Towards a Perceptual Theory of Flow Visualization

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Abstract

At present there is very little attention paid to vision science by most visualization researchers or developers. To remedy this a theoretical approach to flow visualization is proposed based on the applied theory of perception. The approach has the following components: First, mappings must be defined between data and a visual representation. Second, analytic tasks must be identified that can be executed by means of a visual search for patterns. Third, the theory of perception is applied to the analytic tasks to make predictions regarding which mappings will be most effective. An extended example is provided, concerning the representation of advection pathways in steady flow. It is argued that such a disciplined approach can be beneficial to both visualization research and research into human perception.

Introduction

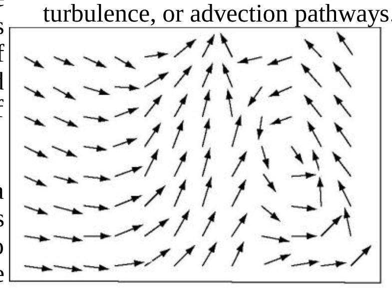
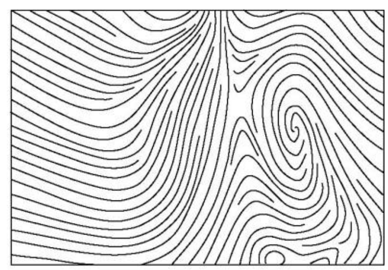
What constitutes *good visualization research* is a basic question that defines the discipline. Are researchers aiming at better algorithms, better theory, or design guidelines for producing better visualizations?

One possible approach is to model visualization research on natural and physical sciences and develop a body of theory. A good theory should be able to make testable predictions about which mappings from data to display will be most effective, allowing researchers to gain insights about their data (exploration) or help others understand what the data shows (explanation). More effective visualizations should result from applications of this theory. In this paper, I argue that the theory of human perception, pragmatically applied, should provide a substantial part of a testable theory of visualization.

The best way of making this case is to provide a convincing example and most of what follows is intended to show that perceptual theory has much to tell us about *effective flow visualization*. Since visualization is a practical tool, a meaningful theory must be constructive, not just descriptive, leading to more effective representations of data. I shall argue that such a useful body of theory does exist and even though it is incomplete it still can be useful. The major gaps in the theory provide promising avenues for future research in a multidisciplinary program that can benefit both the field of human perception and the applied science of data visualization.

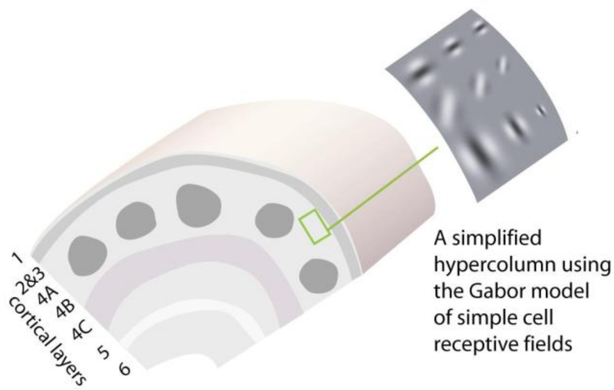
The proposition that the main purpose of visualization is to allow us to perceive patterns in data (and hence discover meaing) seems uncontroversial and this leads to a body of science that bears directly on the problem but is rarely taken into account. Modern *neuropsychology* has much to say about visual pattern perception. This discipline has made great strides over the past several decades, driven by advances in psychophysics, single cell recording in the visual parts of the brain of animals, and lately functional magnetic resonance imaging which reveals the parts of the brain using the most oxygen and hence presumed to be the most active at a given time.

The patterns we are interested in when we look at flow vary depending on what aspects of the data we wish to analyze – the cognitive task. For visualization to be a useful tool aspects of this cognitive task must be transformed into visual pattern queries.[1] In flow visualization there are many different types of visual pattern queries such as finding locations of critical points, areas of high turbulence, or advection pathways.


1. A grid of arrows is still the most common way of visualizing a flow field. The tail of each arrow is tangential to the flow. Most other flow visualizations also produce graphical contours that are tangential to the flow.

