

# A model of short and long range selective processing in neostriatum

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## Abstract

We present a simple point neuron model of neostriatum based on two of its major neural populations (medium spiny projection neurons and fast spiking interneurons). The model's biological features include gap-junctions between interneurons, lateral connectivity between projection neurons and GABAergic innervation of the latter by the interneurons. The model predicts independent but cooperative selective function over short and long range spatial scales mediated by the projection and interneuron populations respectively. It also predicts a role for the pallido-striatal pathway as an automatic gain control, dopaminergic control of selectivity, and can account for the relative paucity of the interneurons.

**Keywords:** basal ganglia, neostriatum, interneuron, projection neuron, gap-junction

## 1 Introduction

### 1.1 The basal ganglia, neostriatum and action selection

The basal ganglia are a large group of structures in the vertebrate forebrain and have a critical influence over movement and cognition. These nuclei have a gross anatomical division between ventral and dorsal components and, within the dorsal division, the neostriatum is the main input nucleus, constituting (in the rat) approximately 95% of the neural cell count in the division as a whole. In seeking the function of this nucleus, it is reasonable to suppose that it must be consonant with the operation of the basal ganglia *in toto*. While the basal ganglia appear to be implicated in a perplexing diversity of processes, one recurring theme in the literature is that they are associated with some kind of selective processing. Our recent work [7] has

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developed the idea of *action selection* - the resolution of conflicts between functional units within the brain that are in competition for behavioural expression - as a unifying theoretical framework for understanding basal ganglia function. We have also shown that the selection hypothesis is consistent with basal ganglia anatomy and physiology in computational models [1, 2, 3]. In all of these models, the emphasis was placed on the selection processes implemented via circuits between nuclei. We explore here the possibility of selection mechanisms within the major nucleus of the dorsal division - the neostriatum

## 1.2 Selective function within neostriatum

The possibility that neostriatum implements a selective function is a widespread notion, although computational models have hitherto emphasised the importance of competition between members of the dominant cell population of medium spiny (MS) projection neurons [8, 5, for example]. However, the neostriatum also contains three populations of interneurons, comprising only 5% of the total cell count. One of these, the fast spiking GABAergic (FSG) interneurons, have the capability of mediating short timescale selection dynamics (the other two classes appear to be implicated in longer term modulatory processes). These neurons receive significant cortical input and make contact with MS neurons at synapses with fast acting GABA<sub>A</sub> receptors. Further, FSG interneurons are interconnected via electrical gap junctions [4] and have larger projective fields than MS neurons. The inhibitory nature of FSG interneurons makes them good candidates for mediating a selective function and their connectivity suggests that this might operate over a larger spatial scale than that of MS neurons. We therefore sought to examine the possible role that FSG interneurons might play in mediating a long range selective function in neostriatum, and how this might interact with short range processes making use of MS neurons.

## 2 Methods

The basic functional units for both populations are point neurons which obey a simple leaky-integrator membrane equation. The afferent drive is a weighted sum of inputs and the resulting ‘membrane potential’  $a$  is used to determine a continuous-valued output  $y$  (‘firing rate’) from a piecewise linear compressive function

of the form

$$y = \begin{cases} 0 & : a < \epsilon \\ m(a - \epsilon) & : a \leq \epsilon \leq 1/m + \epsilon \\ 1 & : a > 1/m + \epsilon \end{cases} \quad (1)$$

The MS neurons and interneurons used  $\epsilon = 0.1$  and 0 respectively. The MS cell network is designed on a  $90 \times 90$  grid with a MS cell and ‘cortical’ input at each grid location. Each such input is supposed to represent the total external afferent drive to that point in neostriatum. The MS cells are connected via inhibitory, lateral recurrent links within local square *domains* 12 cells wide (with one domain per cell). The strength of the links for each domain declines according to a gaussian distribution.

Inhibitory interneurons are regularly spaced on a square grid whose locations form a sparse subset of those on the MS cell grid. The interneurons innervate the MS cells with synaptic strength  $w_b$ , over a gaussian domain whose extent is twice that of the MS-cell’s self-domain.

