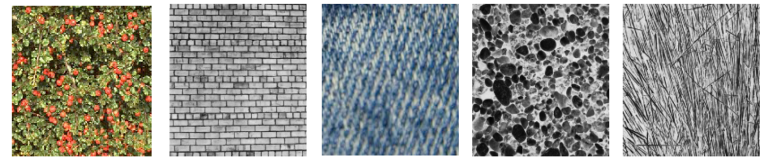
Nature of Texture: Visual or Tactile?

CSCE 644 Cortical Networks

Yoonsuck Choe
Department of Computer Science and Engineering
Texas A&M University

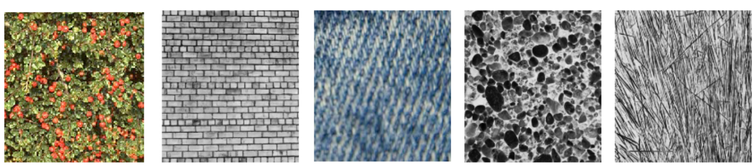
Joint work with Yoon H. Bai, Heeyoul Choi, and Choonseog Park

What is Texture?



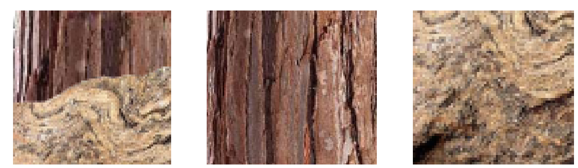
- Statistical definition (Beck 1983; Zhu et al., 1999)
- Surface characteristics (Urdang, 1968)
- Texton theory (Julesz and Bergen 1982)

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)

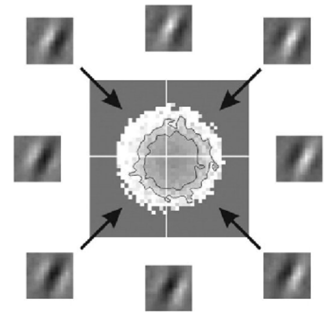


- A mixed texture (left), with two different component textures (middle & right).
- Looks distinctly visual.
- However, ...

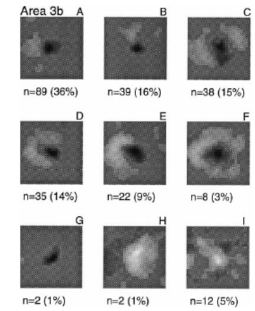
Texture in Nature (2/2)

- 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:

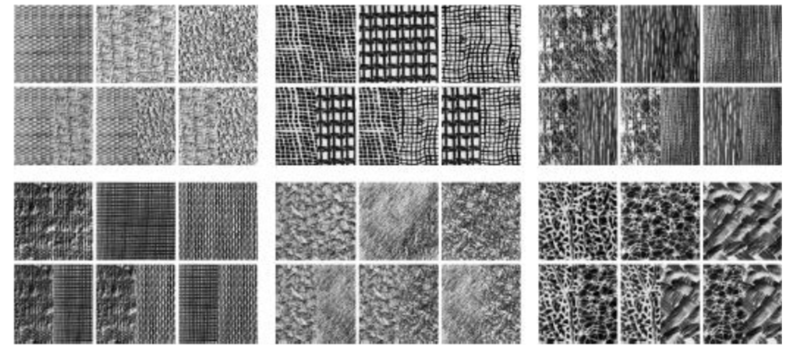
1. Can tactile RFs outperform visual RFs in texture tasks?
2. How are tactile RFs related to texture in a cortical development context?
3. Is the representational power of tactile RFs higher than visual RFs in texture tasks?

