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Lightness anchoring in neural networks

DRAŽEN DOMIJAN

Lightness anchoring is a process that transforms the scale of relative luminance ratios into a scale of perceived shades of greys. Recent psychophysical investigations suggest that a surface with the highest luminance in a scene appears white. In order to provide a mechanicistic account of this process, a new neural network is proposed based on presynaptic inhibition of feedforward inhibitory pathways and self-excitatory feedback. Presynaptic inhibition serves as a gate that controls the amount of inhibition that cells may receive. Computer simulations showed that the proposed model correctly simulates human psychophysical data on the staircase Gelb effect, and the role of field size and insulation on its appearance.

However, the model is not able to account for the perception of luminosity and the role of articulation in lightness perception. A neural network for size estimation is presented which may partially circumvent the problem, but how such a network interacts with an anchoring network in order to provide complete representation of lightness values is not yet clear.

Surface lightness perception is a two-stage process. In the first stage, local luminance ratios among surfaces are computed. These ratios are invariant with respect to changes in illumination and provide a basis for lightness constancy (Arend & Goldstein, 1987; Land & McCann, 1971). However, computed ratios could not be directly related to perceptual experience because different surface lightness combinations may have the same ratio (Figure 1a). Therefore, a second stage is needed which attaches computed surface ratios to a common frame or anchor (Bruno, Bernardis & Schirillo, 1997; Gilchrist *et al.*, 1999). While the first stage was thoroughly investigated from psychophysical, neurophysiological and computational perspective, the anchoring process received much less attention. In order to explain how anchoring operates, two rules have been postulated: one rule stated that average luminance in the scene is an anchor for perceived greys (Helson, 1964), while the second rule posits that the highest luminance is perceived as white (HLW rule; Wallach, 1948). Recent experimental evidence favoured HLW rule (Bruno, Bernardis & Schirillo, 1997; Cataliotti & Gilchrist, 1995; Gilchrist *et al.*, 1999; Schirillo & Schevell, 1993). For instance, McCann (1992) showed that in a Mondrian, changing the highest luminance in the scene changes the appearance of all other surfaces, while changing the luminance of some other surface and keeping the highest luminance constant does not change the perceived lightness of the rest of the Mondrian. A simple demonstration of the HLW rule is a staircase Gelb effect. When a single surface on a dark background is illuminated with a bright light it will be perceived as white. However, when a second surface with higher luminance is inserted in a display, it will be perceived as white while the first surface will appear as light grey. Insertion of the third surface with even higher luminance will cause darkening of the first and the second surface, while the third surface will be perceived as white. This process of insertion of new surface with highest luminance in a display could be continued and perceptual consequence will be the same, surface with highest luminance will be perceived as white while all other surfaces will become darker (Cataliotti & Gilchrist, 1995). Gilchrist *et al.* (1999) extended their findings and discovered a set of variables that alter perception of surface lightness in staircase Gelb effect such as configuration, articulation, field size and insulation.

From a computational perspective, a space-average rule is much easier to implement in a visual system, because it is closely related to a low-pass filtering which may estimate average input intensity. Neumann (1996) suggested that combination of information from ON and OFF channels allowed processing of input luminance in a shunting neural model of local contrast detectors. Whether a visual system actually uses this information is investigated in ganzfeld experiments (i.e. homogeneous visual field). Barlow and Verillo (1976) concluded that observers are capa-

Dražen Domijan, Department of Psychology, Faculty of Philosophy, University of Rijeka, I. Klobučarića 1, 51000 Rijeka, Croatia. E-mail: ddomijan@human.pefri.hr (Correspondence concerning this article should be sent to this address).

