SUPPLEMENTARY MATERIAL
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# Probabilistic model of onset detection explains paradoxes in human time perception

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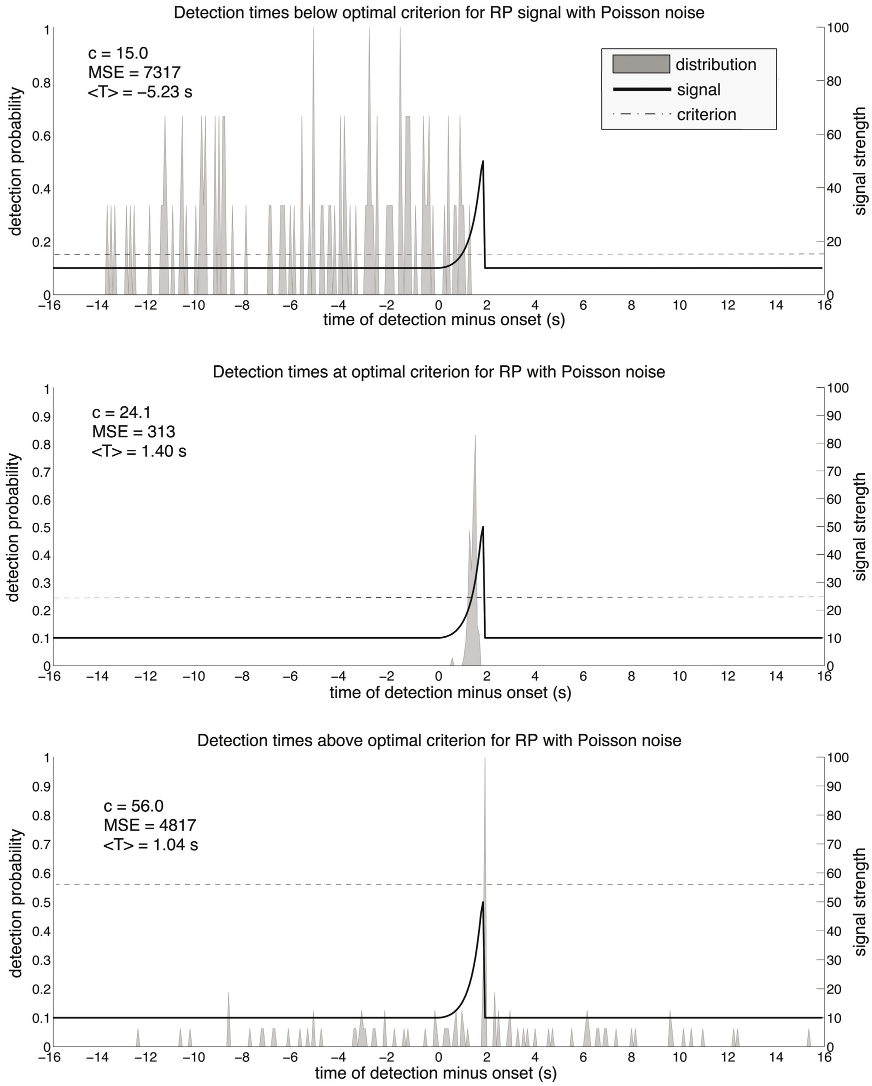


**FIGURE S1 | We performed detection independently at each time point on an RP signal with Poisson-like noise.** Unlike Gaussian noise, which has a constant variability, the variability of Poisson noise increases with strength of the signal. Each noisy sample was generated by sampling from a Poisson distribution with mean and variance equal to the noiseless sample. Because a signal of 0 would generate no noise and render the experiment trivial, we assumed a background signal of 10 Hz outside the stimulus interval, and a peak signal strength of 50 Hz during the interval. Detection time distributions are shown for criteria below, above and at the optimal criterion. As observed when performing detection independently at each time point, a low criterion mistakes the noise for a signal and results in premature detection, and a high criterion results in late detection or no detection at all. We performed 500 trials, in which the onset was varied uniformly at random.