To illustrate how perceptual theory can be fruitfully applied to a common visualization problem this paper will focus mainly on a single task − judging advection pathways in steady flow. To perceive an advection pathway we must *perceptually trace a path* from a starting point in the flow. This suggests that the best representation of an advection pathway will be a visual contour because the brain has mechanisms to rapidly find contours marking the boundaries of objects or linear features in the environment.[2] Whatever allows us to perceive pathways as contours anywhere in a flow field is likely to be the most effective graphic design to support judgments about advection pathways. We shall call this proposition our *mapping hypothesis*. It is worth noting that there are alternatives. For example the orientation of flow has been represented by a cycle of colors or by the actual advection of scattered random points seeded through the flow field. Nevertheless using contour orientation to reveal flow direction is the most common technique.



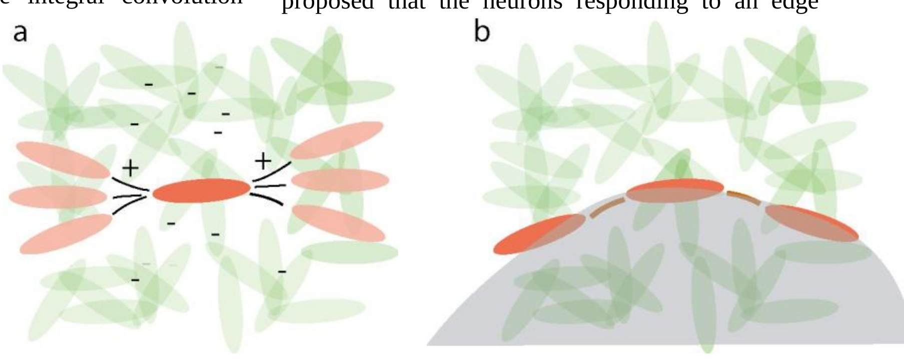
2. The primary visual cortex contains neurons that respond to oriented patterns in particular parts of the visual field. Each part of visual space is processed for orientation and size information. The grey image in the upper right shows a set of receptive fields of individual neurons, each responding best to a particular feature size and orientation.

Almost all static flow visualization methods generate contours that are tangential to the directions of flow (Figure 1). The most common method is to use a grid of little arrows with the starting point of each arrow tangential to the flow. Some methods use curved arrows, and still other methods use continuous contours.[3,4] Line integral convolution typically produces rather blurred contours.[5]

There is a well developed body of perceptual theory relating to contour perception. Since the pioneering work of Hubel and Wiesel[6] in the 1960's, it has been known that the primary visual cortex (called V1) at the back of the brain contains large numbers of neurons each responding to a small patch of visual space and each selectively tuned in terms of the orientation of the pattern to which they respond most strongly. One mathematical model of filtering operation is the Gabor function (see Figure 2) — the product of a sine wave grating and a Gaussian. These neurons respond strongly when either an edge or a line is oriented with the *receptive field* of the neuron and weakly, or not at all, when the edge or line is not so aligned. These orientation filtering neurons are arranged in a specific architecture called hyper-columns. As we progress into the cortex down a hyper-column the receptive fields get larger. As we progress laterally across the cortex, the different orientations are found, for that same part of visual space. As a whole, the primary V1 operates as a set of parallel filters, with hundreds of millions of neurons operating in parallel so that every part of the visual field is simultaneously processed for every orientation and size of elementary feature.

These simple orientation detecting neurons have been found in every higher animal and are the basis for all theories of contour detection. The signals from individual neurons, however, are not sufficient to account for the perception of long continuous contours that might make up an advection pathway. They can only signal the local orientation of a section of contour.

