Demonstration of Efficient Visual and Auditory Neural Coding

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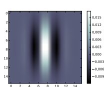
Motivation

Traditionally, visual processing and auditory processing were studied as distinct methods with separate research groups, terminology, and approaches; however, computational neuroscientists have discovered that these sensory areas (and likely others) are actually performing essentially the same computation, with only a change in inputs. This work is an illustration of this approach to sensory neuroscience.

Abstract

We can understand neural responses using the concept of a receptive field — essentially images which tell us what stimuli a neuron responds to. But although these receptive fields answer "what" a neuron responds to, we often want to answer "why" neurons respond in this unusual way.

A visual receptive field. This depicts a neuron selective to vertical stimuli (e.g. a bright line in the center, or a dark line slightly off-center)



We demonstrate that these neurons form an efficient code by deriving similar neural receptive fields (linear filters in engineering terms) from an efficient coding of natural scenes. Note, efficient coding for neurons is not like an efficient code on a computer. An apt analogy is that instead of compressing the signal (minimizing the number of 1s and 0s, like when compressing images on your computer) we want a sparse code minimizing the number of metabolically costly neural action potentials (as if only the 1s are being minimized).

Methods

1. Natural images and sounds were collected. For example: pictures of rocks, trees, etc. and sounds ranging from anharmonic environmental sounds (like crunching leaves) to human speech or other animal vocalizations.
2. The image or sound was randomly sampled to create tens of thousands of smaller images patches (8x8 pixels) or audio clips (100 samples in size)
3. The samples were encoded using an efficient coding technique, specifically independent components analysis (ICA).
4. The resulting filters were then visualized producing the expected Gabor-like filters for the images and gammatone filters for the sounds, which matches similar receptive fields measures directly from neurons in the brain.

Results

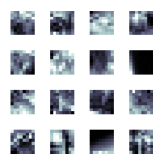
Efficient Coding Hypothesis: Theoretical model proposed as a way of understanding neural responses by reducing redundancy in the neural code for natural sensory experiences.

Visual Neural Code

Original

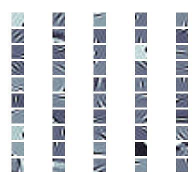
Above is an example of an original image to be encoded.

Samples



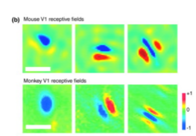
These are random samples taken from the original photo.

Produced Filters



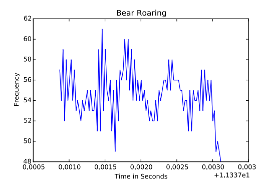
The figures above are the resulting visual filters from ICA. These filters resemble the gabor filter-like response properties of a V1 simple cell.

Actual Filters

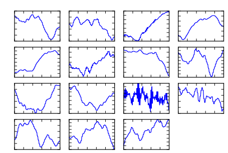


The figure above illustrates measured visual neural receptive field filters.
(Huberman, 2011)

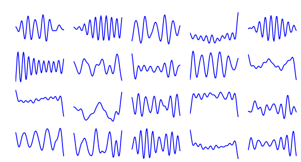
Auditory Neural Code



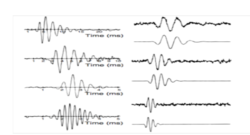
Above is an example of an original sound to be encoded.



These are random samples taken from the original sound clip. These 15 graphs are random 100 sample clips.



The figures above are the resulting auditory filters from ICA. A subset of these filters resemble the gammatone response properties of neurons that make up the auditory nerve.



The figure above shows measured auditory neural receptive field filters.
(Lewicki, 2002)

Future Objective

The current Python program requires users to have previous coding experience and to find images/sounds online to use all the functionality.

The next step is to port this work into a phone application to make it easier for people to use. The Android application will use the camera and microphone to collect images and sound samples, allowing the effect of different data sources on the resulting neural codes to be more readily accessible and intuitive.

Conclusion

Our program analyzes visual and auditory scenes using the same efficient coding method — in this case, ICA. It is clear in using it that different types of images and sounds have different impacts on the resulting code — although these results are not presented in this poster. However, the code is ready to port into an Android application to make it more accessible to users, allowing them to compare resulting codes for different images and sounds for themselves.

References

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Acknowledgements

This work was supported by the "Sustaining Excellence" HHMI grant #52008101, enabling the Loyola University Chicago FYRE program, and supporting the LUC Computer Science Undergraduate Summer Research Program.