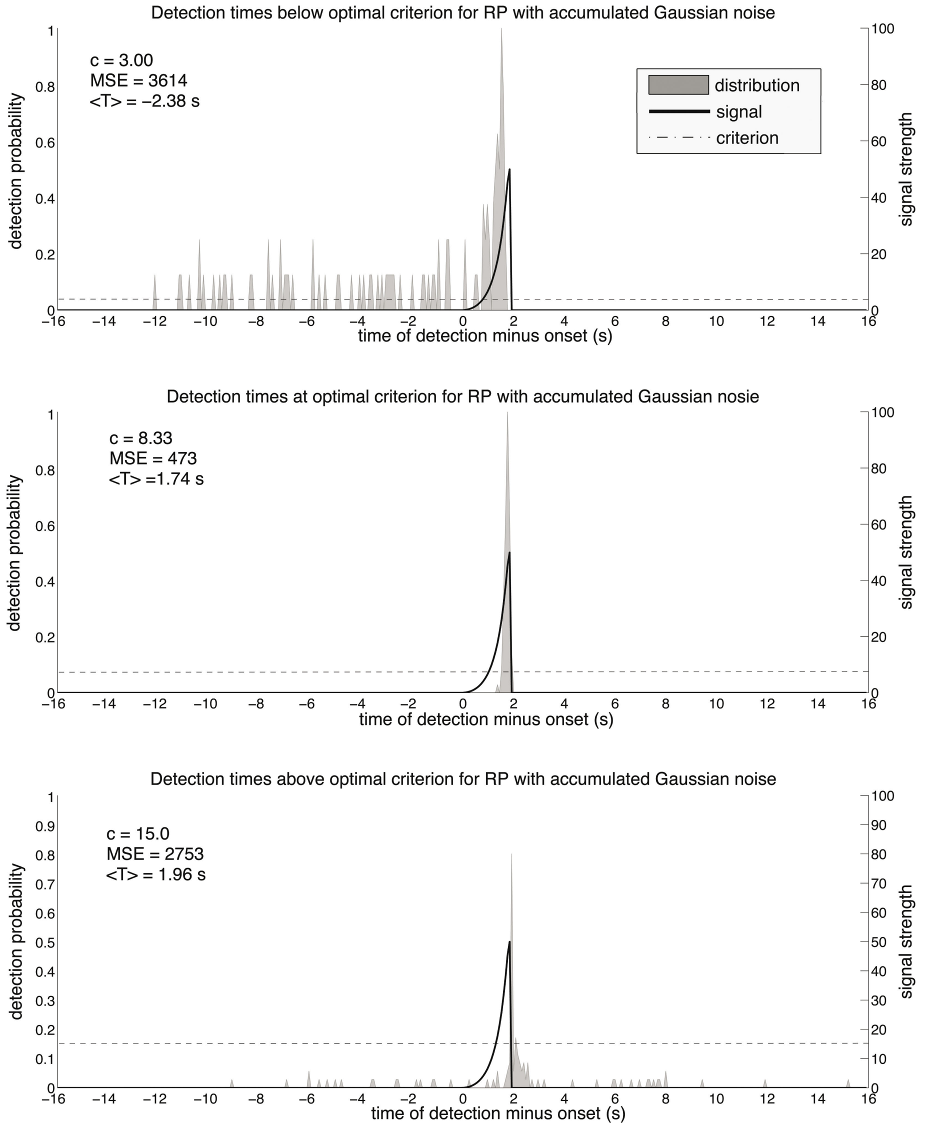


**FIGURE S2 | We used an evidence accumulation model (Ratcliff and McKoon, 2008) to perform detection of an RP signal with a peak strength of 50 Hz and additive Gaussian noise with a SD 10 Hz.** Evidence was accumulated using a window of size 20, i.e., detection was recorded when the mean of the last 20 samples exceeded the criterion. Detection time distributions are shown for criteria below, above and at the optimal criterion. As observed when performing detection independently at each time point, a low criterion mistakes the noise for a signal and results in premature detection, and a high criterion results in late detection or no detection at all. We performed 500 trials, in which the onset was varied uniformly at random.

