

Supportive material for *Predictive encoding of moving target trajectory by neurons in the parabigeminal nucleus*, published in the Journal of Neurophysiology, 2013.

Rui Ma, He Cui, Sang-Hun Lee, Thomas J. Anastasio, and Joseph G. Malpeli

Section A: Comparison of response functions with and without saccades

It is challenging to find differences between corresponding panels of the following two figures. The similarities between the two figures result from two factors. First, only a small fraction of spikes occurred during saccadic intervals. Second, PBN cells compensate for changes in retinal target location due to saccades in about 60 ms, which corresponds to a target displacement of only 0.36 deg for the following data.

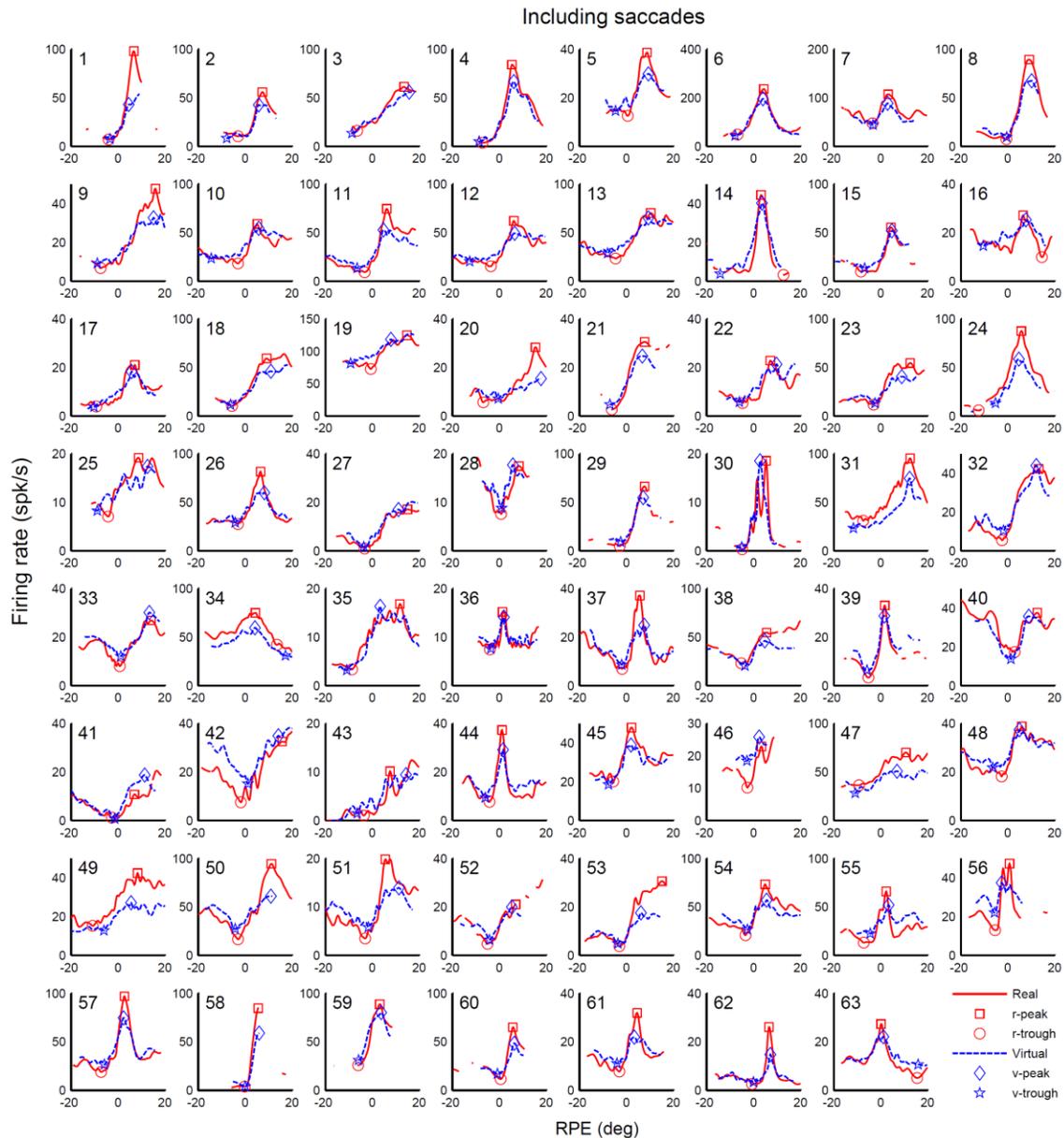


Figure. 1 Response functions for real and virtual targets, calculated for full spike trains (i.e., including saccades), plotted separately for each cell. Assigned peaks and troughs marked as indicated in legend. Panel 6 shows the response functions for the example cell of Fig. 3, 4 & 5 in Ma et al. (2013).

