
  - 3D Sketch: Object Centered Representation









# Why did that 'fail'? Two reasons

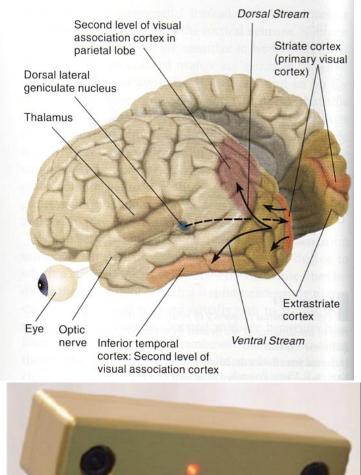
- The project was too ambitious at Marr's time
  - Lack of knowledge on low-level modalities
    - •Optic flow
    - Edge detection
    - Stereo
    - Structure-from-Motion
- Lack of computational resources
  - Slow clock frequency
  - No GPUs





# 'Computer Vision' and 'Biological Vision'

- In the 80<sup>th</sup> and 90<sup>th</sup> there was a strong link
- This link has been kind of diluted from 'both sides'
  - Computer Vision became a subdiscipline of Machine Learning
  - Many neurophysiologists have given up on understanding the brain on a functional level
- 'Biologically inspired' got a somehow bad reputation
  - Not efficient
  - Everything could somehow be biologically inspired



# Maybe a restart is worthwhile

- Much better understanding of early vision
- Significantly larger computational resources
- Still many unsolved problems in CV
- Aim of the paper
  - Distill essential knowledge on the human visual system for Engineers

EEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, DOI: 10.1109/TPAMI.2012.272 AUTHOR FINAL DRAFT

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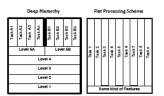
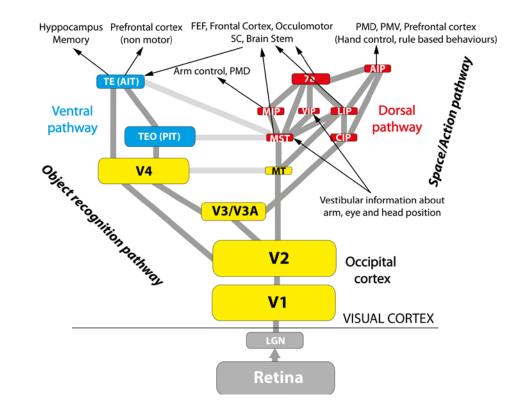


Fig. 1. Deep hierarchies and flat processing schemes

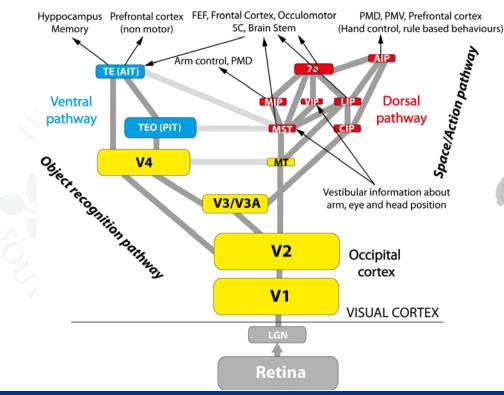
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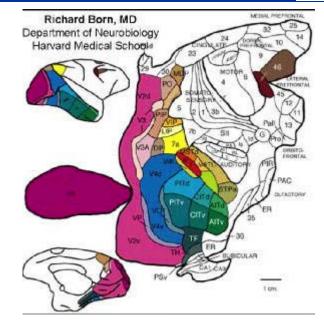


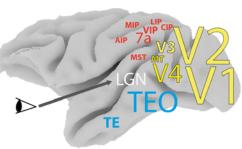
# **Basic facts**

- 55% of the neo-cortex of the primate brain is concerned with vision
- Devision in
  - Occipitel Cortex
  - Dorsal Pathway
  - Ventral Pathway



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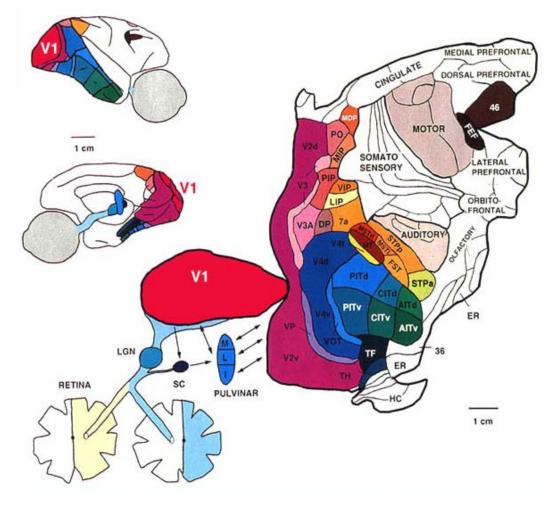
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Dr. Alesha Sivartha in the late 1800s (published in his metaphysical book The Book of Life: The Spiritual and Physical Constitution of Man)