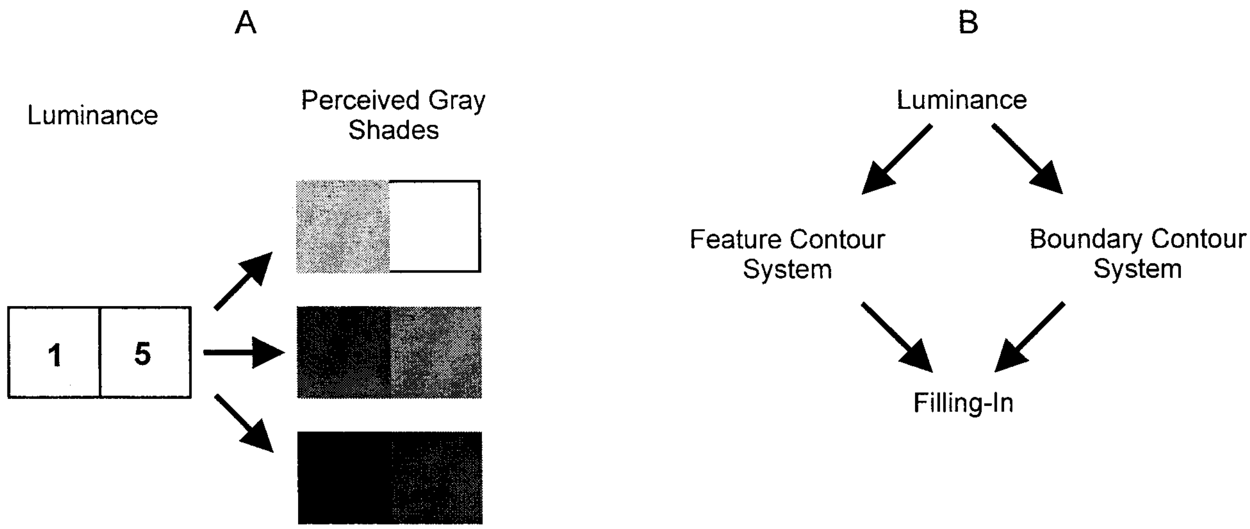


Figure 1. A) Problem of lightness anchoring. The same ratio between two surfaces may correspond to different combinations of perceived shades of grey. B) Simplified illustration of the basic components of the neural network theory of lightness perception proposed by Grossberg. Input is analysed in parallel by a feature contour system and boundary contour system and the result is passed to a filling-in stage, which integrates all information in a unique lightness percept.

ble of discriminating ganzfelds of different lightness, indicating processing of absolute luminance. However, Schubert and Gilchrist (1992) questioned this result, because observers may respond to luminance transients at the onset of each trial. Therefore, they used ganzfeld whose luminance varies very slowly, and asked the observers to indicate the direction of the brightness change. Observers have great difficulty in performing this task, which suggests that direct luminance information is not available. Gilchrist (1994) even challenged the assumption that absolute luminance is registered at photoreceptors as an input to the visual system. Given the evidence above, it is an important research task to search for a plausible neural mechanism of the HLW rule.

Neural networks for lightness perception

A very influential theory of lightness perception based on a neural network is provided by Grossberg and his colleagues (Cohen & Grossberg, 1984; Grossberg, 1987; Grossberg & Todorović, 1988; Kelly & Grossberg, 2000; Neumann, Pessoa & Mingolla, 1998; Pessoa, Mingolla & Neumann, 1995). The theory has been rigorously tested through a large set of computer simulations which demonstrated that it is capable of explaining a variety of phenomena in lightness perception such as lightness constancy, lightness contrast, Craik-O'Brien-Cornsweet effect, Mach bands, interactions between lightness and depth. Basic components of the theory are: boundary contour system (BCS), feature contour system (FCS) and filling-in stage. Interactions between components are illustrated in Figure 1b. BCS consists of oriented contrast detectors that locate edges while FCS extract luminance ratios between adjacent surfaces in a visual scene. Filling-in stage provides an integration of information from BCS and FCS by a diffusion that spreads FCS signals within gates that are provided by BCS signals, which prevent activity spreading between surfaces. Neural activity in filling-in stage is compared with human perception. However, filling-in does not have anchor, and comparison between network and human performance is just qualitative not quantitative.

Ross & Pessoa (1995) have developed an extension of the neural model of lightness perception, which incorporate HLW rule for anchoring. They introduced a fixed minimum, fixed maximum, linear scaling rule for anchoring of computed surface values,

$$c_i = a\frac{I_i - \min}{\max - \min} + b \qquad (1)$$

where x_i is the output of the anchoring process at spatial position i, I_i is the input from the filling-in stage, max is the largest I_i and min is the smallest I_i in the scene. Parameters a and b define the range of output values. Since the usual scale in research on lightness perception are Munsell values, where white surfaces are assigned value 9 and black

