A Supporting Material

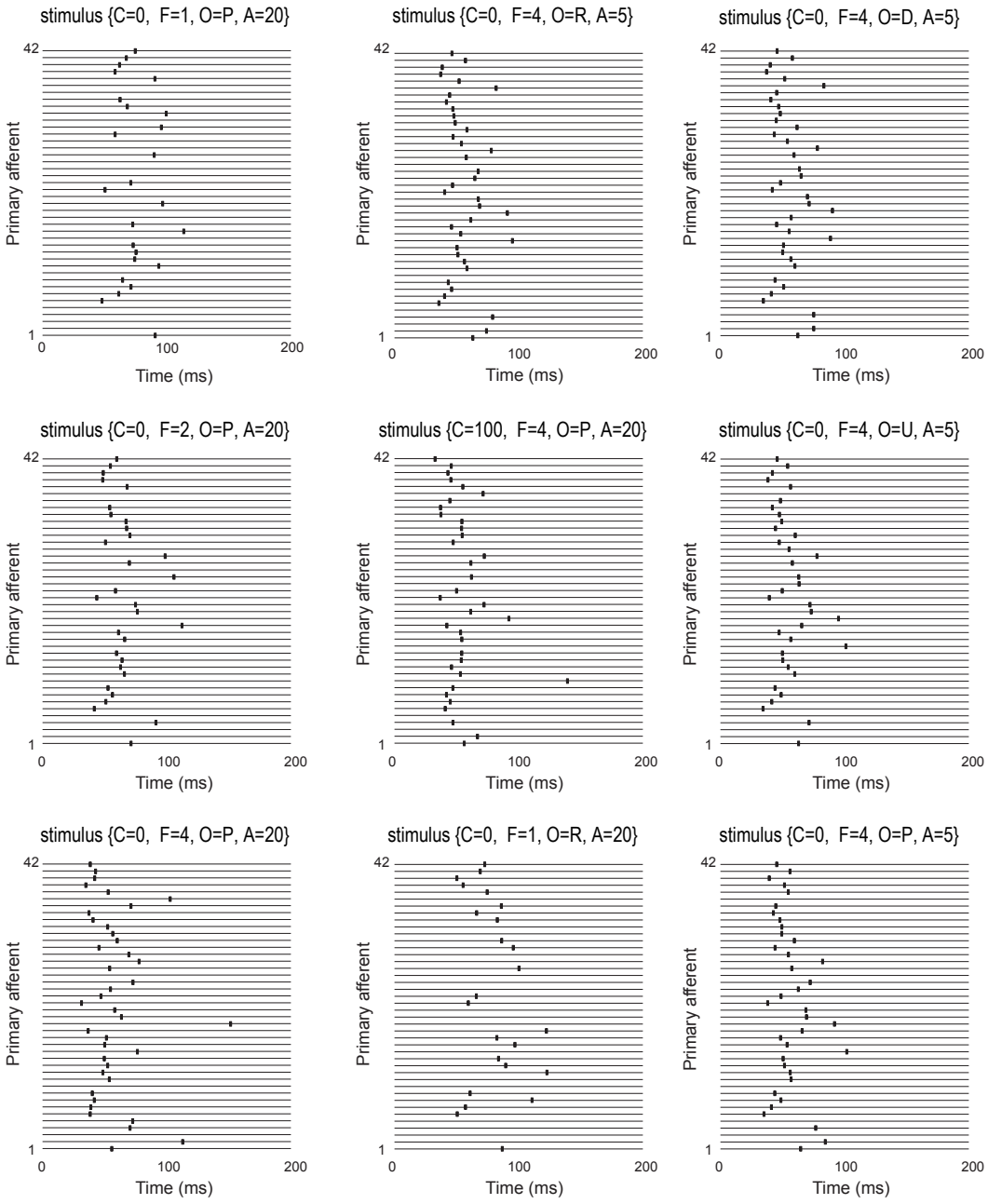

Figure S1. Examples of human microneurography recordings. Spike waves across 42 afferents evoked by 9 distinct tactile stimuli. The contact parameters are the curvature C, the force amplitude F, the orientation O and the angle A.

