Nature of Texture: Visual or Tactile?

CSCE 644 Cortical Networks

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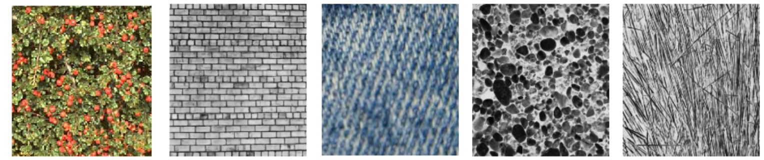
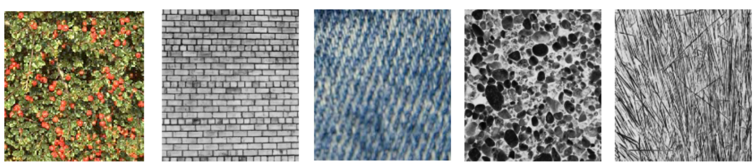
What is Texture?



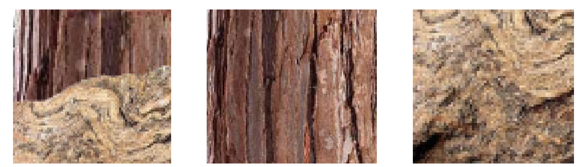
- Statistical definition (Beck 1983; Zhu et al., 1999)
- Surface characteristics (Urdang, 1968)
- Texton theory (Julesz and Bergen 1982)

The Nature of Texture: Visual?



- Most previous works treat texture as a vision problem, and this seems quite natural (e.g., Malik and Perona, 1990).
- However, a deeper thought leads us into a new direction.

Texture in Nature (1/2)

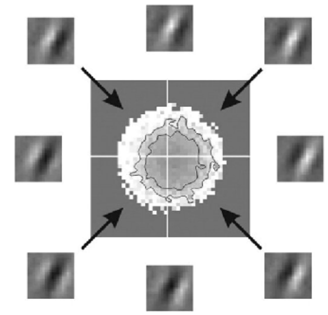


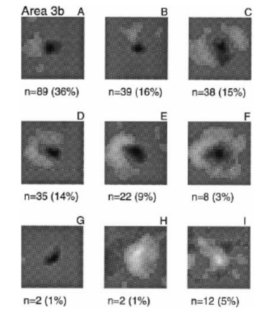
- A mixed texture (left), with two different component textures (middle & right).
- Looks distinctly visual.
- However, ...

Texture in Nature (2/2)

- Texture is a surface property: Surfaces of 3D objects usually have a uniform texture.
- Typical texture segmentation problem arises through occlusion.
- **Is the nature of texture fundamentally tactile?**

Links Between Vision and Touch





Chen, Han, Poo, Dan, PNAS (2007) DiCarlo et al., J Neurosci (1998)

- 2D sensory surface: Retina vs. skin.
- Similar receptive field structure (with differences!).
  - Receptive field: Part of sensory surface sensitive to stimulus, especially to a specific pattern.

Research Questions

Relationship between texture and tactile RFs:

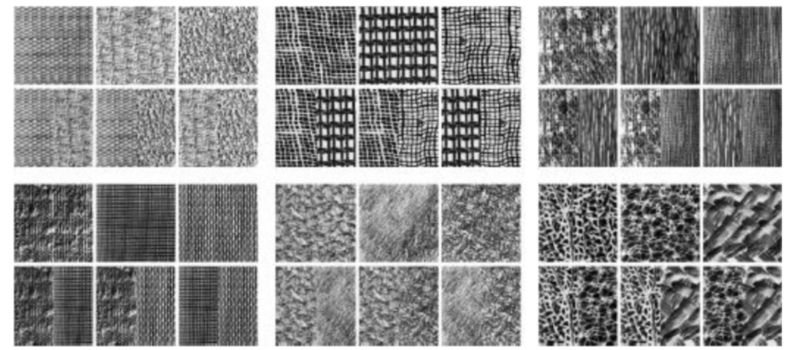
1. Can tactile RFs outperform visual RFs in texture tasks?
2. How are tactile RFs related to texture in a cortical development context?
3. Is the representational power of tactile RFs higher than visual RFs in texture tasks?