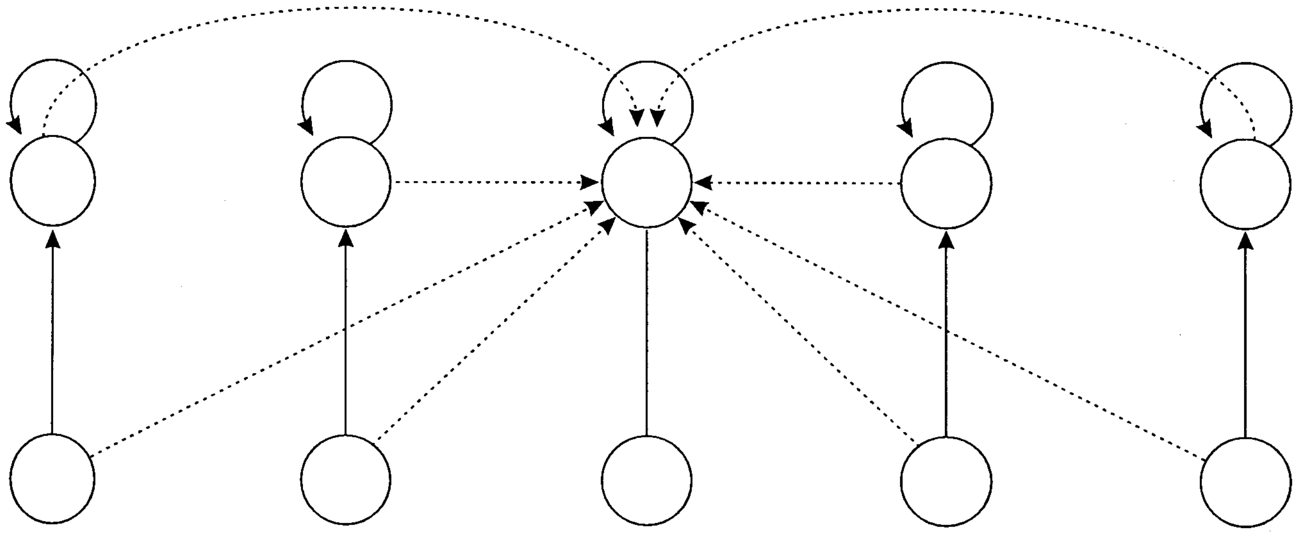


Figure 2. Feedforward and feedback neural networks which are unable to implement HLW rule of lightness anchoring. Full arrows denote excitatory connections and dashed arrows denote inhibitory connections. In feedforward case, since all cells may inhibit each other, cell with the largest input will not retain the largest possible activity level. Feedback networks with strong lateral inhibition usually behave as a winner-take-all where only the cell with the largest input remains active, while all other cells are shut down.

surfaces are assigned value 2, therefore a = 7 and b = 2. Ross & Pessoa (1995) showed that their rule could simulate staircase Gelb effect, but only partially. Their rule could not reproduce the compression of perceived shades of grey for higher luminance due to the lack of nonlinearity. Also, their rule could not explain the result of Li & Gilchrist (1999) who showed that in a large dome which is painted half in black and half in middle grey, observers reported that they perceive black surface as middle grey and middle grey surface as white. A linear scaling rule would correctly assign 9 to middle grey surface since it is the highest luminance in the scene but incorrectly assign 2 to black surface since it is the smallest luminance in the scene. Another problem for Ross & Pessoa's rule is that it does not have any physical interpretation that could be implemented in a neural network. The same is true for the recent revision of the model (Ross & Pessoa, 2000). Although they use a different equation, which is able to implement HLW rule without forcing the lowest luminance to be black, their model lacks quantitative treatment of the staircase Gelb effect and the variables that affect its appearance such as size and insulation. Also, the model relies on an unrealistic assumption that initially all activities are set to the largest value, which means that we should see a white colour before we open our eyes.

The aim of the present paper is to introduce the neural mechanism for lightness anchoring that can implement the HLW rule and provide a quantitative account of the basic features of the staircase Gelb effect.

Model description

Since the range of perceived grey values is restricted, the additive network model is not appropriate because its range of activities depends on input and different inputs may produce a different ranges of activities which is difficult to translate to perceptual scale of lightness values. Instead, a shunting or multiplicative model should be used. It has upper and lower bounds on activity values that are consequences of physiological mechanisms at the cell's membrane (Grossberg, 1988). However, a shunting neural model with feedforward or feedback lateral inhibition is not enough (Figure 2). In feedforward case, the network extracts the ratio between inputs, which is useful in the early stages of visual processing but it could not implement the HLW rule. The reason is that the cell with the largest input will reduce its activity level depending on the number of active cells in input.