Gap junctions between interneurons are modelled by supposing that these contacts give rise to two interneuron communication phenomena. First PSPs from cortical input on one interneuron can generate potential changes directly in neighbouring cells. This is modelled by giving each interneuron an extended receptive field (with respect to external input), which encompasses a square neighbourhood of this input. Second, back-propagating action potentials in an interneuron propagate graded potential changes in the dendrites which can, in turn, cause similar changes in neighbouring interneurons. This is modelled by supplying the interneuron network with a set of lateral recurrent excitatory connections over a square domain (whose extent is the same as the receptive field). Both mechanism are governed by a common gap junction weight,  $w_g$ .

## 3 Results

### 3.1 Selection at two spatial scales

The overall selection abilities of the model are illustrated using quasi-randomised inputs, supplied in such a way that only a relatively sparse subset,  $S$ , of the afferents were non-zero. Members of  $S$  were, in turn, drawn uniformly from the interval  $(0,1]$ . A typical set of inputs is shown on the left in figure 1.

With no interneuron network (MS cells only), the output consists of a set of clear ‘winners’ from the local MS-neuron competitions. This is shown in the right hand bubble plot in figure 1 by the filled symbols.

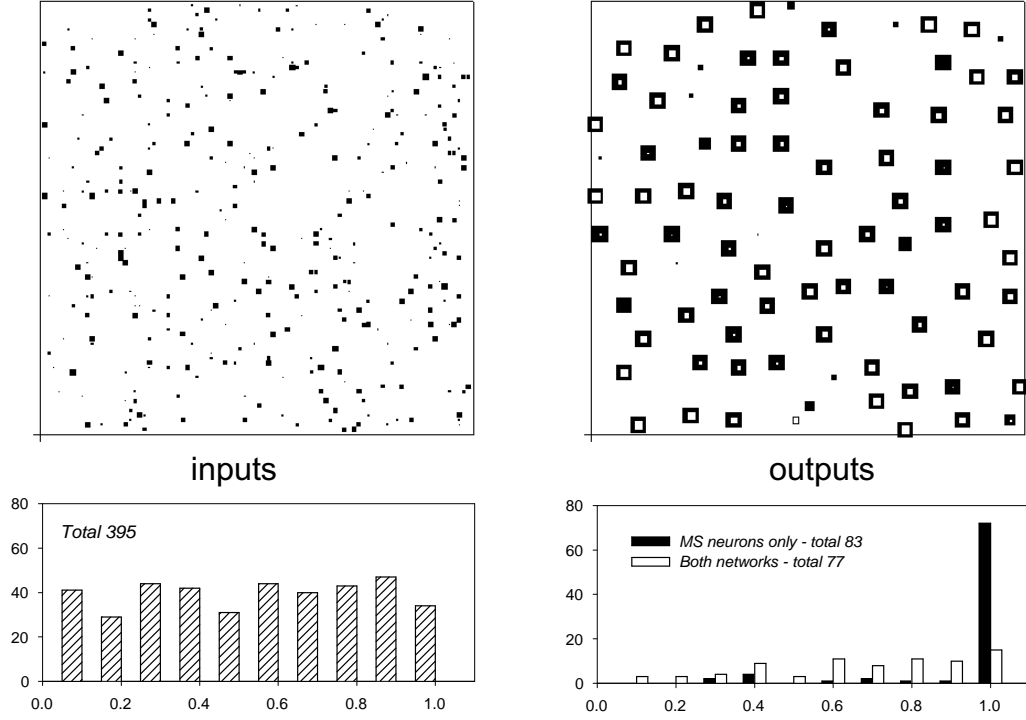


Figure 1: Response to random inputs. The top panels are bubble plots in which the diameter of the symbol is proportional to the value of the signal encoded. The left hand plot shows inputs, and below it is a histogram of values. The right hand bubble plot shows the outputs with and without the interneuron network, with open and closed symbols respectively. The two sets of symbols are differentially scaled (with those for both networks being smaller) to enable comparison. Both sets are at a larger scale than those for the inputs. The corresponding histogram is shown below.