Overview

1. Performance: Tactile RF vs. Visual RF
2. Development: Self-organization of TRF and VRF
3. Analysis: Manifold analysis of TRF and VRF

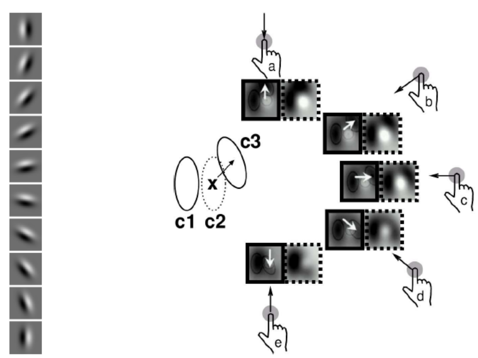
Part I: Performance

Task: Texture Boundary Detection



- Six sets of texture inputs.
- Boundary vs. non-boundary.
- Task is to detect presence of boundary in the middle.

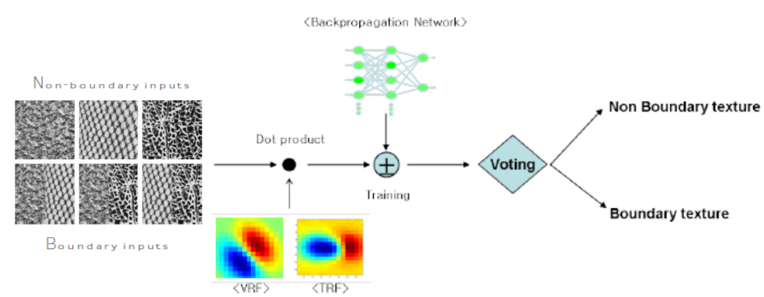
VRF and TRF Models



(a) Visual RFs (b) Tactile RFs

- VRF (Gabor) and TRF similar, with slight difference.
- Dynamic inhibitory component in TRF (dependent on scanning direction).

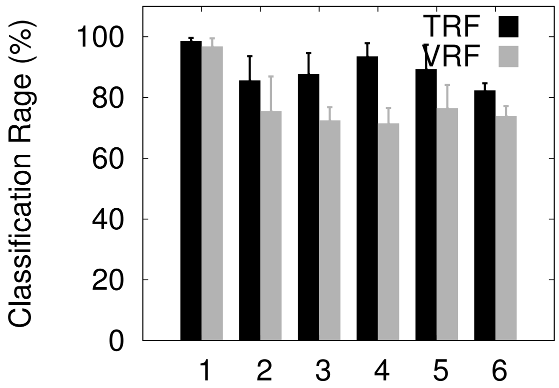
Methods



Texture boundary detection task:

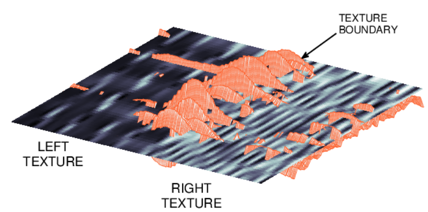
- Generate response vectors using TRF & VRF filters.
- Train backprop network for classification.
- Voting based on multiple sample positions.

Results

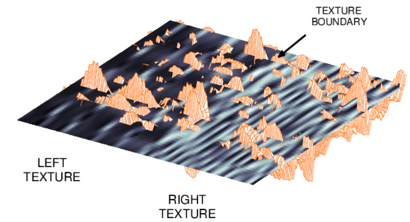


- TRF response vectors significantly better than VRF for representing texture boundary.

