[Note. One general advantage of putting together these methods sections and making all of the analysis decisions is that we can do this in advance of collecting data from additional monkeys. What I like about that is that it protects us against data mining. I’m not sure how much the rest of the field worries about that in Neuroscience; it is becoming a big concern in some areas of Psychology (more social and cognitive than perception) where it basically turns out that many published results fail to replicate. The physicists are also big on this, particularly in particle physics. Anyway, it seems like we have the opportunity to specify fairly precisely and in advance how we are going to do the analysis of the next data sets, and this seems attractive.]

[Note. We will probably setting on ‘no shadow’ and ‘shadow’ rather than ‘paint’ and ‘shadow’. Need to modify text here and in the psychophysics document to reflect this usage once we finalize.]

**Decoding Methods**

The data from any session consist of responses on each electrode to paint and shadow images with varying probe luminances. These included a blank (no probe) and probe luminances between 0.05 and 1.00 in steps of 0.05.

[Note for Doug: Description of electrodes, stimulus presentation times, image locations and sizes, actual stimulus luminance (i.e. luminance corresponding to 1), when spikes were recorded after the stimulus, how ‘good’ electrodes/trials were defined for each session, and spike sorting method needed here. Also please check that I’m correct about the set of probe luminances used.

Monitor pixels per inch ~61.105. Distance to monitor ~54 cm.

Stimulus size is data files is the length of one side of the checkerboard in pixels

Stimulus position in data files is in pixels, in the following coordinate system:

Position is center of checkerboard.

[0,0] is center of screen.

Positive X values are to the right of fixation (from monkey’s viewpoint)

Positive Y values are above fixation (from monkey’s viewpoint)

We analyzed sessions in which there were at least 20 paint trials and 20 shadow trials. The average number of trials per session that was analyzed was XX (paint) and YY (shadow).

[Note for DB. Modify program to compute these averages. In the final paper we are likely to have multiple experiments (different context images studied and some of these facts about number of trials, number of electrodes, etc. might best go into a table.]

We excluded from the analysis trials with no probe or a probe luminance less than that of the local surround of the probe (that is, we excluded decrements). These latter were probe luminances of 0.05, 0.10, 0.15. It is well-known that increments and decrements are represented by separate sets of neurons at early stages of the visual pathways (ON and OFF pathways), and we sought to avoid complexity that would be introduced by trying to decode incremental and decremental stimuli with a single decoder.

[Note. This is an analysis design decision. I suppose we could also look at the decrements, or try to show some electrodes where decrements behaved really differently from increments in supplemental material.]

Thus for each trial the data consist of a probe luminance, whether the context image was paint or shadow, and the response on each good electrode for that trial. Let be a column vector with length equal to the number trials analyzed (). Both paint and shadow context image trials were included together in . Let be a matrix with  rows and one column for each electrode (). We asked how well we could decode probe luminance from the electrode responses using affine regression. That is, we sought weights  for each electrode and an additive constant  that provided the best least-squares fit to the equation



To minimize the possibility of over-fitting, in practice we used a leave one out (LOO) procedure to determine the decoded luminance for each trial. Let  be the probe luminance on the  trial (that is, the  entry of ) and let  and  be the luminance vector and response matrix with the row for the  trial excluded. For each trial  we found weights  and additive constant  as the least squares solution to the equation



We then took the predicted luminance for the  trial as



where  is the  row of the response matrix  (that is, the  row vector containing the responses on the  trial.)

[Note. There are a couple of analysis decisions here. i) One could leave out probe levels rather than trials, for example. I have this implemented and when I last explored it I thought the main effect was to make the analysis noisier. ii) There are non-linear regression methods that one could consider. I played around with some of these when we started but didn’t manage to produce anything that led to substantially improved decoding. I think linear has the advantage of simplicity. iii) We’ve settled on decoding probe luminance from both shadow and paint images, rather than developing the decoder for one and then decoding the other. I think this is sensible as it pushes against finding an effect and is thus conservative. We may want to show the result of the other in supplemental material, to make the point that the basic features of the decoding don’t change between shadow and paint. That is, a decoder based on the paint data will do a good job of decoding the shadow data and vice-versa.]

Decoding Figure 1 shows the results of the decoding process for four sessions, two from V1 and two from V4. [I have in mind here a figure like the top right of the poster. Need to modify program so that axes say luminance rather than intensity, and so that scale is 0-1 not 0-100.] On the left side of each of the four panels is a plot of the decoded luminance for each probe level versus the actual probe luminance. Although the paint and shadow context images were decoded together, the decoding is plotted separately for the two types of context images. Each point (paint in green, shadow in black) shows data for one probe luminance/context image trail type. [Change plot color convention to match the summary plots, where paint is black and shadow is red.] The plotted points are the mean of all trials of that type, and the error bars show +/- 1 SEM. The figure shows that for these sessions, the decoding is reasonably effective both in V1 and V4: the decoded luminance increases systematically with the probe luminance. The quality of the decoding can be summarized for each context image by the range of the decoded probe luminances for paint and shadow (maximum decoded luminance minus minimum decoded luminance). These decoded luminances are provided in each plot.