In a feedback case, the network may behave in three different ways, depending on the choices of output functions (Grossberg, 1988). When output function is faster than linear, the network behaves as a winner-takes-all network. This means that the cell, which receives the largest input, remains active while all other cells are shut down and we could perceive only one surface at the time. If output function is linear, the network will allow the largest input to attain the largest activity value, but it is not possible to obtain compression of lightness values observed by Cataliotti & Gilchrist (1995). Slower-than-linear function produces uniform activity distribution, which is clearly inappropriate. The same is true for more complex output functions such as sigmoid function since it is a combination of previously described functions.

In order to explain how highest-luminance-as-white rule of lightness anchoring may arise in a neural tissue, a new neural network is proposed based on feedforward presynaptic inhibition. The model is illustrated in Figure 3. Cells in input layer send excitatory signals to corresponding cells in anchoring layer and also inhibitory signals to all other cells. This connectivity pattern implements feedforward lateral inhibition. Furthermore, inhibitory pathways are gated by presynaptic inhibition, which also originates from input layer. Presynaptic inhibition could be mediated by the same interneurons that are responsible for feedforward lateral inhibition or separate sets of units. Finally, self-excitatory feedback pathways amplify signals received by feedforward axons, which is responsible for compression observed in staircase Gelb effect. Mathematically, the model is described by a set of differential equations,

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)(E_i + f(x_i)) - (C + x_i)\sum_{j=1}^{n} D_{ij}\left[(I_j - I_i)\right]^+ \quad (2)$$

where $[w]^+ = \max(w,0)$, $f(w) = w$. x_i denotes activity of cell at position i in an anchoring layer, E_i and I_j are excitatory and inhibitory inputs, and I_i is presynaptic inhibition of lateral inhibitory pathways I_j. Parameters A, B, C, and D_{ij} describe the cell's passive decay, activity upper and lower bound, and the strength of the feedforward inhibitory interactions, respectively. The model behaviour will be essentially identical if we replace shunting inhibition with additive

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)(E_i + f(x_i)) - \sum_{j=1}^{n} D_{ij}\left[(I_j - I_i)\right]^+ \quad (3)$$

but shunting excitation is necessary for correct implementation of the anchoring rule since it provides upper bound for an activity which corresponds to the white colour on a perceptual scale.

Computer simulations

To test the validity of the proposed model, computer simulations were performed. Since the model includes feedback connections, a system of differential equations could not be solved explicitly. Instead, numerical integration was used in a software package Wolfram Mathematica 4.0 with *NDSolve* command. Parameters were set to the following values: A = 0.1; B = 9.0; C = 0.0; D_{ij} = 0.3 for all i and j. For simplicity, surfaces are approximate by one cell, that is, every cell represents a different surface. The surface with the lowest luminance was assigned value 1.0 and every new surface that was introduced in the network was incremented by 1.0, to obtain luminance staircase.

The results of computer simulations are presented in Figures 4 and 5. Figure 4 (left) shows that the model correctly simulates the staircase Gelb effect. This is due to the