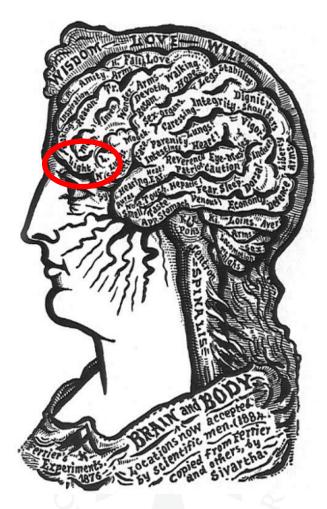
## **Brain Maps**



#### From: van Essen 1992

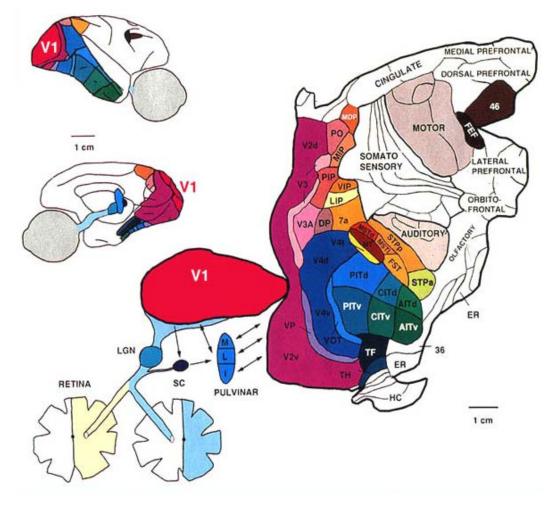
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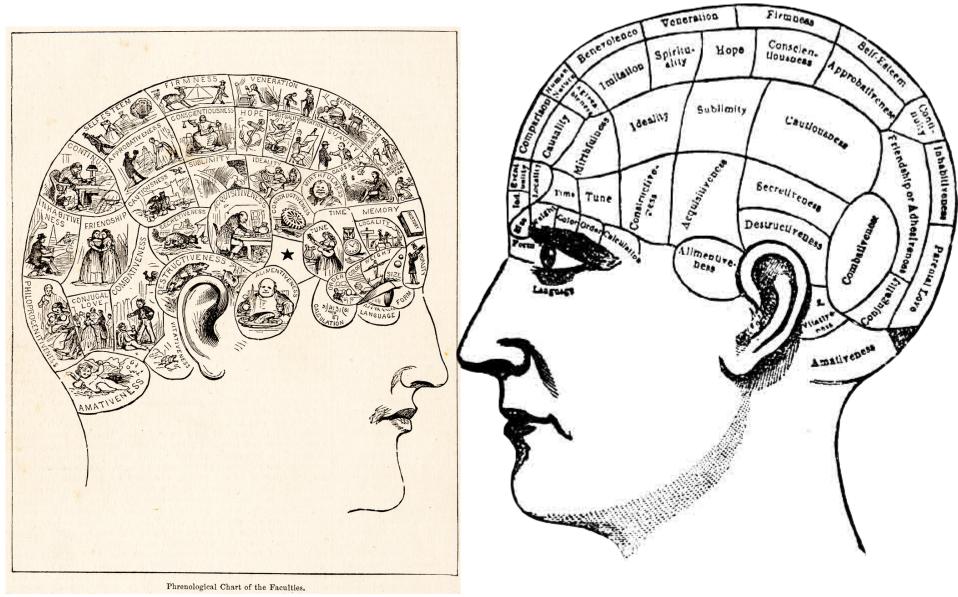
## **Brain Maps**



#### From: van Essen 1992

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Gall (1758–1828): Phrenology



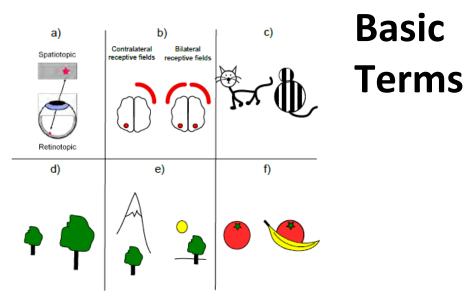
# **Basic Facts**

Area	Size (mm <sup>2</sup> )	RFS	Latency (ms)	co/bi lat.	rt/st/cl/co	CI/SI/PI/OI	Function	
	Sub-cortical processing							
Retina	1018	0.01	20-40	bl	+/-/-/-	-1-1-1-	sensory input, contrast computation	
LGN		0.1	30-40	co	+/-/-/-	-/-/-	relay, gating	
	Occipital / Early Vision							
V1	1120	3	30-40	co	+/-/-/+	-/-/-/-	generic feature processing	
V2	1190	4	40	co	+/-/-/+	-/-/-/-	generic feature processing	
V3/V3A/VP	325	6	50	co	+/-/-/+	-/-/-/-	generic feature processing	
V4/VOT/V4t	650	8	70	co	+/-/-/+	+/-/-/-	generic feature processing / color	
MT	55	7	50	co	+/-/-/+	+/+/-/+	motion	
Sum	3340							
	Ventral Pathway / What (Object Recognition and Categorization)							
TEO	590	3-5	70	co	(+)/-/-/+	?/-/-/?	object recognition and	
TE	180	10-20	80-90	bl	-/-/+/+	+/+/+/+(-)	categorization	
Sum	770							
	Dorsal Pathway / Where and How (Coding of Action Relevant Information)							
MST	60	>30	60-70	bl	+/-/+/-	I	optic flow, self-motion, pursuit	
CIP	?	?	?		+/-/?/?	+/?/?/?	3D orientation of surfaces	
VIP	40	10-30	50-60	ы	-/+/-/-	I	optic flow, touch, near extra personal space	
7a	115	>30	90	bl	(+)/-/-/-	?/?/+/?	Optic flow, heading	
LIP	55	12-20	50	cl	+/-/-/-	?/-/-/-	salience, saccadic eye movements	
AIP	35	5-7	60	bl	?/+/+/?	?/+/+/?	grasping	
MIP	55	10-20	100	co	+/-/?/?	I	reaching	
Sum	585							

#### TABLE 1

Basic facts on the different areas of the macaque visual cortex based on different sources [44], [28], [95], [141], [161] First column: Name of Area. Second column: Size of area in mm<sup>2</sup>. '?' indicates that this information is not available. Third column: Average receptive field size in degrees at 5 degree of eccentricity. Fourth column: Latency in milliseconds. Fifth Column: Contra versus bilateral receptive fields. Sixth Column: Principles of organization: Retinotopic (rt), spatiotopic (st), clustered (cl) columnar (co) Seventh Column: Invariances in representation of shape: Cue-Invariance (CI), Size Invariance (SI), Position Invariance (PI), Occlusion Invariance (OI). 'I' indicates that this entry is irrelevant for the information coded in these areas. Eighth Column: Function associated to a particular area.

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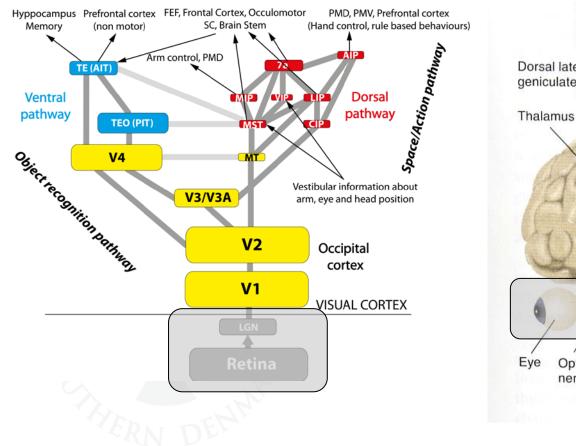


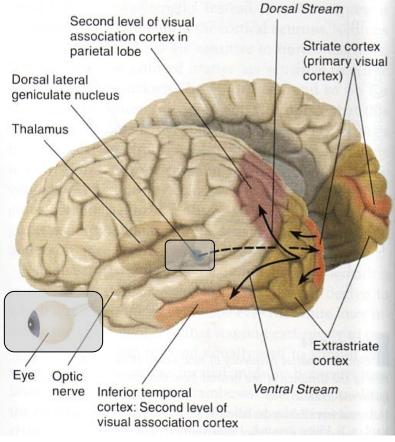
- Retinotopic/Spatiotopic
- Different kinds Of Invariances
  - Cue Invariance
  - Size Invariance
  - Position Invariance
  - Occlusion Invariance

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Area	co/bi lat.	rt/st/cl/co	CI/SI/PI/OI						
	Sub-cortical processing								
Retina	bl	+/-/-/-	-/-/-/-						
LGN	co	+/-/-/-	-/-/-/-						
	Occipital / Early Vision								
V1	co	+/-/-/+	-/-/-/-						
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MT	co	+/-/-/+	+/+/-/+						
Sum									
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TE	bl	-/-/+/+	+/+/+/+(-)						
Sum									
	/ Where and How (Coding of Action R								
MST	bl	+/-/+/-	I						
CIP		+/-/?/?	+/?/?/?						
VIP	ы	-/+/-/-	I						
7a	ы	(+)/-/-/-	2/2/+/?						
LIP	cl	+/-/-/-	2/-/-/-						
AIP	bl	?/+/+/?	?/+/+/?						
MIP	co	+/-/?/?	I						
Sum									

