Saliency and saccade encoding in the frontal eye field during natural scene search

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SUPPLEMENTARY MATERIAL

Supplementary Text and Figures

Description of IK-Saliency algorithm and generalized linear model

We considered IK-saliency (Itti L and C Koch 2000; Walther D and C Koch 2006) as our definition of saliency. This is a bottom-up definition of saliency, i.e. based only on basic image features, independent of task objectives (see **Sup. Fig. S1A**): (a) A total of 7 vision features (color channels tuned to red/green and blue/yellow hues, four orientations and brightness) are computed; (b) Each is computed at several different spatial scales using Gaussian pyramids as linear filters which consist of progressively low-pass filtering and subsampling; (c) This is followed by center surround differences across spatial scales, which compute local spatial contrast in each feature generating 6 maps for each feature - a total of 42 maps; (d) Non-linear iterative lateral inhibition incorporates center surround competition within each map. This iterative scheme uses Differences-of-Gaussians followed by a negative shift and half-wave rectification in order to suppress areas that are balanced in terms "excitation" and "inhibition" (with values near zero after the Differences-if-Gaussians is applied) and set every pixel to a non-negative value; (e) After competition, feature maps are combined into a single conspicuity map for each of the 3 feature types (color, intensity and

orientation) and step d) - center surround competition - is repeated for each of the three conspicuity maps; (f) The three conspicuity maps are finally summed into the single map, the saliency map. We used the publicly available toolbox (http://www.saliencytoolbox.net/index.html (Walther D and C Koch 2006)) for computing IK-saliency for each image with the default parameter values and considered the three, equally-weighted, channels: color, intensity and orientation.
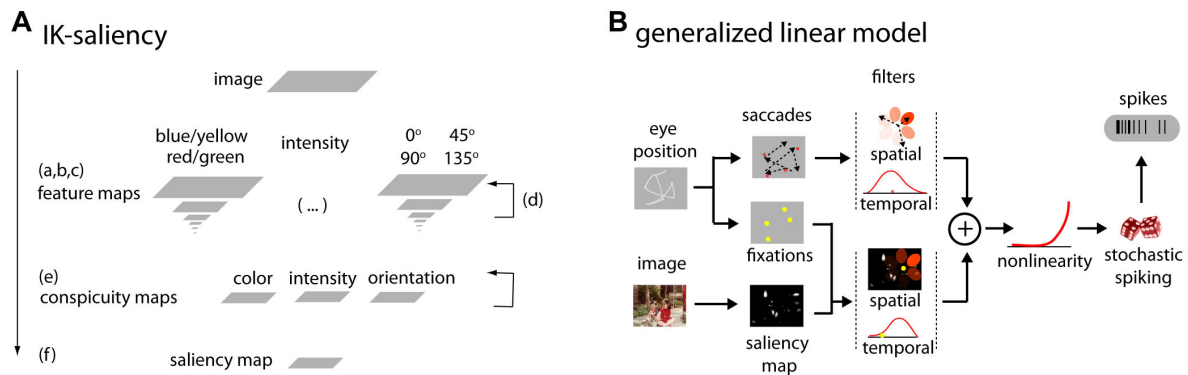

Figure S1. IK-saliency and generative model. (*A*) IK-saliency algorith. Scheme of the several steps of the the computation of IK-saliency (see description in the text above). (*B*) Generative model. We assume that the firing rate of the neuron depends on eye movement (saccades) and/or on the saliency of the image surrounding the fixation point. Each neuron has a preferred direction for saccade and a preferred direction for saliency. Also, each neuron has a temporal reaction to saccades and another one for saliencies that are centered on saccade onset and fixation onset respectively. We assume that the spiking activity is Poisson generated from the firing rate.

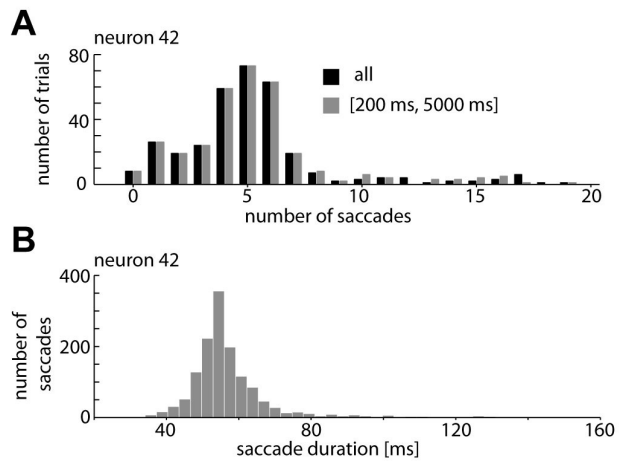*Saccade statistics and saccade modulation*

Figure S2. Saccade statistics. *(A)* Distribution of the number of saccades for the trials of one of the example neurons (neuron 42) using all the data (black) or only the saccades that we considered (grey; the ones in the interval [200 ms, 5000 ms]). *(B)* Variability in saccade duration. Histogram of saccade durations for the eye movements during the trials for neuron 42. This variability could be the reason why, even for neurons only encode saccade, the saccade only model fails to completely explain away the joint model (see Fig 5A,B, center panels and Supp. Fig. S4).