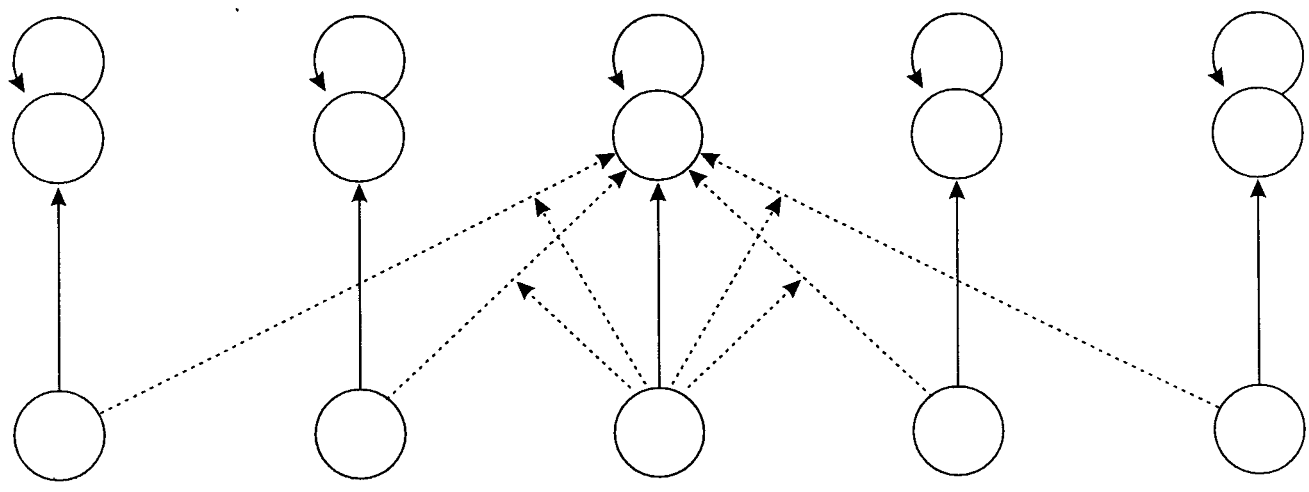


Figure 3. Neural model of lightness anchoring. With respect to standard neural network model, inhibitory feedback connections are removed and only self-excitatory feedback is retained. Also feedforward presynaptic inhibition is introduced which inhibit feedforward lateral inhibitory connections.

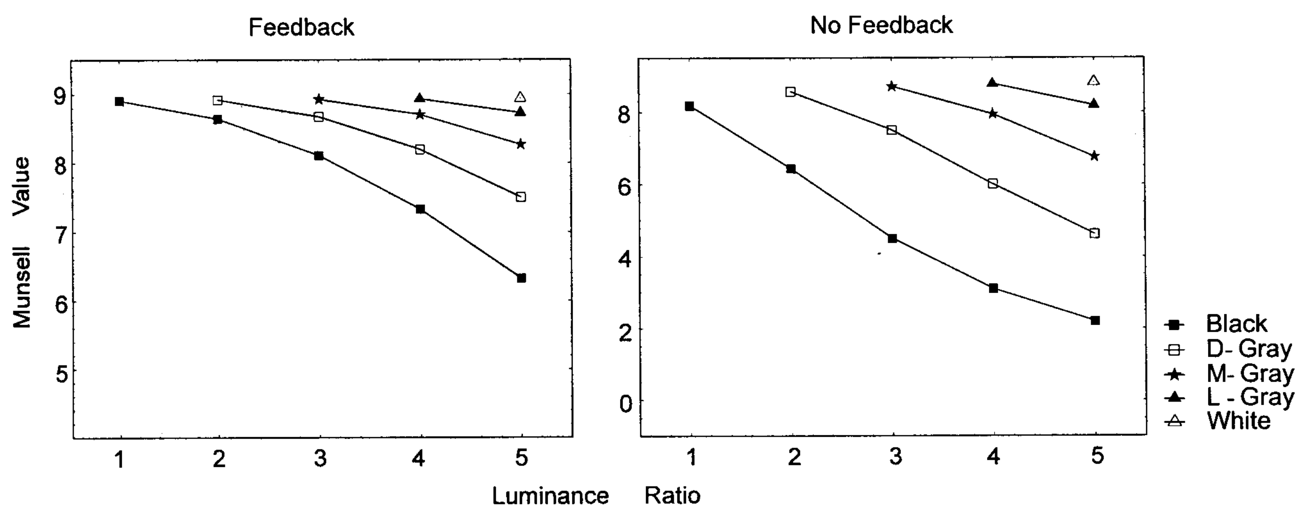


Figure 4. Computer simulation of the staircase Gelb effect. Perceived shades of grey measured on a Munsell scale are plotted against a contrast between surfaces with largest and smallest luminance. A) Full network. B) Network without self-excitatory feedback, which demonstrate its importance in explanation of the effect.