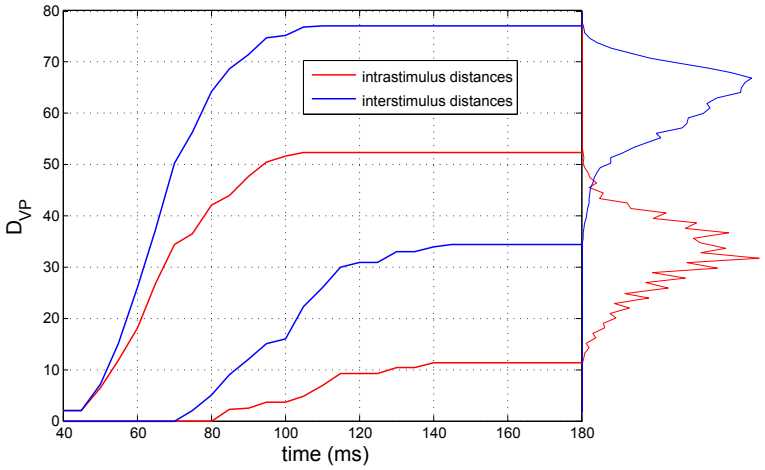

Figure S2. Example of intra- and inter-stimulus distances D_{VP} (red and blue curves, respectively) over time for a VP cost parameter $C_{VP} = 1.2$. The optimal discrimination condition is never met: the distributions of intra- and inter-stimulus distances always overlap (right plot).

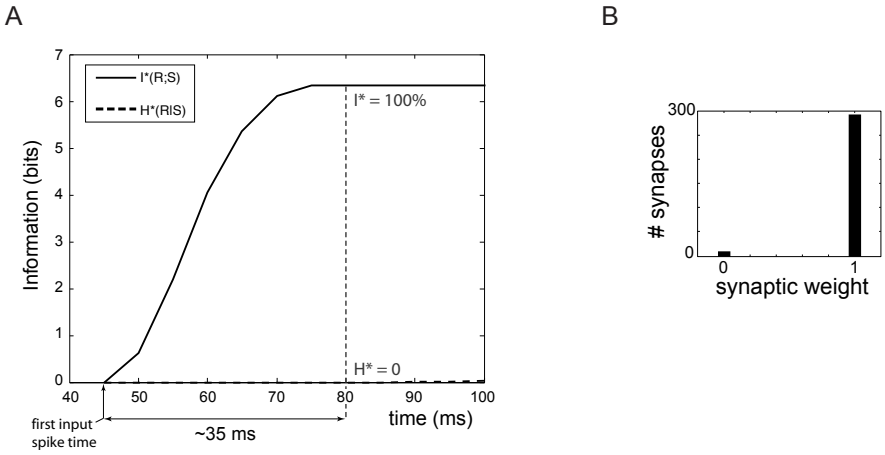

Figure S3. (A) Information $I^*(R;S)$ and conditional entropy $H^*(R|S)$ over time when using a classical STDP rule to train a CN network of 50 cells. The 81 tactile stimuli are presented 100 times each. Optimal discrimination is reached within 35 ms of the first afferent spike. (B) Distribution of CN synaptic weights after learning. 98% of the weights are set to 1 after traning.

A.1 Neuronal model

Single unit discharges at the level of the cuneate nucleus (CN) were modeled based on the spike-response model (SRM). The SRM formalism provides a linear probabilistic neuronal model, as opposed to the more classical integrate-and-fire model which is non-linear and deterministic. Compared to the Hodgkin-Huxley formalism, the SRM permits a higher transparency and controllability of all free parameters (e.g. synaptic integration time constant, amplitude and shape of excitatory post-synaptic potentials, and so on).

Let V denote the membrane potential of a SRM unit. If an input spike arrives at time t, the membrane potential undergoes a depolarization $\Delta V(t)$ whose time-course is stereotyped and taken as:

$$\Delta V(t) \propto \sqrt{t} \exp(-t/\tau) \tag{5}$$

where the free parameter τ determines the decay time constant of the EPSP (excitatory post-synaptic potential) of the neuron. We took $\tau = 7ms$ in our simulations.

If several afferent spikes excite the neuron within a short time window, then the EPSPs add linearly:

$$V(t) = V_r + \sum_{i,j} w_i \, \Delta V(t - \hat{t}_i^j) \tag{6}$$

where i denotes the pre-synaptic neurons, j indexes the spikes emitted by a pre-synaptic neuron i at times $\hat{t}_i^j$, $V_r = -65mV$ is the resting potential, and w_i indicates the synaptic weight of the projection from the pre-synaptic unit i, and it is defined as:

$$w_i = W \cdot w_i^{0,1} \tag{7}$$

where the factor W is the upper bound of the synaptic efficacy, and $w_i^{0,1}$ is constrained within the range $[0, 1]$. W was set to 20 mV in our simulations.

At each time step, a function $g(t)$ – that can be thought of as the instantaneous firing rate of the cell – is computed according to:

$$g(t) = r_0 \log\Big(1 + \exp(\frac{V(t) - V_0}{V_f})\Big) \tag{8}$$

where the constants $r_0 = 1Hz$, $V_0 = -60mV$, $V_f = 0.5mV$ are the spontaneous firing rate, the probabilistic threshold potential, and a gain factor, respectively.