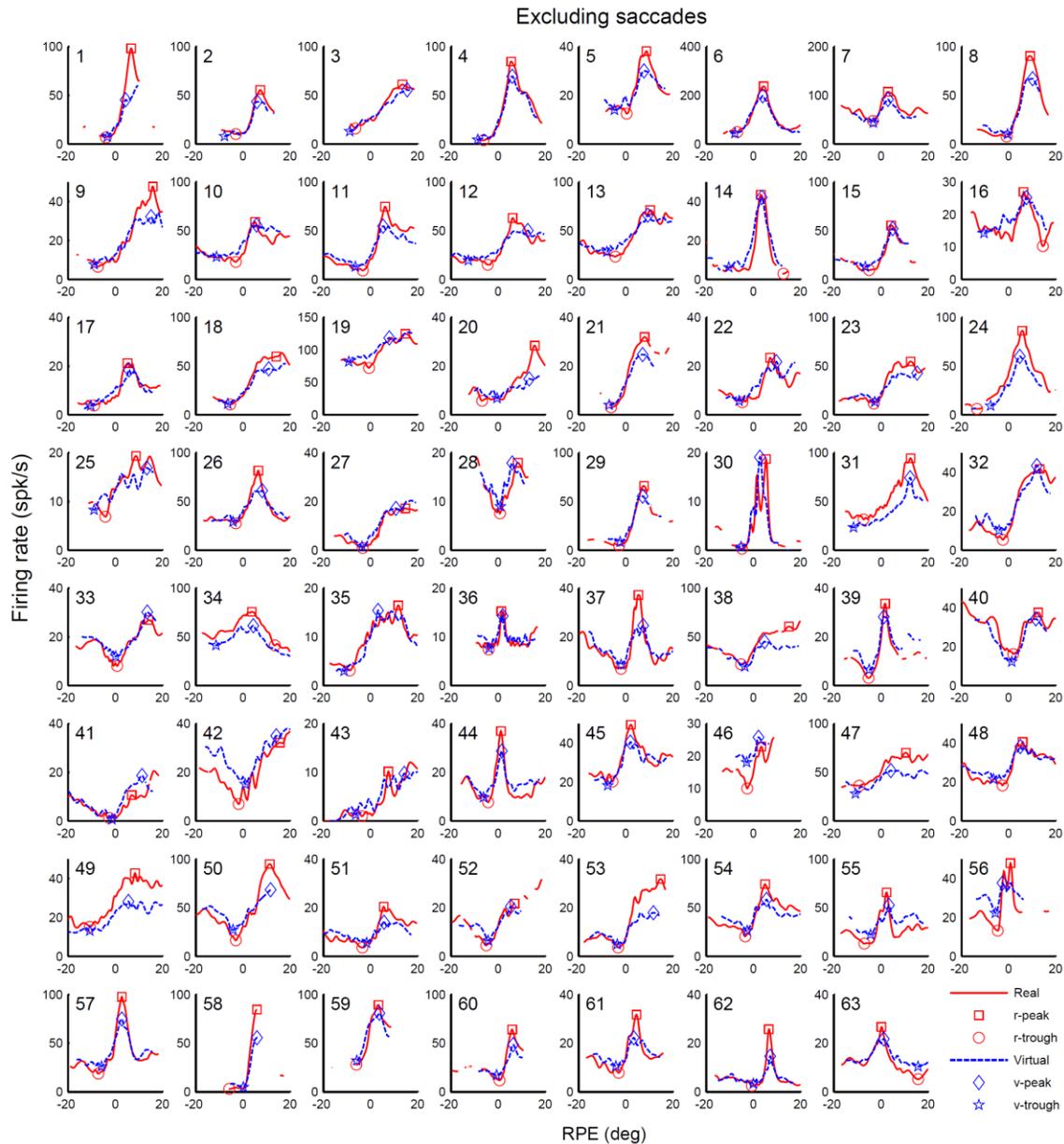


Figure 2. Response functions for real and virtual targets, calculated from inter-saccadic periods, plotted separately for each cell. Assigned peaks and troughs marked as indicated in legend. Panel 6 shows the response functions for the example cell of Fig. 3, 4 & 5 in Ma et al. (2013). A cell-by-cell comparison with Fig. 1 reveals few differences between response functions calculated with and without saccades.

Section B: Response functions for real targets analyzed separately for ipsiversive and contraversive directions of motion

Here we evaluate the assumption that the response functions of PBN cells are the same for targets moving in opposite direction. This is equivalent to assuming that the primary determinant of PBN activity is target position on the retina (i.e., RPE), and that retinal slip velocity per se does not play an important role. As reported in Results, the average gain of smooth pursuit was about 0.3 deg (0.25 and 0.33 deg/s

for real and virtual targets, respectively). Since the targets moved at a constant speed of 6 deg/s, between saccades the eye followed the target at an average speed of 1.8 deg/s, for an average retinal slip speed of 4.2 deg/s. However, although the speed of retinal slip was the same for ipsiversive and contraversive tracking, the direction of slip was the opposite: +4.2 deg/s versus -4.2 deg/s, for an average difference in retinal slip velocity of 8.4 deg/s. Consequently, if retinal slip velocity, independent of RPE, is an important determinant of PBN activity, then response functions should differ substantially for ipsiversive and contraversive directions of stimulus motion. No such difference is apparent when the response functions for real and virtual targets are separately calculated for ipsiversive and contraversive motion, as can be seen by examination of the individual response functions (Fig. 3 and 4 for real and virtual targets, respectively), or for response functions derived by summing activity across all cells (Ma et al., 2013, Fig. 7). Thus, although we cannot exclude some effect of retinal slip velocity per se on PBN responses, any contribution would appear to be secondary compared to that of retinal position error.