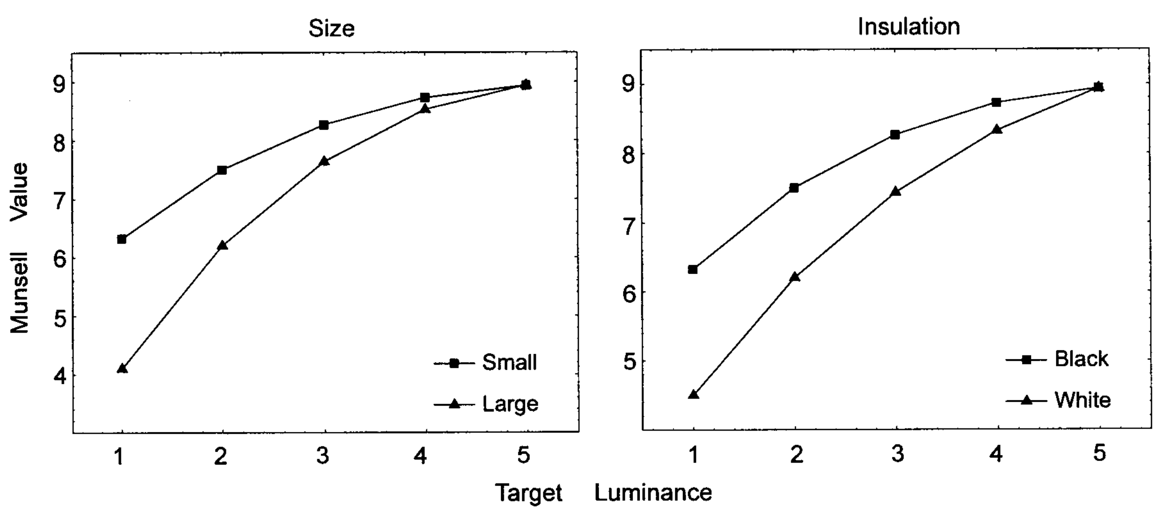


Figure 5. Simulation of the effect of surface size and insulation on the staircase Gelb effect. A) As the size of the surfaces increases, the total amount of inhibition that particular cell receives also increases so perceived grey value become darker. B) Insulation is explained as a variant of the surface size effect. A white border has a strong influence on the network because it is a surface with the highest luminance so it may override presynaptic inhibition from target surfaces. Therefore, they will appear darker.

joint operation of presynaptic inhibition and self-excitatory feedback. A cell that encodes the surface with the largest luminance in the scene does not receive any inhibition from other cells because it is protected by presynaptic inhibition. All other cells receive inhibition but only from those cells which have a higher level of activity. In this way, the order of activity levels from input layer is preserved, while anchoring is achieved by assigning the largest activity value to the largest input, that is, highest luminance in the scene. Figure 4 (right) shows what happened when self-excitatory feedback was removed from the network. Lightness estimates become much darker and the relative distance between them becomes almost linear. However, empirical evidence suggests that difference in lightness is smaller for lighter surfaces (Cataliotti & Gilchrist, 1995, Experiment 1). This simulation illustrates the importance of the self-excitatory feedback in quantitative modelling of the staircase Gelb effect.

How the model treats size and insulation is demonstrated in Figure 5. Different sizes are simulated by changing the number of the cells with the same activity level. Small surfaces are represented with one cell for each surface and large surfaces by two cells. Since increasing the size of the surface increases the amount of inhibition that each cell receives, darkening is observed for larger surfaces (Figure 5 left).

Cataliotti & Gilchrist (1995) showed that there is no effect of size on perceived lightness because changing the distance between observers and stimulus did not change the appearance of the surfaces. However, Gilchrist *et al.* (1999) distinguished between retinal and perceived size. They concluded that changes in perceived size change the appearance of the surfaces but not the retinal size. It seems that this is in contrast with the present model, but the filling-in stage is not a retinal stage of processing. It is hypothesised that filling-in operates in a cortex after computations in BCS take place. Grossberg (1987; Kelly & Grossberg, 2000) claims that multi-scale version of the BCS is capable of computing object boundaries with respect to its depth. Also, he points out that BCS may detect the correlation between changes in object size and changes in object depth as illustrated by Emmert's law. Final surface representation will not change the size of the object's surface if there is such correlation. In other words, the filling-in stage may code the object's perceived size and not the retinal size.

Insulation is explained as a variant of the size effect (Figure 5 right). Since only white border has potential to change the appearance of the surfaces, it is assumed that white surface is grouped with white border into a single large white surface. Then the same argument as in the case of size may be applied, that is, a larger surface produces stronger inhibition and all surfaces except white become darker. Consistent with this explanation is the fact that a black border has no effect on lightness since the lightness estimates are approximately the same with or without border (Gilchrist *et al.*, 1999). A black border simply could not influence any other surface since its signal is weakest in the network and it is blocked by presynaptic inhibition from other parts of the input.

Gilchrist *et al.* (1999) also found the effect of configuration on lightness. Mondrian configuration produces darker lightness estimates than simple line arrangement. This is consistent with the present model because it assumes that before anchoring, local ratio measures are computed. Therefore, a configuration effect is attributed to the operation of lateral inhibition in the retina or lateral geniculate nucleus, which results in darker lightness values for surfaces embedded in Mondrian. An anchoring network only reflects this difference which is created earlier in the processing of visual input.