TRF vs. VRF Response Vectors



TRF response

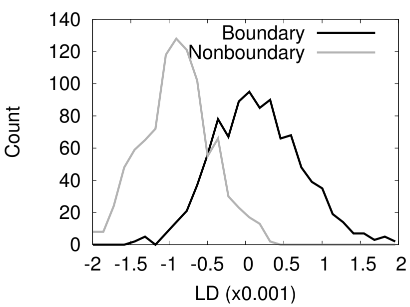


VRF response

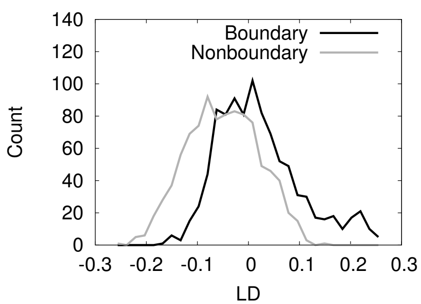
Why does TRF outperform VRF?

- Response vectors from TRF emphasize the boundary.

LDA of Response Vectors



TRF



VRF

Why does TRF outperform VRF?

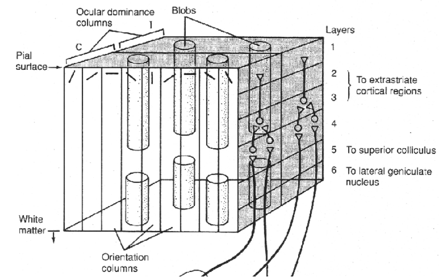
- Linear Discriminant Analysis on response vectors.
- LDA distribution for TRF more clearly separated.

Summary (Part I)

- Tactile RF response is better suited for texture boundary detection tasks than visual RF response.
- TRF response representation more separable than VRF.
- Suggests an interesting link between texture and touch.

Part II: Development

Cortical Organization

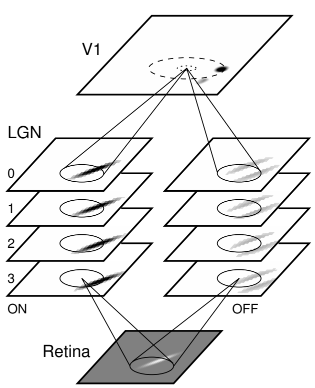


Kandel et al. (2000)

- The cerebral cortex has a similar organization overall (6-layer architecture).
- Same developmental rule may govern all cortical regions:
  - E.g., visual development in the auditory cortex of rewired animal (von Melchner et al. 2000)

Cortical Development Model

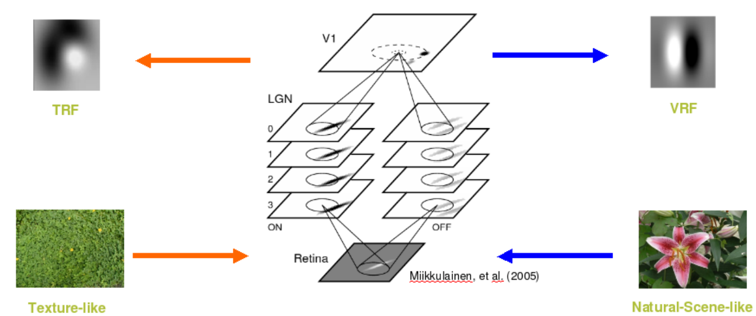
LISSOM



(Miikkulainen et al. 2005)

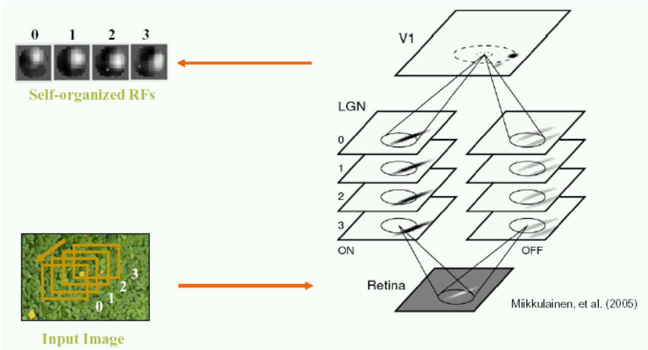
- Input-driven self-organization (Hebbian learning).
- Model of visual-cortical development and function.
- Can be applicable to other sensory modalities.
- `http://topographica.org`

Methods



- Self-organize LISSOM with two kinds of inputs:
  - Texture-like
  - Natural-scene-like
- Observe resulting RF structure.

