SI Text

Simplified Model

To understand the functional consequences of the suggested connection pattern in the VS network, we developed a simplified model in which individual neurons were regarded as compact. The connection of VS cells with electrical synapses could be compared to a discrete model of a cable. In this model (the compartments consisting of the individual cells) the current flowed inside to other cells via electrical synapses and out through their respective input conductances. The inhibitory connection between distal VS cells caused deviation from this simple scheme. The inhibition between VS1 and VS10 was considered, mathematically, as an apparent inverse electrical synapse. This resulted in the following compartmental model (note that non-zero elements are separated by parentheses for clarity):

$$G = \begin{pmatrix} (g_{IN_1} + g_{e_1} - g_i) & (-g_{e_1}) & 0 & 0 & \cdots & (g_i) \\ (-g_{e_1}) & (g_{IN_2} + g_{e_1} + g_{e_2}) & (-g_{e_2}) & 0 & & 0 \\ 0 & (-g_{e_2}) & (g_{IN_3} + g_{e_2} + g_{e_3}) & (-g_{e_3}) & & 0 \\ \vdots & & & \ddots & & \vdots \\ 0 & 0 & & (-g_{e_{n-2}}) & (g_{IN_{n-1}} + g_{e_{n-2}} + g_{e_{n-1}}) & (-g_{e_{n-1}}) \\ (g_i) & 0 & \cdots & 0 & (-g_{e_{n-1}}) & (g_{IN_n} + g_{e_{n-1}} - g_i) \end{pmatrix} \quad \textbf{[1]}$$

where n is the number of VS cells, $g_{e1.n-1}$ were the electrical synapses connecting VS1 to VS2, etc.… g_i was the inhibitory inverse electrical synapse conductance and $g_{IN1.n}$ were the input conductances of the separated individual cells. The relation given by this matrix to potential and current was simply

$$G \cdot V = I \quad \textbf{[2]}$$

where V was a vertical vector of potentials in the different VS cells, and I was the corresponding horizontal current vector. This described the current spread in the network in the steady state since the capacitive properties of the cells were neglected. To obtain good results, we chose the following parameters: a homogeneous electrical coupling $g_{e1\text{-}9}$, the negative conductance g_i and different input conductances $g_{IN1,10}$ for VS1 and VS10, and for VS2-9 $g_{IN2\text{-}9}$. This separation of individual input conductances was necessary because in VS1 and VS10, effective input conductances were increased by an additional conductance to only one neighboring neuron as opposed to two neighbors in the other VS cells and decreased by the negative conductance representing inhibition which connected them both to each other. Since the main attenuation is most likely to occur on the way from the electrode to the location of the synapses within the VS cells, we chose to inject only 0.5 nA (instead of 10 nA as in the experiment) in this simplified model. In this constellation, the model could be fitted to a linearly decaying voltage from VS1 model (for parameters, see SI Table 1) while keeping the input resistance of the cells in the network at measured 4 MΩ (SI Fig. 5*A*). This resulted in an entirely symmetrical system. Simulation of current injection in all VS cell models yielded a linear signal decay in both directions as was the case in the full model (SI Fig. 5*B*). By means of this connectivity, signals of VS cells become filtered by a triangular filter function.

Analytical Formulation of the Linear Relationship

In opposition to a passive cable in which the potential decays exponentially, as in

$$f(X) = e^{-X} \quad \textbf{[3]}$$

where X is the spatial distance in electrotonic terms (in units of the electrotonic length constant λ), the connectivity scheme in the VS network can be interpreted as a realization via inhibition of a subtraction from Eq. **3** of an exponentially decaying signal spreading backwards from VS10 at an electrotonic distance X_C away from VS1:

$$g(X) = e^{-X} - e^{X - X_C} \quad \textbf{[4]}$$

This equation (**4**) becomes linear earlier (at higher electrotonic distances) than the simple exponential decay. SI Fig. 5*C* shows example traces of both equations for different electrotonic distances X_C. This effect can be better understood when observing the Taylor expansion of both equations. The Taylor expansion of Eq. **3** using $X_0 = 0$ is

$$f(X) = \sum_{i=0}^{n} \frac{(-1)^i X^i}{i!} + R_n \quad \textbf{[5]}$$

and of Eq. **4** is

$$g(X) = \sum_{i=0}^{n} \left((-1)^i - e^{-X_C}\right) \frac{X^i}{i!} + R_n \quad \textbf{[6]}$$

This equation reveals that the second order term (together with all other even order terms) becomes zero when X_C gets smaller. To illustrate that this happens in a relevant range of X_C, the difference between both functions and a simple line is displayed in SI Fig. 5*D*. To obtain the linearity measure for Eqs. **3** and **4** at different X_C, the curves were individually scaled to the interval [0, 1]. Subsequently, the integral over the absolute difference between each curve and a straight line was calculated and plotted in SI Fig. 5*D* as a function of X_C. As a comparison, fitting the current transfer in the VS network model at the axon (as in Fig. 2*F*) to Eq. **4** yielded an electrotonic distance of 2.3 λ between VS1 and VS10.

Eqs. **3** and **4** represent the potential decay in cables of infinite length. To additionally consider first order edge effects in this small network, the exponential decay in Eq. **3** can be complemented by an additional term:

$$f_2(X) = e^{-X} + e^{X - 2X_C} \quad \textbf{[7]}$$

The corresponding VS network potential decay of Eq. **4** becomes

$$g_2(X) = e^{-X} - e^{X-X_C} + e^{X-2X_C} - e^{-X+X_C} \quad \textbf{[8]}$$

The additional part therefore represents just a subtraction of spatially separated exponential decays which equally becomes linear.

Significance of Triangular Filter

Triangular filters such as we find in the VS network have the characteristic to linearly interpolate input signals from neighboring points where the signal is zero. This can be seen in SI Fig. 5*E* in which the responses to different input conditions in the VS cell network model are plotted, once in the primary dendrite and at the axon terminal region. When the signal of one VS cell is severely compromised in the dendrite, the missing value at the input is interpolated linearly in the axon terminal (SI Fig. 5*E*). Even when many input values are missing, the VS cell network model interpolates a good approximation of the linear relationship from the actual input signals it receives (SI Fig. 5*F*). In this way, the VS network is able to fill in, by linear interpolation, the gaps in the optic flow signal which result from textureless areas. The linear interpolation makes sense when put in the context of self-rotational optic flow in which amplitudes of motion vectors scale linearly with horizontal disparity (SI Fig. 5*G*).