Finally, a separate set of computer simulations (which is not shown) has been performed in order to test the network resistance to the changes in parameter values. The model is robust with respect to the variations in the passive decay rate and strength of the inhibitory feedforward connections, that is, the network behaviour remains invariant under parametric changes. This is an important fact because real neurons are subject to large fluctuations in parameters that define them due to variations in physiological variables such as blood or oxygen supplies and chemical or electrical properties of cell membrane. Such variations may cause large disturbances in the network operation if the mechanisms responsible for producing desired behaviour are not resistant enough.

DISCUSSION

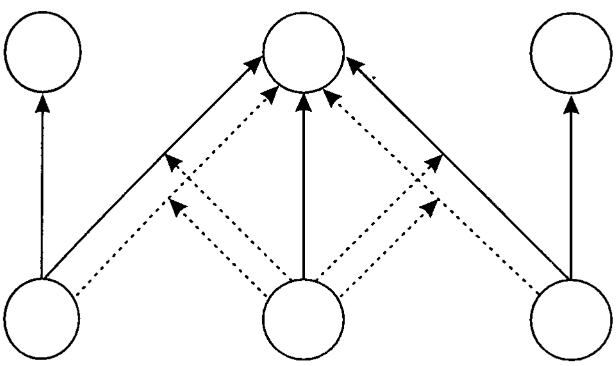
Computer simulations suggested that neural network with feedforward presynaptic inhibition of lateral inhibitory pathways and self-excitatory feedback is able to implement HLW rule of lightness anchoring. This is illustrated by simulating the staircase Gelb effect and the influence of field size and insulation on lightness anchoring. This is achieved through the operation of presynaptic inhibition which acts as a gate that controls the amount of inhibition that particular cell in an anchoring layer may receive. An input cell with the largest activity completely prevents lateral inhibition from the surrounding cells, and its target cell in an anchoring layer receives only excitation which will drive the cell's activity to the upper bounds in a shunting model. Other cells receive inhibition depending on the difference between cell activity and surrounding cells with higher activity, since only they could override a gate provided by presynaptic inhibition. Therefore, the cell's activity in an anchoring layer will be ordered as in input layer with a certain amount of compression provided by self-excitatory feedback. Self-excitation drives cell's activity toward higher values, which is consistent with psychophysical measurements provided by Cataliotti and Gilchrist (1995).

However, the HLW rule is not sufficient for a complete understanding of lightness anchoring because it could not account for the perception of objects that are light sources since they have higher luminance than other surfaces in the scene but they do not appear white. Rather they are described as glowing or luminous surfaces (Bonato & Cataliotti, 2000; Bonato & Gilchrist, 1994; 1999). Within the present model, such a surface will be treated as white and no distinction is possible between white and self-luminous surfaces.

Gilchrist and Bonato (1995) investigated the relation between photometric and geometric factors in center-surround displays and proposed a rule which specifies that the surround should be perceived as white. Li and Gilchrist (1999) revised their findings using large acrylic dome and showed that relative luminance and relative size jointly predict the appearance of surfaces in a simple stimulus condition. They proposed an additional area rule, which states that the largest surface in the scene should be perceived as white. When the surface with the largest area is also the surface with the highest luminance, it will appear white, but when the surface with the highest luminance is not the largest, it starts to appear as a self-luminous surface. As the area of the surface with highest luminance becomes smaller, its luminosity becomes stronger. At the same time, a surface with a larger area becomes white. The existence of two rules that jointly determine the final perception makes it difficult to propose a model of the whole process of lightness anchoring. Further research will explore how to design a neural network that could combine an area rule with the HLW rule in order to correctly predict perceived lightness in a simple stimulus condition.