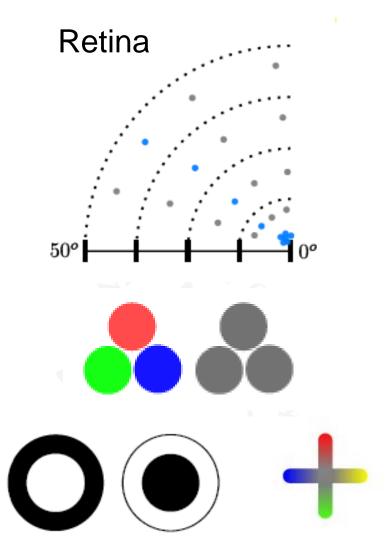
## **Pre-cortical Areas**

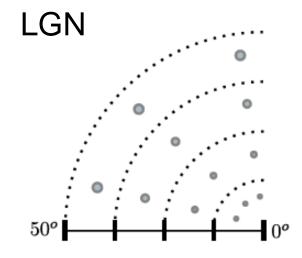




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# **Precortical Areas**

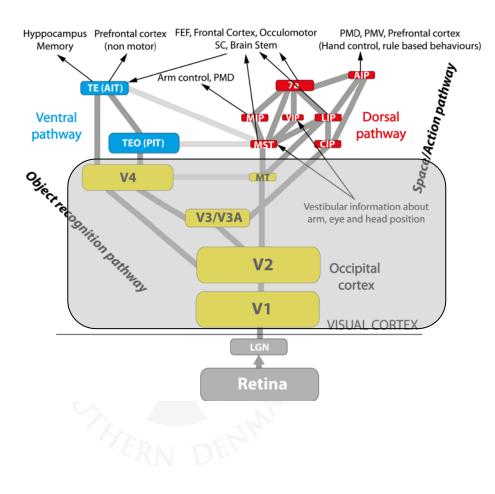


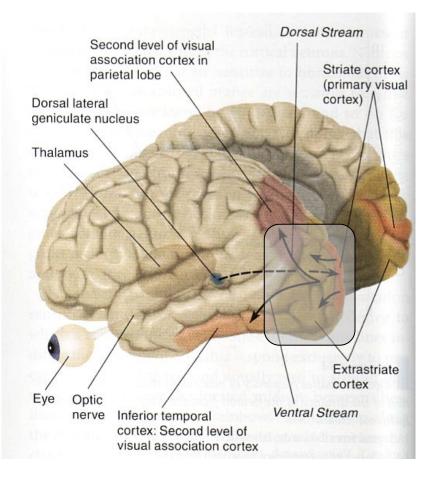


- No Feature Transformation
- Preparing for Stereo



# **Occipital Cortex**





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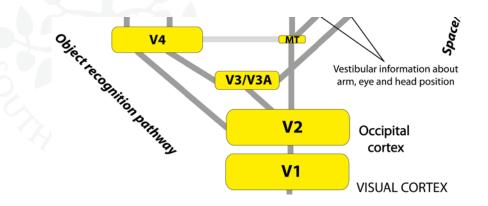
## **Occipital Cortex**

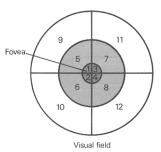
## More than 70% of the visual cortex

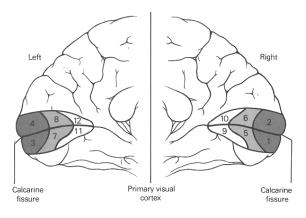
- Occipital Cortex 3340mm<sup>2</sup>
- Ventral Pathway 770mm<sup>2</sup>
- Dorsal Pathway 585mm<sup>2</sup>

## Processing

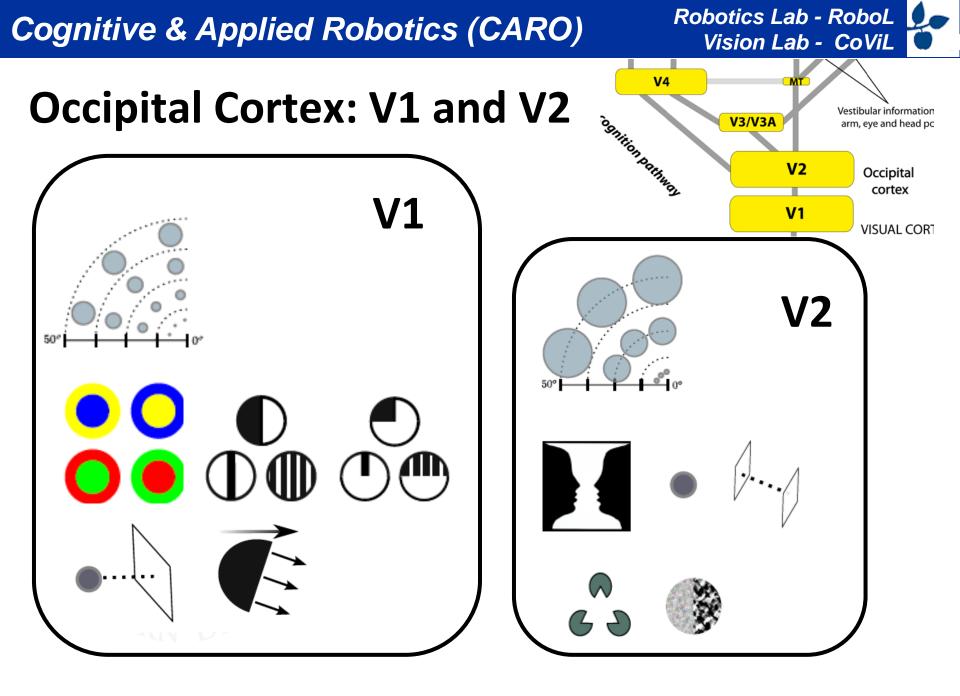
 Task unspecific generic scene representation