[Note. I take decoded luminance as the full range (max decoded – min decoded), not the difference between the decoded luminance for max and min probe luminance. These two measures will agree when the decoding is monotonic, and in practice are probably quite similar. We could do it the other way, or take the range of the fits, which are constrained to be monotonically increasing.]

We fit the decoded luminances separately for paint and shadow trials with a smooth monotonically increasing function of the form



where  is the cumulative distribution function of the beta distribution,  were the parameters of the beta, and  were scalar parameters. The parameters were chosen by numerical search to minimize the squared error between the fit and the decoded luminances. The fits are shown by the smooth lines in Decoding Figure 1.

[Note. There are many possible functional forms we could use to fit the data. I choose the betacdf after some screwing around. It has the nice feature that it maps the domain [0-1] onto the range [0-1] and that it is guaranteed to be monotonically increasing. There are parameter choices for which it is linear, and it can also capture saturation. I have not done any formal analysis of the quality of fit, but I think it is OK for present purposes.]

To relate the psychophysics and the physiology, we need a method for comparing the two data sets. The psychophysical data is conveniently summarized as shown above in Figure Y, which plots the luminance of probes seen in the shadow context image against the luminance of perceptually matched probes seen in the paint context image. We can represent the decoded luminances in a similar format. For a series of decoded luminance levels , we invert the smooth fits and obtain corresponding probe luminances  (for probes in the no shadow context) and  (for probes in the shadow context). The inversion is given analytically by

.

In the actual code, however, we do it numerically. [Maybe we should change this, but numerically works with any function we decide to fit through the decoded intensities.]

We then connect the physiology to the psychophysics via the linking assumption that probe luminances in their respective contexts that decode to the same luminance would appear to have the same lightness if judged psychophysically. Thus we plot  against , as shown Decoding Figure 2 for the same four example decodings shown in Decoding Figure 1. This produces a representation that is commensurate with Figure Y. As in the case of the psychophysical data, we summarize the shadow/no shadow effect on lightness by the intercept of a line of unity slope fit to the  versus  plot. To match the probe luminance range 0.25 to 0.75 that was fit in analyzing the psychophysical data, we chose six levels of  that led to values of of 0.25 0.35, 0.45, 0.55, and 0.65, and 0.75. For some sessions, the range of probe intensity values where the fit beta cumulative distribution had overlapping output for paint and shadow did not include some of these choices of , when the fit was computed over the probe intensity domain 0.20 to 1.00 used to produce the fit to the decoded luminances. For such  it was not possible to determine both and , and thus such were not used in fits to determine the intercept.

[Note. There are a number of analysis choices here. We could extrapolate the fits (a bad idea, I think). We could use a different choice of . In the psychophysics, levels of 0.25, 0.50, and 0.75 are always included. Other levels are included if the PSE for the case where the test probe is in the shadow image fall in the range 0.25 to 0.75. I tend to think this choice is as reasonable as anything.]

Given this analysis, we can compare directly the intercepts obtained for recordings in V1, for recordings in V4, and from the psychophysics. Decoding Figure 3 summarizes this comparison. [Need to write a description of this summary figure.]

We can also look at how the decoded range varies with session as well as how the intercepts vary with the decoded range. This is shown in Decoding Figure 4. There is a hint of a relation for V4, and maybe in the opposite direction for V1. [I don’t think we should make much of this given the amount of data that we have, but we might keep an eye on it as we move forward. Note that the difference between paint and shadow inferred matches at the discrete points is the same as the intercept, so this figure is commensurate on the y-axis with that shown in Decoding Figure 3. If we fit a slope and intercept, then they would diverge as measures.]

We constructed decoders based on the best single electrode and best two electrodes, with the figure of merit being to maximize the average (over paint and shadow) decoded range. Decoding Figure 5 shows the results. The left panels show the decoded range over session. Comparison with Decoding Figure 4A makes clear that one or two electrodes do not do nearly as well in terms of decoding intensity, at least when measured in this way. The right hand panels in Decoding Figure 5 show that the trend towards the psychophysical effect remains present when we analyze the inferred match difference (aka intercept) for the subset of sessions that decode above criterion 0.2 with one or two electrodes. With the small number of sessions meeting this criterion for a single electrode, the effect is pretty weak. It seems clear enough for the two electrode case. I didn’t do any statistics.

[Note: My code seems to contain options for additional analysis:

• Plots of weights against electrode number. Can try to understand how distributed the information is. ]

[Note: Other analyses we could do:

• How effectively can we classify no shadow versus shadow, independent of probe luminance?

• Analysis looking at RF properties in V1 and V4 and trying to link these to the decoding.

**Control Analyses**

See ShuffleAnalysis.doc for write-up of some shuffling controls.