Perceptual Multistability in a Temporal Illusion

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Abstract

In this project, we model the cognitive conception of a visual illusion that can be perceived in four primary modes. We model perceptual multistability using a generative Bayesian network that captures the relations between high level features that are extracted from the illusion and the different overall conceptions of the illusion that the viewer can have. Due to the high complexity of the illusion itself, we simplify the visual stimulus down to a single unit that corresponds to the viewer's observation of the visual stimulus. Despite this simplifying assumption, our model is sophisticated enough to allow it to exhibit human-like perceptual multistability using Markov Chain Monte Carlo (MCMC) methods to sample from the model conditioned on the observed stimulus. (once we actually get results we should write the rest)

1 Perceptual Multistability

The mental phenomenon of perceptual multistability is a commonly modeled aspect of human cognition, because it is a well-defined and well-measured phenomenon, and it is fairly easy to model simple illusions that give rise to multistability. However, little research has gone into modeling perceptual multistability in complex illusions, such as those with a temporal component, multiple stable percepts, and complex structure. In our project, we aim to model a high-dimensional temporal illusion with 6 stable percepts (which can be found at bit.ly/c3uGK2) and accurately reconstruct the dynamics of perceptual multistability as it naturally arises from the illusion using MCMC sampling.

2 Our Model

Due to the high complexity of the illusion, a number of simplifying assumptions have to be made in order to construct a computationally tractable model. Before we constructed our model, we decided to reduce the number of stable percepts in the illusion to 4 instead of 6, because the mirror images of the double helix and wave forms (see the illusion) are very similar, to the point where they are practically interchangable. The difference between the helix, wave, horizontal motion, and bouncing dots percepts is much more significant than the difference between the 2 wave and helix configurations.

Using this simplification, we constructed a 3-layer generative Bayesian network for our model. Each unit in each layer (except the bottom layer) contains directed edges going from that unit to every unit in the layer immediately below it. (figure would be nice) The top layer contains (4? a variable number?) 'percept' units, where each unit can take on a value 1 to 4 that corresponds to a different percept of the illusion. The top layer generates the second layer, which contains intermediate 'high-level feature' units that correspond to different characteristics one might observe. We have five of these units, which correspond to observed dimensionality (2d or 3d), planar rotation, horizontal velocity, correlation between dots in each column, and number of objects in the illusion. Lastly, the bottom layer captures the observed illusion. For the bottom layer, we model the input of the illusion as a single 'illusion unit', which has two values corresponding to whether the illusion is being observed or not. This is a very large but necessary simplification, because modeling configurations of the dots in the illusion would've taken hundreds of variables and a temporal model. Also, our approach is still wholly valid, because we can encode the configurations of high-level features that are likely to be observed in the illusion in the conditional probability distribution of the bottom-layer unit. For example, if a configuration of high-level features are observed that *don't* correspond to any percept of the illusion (say, rotation and 2-dimensionality were observed), the illusion unit has a near-zero probability of being active, whereas if a configuration of high-level features that correspond to one of the percepts is observed, then the illusion unit has a near-one probability of being active.

3 Results

3.1 Switching between percepts

3.2 Visual Cues

4 Discussion

Table 1: Sample table title

PART	DESCRIPTION
Dendrite	Input terminal
Axon	Output terminal
Soma	Cell body (contains cell nucleus)

COOL $\LaTeX\ 2_{\varepsilon}$STUFF!!! alright! LOL?

4.1 Footnotes

Indicate footnotes with a number[1] in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).[2]

4.2 Figures

All artwork must be neat, clean, and legible. Lines should be dark enough for purposes of reproduction; art work should not be hand-drawn. The figure number and caption always appear after the figure. Place one line space before the figure caption, and one line space after the figure. The figure caption is lower case (except for first word and proper nouns); figures are numbered consecutively.

Make sure the figure caption does not get separated from the figure. Leave sufficient space to avoid splitting the figure and figure caption.

You may use color figures. However, it is best for the figure captions and the paper body to make sense if the paper is printed either in black/white or in color.

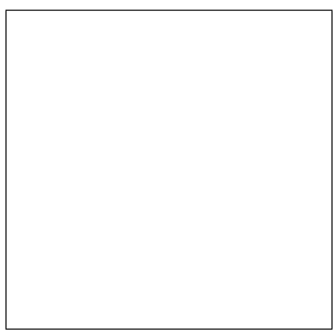

Figure 1: Sample figure caption.

4.3 Tables

All tables must be centered, neat, clean and legible. Do not use hand-drawn tables. The table number and title always appear before the table. See Table 1.

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

LaTeX users:

- Consider directly generating PDF files using `pdflatex` (especially if you are a MiKTeX user). PDF figures must be substituted for EPS figures, however.

[1] Sample of the first footnote

[2] Sample of the second footnote

- Otherwise, please generate your PostScript and PDF files with the following commands:

  ```
  dvips mypaper.dvi -t letter -Ppdf -G0 -o mypaper.ps
  ps2pdf mypaper.ps mypaper.pdf
  ```

  Check that the PDF files only contains Type 1 fonts.
- xfig "patterned" shapes are implemented with bitmap fonts. Use "solid" shapes instead.
- The `\bbold` package almost always uses bitmap fonts. You can try the equivalent AMS Fonts with command

  ```
  \usepackage[psamsfonts]{amssymb}
  ```

  or use the following workaround for reals, natural and complex:

  ```
  \newcommand{\RR}{I\!\!R} %real numbers
  \newcommand{\Nat}{I\!\!N} %natural numbers
  \newcommand{\CC}{I\!\!\!\!C} %complex numbers
  ```
- Sometimes the problematic fonts are used in figures included in LaTeX files. The ghostscript program `eps2eps` is the simplest way to clean such figures. For black and white figures, slightly better results can be achieved with program `potrace`.

Acknowledgments

Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper.

References

References follow the acknowledgments. Use unnumbered third level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to 'small' (9-point) when listing the references. **Remember that this year you can use a ninth page as long as it contains *only* cited references.**

[1] Alexander, J.A. & Mozer, M.C. (1995) Template-based algorithms for connectionist rule extraction. In G. Tesauro, D. S. Touretzky and T.K. Leen (eds.), *Advances in Neural Information Processing Systems 7*, pp. 609-616. Cambridge, MA: MIT Press.

[2] Bower, J.M. & Beeman, D. (1995) *The Book of GENESIS: Exploring Realistic Neural Models with the GEneral NEural SImulation System.* New York: TELOS/Springer-Verlag.

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.