Saccade PSTH for example neuron number 42

For completeness we show the PSTH centered at saccade onset for neuron 42 (see Supp. Fig. S3), the example neuron in Figures 4A, B and 5C.
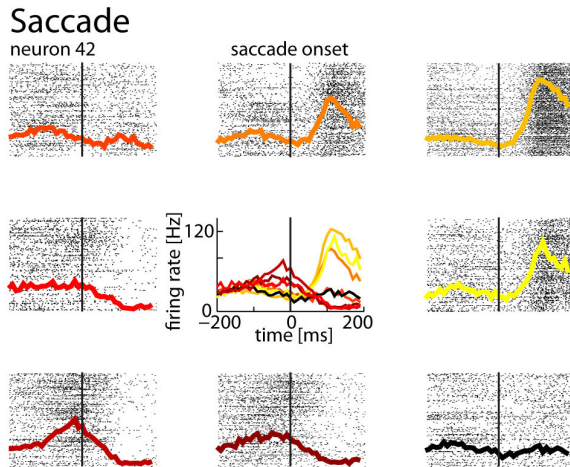

Figure S3. Saccade PSTH for neuron 42. Rasters sorted by direction of saccade, centered on saccade onset and the correspondent peri-stimulus time histograms (PSTHs) for neuron 42 from Fig. 4A, B and Fig. 5C.

Full-saccade model doesn't explain away saccade spatial modulation at end of saccade

We tested an extra model - the *complete saccade* model- similar to the joint model but with saccade direction modulation at end of saccade/beginning of fixation instead of saliency modulation. We then computed the relative pseudo R^2 of the complete saccade model relative to the full saccade model and observed that the full saccade model does not completely explain away the direction of saccade modulation at end of saccade/beginning of fixation. In other words, saccade direction information at end of saccade adds predictive power to the model. This suggests that saccade duration variability (see Supp. Fig. S2B) is what prevents the saccade model from completely explaining away the joint model.
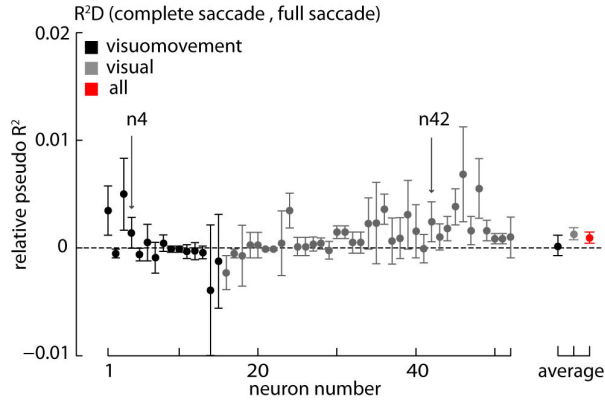
Figure S4. Predictive power of end of saccade modulation terms. Relative pseudo R^2 between the complete saccade model and the full saccade model (±2SEM, 10-fold cross-validation for each individual neuron; 95% bootstrap confidence intervals for the averages across the recorded population and subpopulations). Arrows signal neurons 4 and 42, the example neurons of Figures 3 and 4 respectively.

Robustness of explaining away to changes in the parameters

We tested the robustness of our results to changes in the parameters of the models, specifically to width and number of basis functions that parameterize the temporal responses. We also tested whether centering (subtracting the mean) or smoothing (low-pass filtering) the IK-saliency definition had any influence in the conclusions of our analysis. We find that our results are robust to all these changes (see Supp. Fig. S5).
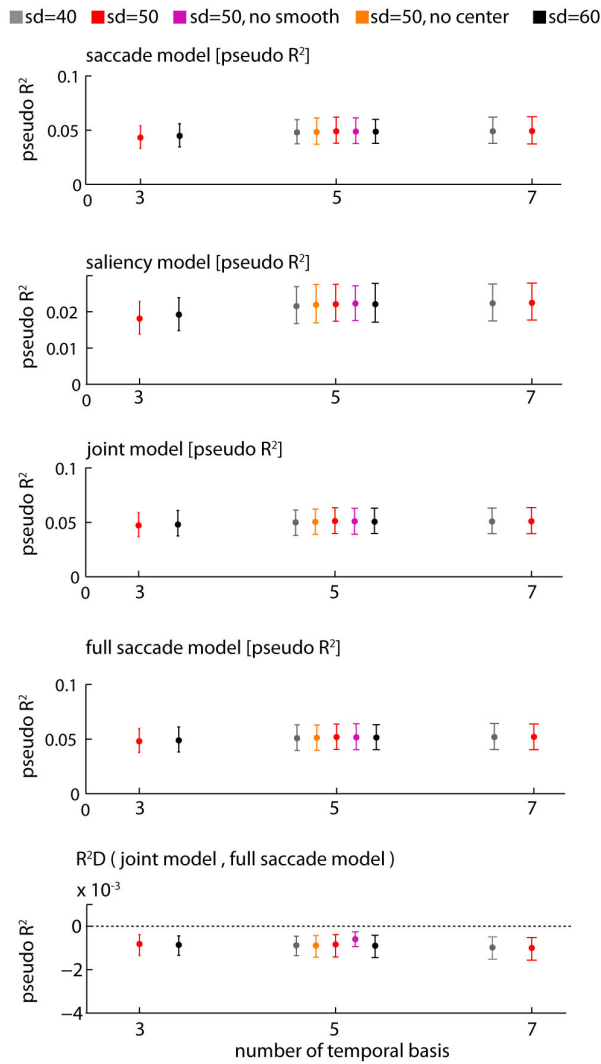
Figure S5. Robusteness of expaining away to change in some of the parameters. Pseudo R^2 for the saccade, saliency, joint and full saccade models and relative pseudo R^2 between the joint model and the full saccade model (95% confidence intervals, bootstrap across neurons). We considered not smoothing or not centering the IK-saliency definition and also several values for the parametrization of the temporal receptive fields, namely the number and standard deviation of the temporal basis functions.