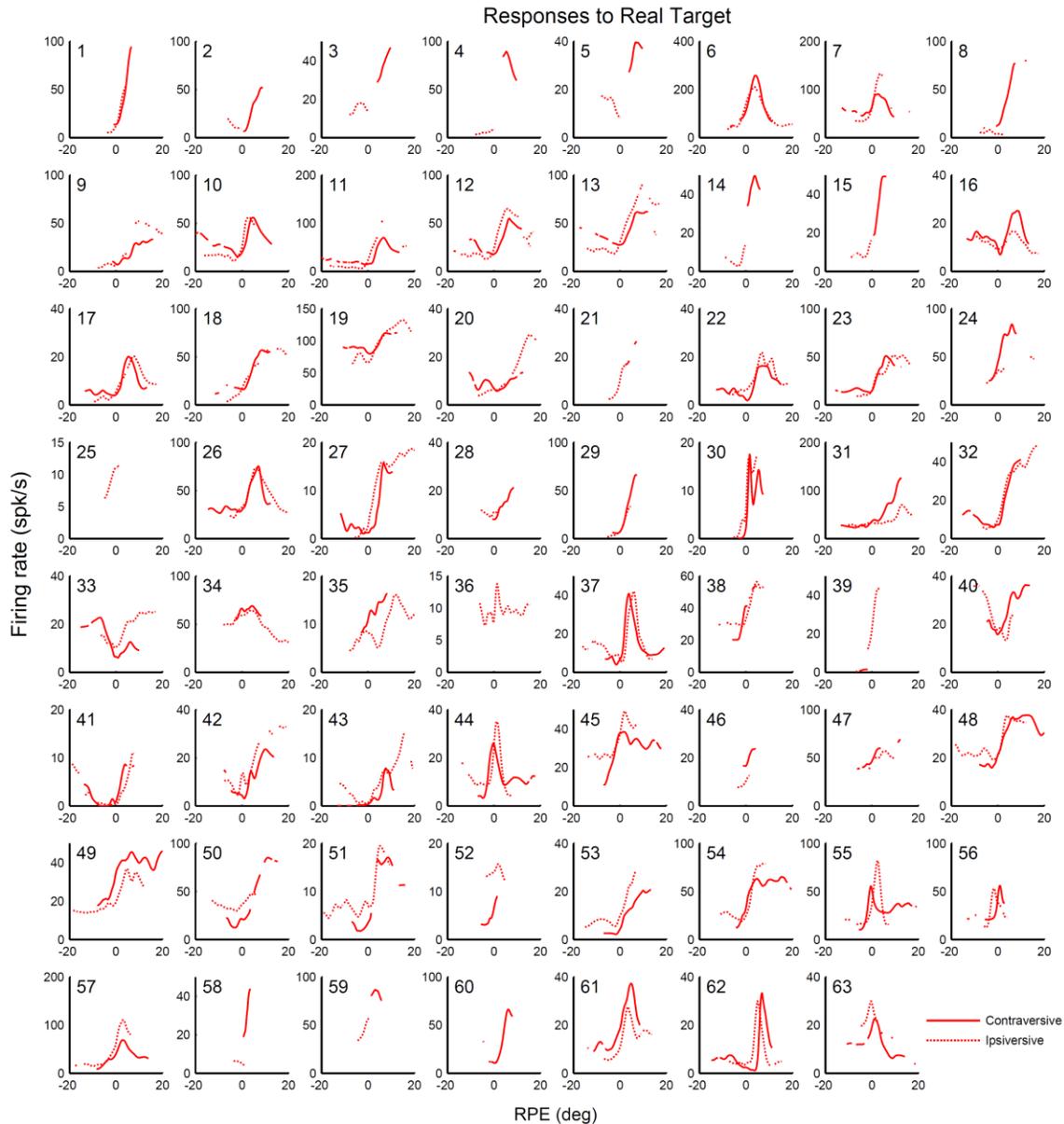


Figure 3. Response functions for real targets, calculated separately for contraversive (solid curves) and ipsiversive (dotted curves) target movements. Because the data set is cut in half for the separate analyses, response functions are considerably less complete and considerably noisier than those calculated from the full data set shown in Fig. 1 and Fig. 2.