Under the addition of the interneuron network, there is another competitive process which limits the number of such local winners (open symbols in the bubble plot). Here, all but one of the remaining non-zero outputs are coincident with those of the MS-only network, showing that the interneuron selection acts to ‘prune’ the winners of local competitions. However, while usefully limiting the number of clearly selected outputs, the selection process mediated by the interneurons gives a graded set of signals with this input regime, and does not completely eradicate all ‘losing’ nodes. The result of this ‘softer’ selection may be cleaned up by subsequent basal ganglia selection mechanisms (e.g. feedforward networks, [1] or local inhibitory recurrence in the output nuclei [3]). Soft selection is less apparent, however, with a more sparse, focused input scheme, which also allows a closer examination of the selection processes mediated by each network. Thus, inputs

were constructed in small clusters across three cell rows, as shown in the left hand pair of panels in figure 2

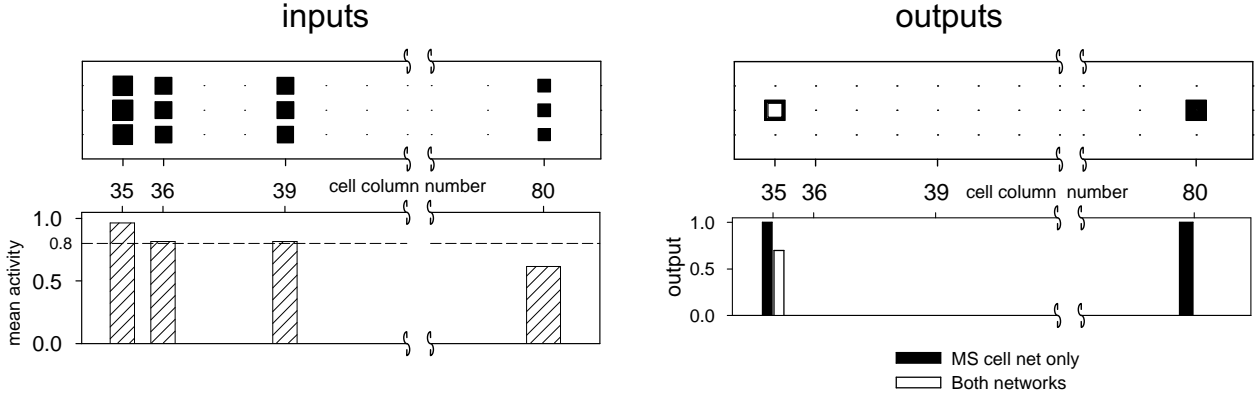


Figure 2: Sparse inputs. The top left hand panel shows the inputs as a bubbleplot (only the local region of non-zero values is shown). The bar graph below this shows the mean activity in each column across all three rows of cells in the network. The right hand pair of panels shows output activity for a network with MS neurons only (filled symbols and bars) and for a full model that includes interneurons (open symbols and bars). Because there is only a single active row, the (grouped) bar graph shows the individual node activities in each case.

Each column of inputs contains values which vary slightly around a mean value, in order to break the symmetry within competitive processing. With no interneuron network, there are two clear winners of the local, short range competitions. With the addition of interneurons, these two nodes then compete between themselves (across a larger spatial scale) to ensure that only a single active node remains.

### 3.2 Selection depends on the interaction strength between the cell populations

The sparse-input experiment described above was repeated with a series of values for the interneuron-to-MS-cell weight  $w_b$ . Let the outputs of the two maximally responding nodes (central row, columns 35, 80 - see figure 2) be  $y_w, y_l$ , where  $y_w > y_l$  (winning and losing nodes respectively). These values are plotted against  $w_b$  in figure 3

Now let  $Y_{opt} = \max_{w_b} \{y_w : y_l = 0\}$  be the optimal signal contrast as  $w_b$  is varied. This condition defines the point of optimal selectivity and, in the example in figure 3, occurs for  $w_b = 0.045$ . It would appear that, in order for the network to achieve optimality in this respect, it has to adapt  $w_b$  very precisely. The net

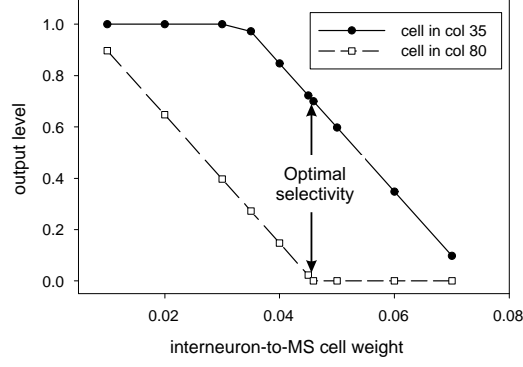


Figure 3: Optimal selectivity. Activity  $y_w$ ,  $y_l$  of the two maximally responding nodes in the sparse input paradigm, plotted against the interneuron-to-MS-cell weight.