The neural mechanisms that *bind* multiple individual neurons firing in response to different sections of an extended contour are more speculative, but most theorists agree on something like the following: Individual neurons within V1 are reciprocally connected with other neurons also within V1. Neurons in *spatial proximity* and *aligned* with one another as shown in Figure 3 have mutually excitatory connections.[2] Neurons that are in proximity and not so aligned inhibit one another. The result of such a network is that neurons that are stimulated by the image of a continuous line or edge will fire more strongly than neurons that are stimulated by little fragments of edges such as might occur in a rough texture. Some theorists have also proposed that the neurons responding to an edge

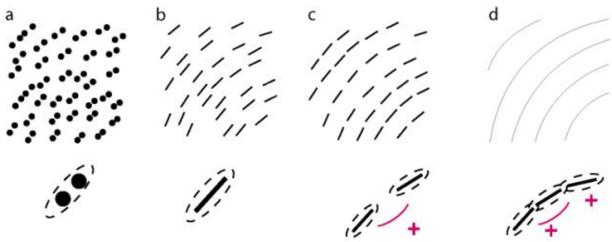


3. (a) Neurons that have spatially aligned receptive fields mutually reinforce each other. They also inhibit other nearby neurons. (b) When a smooth continuous contour or edge is imaged in the eye, those neurons along its path become excited while nearby neurons not on the edge become inhibited.

rapidly come to fire in synchrony with one another.[7]

This basic theory of contour perception is already sufficient to make a number of straightforward predictions about which visualization methods will result in better advection perception.

Figure 4 illustrates, in simplified form, a set of methods that have been used to illustrate flow patterns. The theory predicts that the rank order of effectiveness of these methods will be a,b,c,d for the following reasons. Method 'b' should be better than method 'a' because a short line segment will give a stronger signal to orientation sensitive V1 neurons than will the pairs of dots shown in method 'a'. Method 'c' should be better than method 'b' because having the line segments aligned will produce mutual excitation as described. Method 'd' should be better than method 'c' because a continuous contour will produce stronger mutual excitation than broken but aligned contours.

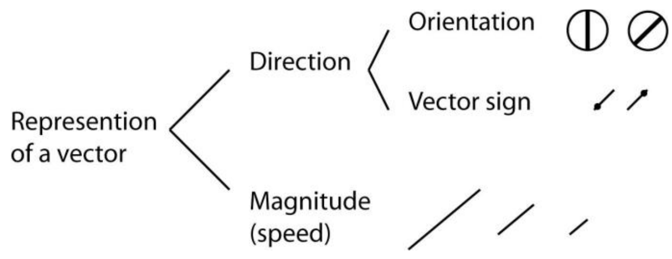


4. TOP: a set of methods which have been used for flow visualization. Note that there are no arrowheads here and so the direction of flow is ambiguous. BOTTOM: the predicted effect of the patterns generated by each method on orientation selective neurons.

Although they were not testing this theory, Laidlaw et al.[8] carried out a study that relates to cases 'b' and 'c' in Figure 4. They compared jittered arrows with head to tail aligned arrows (as well as other methods) and found that the head to tail aligned method produced reduced error for advection perception. However, the two cases also used different styles of arrows which may have been a factor. Also relevant is a study that measured the responses of neurons in the visual cortex of a Macaque monkey to patterns similar to Figure 4a.[9] Although the neurons responded to these patterns, they responded more strongly to gratings of continuous contours similar to the pattern shown in 4d.

Vector sign

The theory presented thus far is incomplete in a critical respect. The advection pathway for the patterns shown in Figure 4 are ambiguous. It is normal to decompose a vector into a direction and a magnitude (speed). For the purposes of understanding flow visualization, it is convenient to further decompose the direction component into an orientation and a vector sign, as shown in Figure 5. Many flow visualization methods such as line integral convolution (Figure 1c) clearly show the orientation, but fail to show the vector sign.

