studying the molecular basis of many neuronal functions. Let's just wait and see, staying hungry for more pie charts.

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The Speed of Categorization in the Human Visual System

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A new study by Liu et al. in this issue of *Neuron* looks at how information about object category can be extracted from intracerebral recordings from the visual cortical areas in epileptic patients. It shows that information about whether the object is a face, an animal, a chair, a fruit, or a vehicle is present as early as 100 ms after the onset of a stimulus.

Vision feels fast. When you zap between channels on a television, you often have the impression that you know almost instantaneously what is being shown. You might, for example, spot that it is an episode of The Simpsons, especially if you are a fan of the show. Of course, that process of recognition cannot really be instantaneous—it takes time, and measuring precisely how long it takes to recognize an object or a scene can provide vital clues about the way in which computations are performed in the visual system. We know that the visual system has many levels, and that processing involves both feedforward connections and feedback connections between these different levels. But sorting out which computations can be performed on the first pass through the system, and which are those that require iterative processing, is a major challenge for neuroscience.

Over a decade ago, there were reports of differential event-related potential (ERP) responses that differentiated between photographs containing an animal target and a wide range of distractors at around 150 ms following stimulus onset (Thorpe et al., 1996). At the time, it seemed possible that this differential response might reflect processing using just a feedforward pass. However, over the years, is has become increasingly clear that information can be processed by the visual system even more quickly. As a result, it could well be that this differential activity at 150 ms might not represent the first responses in a particular structure, but may instead reflect changes in activation produced by feedback from other areas. For example, intracerebral recordings from the Frontal Eye Fields in humans have recently demonstrated that visual inputs can reach the frontal lobe in as little as 45–60 ms (Kirchner et al., 2009). This clearly leaves enough time for areas in the frontal lobe to be involved in modulating responses in posterior regions (see for example Bar et al., 2006). A paper in this edition of *Neuron* puts some hard numbers on the time taken for the human visual system to extract information about object category (Liu et al., 2009). The results, based on intracerebral recordings from epileptic patients undergoing investigation prior to surgery, show clearly that category-related information is present in the responses of areas in the ventral visual pathways from as little as 100 ms after stimulus onset.

Intracerebral recordings from epileptic patients have provided a wealth of fascinating information over the past decade. In particular, single-unit recording studies from temporal lobe structures such as the hippocampus have revealed the existence of neurons that can respond in a remarkably invariant way to photographs of particular individuals that are well known to the patient—the famous ''Jennifer Anniston'' cell being a particularly well-known example (Quiroga et al., 2005). A more recent study described a cell that responded when the patient watched a short sequence from an episode of the Simpsons (!). Remarkably, the same cell would also respond when the patient was asked to recall what they had seen, in other words, even when the stimulus itself was no longer physically present (Gelbard-Sagiv et al., 2008). Such selectivity is truly remarkable, but it is important to realize that the response latency of these hippocampal neurons is relatively long, often 300 ms or more, and rarely earlier than about 200 ms (Mormann et al., 2008).

Nevertheless, there is increasing evidence that the cortical areas providing inputs to temporal lobe structures also have information useful for categorizing and identifying objects, even though we don't yet have as much single-unit data from human cortical areas as for structures in the medial temporal lobe. Some of the evidence comes from studies that have used sophisticated classification techniques to see whether the pattern of activation across voxels in an fMRI study can be used to determine the type of stimulus being presented (for a recent example, see Weber et al., 2009). Similar methods can also be applied to single-unit recording data. For example, another recent study analyzed the responses of several hundred neurons in monkey inferotemporal cortex to over 1000 different photographs and demonstrated that the pattern of activity across the population can be used to derive quite detailed information about the type of stimulus presented (Kiani et al., 2007). Interestingly, it appears that there are close parallels between the way in which category-related information can be read out from fMRI voxels in humans, and single-unit recordings from monkeys (Kriegeskorte et al., 2008). However, it is important to realize that none of these studies looked at the temporal aspects of the response, and therefore cannot provide insights about whether or not category-related information can be extracted using just the initial wave of processing.

One early study that attempted to answer such questions looked in detail at the responses of view-dependent face- and head-selective cells in inferotemporal cortex (IT) and found that the very start of the responses was already selective (Oram and Perrett, 1992), a result that is a hallmark of feedforward processing. More recently, another study looked in more detail at how information can be read out rapidly from IT cells (Hung et al., 2005), and yet another study looked at how the pattern of local field potentials can be used to extract information about object identity (Kreiman et al., 2006). But the study published in the current issue of *Neuron* is the first to apply this same sort of approach to recordings made in humans. A key feature of such work is that the authors are particularly interested is seeing how much information can be extracted from data from a single trial, rather than averaging data across a whole session, the approach that has been used almost exclusively until recently.

Another important feature of the study is that the authors not only looked for information about object category in the neural responses, but were also keen to learn whether the information could still be extracted in the face of variations in the size and 3D orientation of the object. This is a very important point, because recent work in computer vision has shown that it can be disarmingly easy to train a system to categorize standard benchmark image sets such as the CalTech 101 image database. For example, it was recently demonstrated that if you use stimuli that are too simple, it is possible to train a classifier using just the outputs of neurons at the first stage of cortical processing, i.e., V1, and still get reasonable performance (Pinto et al., 2008). The problem is that a good algorithm can find ways to categorize images using ''tricks'' that may have little to do with the way in which humans categorize objects. Lui et al. attempted to avoid this problem by training their classifier using images at one scale or 3D view, and then testing the classifier on a different scale or view. Reassuringly, the classifier was quite good at coping with such changes, suggesting that the human visual system can rapidly generate responses that can be remarkably robust to variations in size and viewing angle.

But there are other reasons for believing that neural activity well before the 150 ms time frame can be useful for encoding the category of a stimulus. One is the fact that, in humans, behavioral responses can be seen that are category selective well before this time. Specifically, when two images are flashed left and right of fixation, subjects can make statistically reliable saccades in the direction of the animal as early as 120–130 ms after the onset of the stimulus (Kirchner and Thorpe, 2006). Clearly, if the eyes can start to move so quickly, something must have happened in the brain before this time. The results of Liu et al. show that as early as 100 ms, there are indeed clear category-selective responses—just as would be needed to help orient very fast saccades in the direction of important categories of stimulus.

In the end, it is clear that our ability to decide rapidly in real time whether an important stimulus such as an animal or another human is present is vital for survival. By testing the ability of classification algorithms to make decisions on the basis of neural activity on a single trial, Liu et al. are effectively challenging the visual system with the same sort of challenge that has been a major force in the evolution of our sensory systems. Unlike experimentalists who try to see whether information is present in the activity of a brain region over a block of trials, the brain has to make decisions as quickly and as reliably as possible, and on the basis of data present on a single trial. This is precisely the type of problem that this study attempts to address.

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