Overview

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

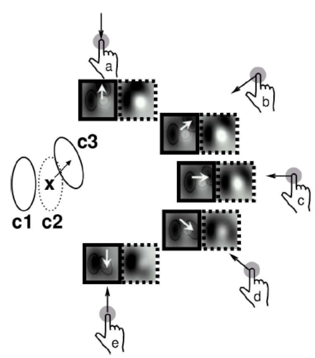
Part I: Performance

Task: Texture Boundary Detection



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

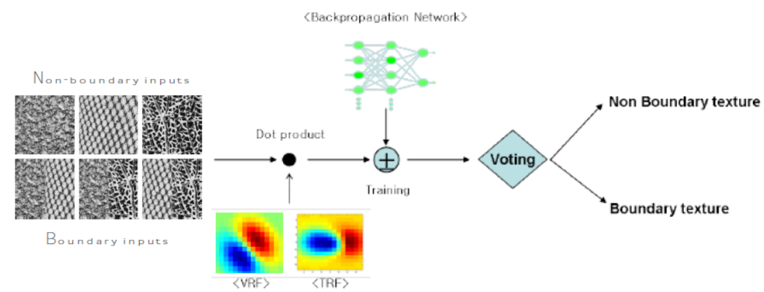
VRF and TRF Models



(a) Visual RFs (b) Tactile RFs

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

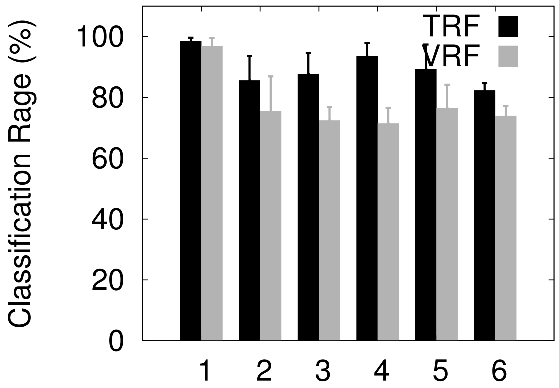
Methods



Texture boundary detection task:

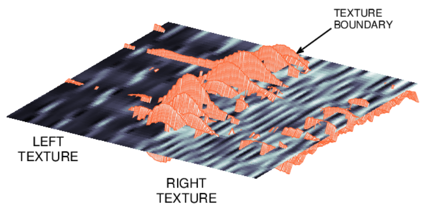
- Generate response vectors using TRF & VRF filters.
- Train backprop network for classification.
- Voting based on multiple sample positions.

Results

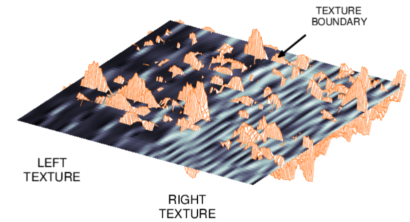


- TRF response vectors significantly better than VRF for representing texture boundary.

TRF vs. VRF Response Vectors



TRF response

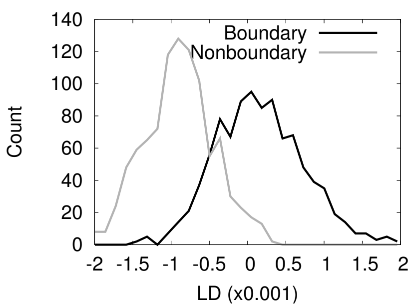


VRF response

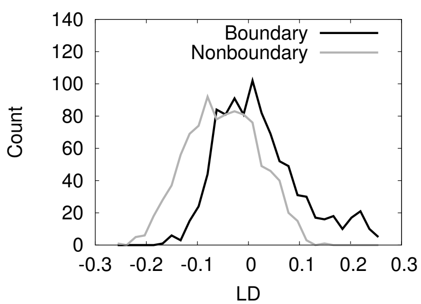
Why does TRF outperform VRF?

- Response vectors from TRF emphasize the boundary.

LDA of Response Vectors



TRF



VRF

Why does TRF outperform VRF?

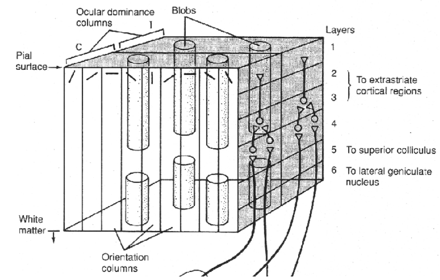
- Linear Discriminant Analysis on response vectors.
- LDA distribution for TRF more clearly separated.