Methods (cont'd)

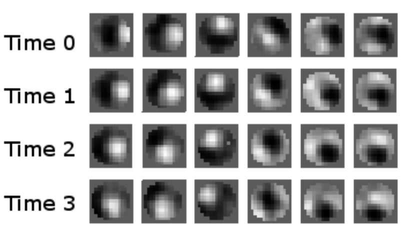


- Use LISSOM direction-map model to learn spatiotemporal RFs.
- Scan across input, and present input samples in the sequence.
- Scanning simulates gaze (vision) or finger tip movement (touch).

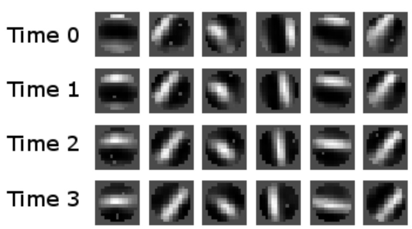
Methods: Inputs

- Natural scene (top)
- Texture (bottom): note that there are multiple scales.

Results: Receptive Fields



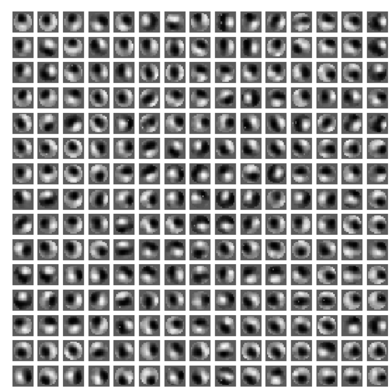
RF from Texture



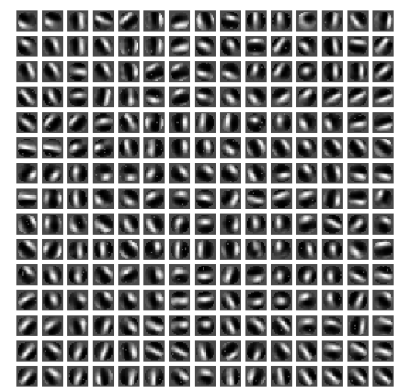
RF from Natural scene

- RFs self-organized with texture-like inputs show TRF-like properties.
- RFs self-organized with natural-scene-like inputs show VRF-like properties.

Results: Map



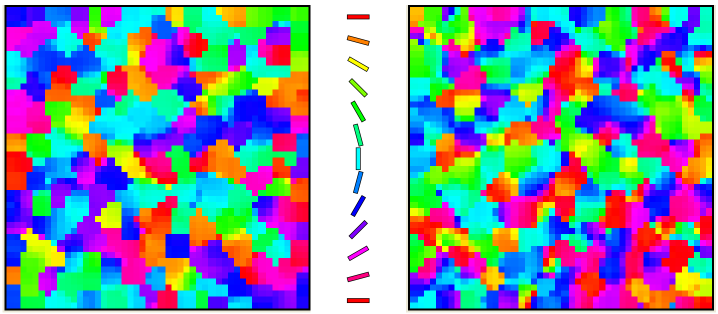
RF from Texture



RF from Natural scene

- Texture-like inputs $\longrightarrow$ TRF-like properties.
- Natural-scene-like inputs $\longrightarrow$ VRF-like properties.

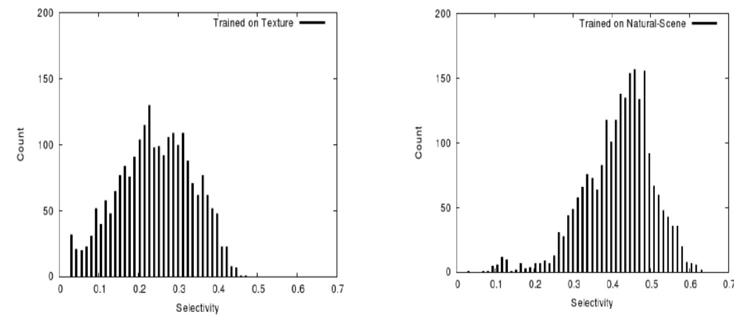
Results: Orientation Map



From Texture From Natural scene

- Both show orientation-map similar to those found in the visual cortex, but the texture-based map shows lower selectivity (next slide).