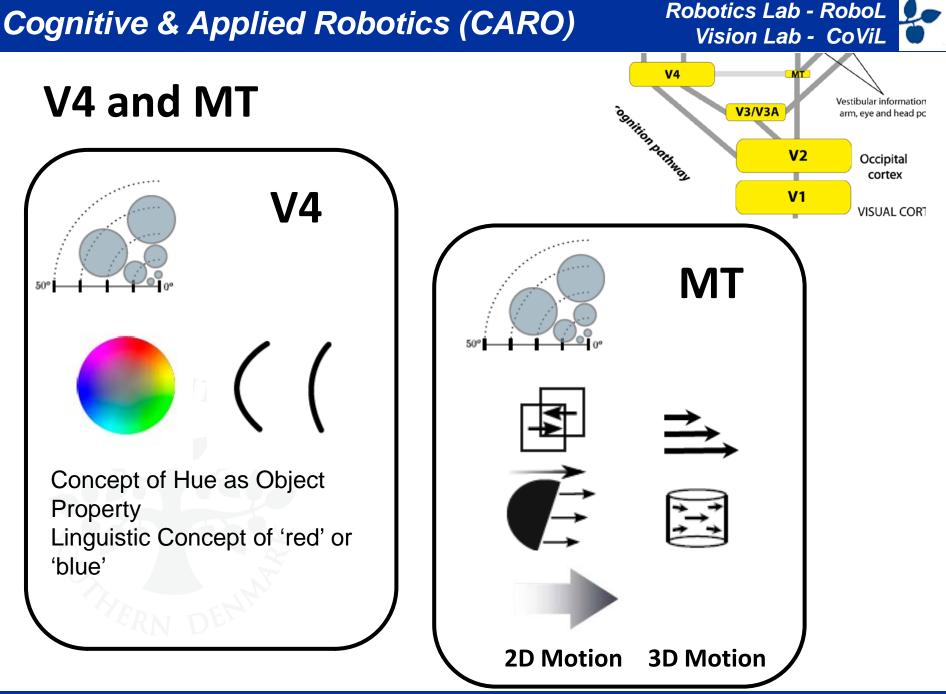




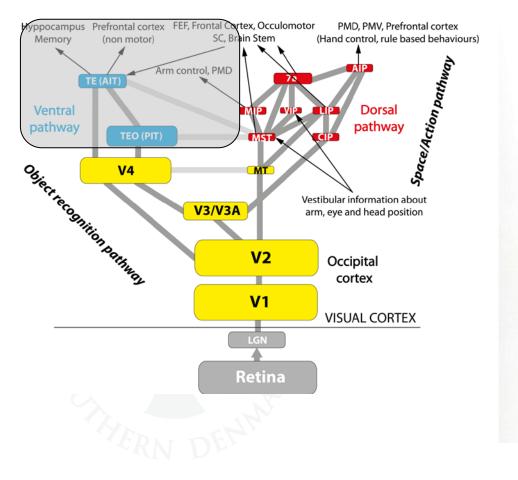


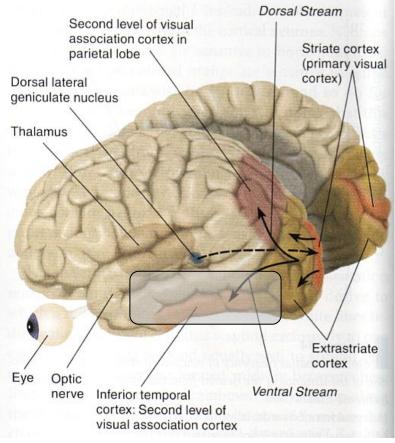
**Retinotopic Organization** 





## Ventral Pathway







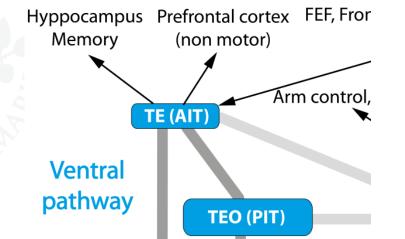
# **Ventral Pathway**

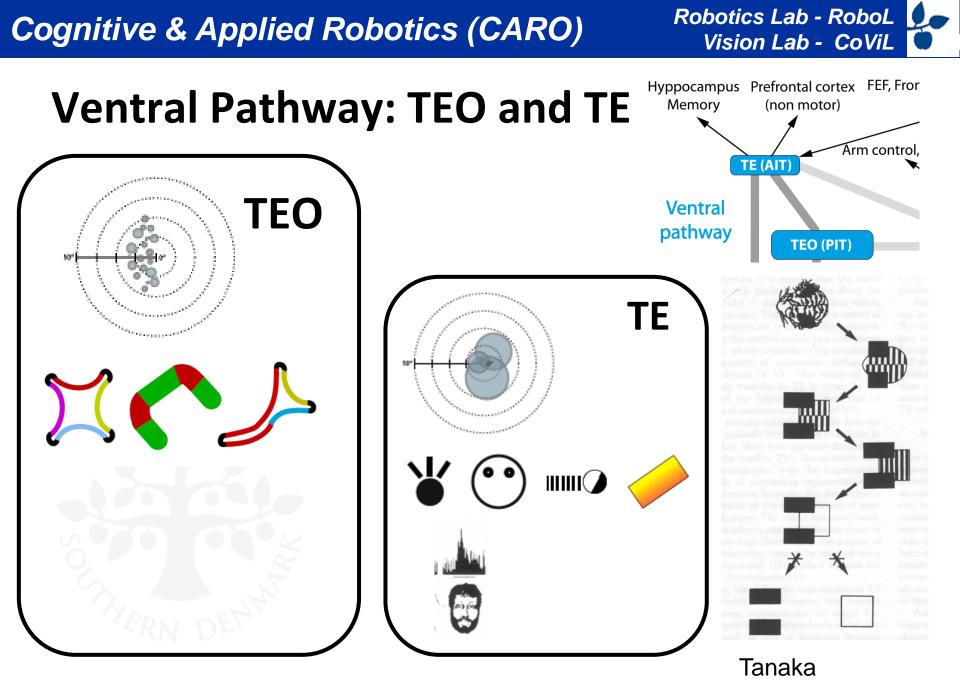
## More than 70% of the visual cortex

- Occipital Cortex 3340mm<sup>2</sup>
- Ventral Pathway 770mm<sup>2</sup>
- Dorsal Pathway 585mm<sup>2</sup>

## Processing

- Object Recognition and Categorization
- Many suggestions for how to divide into areas