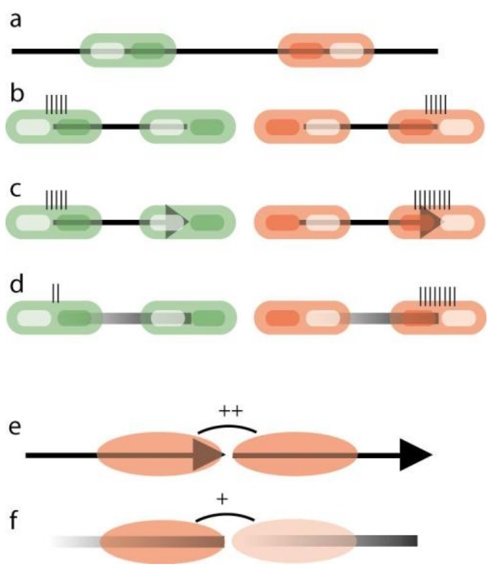


5. A vector can be broken down into three components. Many representation methods only show a subset of these.

What does the theory of perception tell us about how to represent the vector sign? In order to represent this single bit of information it is necessary that there be directional asymmetry along the direction of the contour. The most common device is to use an arrow head. However there are a number of other possibilities some of which are illustrated in Figure 6. One possible neural mechanism for detecting this kind of asymmetry is through complex and hyper-complex cells found in visual areas 1 and 2.[6] These are sometimes called end-stopped cells because they respond most strongly to oriented features that terminate in the receptive field and respond weakly or not at all to features that are extended through it (Figure 7). Heider et al.[10] reported that 50 percent of such end stopped cells responded asymmetrically, responding more strongly if the feature terminates in a particular direction. No studies have been done to test the responses of end stopped cells to patterns like those in Figure 6. However, it seems plausible that some will yield stronger asymmetric responses than the conventional arrow head. In particular the grey ramp pattern marked with an asterisk in Figure 6 has very strong asymmetry. One end completely lacks a distinct termination and so this may be a good choice for indicating the vector sign, at least with static patterns. Fowler and Ware[11] introduced patterns like this for flow visualization and showed that they were unambiguously read with respect to the vector sign of simple flow patterns.

6. A number of ways of creating along-contour asymmetry for showing the vector sign

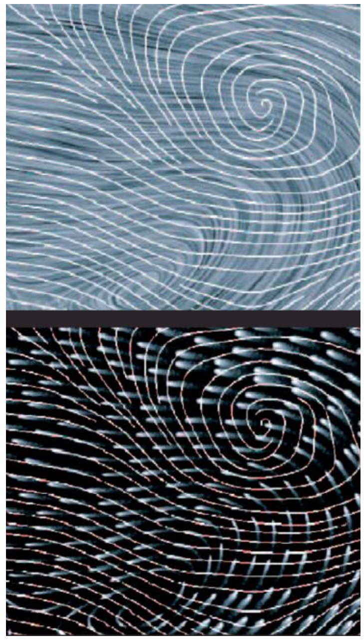
Unfortunately, we do not have a model of a typical asymmetrical end-stopped neuron. If we did it would be possible to make predictions about which pattern is better. Thus we can identify an open question in the perceptual theory of flow visualization, namely, how can we best represent vector sign information while at the same time preserving the perception of flow pathways? Although the gray ramp pattern may be a strong representation of the vector sign it fails to represent the advection pathway with a clear contour. These patterns when arranged head to tail may also not be as effective in stimulating the mutual reinforcement between simple (symmetric) cell responses that seems desirable for contour perception (See Fig. 7, e & f). This provides an interesting research challenge. How to optimally represent the streamlines and the vector sign in a dense pattern that can show as much detail as possible?



7. Asymmetric end stopped neurons that respond to a left-hand terminus are show in green. Those responding to a right hand terminus are shown in red. The level of responding is illustrated by the little bars. (a) End stopped neurons do not respond to contours passing through their receptive field. (b) They do respond to contours that terminate in the receptive field and some do so asymmetrically, not responding to a termination from the other direction. (c) An arrow symbol provides stronger stimulation at the arrow head end than the tail end. (d) An along-contour grey ramp provides greater asymmetry. When arranged head-to-tail arrows provide better contour continuity (e) than grey ramps (f) because of reinforcement between simple neurons.