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

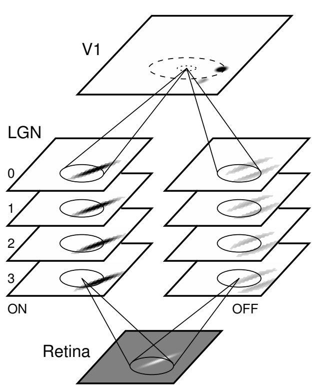


Kandel et al. (2000)

- 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

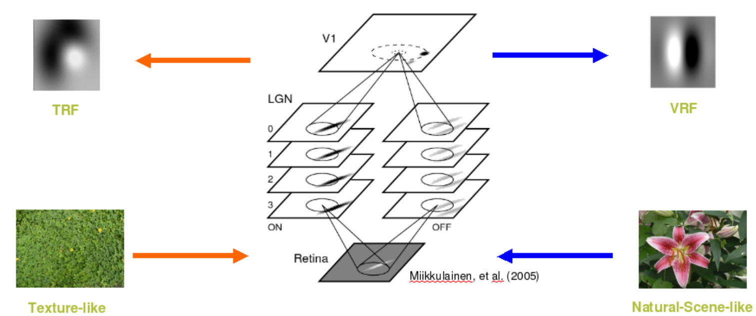
LISSOM



(Miikkulainen et al. 2005)

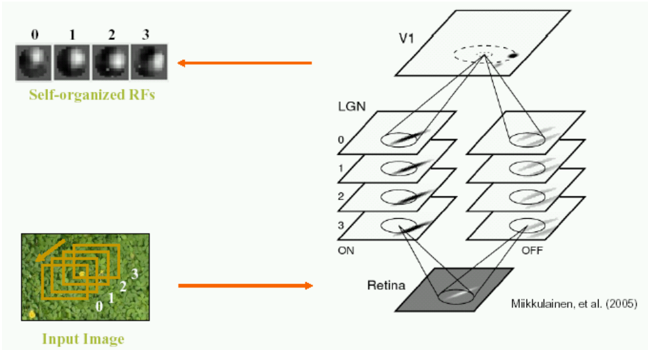
- Input-driven self-organization (Hebbian learning).
- Model of visual-cortical development and function.
- Can be applicable to other sensory modalities.
- `http://topographica.org`

Methods



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

Methods (cont'd)

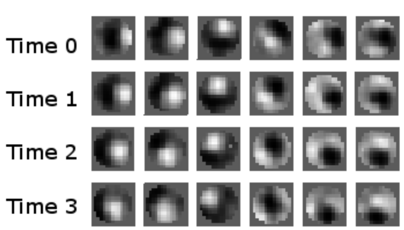


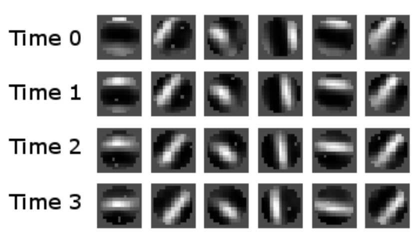
- Use LISSOM direction-map model to learn spatiotemporal RFs.
- Scan across input, and present input samples in the sequence.
- Scanning simulates gaze (vision) or finger tip movement (touch).