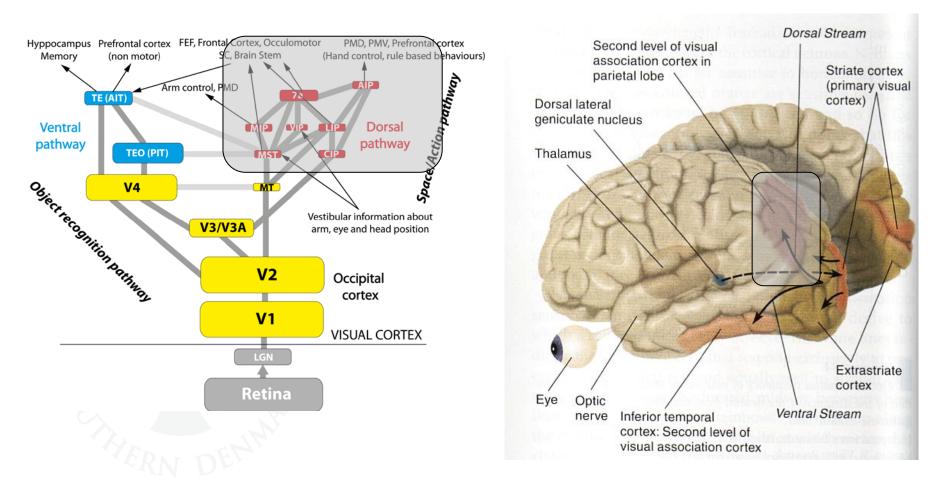


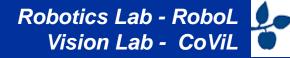


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# **Dorsal Pathway**





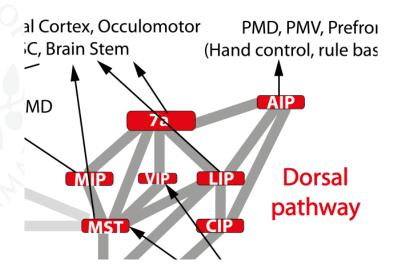
# **Dorsal Pathway**

#### More than 70% of the visual cortex

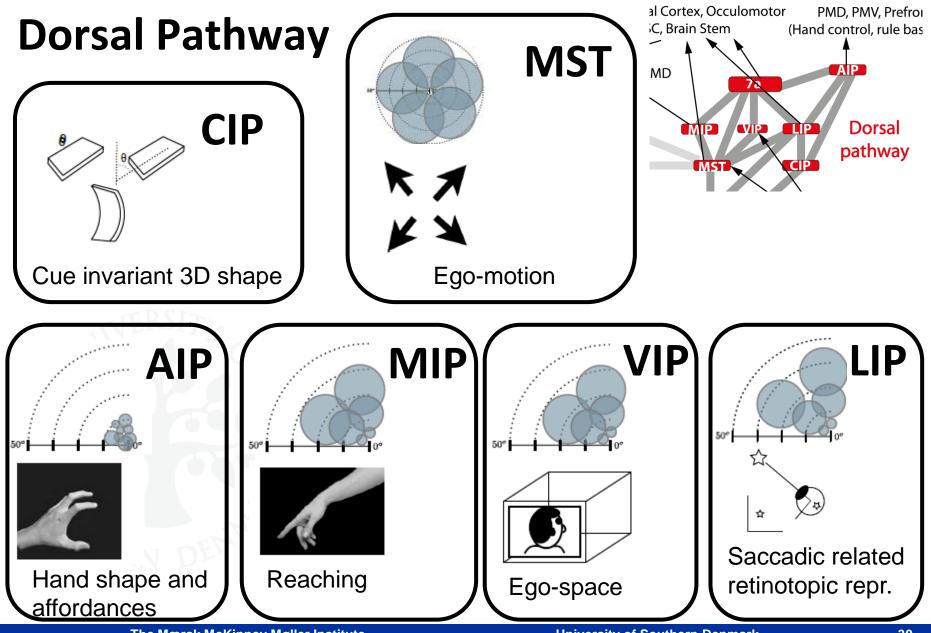
- Occipital Cortex 3340mm<sup>2</sup>
- Ventral Pathway 770mm<sup>2</sup>
- Dorsal Pathway 585mm<sup>2</sup>

#### Processing

- Much less known than Ventral Pathway
- Many more distinguished areas
- Coding visual information related to action and position in space



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30

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VIP

100

60%

<u>416</u>

RF size

MIP

K 7

KX

Ē

Motion

100

e Ē



LIP

CIP

MST

MT

V3/V3A

V2

V1

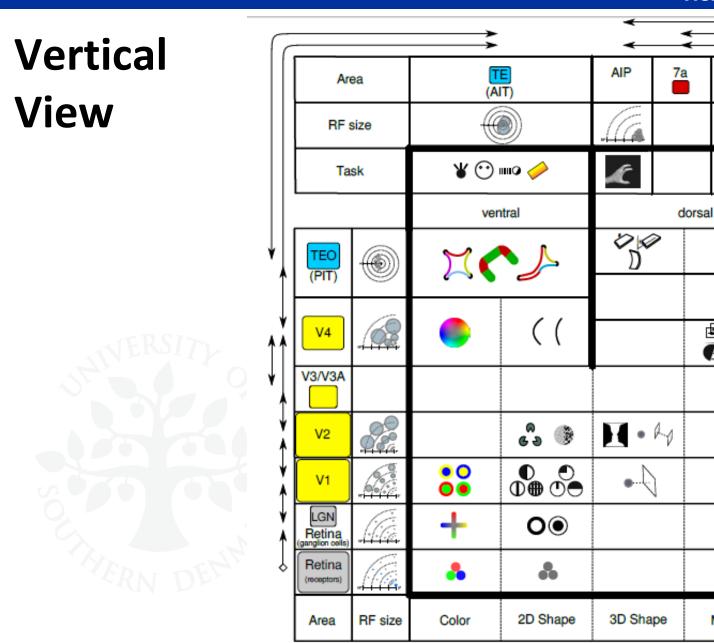
LGN

Retina ganglion cells

Retina

(receptors)

Area



Ô

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# What do we know about primate's vision which is relevant for engineers?

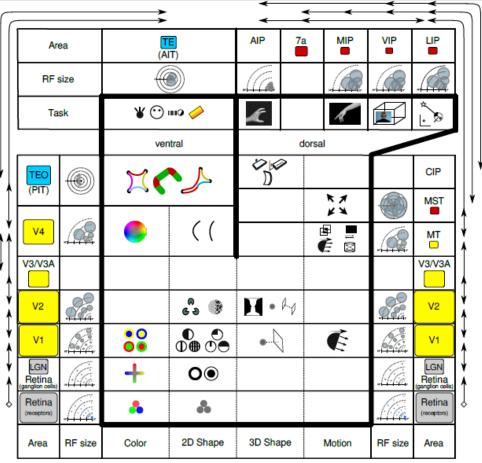
- Richness of representation
- Deep Hierarchy versus flat Architectures
- Separation of information





# **Richness of representation**

- The occipital cortex provides a huge variety of visual aspects at different levels of granularity and different levels of abstractions
  - Zoo of features
  - Challenge: Designing/learning this hierarchy is difficult but maybe required
- What is important for learning a certain task or category is unclear
  - Challenge: Learning algorithms that are able to deal with such a huge and at the same time highly structured input space