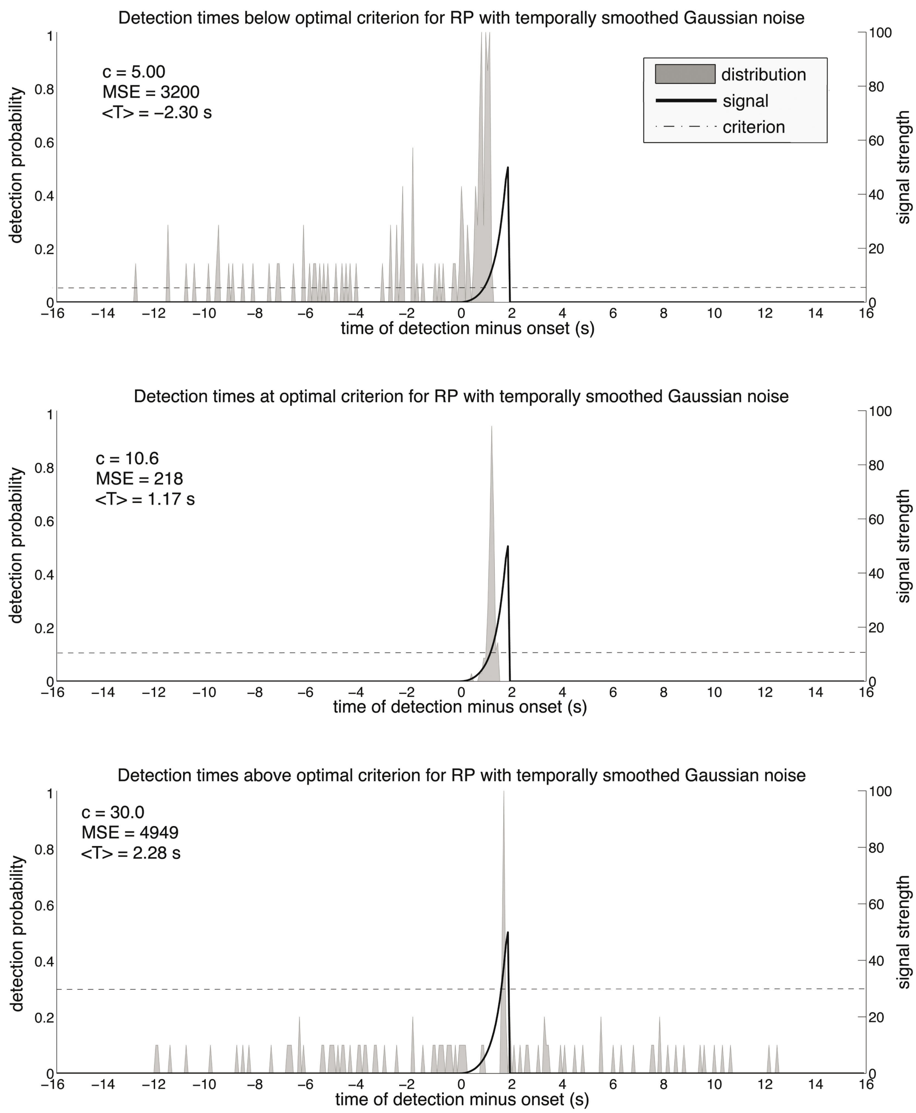


**FIGURE S3 | We used a temporal smoothing model (Rao et al., 2001) to perform detection of an RP signal with a peak strength of 50 Hz and additive Gaussian noise with a SD of 10 Hz**. Temporal smoothing was performed by computing a running correlation of the noisy signal with a centered Gaussian window with SD 0.25 s and a width of 6 SD. Detection was recorded whenever the correlation exceeded the criterion, but only reported retrospectively after all data contributing to the correlation was observed. Detection time distributions are shown for criteria below, above and at the optimal criterion. As observed when performing detection independently at each time point, a low criterion mistakes the noise for a signal and results in premature detection, and a high criterion results in late detection or no detection at all. We performed 500 trials, in which the onset was varied uniformly at random.

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