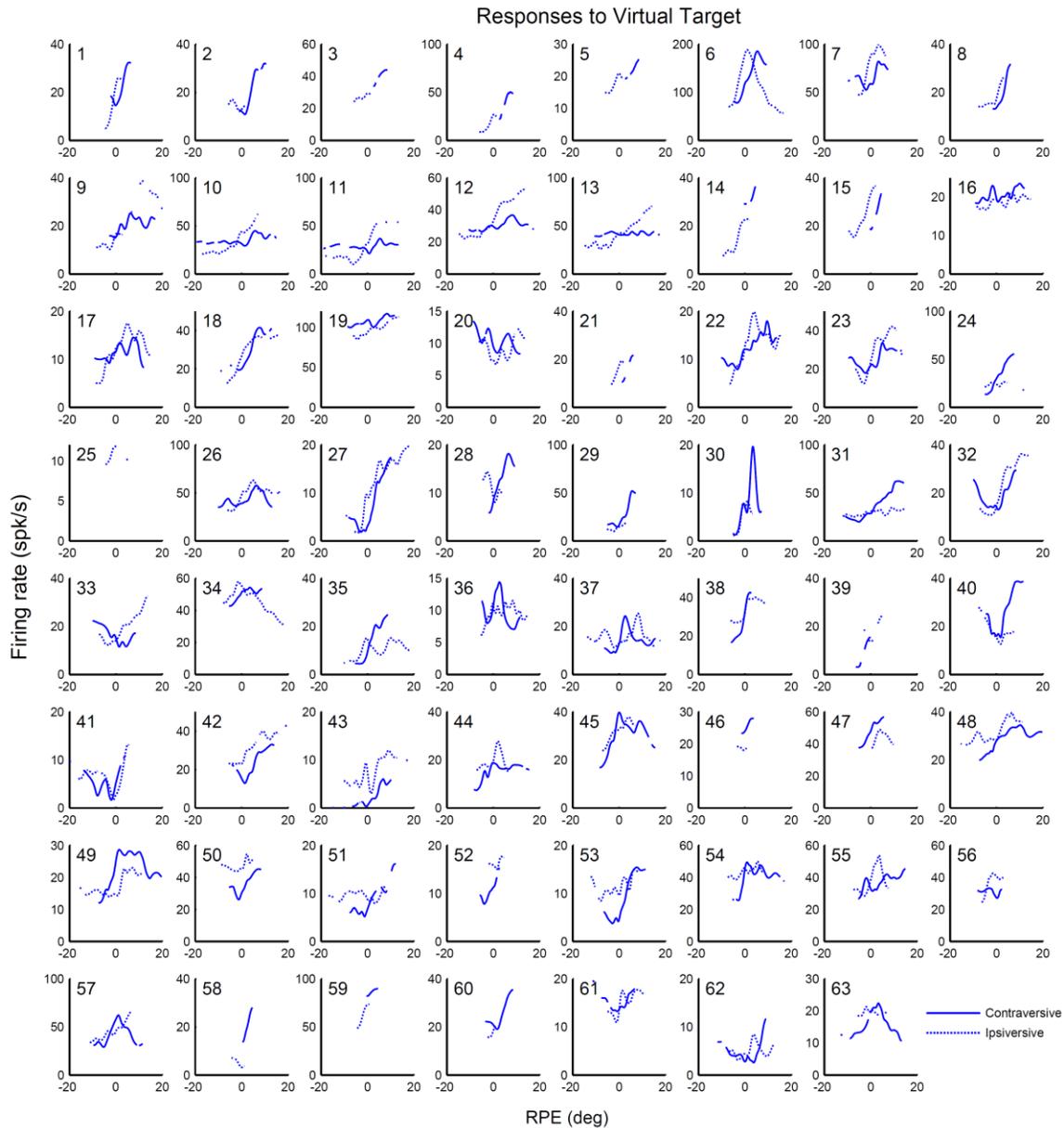


Figure 4. Response functions for virtual targets, calculated separately for contraversive (solid curves) and ipsiversive (dotted curves) target movements. Because responses to virtual targets are usually weaker than responses to real targets, these response functions are even noisier than those of Fig. 3. Still, where comparison between the two directions of tracking are possible, the differences are neither large nor of consistent direction.

Section C: Additional information on Bayesian simulations

This section is intended to additionally illustrate the model of PBN responses to real and virtual targets presented by Ma et al. (2013), relying more on graphic illustrations of relationships that are inherent to the model.