Methods: Inputs

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

Results: Receptive Fields

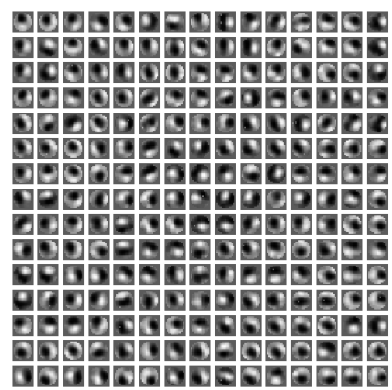


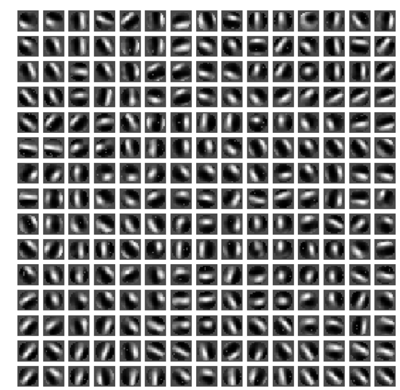


RF from Texture RF from Natural scene

- 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

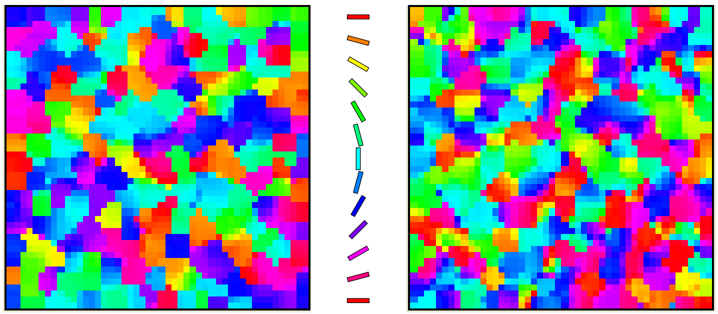




RF from Texture RF from Natural scene

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

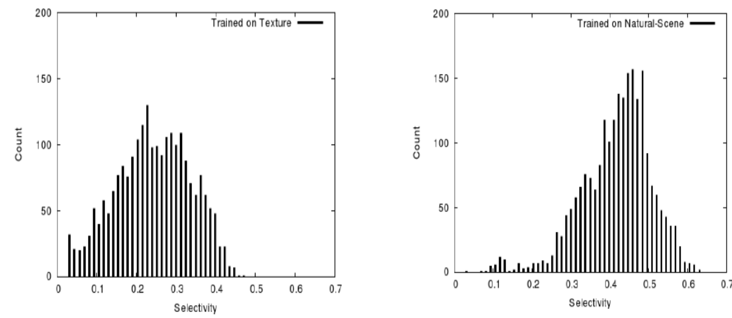
Results: Orientation Map



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).

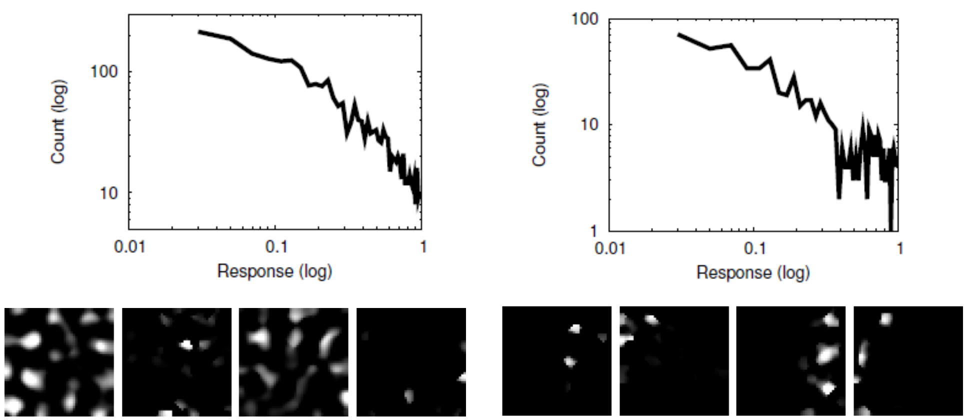
Results: Orientation Selectivity



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

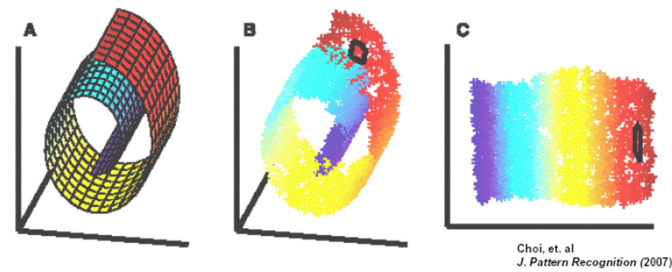
- Both RFs give sparse response to the input.
- Both show power-law property.