effect of setting this weight is, of course, to ensure that the interneurons supply a particular afferent drive to MS cells. However, this may also be modulated by altering the interneuron activity, so that an alternative to careful weight setting is to modulate the interneuron activity so that the appropriate afferent drive is obtained. In our previous model of basal ganglia functional architecture [1, 2], we discovered that one of the basal ganglia nuclei - globus pallidus (GP) - is able to perform a very similar function in dynamically limiting excitation in the system to achieve good selection. That is, the synaptic weights from the excitatory subthalamic nucleus (STN) do not have to be crafted to within precise limits but, rather, GP acts as a dynamic gain control to limit STN activity. This led us to postulate that the GP is a general source of control signals for the basal ganglia selection mechanisms. That a similar function could be implemented in respect of GABAergic interneurons, is supported by evidence from Bevan et al (1998) which showed that GP projects to striatum and, moreover, preferentially innervates the GABAergic interneurons there.

### 3.3 Selection depends on the gap junction weighting

The experiment in the last section was conducted with a gap-junction weight  $w_g$  of 0.3. A series of similar experiments were conducted with different values of  $w_g$  and the results are shown in figure 4. As  $w_g$  is decreased, the activity in the interneuron network decreases (see bubble plots in figure 4) and so its ability to suppress the activity  $y_l$  of the losing node is diminished. This results in progressively smaller values for the difference  $Y_{opt}$ , as shown in the three central plots, and summarised in the bottom panel. This is an