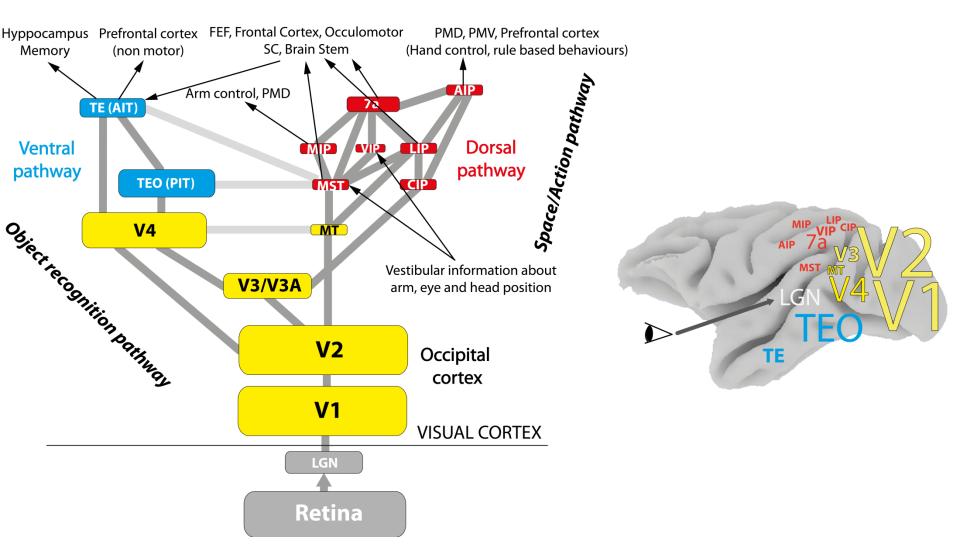


# What do we know about primate's vision which is relevant for engineers and linguists?

- Richness of representation
- Deep Hierarchy versus flat Architectures
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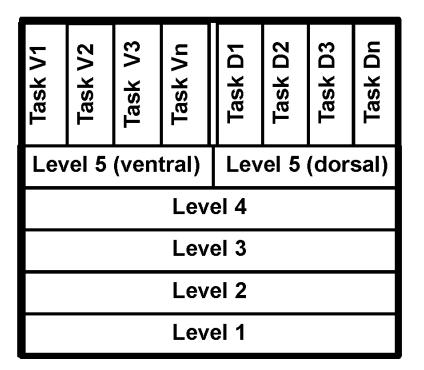
# **Deep Hierarchary**

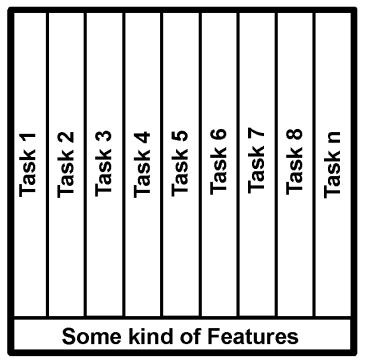


# **Flat versus deep Hierarchies**

**Deep Hierarchy** 

**Flat Hierarchy** 





FRN DET



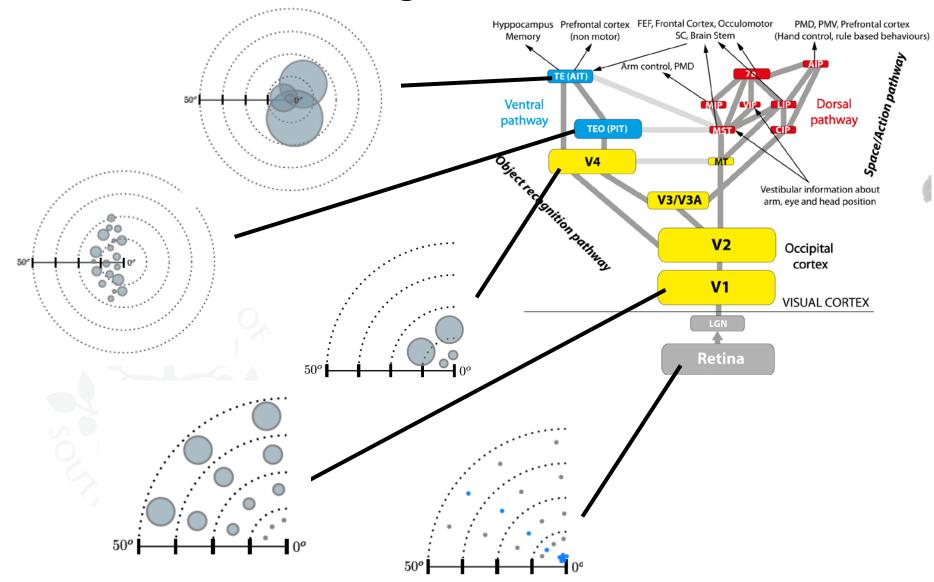
# **Example of a flat hierarchy**



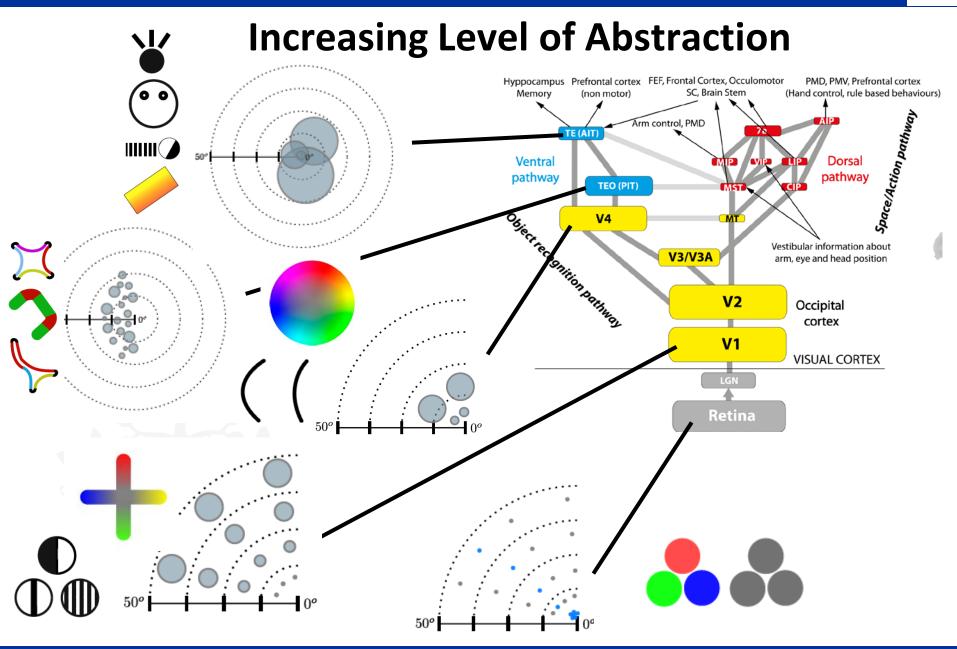
J. Y. Lettvin et al. (1959). What the frog's eye tells the frog's brain. Proceedings of the Institute of Radio Engineers

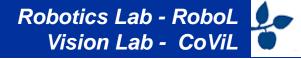
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## **Increasing Level of Abstraction**



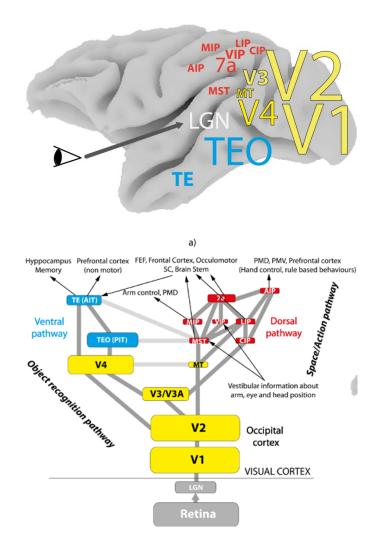
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# Flat versus deep hierarchies