The first step toward this goal is to implement an area rule. How a neural network can encode the size of the surfaces has not been systematically studied. The exception is Grossberg's analysis of relation between depth and size, but he did not investigate how size could be measured. The simplest possible idea is that cells with large receptive fields may measure the size of the input because they sum all excitatory input which they receive. The problem with this idea is that more than one object may be present within a receptive field and the cell could not distinguish one large object from a few small objects. Another possibility is given in Figure 6. This is a feedforward network with lateral excitatory and inhibitory connections. Besides, all input cells send presynaptic inhibition to all feedforward axons. Presynaptic inhibition is slightly smaller on excitatory connections. In this way, presynaptic inhibition will allow excitatory signals that originate from the same object to influence a target cell, while it will prevent inhibitory signals. On the other hand, presynaptic inhibition will completely prevent signals from other objects that are labelled with smaller activity level. Also signals from cells that represent objects that are labelled with higher activity level than target object will pass presynaptic inhibition through excitatory and inhibitory connections. Therefore, their total impact on a target cell will be zero because excitation and inhibition will cancel each other out. It is assumed that different objects are represented with different activity level in the input. How such representation may be achieved is described in Domijan (2001). Figure 6B illustrates how neural network for size estimation works. It takes input and counts the number of units that have the same activity value (i.e., final activity value is equal to the number of cells that have the same input value). It is interesting to note that all cells that code the same object have the same activity value. If this network becomes input to the anchoring network, it implements the area rule (it is assumed that there are two anchoring networks; one that receives input from filling-in stage and the other that receives input from network for size estimation). However, implementation is only partial, because the model will correctly assign white to the largest surface only if it has the highest luminanceas well. If a smaller surface has the highest luminance, conflict arises since two anchoring networks point to different

A



B

Input

$$\begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 2 \\ 3 & 0 & 0 & 0 & 2 & 2 \end{pmatrix}$$

Network Response

$$\begin{pmatrix} 9 & 9 & 9 & 0 & 0 & 0 \\ 9 & 9 & 9 & 0 & 0 & 0 \\ 9 & 9 & 9 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 4 \\ 1 & 0 & 0 & 0 & 4 & 4 \end{pmatrix}$$

Figure 6. Neural model for size estimation. A) The network receives feedforward excitation and inhibition from all cells in the input layer. Every connection is subject to presynaptic inhibition. B) An example that illustrates how the network behaves. The left is input to the network with three surfaces with different sizes. The right is a network response. Larger surfaces are represented with stronger activity.

surfaces that should be assigned as white. How this conflict may be overcome is not yet clear. The source of the problem is that a network has no way to represent luminosity because the largest possible activity value is assigned to white so this is a physical limitation in a model which implies that luminosity may be represented in a different network. Bonato and Cataliotti (2000) even suggest that physiological mechanisms may not be responsible for luminosity perception but it may arise as a consequence of visual experience.

Another problem for the presented neural model is the role of articulation in lightness perception. As a number of surfaces within fixed area increases, perceived lightness of surfaces changes (Agostini & Galmonte, 1999; Bruno *et. al.*, 1997; Schirillo, 1999a; 1999b). This could be related to the problem of size estimation, because increasing the number of surfaces within fixed area implies reduction in surface size. Therefore, articulation requires that the size of all surfaces in the scene should be estimated. Smaller surfaces should receive larger inhibition, since they appear darker than larger surfaces with the same luminance (Gilchrist *et al.*, 1999). However, such a tendency is in contrast with the reported size influence on lightness perception, where larger surfaces exert stronger inhibition and therefore produce darker estimates than smaller surfaces. How to resolve this apparent paradox is not clear. Situation is even more complicated because relative position of the surfaces in the experimental display also has influence on the final perceptual outcome (Agostini & Galmonte, 1999).

The neural network proposed here is not intended to provide an account of the role of perceptual organisation in lightness perception (Agostini & Galmonte, 2000; Anderson, 1997; Gilchrist *et al.*, 1999; Ross & Pessoa, 2000; Todorović, 1997). It is assumed that the process of integration of form and lightness signals is achieved before the stage of filling-in. If BCS and FCS are properly designed they should provide enough information to correctly predict lightness values in different stimulus configurations (Domijan, 2000; Kelly & Grossberg, 2000; Ross & Pessoa, 2000). The present model only transforms the computed relative contrast values into the scale of absolute lightness. On the other hand, Gilchrist et al. (1999) assumed that the process of anchoring is directly related to the organisation of the visual scene embodied in the concept of framework. The most global framework is the whole visual scene while the most local framework is particular surface taken in isolation. Between these two extremes, every surface may engage in different collections of surfaces. The degree with which a particular framework will influence appearance of the surfaces depends on the strength of the framework, that is, how strongly the surface belongs to it. Based on this descriptive idea, Gilchrist *et al.* (1999) showed that a large number of effects and illusions in lightness perception might be explained. One direction for future work is to develop the computational specification of frameworks in the context of neural networks.

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