Multiple Flow Layers

Another challenge is to represent two layers of flow simultaneously. Ocean currents, for example, are often stratified flowing in one direction near the surface and another direction at greater depth. Perceptual theory again points to some possible solutions. Recall that simple cells in the cortex have a columnar organization. Neurons deeper in the cortex respond to larger oriented features whereas those near the surface respond to fine detail. Psychophysical studies have shown that the responses of different cortical layers are somewhat independent. Indeed, the visual system is sometimes said to have spatial frequency "channels" separating out different sizes of features.[12] We might therefore use different channels to apply to different layers of a flow. An example from Urness et al.[13] illustrates this nicely (although the authors were not inspired by the theory) and this is reproduced as Figure 8 here.



8. Illustrations from Urness et al. showing methods for displaying overlapping layers. (permission needed)

Discussion

Although we have discussed only a few problems in flow visualization, the approach outlined here can be applied to any visualization design problem where support of pattern finding in data is a goal. Allowing data-revealing patterns to be clearly seen is a fundamental purpose of visualization which suggests that the application of a perception-based approach can be quite broad.

The proposed approach has the following major elements.

1. Define an analytic task to be carried out using visualization. This task must be cognitively executable by means of a visual patterns search. The example given here has been advection pathway perception.

2. Propose a mapping (or a set of mappings) between the data and its visual representation. This can consist of an arbitrarily complex algorithm. However, it is generally desirable that the mapping be transparent in the sense that it is easy for the analyst to understand the relationship between the data and its representation.

3. Construct a perceptual theory regarding the ease with which the task relevant patterns can be found as a result of visual search. This theory will normally be an adaptation of existing perceptual theory applied to particular patterns produced by the mappings under consideration. Use this theory to construct testable hypotheses regarding either the perceptual efficiency of one mapping versus another, or the optimal values of parameter settings associated with a mapping.

4. Test the theory. Design display algorithms that optimally create the mappings under consideration according to the theory. Conduct experiments to compare how easily visual reasoning tasks about the data can be carried out under various mappings and parametric variation. For example, Laidlaw et al. created a test to evaluate advection pathway perception that involved having subjects mark the point where an advected particle, starting in the center of a circle, would cross the boundary of the circle.

5. Use perceptual theory as inspiration to generate new mappings. A good theoretical understanding of which patterns are likely to be easy to perceive can often lead to insights into new mappings worth investigating.

6. Develop new theory where needed. There are many areas where perceptual theory is inadequate to provide a clear hypothesis regarding which mappings are likely to be the most effective. The patterns that are of interest in representing data may not occur naturally in the real world. Also perceptual theory has often not been fully developed in a way that relates clearly to the particular patterns used in data visualization. In this case the relationship between visualization science and perceptual science becomes reciprocally beneficial. Problems of visually representing data may stimulate new basic research in perceptual science and the result can benefit the applied science of visualization.

Where does perception-based theory stand with respect to other approaches to visualization theory? Clearly it cannot stand alone. Algorithms are required to generate the necessary mappings between data and its visual representation and to do so efficiently. This brings in the fields of computer graphics, numerical algorithms and databases. The discipline of design is also essential. Most visualizations involve the representation of many variables and not all can be made to be maximally distinct. The choice of a set of colors for one class of data objects constrains the colors that can be used to represent others. A good design is usually a complex optimization problem; the choice of which variables should be mapped to color, which to texture and which to motion is generally one that is a matter of judgment rather than science.

Much of what has been said here is implicit in the work of a number of researchers who have applied perceptual theory to visualization. The purpose of this paper has been to make the argument explicit. At present there is very little attention paid to vision science by most researchers in visualization. The exception is when the effective use of color is the subject. Very little research in flow visualization includes a discussion of the related perceptual theory. Nor does it include an evaluation of effectiveness of the display techniques that are generated. This is despite Laidlaw et al's landmark paper showing that such an evaluation is relatively straightforward. Of course it is not always necessary to relate visualization research to perceptual theory. If the purpose of the research is to increase the efficiency of an algorithm then the proper test is one of efficiency not of perceptual validity. But when a new representation of data is the subject of research, addressing how perceptually effective it is, either by means of a straightforward empirical comparison with existing methods, or by analytically relating the new mapping to perceptual theory should be a matter of course. A strong interdisciplinary approach including the disciplines of perception, design and computer science will produce better science and better design in that empirically and theoretically validated visual display techniques will be the outcome.

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