- Flat Hiererachies are inefficient
  - No sharing of computational recources
  - Transfer of experience across tasks is facilitated within the same representations



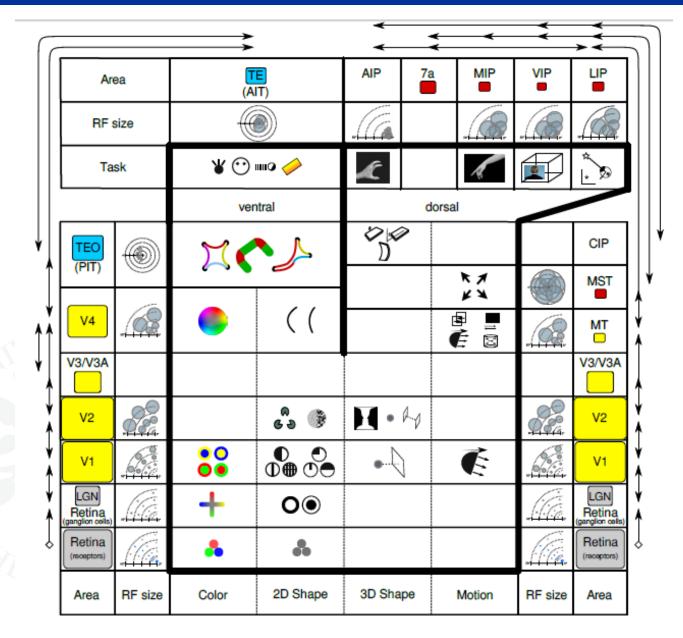
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# What do we know about primate's vision which is relevant for engineers and linguists?

- Richness of representation
- Deep Hierarchy versus flat Architectures
- Separation of information



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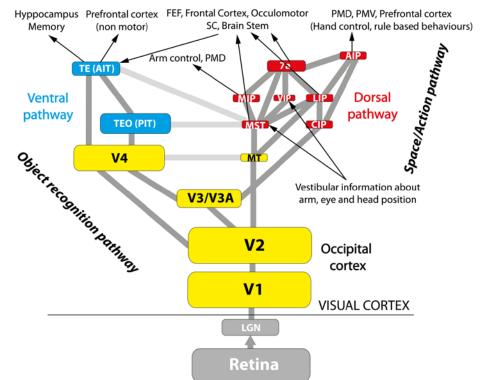
# **Separation of Information**

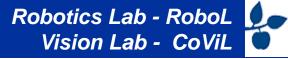
- Colour, 2D shape, 3D shape and motion become separated and are then up to a certain level of the hierarchy processed largely independently (while in the pixel domain these aspects are deeply intertwined)
- For learning problems this allows for cutting off non-relevant dimensions
- It allows also to discover relations between different aspects of visual information on a higher level (e.g., motion and 3D shape)

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- The primate's vision system: A deep Hierarchy
- SotA and Problems of research on deep hierarchical systems
- Reflections





## **Research on Deep Hierarchies (non-exhaustive)**

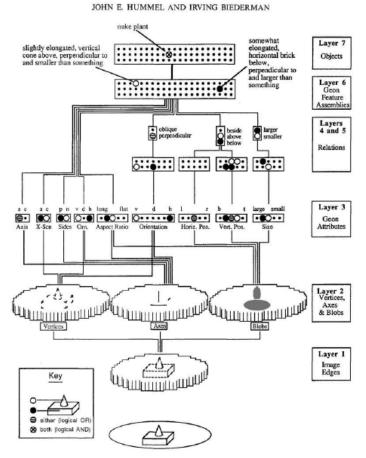
## Meta reasoning

- Tsotsos, Geman et al., Mel and Fiser,
- Learning of Hierarchical Vision Systems
  - Amit, Hawkins, Leonardis, Piater, Ullman, DiCarlo and Cox, Ommer and Buhmann, Serre and Poggio, Bengio, Wiskott, Hinton

## Design of Hierarchical Vision Systems

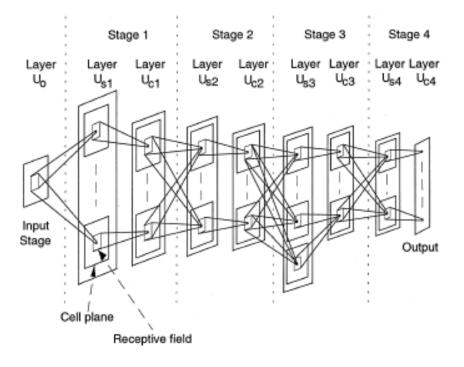
Biederman and Hummel, Fukushima, Pugeault and Kruger

## **Biederman and Fukushima**



#### Figure 1

The architecture of Neocognitron

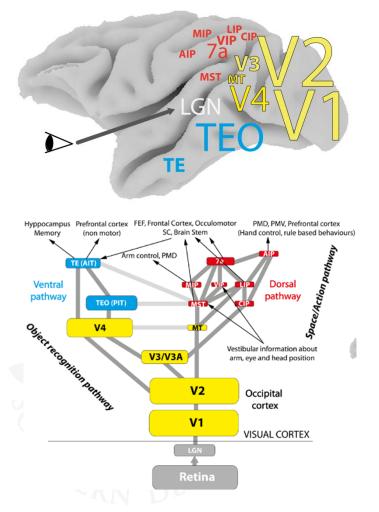


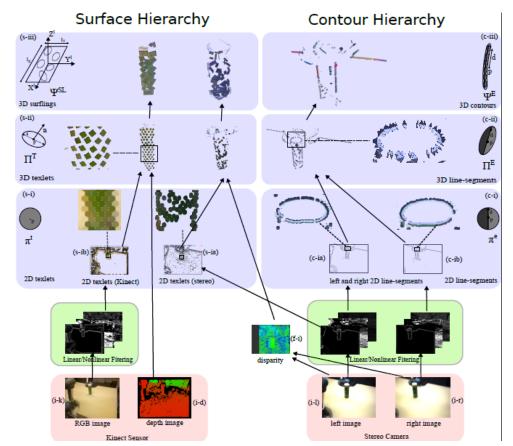
Kunihiko Fukushima 1987

John E. Hummel and Irving Biederman (1992). Dynamic Binding in a Neural Network for Shape Recognition