The refractoriness property of the cell is modeled as a function $A(t)$:

$$A(t) = \frac{(t - \hat{t} - \tau_{abs})^2}{\tau_{rel}^2 + (t - \hat{t} - \tau_{abs})^2} \, \theta(t - \hat{t} - \tau_{abs}) \tag{9}$$

where τ_{abs} and τ_{rel} are the absolute and relative refractory periods, respectively, $\hat{t}$ is the time of the last spike emitted, and $\theta(t)$ is the Heaviside function. We used $\tau_{abs} = 6ms$ and $\tau_{rel} = 1ms$. The functions $g(t)$ and $A(t)$ permit the probability of firing $p(t)$ to be calculated:

$$p(t) = 1 - \exp(-g(t)A(t)) \tag{10}$$

All the simulations were carried out by using a time step of $1ms$.

A.2 Plasticity rule

Conceptually, the learning principle implements a simple gradient rule, such that changes in the input weights increase the mutual information (MI) transmitted by the post-synaptic neuron:

$$\frac{dw_i(t)}{dt} = \frac{\partial MI(t)}{\partial w_i} \tag{11}$$

where w_i denotes the synaptic weight of an afferent projection from a cell i.

The weight change is computed as:

$$\frac{dw_i(t)}{dt} = \alpha C_i(t) B_{post}(t) \tag{12}$$

where α is a gain factor that decreases linearly with time, the function $C_i(t)$ expresses correlations between the pre-synaptic and post-synaptic activities, and the function $B_{post}(t)$ accounts for post-synaptic activity. The function $C_i(t)$ is defined according to:

$$\frac{dC_i(t)}{dt} = -\frac{C_i(t)}{\tau_C} + \sum_j \Delta V(t - \hat{t}_i^j) \frac{g'(V(t))}{g(V(t))} [\delta(t - \hat{t}) - g(V(t))A(t)] \tag{13}$$

where j indexes the spikes emitted by a pre-synaptic neuron i at times $\hat{t}_i^j$, and the Dirac function $\delta(t - \hat{t})$ indicates the timing of the post-synaptic spikes. Therefore, $C_i(t)$ is an exponentially decaying function, with a time constant τ_C, that undergoes changes (positive or negative) every time there are correlations between pre- and post-synaptic discharges.

Finally, the function $B_{post}(t)$, which is the second term in the learning rule (Eq. 12), is taken as:

$$B_{post}(t) = \delta(t - \hat{t}) \log \left(\frac{g(V(t))}{\bar{g}(t)} \right) - A(t)[g(V(t)) - \bar{g}(t)] \tag{14}$$

and is a sum of a term that is almost always nil except when a post-synaptic spike is emitted (denoted by the $\delta(t - \hat{t})$), and a term that is almost always non-zero depending on the value of the instantaneous firing rate g with respect to its mean $\bar{g}$.

A.3 Supplementary results based on classical STDP to modify CN synapses

Here, we present the results obtained by running similar simulations than those used to produce Fig. 4 but with a classical STDP rule [1] instead of the plasticity rule used in the main body (Secs. 2.2 and A.2) [20].

The synaptic weights w_i of the mechanoreceptor-CN projections are initialized randomly (uniform distribution between $[0, 1]$) and then changed according to:

$$\Delta w_i = \begin{cases} A \cdot \exp(\frac{t_{pre} - t_{post}}{\tau}) & t_{pre} - t_{post} < 0 \\ \\ A \cdot \exp(\frac{t_{post} - t_{pre}}{\tau}) & t_{pre} - t_{post} > 0 \end{cases} \tag{15}$$

where $A = 0.1$ and $\tau = 7$ ms.

Figure S3A shows the results, in terms of information $I^*(R; S)$ and conditional entropy $H^*(R|S)$, of tactile discrimination downstream from a network of 50 CN neurons after training (100 presentations of the sequence of 81 tactile stimuli). Interestingly, the time-course of $I^*(R; S)$ and $H^*(R|S)$ is very similar to that on Fig. 4A, meaning that under the constraints governing the connectivity layout of the mechanoreceptor-CN projections (see Sec. 2.2), the classical STDP rule succeeds in optimizing information transfer as rapidly as the rule developed by Toyoizumi *et al.* 2005 [20], which maximizes information transmission explicitly. By contrast, the two learning rules produce significantly different distributions of synaptic weights after training (Fig. S3B *vs.* Fig. 4B): classical STDP tends to set the majority (98%) of weights to 1, whereas the Toyoizumi *et al.*'s rule leads to a bimodal distribution with peaks at 0 (silent synapses) and 1.