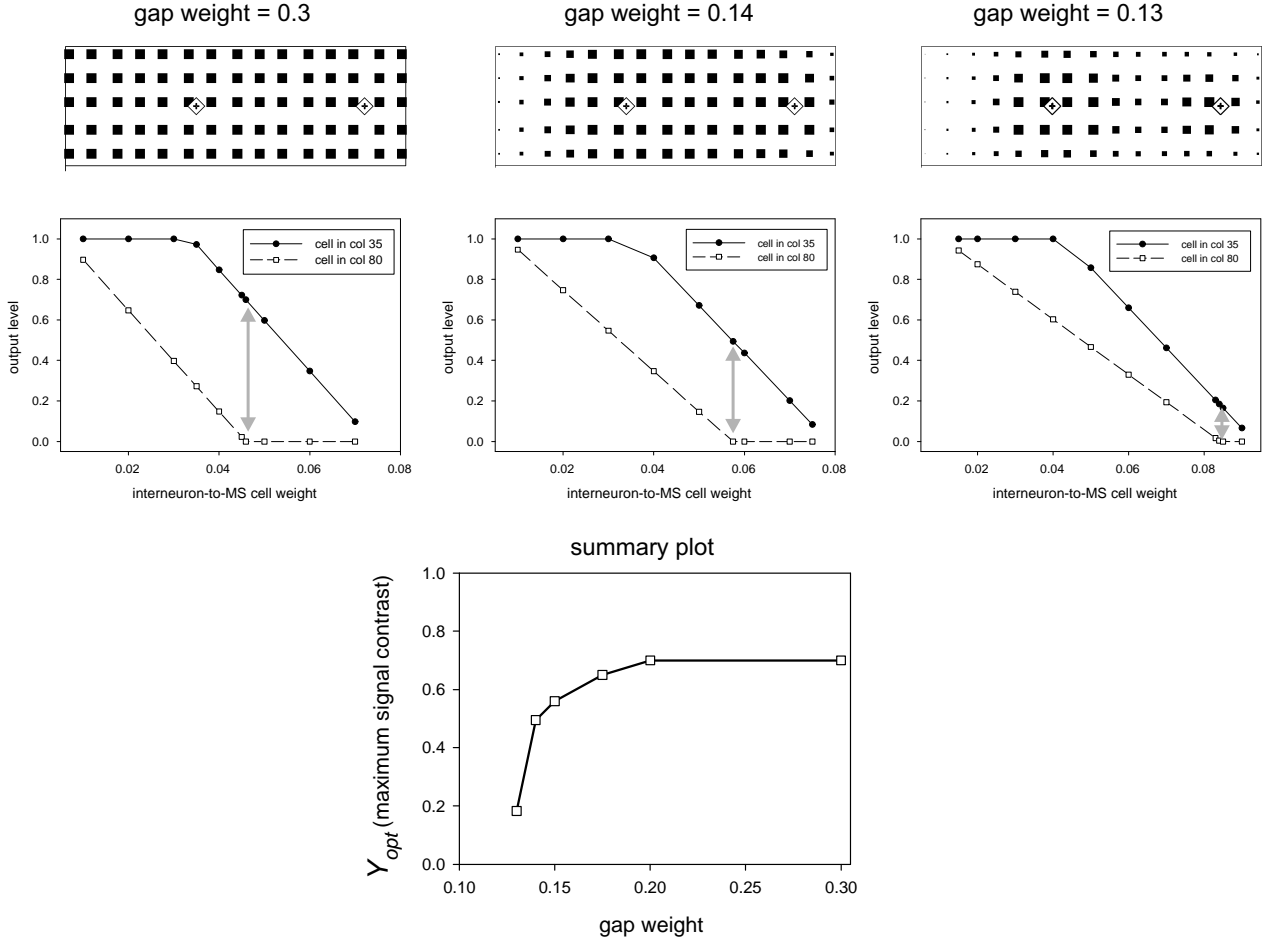


Figure 4: Effect of gap junction weighting. The top panels are bubble plots of interneuron activity in the region of interest (the locations of cells receiving input are marked with diamond symbols). Results are shown for three different values of gap junction weight  $w_g$ , and with interneuron-to-MS-cell weight giving optimal selectivity. The central panels are of the form in figure 3 and correspond to models with the values of  $w_g$  indicated. The point of optimal signal contrast  $Y_{opt}$  is shown by the shaded arrow. The summary panel shows  $Y_{opt}$  plotted against  $w_g$ .

intriguing result because if, as seems possible, dopamine serves to modulate the gap junction weight [6], it could modulate the network selectivity.

### 3.4 Selection is achieved with low interneuron density

Similar results to those shown so far (in terms of selective function) can be achieved with a wide variety of interneuron cell densities  $R = 100 \times N_{inter}/N_{MS}$ , where  $N_{inter}$  and  $N_{MS}$  are the number of interneurons and

MS cells respectively. However, this is only achieved by varying the inter-population weight  $w_b$  so that, as  $R$  increases,  $w_b$  must be decreased. In the extreme case when  $R \approx 100$ , the value of  $w_b$  required to achieve the designated results becomes unrealistically small (see figure 5). In any case, if the required function can

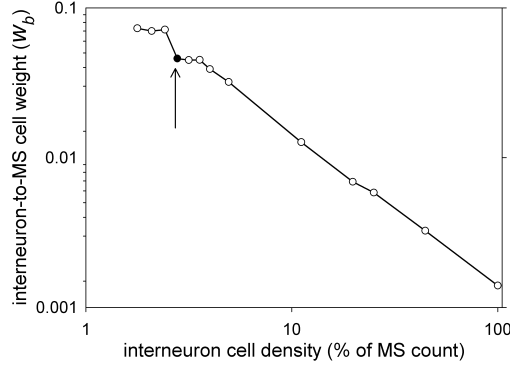


Figure 5: Effect of interneuron density. The value of  $w_b$  required to achieve results comparable to those in previous sections is plotted against interneuron density. The arrow indicates the density used in all the experiments reported here which is comparable to that *in vivo*

be achieved with fewer resources (cells and connections) it seems sensible to do so, which argues for low values of  $R$ . On the other hand, as cell densities become very small, the projective and receptive fields of the interneurons have to become larger to maintain the pattern of results reported here. We therefore hypothesise that the interneuron density in neostriatum represents an optimal tradeoff between the requirements of limiting resources and cell size, while also maintaining realistically feasible and robust synaptic strengths.

### 3.5 Conclusion

Our model of neostriatum, while based on highly simplified neural function is, nevertheless, able to make several predictions about the role of anatomical and physiological features of basal ganglia within the framework of selective function.

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