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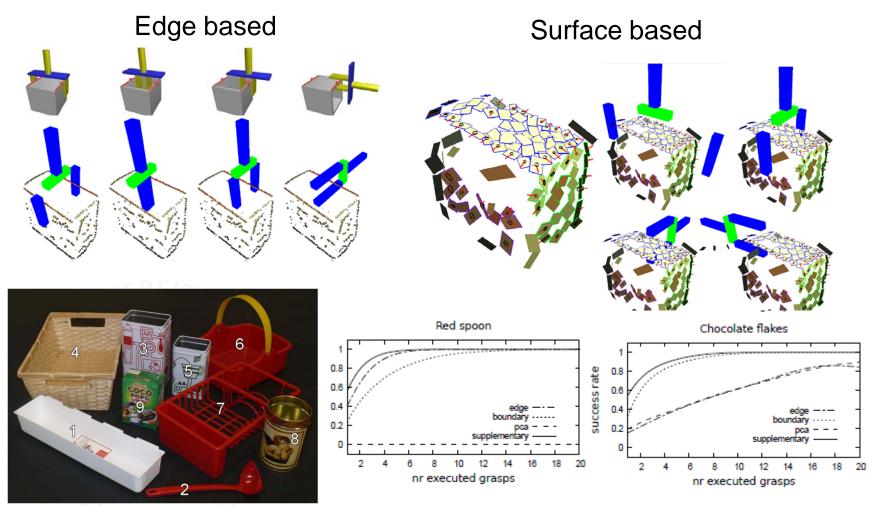
# **Early Cognitive Vision System**





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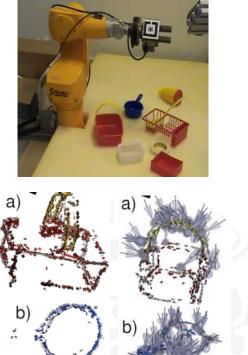
## Edge and Surface based Grasp Affordances

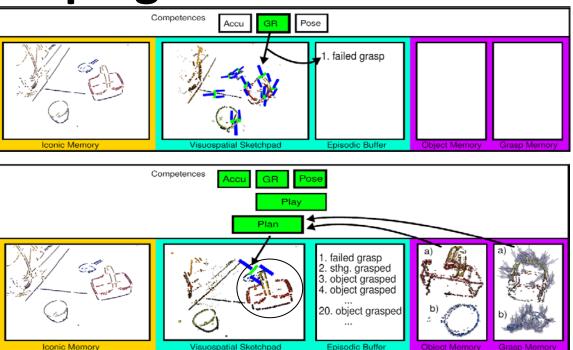


M. Popović, G. Kootstra, J. A. Jørgensen, D. Kragic and N. Krüger. Grasping Unknown Objects using an Early Cognitive Vision System for General Scene Understanding. IROS 2011 (nominated as one of the finalists for an IROS Awards)
G. Kootstra, M. Popovic, J. A. Jorgensen, K. Kuklinski, K. Miatliuk, D. Kragic and N. Krüger. Enabling grasping of unknown objects through a synergistic use of edge and surface information. International Journal of Robotics Research, vol. 31, no. 10, pp. 1190 - 1213, 2012.

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# Bootstrapping Robots: Grounding objects and grasping affordances

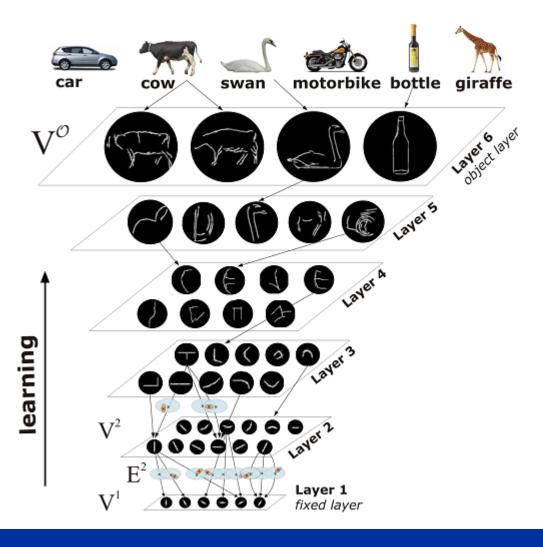




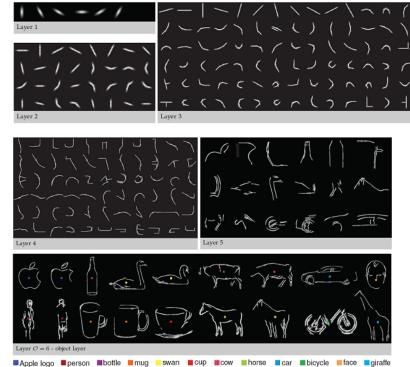
F. Guerin, D. Kraft and N. Krüger. A Survey of the Ontogeny of Tool Use: From Sensorimotor Experience to Planning. IEEE Transactions on Autonomous Mental Development, 5(1), pp. 18–45, 2013. D. Kraft, R. Detry, N. Pugeault, E. Başeski, F. Guerin, J. Piater and N. Krüger. Development of Object and Grasping Knowledge by Robot Exploration. Autonomous Mental Development, IEEE Transactions on, vol.2, no.4, pp.368-383, Dec. 2010.

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## Learning Hierarchies: Work from Ales Leonardis



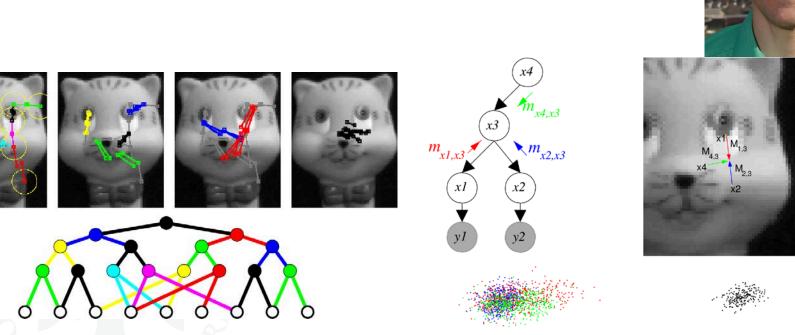




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## **Learning Hierarchies: Work from Justus Piater**

## Layered Graphical Model



- Each vertex represents a (composite or primitive) feature.
- Each edge is annotated with a spatial relation (scalenormalized distance and relative orientation).



# **Revival of deep neural net working**

- Deep Nets seem to recently beat other algorithms on important benchmarks
- Christian Szegedy et al. (2014). Intriguing properties of neural networks. ICLR 2014. (quotes from article of Mike James)
  - A single neuron's feature is no more interpretable as a meaningful feature than a random set of neurons.
  - Every deep neural network has "blind spots" in the sense that there are inputs that are very close to correctly classified examples that are misclassified.





# **Some Reflections**

- Vision is probably a quite hard problem
  - It uses resources occupying more than 50% of our brain
  - It is far from 'being solved'

## • Of that 70% is generic scene processing

- Deep hierarchy with increasing invariant representations
- It spans a huge feature space as a basis for grounding processes
- This space has a high degree of structure
  - Motion

Spatial Relations

## • We can learn from the human visual system?

- It is worthwhile to build/learn deep hierarchical systems
- Number of levels
- Receptive field size
- What features to extract at what stage in the hierarchy