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.

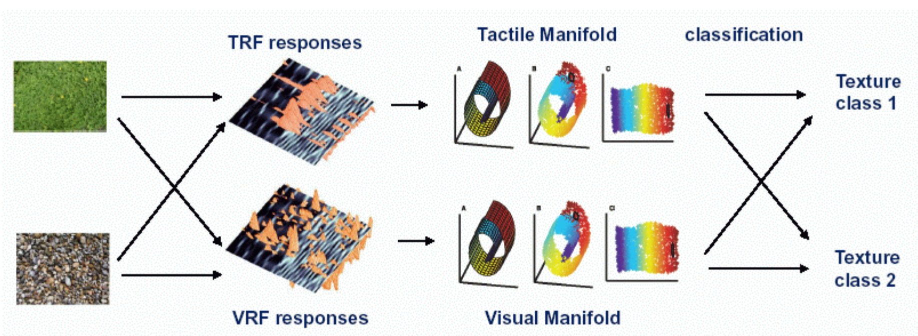
Part III: Analysis

Analysis of RF Resp. with Manifold Learning



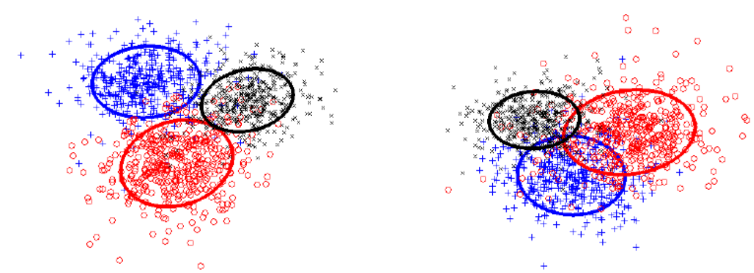
- We want to quantitatively analyze the representational power of self-organized VRF and TRF responses.
- RF response vectors live in a high-dimensional space.
- However, they may actually occupy a low-dimensional manifold.

Methods



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

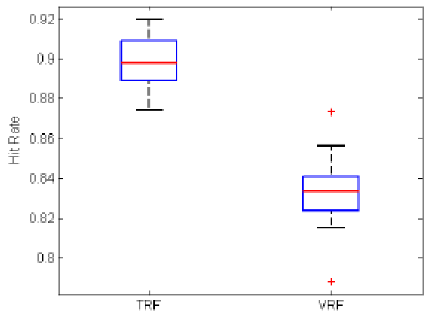
KFD Analysis: Texture Input



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

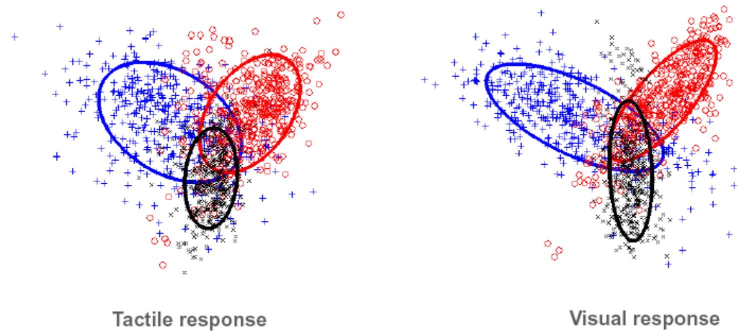
- Kernel Fisher Discriminant Analysis.
- TRF response to texture input more separable.

KFD on Texture: Classification



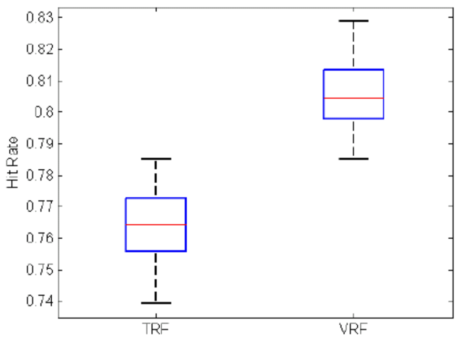
- Classification based on projection of top two KFD eigenvectors.
- KFD of TRF responses gives higher performance.