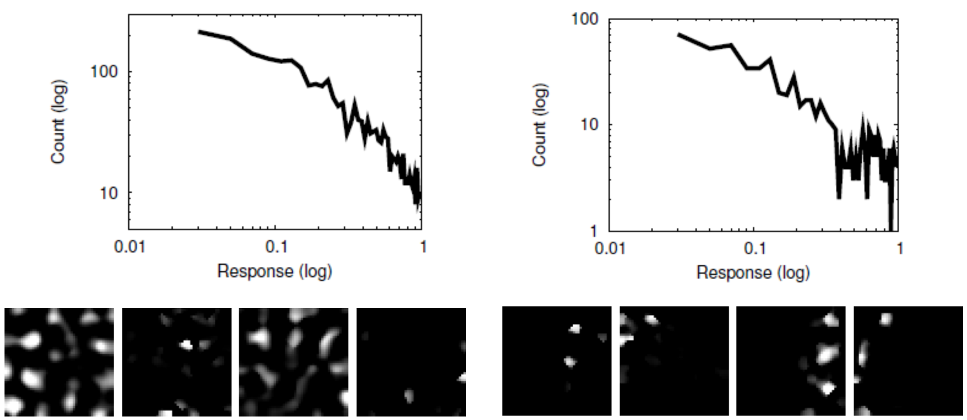
Results: Orientation Selectivity



From Texture From Natural scene

- Texture-based map shows lower selectivity (i.e., RFs are less line-like and more blobby).

Response Properties of RFs



From Texture From Natural scene

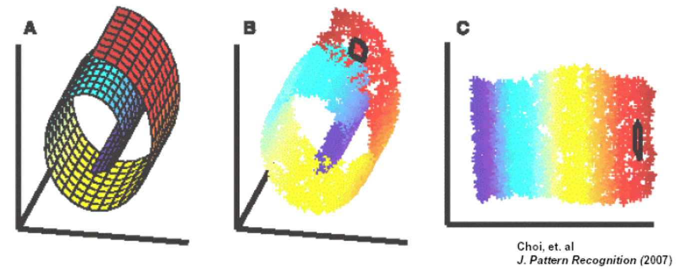
- Both RFs give sparse response to the input.
- Both show power-law property.

Summary (Part II)

- Texture-like (nat. scene-like) input leads to TRF-like (VRF-like) RFs with a general cortical development model (LISSOM).
- Response properties of these RFs are similar, to their respective input type, suggesting a possible common post-processing stage in the brain (parietal cortex?).
- Results further support the idea that texture and touch are intimately linked.

