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Coding properties of spiking neurons: modeling reverse correlations.

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We analyze the reverse correlation function for a spiking neuron model of the integrate-and-fire type. Spikes are generated whenever the membrane potential crosses a threshold. After a spike the neuron passes through a period of refractoriness during which responsiveness is reduced. Two different types of noise are studied (1): a fast 'escape noise' where the instantaneous firing probability depends on the distance between the value of the membrane potential and the threshold; and a slow noise in the parameters where the value of the threshold or the amount of refractoriness changes after each spike. The theory of population dynamics that has been reconsidered recently (1; 2; 3; 4) (see also (5)), can be applied to calculate the average coding properties of a single neuron (6; 7). The coding properties can be demonstrated by a reverse-correlation measurement (6) that is similar in spirit to that of standard neurophysiological experiments. We show the dependence of reverse-correlation measurements upon neuronal parameters (such as the membrane time constant and the threshold) as well as on the type and amount of noise. Instead of studying reverse correlations, the theory allows us also to calculate 'forward' correlations, i.e., the effect of a single presynaptic input spike on the firing probability of the postsynaptic neuron (8). The theoretical results can be compared to the experimental cross-correlations results measured on motoneurons (9). The cross-correlation function between pre- and postsynaptic neurons is particularly interesting since it controls the effects of spike-time dependent Hebbian learning (10; 11; 12; 13; 14).

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