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

- Students: Choonseog Park, Yoon H. Bai, Heeyoul Choi
- Partly funded by NIH/NINDS.

References

Beck, J. (1983). Textural segmentation, second-order statistics and textural elements. *Biological Cybernetics*, 48:125–130.

Choe, Y., Abbott, L. C., Han, D., Huang, P.-S., Keyser, J., Kwon, J., Mayerich, D., Melek, Z., and McCormick, B. H. (2008). Knife-edge scanning microscopy: High-throughput imaging and analysis of massive volumes of biological microstructures. In Rao, A. R., and Cecchi, G., editors, *High-Throughput Image Reconstruction and Analysis: Intelligent Microscopy Applications*. Boston, MA: Artech House. In press.

Choe, Y., and Miikkulainen, R. (2004). Contour integration and segmentation in a self-organizing map of spiking neurons. *Biological Cybernetics*, 90:75–88.

Choe, Y., and Smith, N. H. (2006). Motion-based autonomous grounding: Inferring external world properties from internal sensory states alone. In Gil, Y., and Mooney, R., editors, *Proceedings of the 21st National Conference on Artificial Intelligence(AAAI 2006)*. 936–941.

Choe, Y., Yang, H.-F., and Eng, D. C.-Y. (2007). Autonomous learning of the semantics of internal sensory states based on motor exploration. *International Journal of Humanoid Robotics*, 4:211–243.

Choi, H., Choi, S., and Choe, Y. (2008a). Manifold integration with markov random walks. In *Proceedings of the 23rd National Conference on Artificial Intelligence(AAAI 2008)*, 424–429.

Choi, H., Gutierrez-Osuna, R., Choi, S., and Choe, Y. (2008b). Kernel oriented discriminant analysis for speaker-independent phoneme spaces. In *Proceedings of the 19th International Conference on Pattern Recognition*. In press.

Chung, J. R., Kwon, J., and Choe, Y. (2009). Evolution of recollection and prediction in neural networks. In *Proceedings of the International Joint Conference on Neural Networks*, 571–577. Piscataway, NJ: IEEE Press.

Julesz, B., and Bergen, J. (1982). Texton theory of preattentive vision and texture perception. *Journal of the Optical Society of America*, 72:1756.

Kandel, E. R., Schwartz, J. H., and Jessell, T. M. (2000). *Principles of Neural Science*. New York: McGraw-Hill. Fourth edition.

Kwon, J., and Choe, Y. (2008). Internal state predictability as an evolutionary precursor of self-awareness and agency. In *Proceedings of the Seventh International Conference on Development and Learning*, 109–114. IEEE.

Mayerich, D., Abbott, L. C., and McCormick, B. H. (2008). Knife-edge scanning microscopy for imaging and reconstruction of three-dimensional anatomical structures of the mouse brain. *Journal of Microscopy*, 231:134–143.

Miikkulainen, R., Bednar, J. A., Choe, Y., and Sirosh, J. (2005). *Computational Maps in the Visual Cortex*. Berlin: Springer. URL: http://www.computationalmaps.org.

Nakayama, K., He, Z. J., and Shimojo, S. (1995). Visual surface representation: A critical link between lower-level and higher-level vision. In Kosslyn, S. M., and Osherson, D. N., editors, *An Invitation to Cognitive Science: Vol. 2 Visual Cognition*, 1–70. Cambridge, MA: MIT Press. Second edition.

Oh, S., and Choe, Y. (2007). Segmentation of textures defined on flat vs. layered surfaces using neural networks: Comparison of 2D vs. 3D representations. *Neurocomputing*, 70:2245–2255.

von Melchner, L., Pallas, S. L., and Sur, M. (2000). Visual behaviour mediated by retinal projections directed to the auditory pathway. *Nature*, 404(6780):871–876.