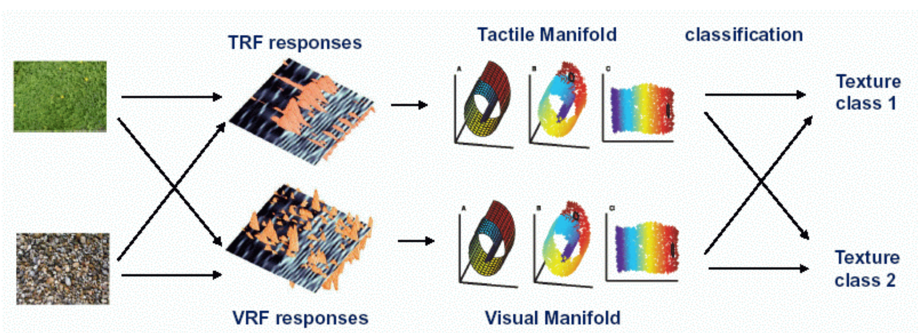
Part III: Analysis

Analysis of RF Resp. with Manifold Learning



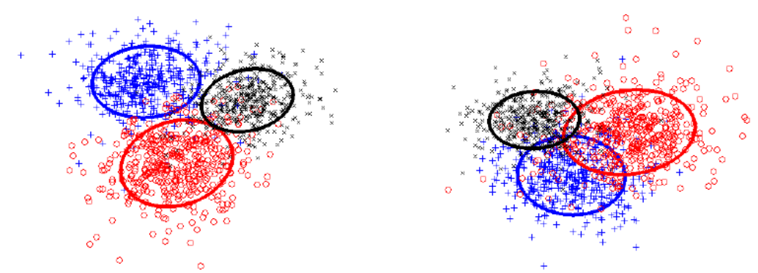
- We want to quantitatively analyze the representational power of self-organized VRF and TRF responses.
- RF response vectors live in a high-dimensional space.
- However, they may actually occupy a low-dimensional manifold.

Methods



- Generate response vectors from all input-to-RF combinations, and conduct manifold anlaysis on the response vectors.

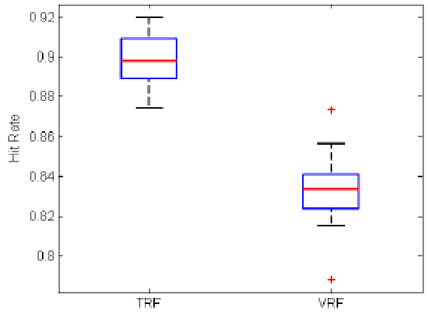
KFD Analysis: Texture Input



(a) TRF feature space (b) VRF feature space

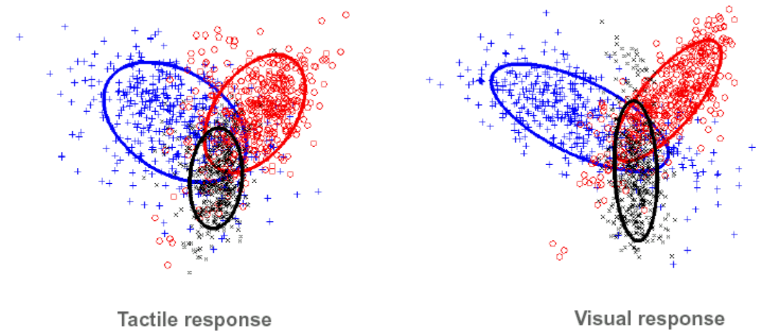
- Kernel Fisher Discriminant Analysis.
- TRF response to texture input more separable.

KFD on Texture: Classification



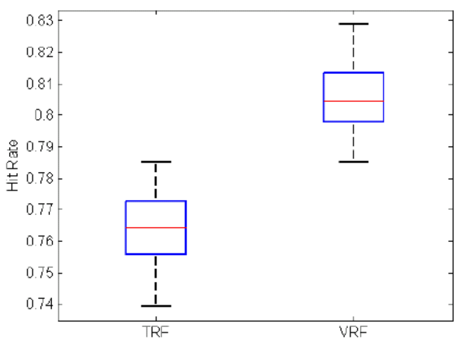
- Classification based on projection of top two KFD eigenvectors.
- KFD of TRF responses gives higher performance.

KFD Analysis: Nat. Scene Input



- Kernel Fisher Discriminant Analysis.
- VRF response to natural-scene input more stretched.

KFD on Nat. Scene: Classification



- Classification based on projection of top two KFD eigenvectors.
- KFD of VRF responses gives higher performance.

Summary (Part III)

- Manifold analysis shows that TRF more suitable for texture than VRF.
- Likewise, VRF more suitable for natural scene.
- Results further support the link between texture and touch.

Wrap Up

Discussion

- Contribution: Intimate link between texture and touch revealed in multiple aspects.
- Relationship to our earlier work on 2D vs. 3D textures (Oh and Choe 2007).
- Relationship to Nakayama et al. (1995) on the primacy of surface representation in the visual pathway.
- Limitations: scaling property for TRF unclear?

Conclusion

- Texture may be intimately linked with tactile processing in the brain.
- In other words, te nature of texture may be more tactile than visual.
- Our results are expected to shed new light on texture research, with a fundamental shift in perspective.

Acknowledgments

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