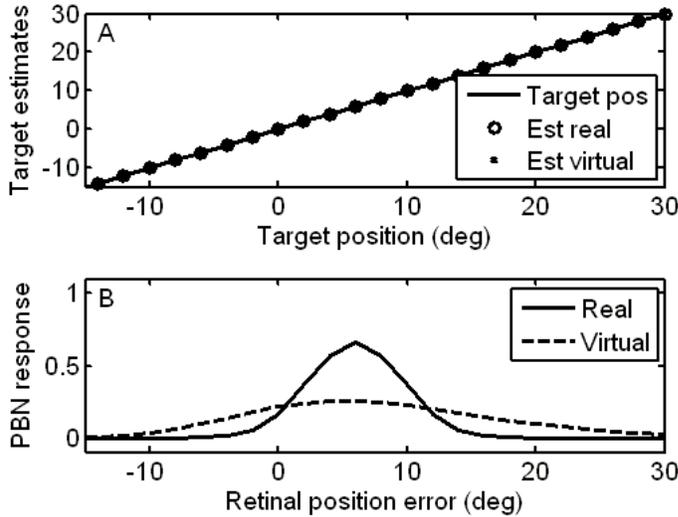


Figure 5. Estimates of target position using the Bayesian predictor-corrector model. (A) The simulated target (solid line) moves two deg per time step. At each time step, the model takes as its estimate of target position that position having the highest posterior target probability (see Eq. 3 in the main text). The model accurately estimates target position whether it is real (circles) or virtual (dots, which coincide with and so fall inside the circles). (B) The simulated PBN responses to real (solid curve) and virtual (dashed curve) targets are reproduced from Fig. 10 of Ma et al. (2013) for convenience.

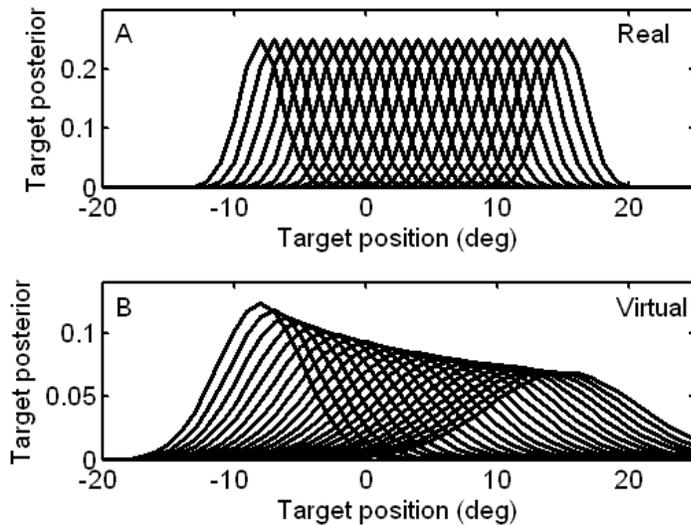


Figure 6. The target posterior probability distributions from the Bayesian predictor-corrector model at each time step for real (A) or virtual (B) targets. These posterior probabilities were used to compute the simulated PBN responses (Fig. 5B; Ma et al., 2013, Fig. 10). The variances of the Gaussians describing the sensory input (likelihood $P(V(t)|T(t))$) for the real target, and the internal model of target motion ($P(T(t)|T(t-1), S(t-1)=0)$) (see Ma et al., 2013, Eqs. 2-4), are 6 and 2 deg, respectively. For the real target

(A) the posterior distribution starts off with an observation of the real target, so its distribution is relatively sharply peaked (i.e., has a relatively small variance), and this peakedness is maintained as long as visual observation of the real target is available. For the virtual target (B) the initial posterior distribution is flattened (made less sharply peaked with a relatively larger variance) by the high variance of the uniform virtual target likelihood distribution. The predictor-corrector algorithm is run within a simulated environment that ranges from -160 to +160 deg, and the variance of the uniform distribution in this range is over 2,000 deg. Thus, the variance of the uniform distribution is larger by over two orders of magnitude than the variance of any of the Gaussians used in the simulations. As the virtual target moves, the peak of the posterior distribution follows it, but the variance of the posterior continually increases because the virtual target likelihood distribution remains uniform. For the virtual as compared with the real target, the variance of the posterior target probability distribution is higher, and consequently the peak values of the posterior probability are lower. Since the simulated PBN neuron response is computed as the sum of these posterior probabilities over its preferred target position (i.e., RPE) range (see Ma et al., 2013, Eq. 5), its response to the virtual target is lower within its preferred range but higher outside of it. However, the peaks of the virtual posterior distributions coincide with those of the real distributions. Since the model takes as its estimate of target position that position having the highest posterior probability, the target position estimate is the same for the virtual as for the real target (see Fig. 5A).