Interactions between Rough Parts in Object Perception

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Abstract. The visual systems of humans and primates outperform the best artificial vision systems by almost any measure. Humans can easily recognize as complex objects as faces even if they haven't seen them in such conditions before. However, experiments with the inverted faces (Thatcher illusion) show strong dependences between parts and their configuration. We propose pattern recognition rules similar to the primate visual brain on the basis of the simple shape classification in the intermediate area of the visual cortex (V4). In the present work we have described interactions between parts and their configurations using single cell responses as the brain expertise (decision attribute). Experimental data as the set of condition (stimulus) and decision (cell responses) attributes were placed into a decision table. Applying the rough set theory (Pawlak, 1992) we have divided our stimuli into equivalent classes determined by evoked cell responses. On the basis of the decision table, we found the decision rules. Comparing decision rules for responses to object and to its parts, we have found the interaction rules in the receptive fields of the area V4. We have proposed the interaction rules for objects that are simpler than faces but we expect that such rules can give us neurophysiological basis for the Gestalt perception of the complex objects. By comparing responses of different cells we have found equivalent concept classes. However, many different cells show inconsistency between their decision rules, which may suggest that the brain uses several different decision logics in order to make object perception insensitive to changes in properties of its parts (rough parts).

Keywords: Visual brain, imprecise computation, bottom-up, top-down processes, neuronal activity.

1 Introduction

After Pawlak [1], we define an information system as $S = (U, A)$, where U is a set of objects and A is a set of attributes. If $a \in A$ *and* $u \in U$, the value $a(u)$ is a unique element of V (a value set). The *indiscernibility* relation of any subset B of A, or $IND(B)$, is defined [1] as the equivalence relation whose elements are the sets $\{u: b(u) = v\}$ as v varies in V, and $[u]_B$ - the equivalence class of u form *B-elementary granule*. The concept $X \subseteq U$ is *B-definable* if for each $u \in U$ either $[u]_B \subseteq X$ or $[u]_B \subseteq U \backslash X$. $\underline{B}X = \{u \in U: [u]_B \subseteq X\}$ is a lower approximation of X. The concept $X \subseteq U$ is *B-indefinable* if exists such $u \in U$ such that $[u]_B \cap X \neq \phi\}$. $\overline{B}X = \{u \in$

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U: $[u]_B \cap X \neq \phi$ } is an upper approximation of X. The set $BN_B(X) = \overline{B}X - \underline{B}X$ will be referred to as the *B-boundary region* of. If the boundary region of X is the empty set then X is *exact* (*crisp*) with respect to B; otherwise if $BN_B(X) \neq \phi$ X is not *exact* (*rough*) with respect to B.

In this paper the universe U is a set of simple visual patterns that were used in our experiments [2], which can be divided into equivalent indiscernibility classes or *B-elementary granules*, where $B \subseteq A$. The purpose of our research is to find how these objects are classified in the brain. Therefore we will modify definition of the information system as $S = (U, C, D)$ where C and D are condition and decision attributes. Decision attributes will classify elementary granules in agreement with neurological responses from the specific visual brain area. In this work we are looking into single cell responses only in one area - V4 that will divide all patterns into equivalent indiscernibility classes of *V4-elementary granules.* Neurons in V4 are sensitive only to the certain attributes of the stimulus, like for example space localization – the pattern must be in the receptive field, and most of them are insensitive to contrast changes. Different V4 cells have different receptive field properties, which means that one *B-elementary granule* can be classified in many ways by different *V4-elementary granules.*

2 Method

We will represent experimental data ([2]) in the following table. In the first column are neural measurements. Neurons are identified using numbers related to a collection of figures in the previous paper [2]. Different measurements of the same cell are denoted by additional letters (a, b,…). For example, 11a denotes the first measurement of a neuron numbered 1 Fig. 1 of [2], 11b the second measurement, etc. Stimuli typically used in neuroscience have the following properties (see Fig 1):

1. orientation in degrees appears in the column labeled *o*, and orientation bandwidth is labeled by *ob*.
2. spatial frequency is denoted as *sf*, and spatial frequency bandwidth is *sfb*
3. x-axis position is denoted by *xp* and the range of x-positions is *xpr*
4. y-axis position is denoted by *yp* and the range of y-positions is *ypr*
5. x-axis stimulus size is denoted by *xs*
6. y-axis stimulus size is denoted by *ys*
7. stimulus shape is denoted by *s*, values of s are following: for grating $s=1$, for vertical bar $s=2$, for horizontal bar $s=3$, for disc $s=4$, for annulus $s=5$

Decision attributes are divided into several classes determined by the strength of the neural responses. Small cell responses are classified as *class 0*, medium to strong responses are classified as *classes 1 to n-1* ($min(n)=2$), and the strongest cell responses are classified as class n. Therefore each cell divides stimuli into its own family of equivalent objects.

Cell responses (r) are divided into $n+1$ ranges:

class 0 : activity below the threshold (e.g. 10 sp/s) labeled by r_0;

class 1: activity above the threshold labeled by r_1; …

class n: maximum response of the cell (e.g. 100-200 sp/s) labeled by r_n.

Thus the full set of stimulus attributes is expressed as $B = \{o, ob, sf, sfb, xp, xpr, yp, ypr, xs, ys, s\}$.

3 Results

3.1 Analysis of the Interactions between Parts

We have analyzed the experimental data from several neurons recorded in the monkey's V4 [2]. One example of V4 cell responses to thin (0.25 deg) vertical bars in different horizontal - x positions is shown in the upper left part of Fig. 1 (Fig. 1E). Cell responses show a maximum for the middle (*XPos* = 0) bar position along the x-axis. Cell responses are not symmetrical around 0. In Fig. 1F the same cell (cell 61 in table 1) is tested with two bars. The first bar stays at the 0 position, while the second bar changes its position along the x-axis. Cell responses show several maxima dividing the receptive field into four areas. However, this is not always the case as responses to two bars in another cell (cell 62 in table 1) show only three maxima (Fig. 1G). Horizontal lines in plots of both figures divide cell responses into the three classes: r_0, r_1, r_2, which are related to the response strength (see Methods). Stimuli attributes and cell responses divided into two: r_1 and r_2 classes are shown in table 1 for cells from Fig. 1 and in table 2 for cells from Fig. 2.

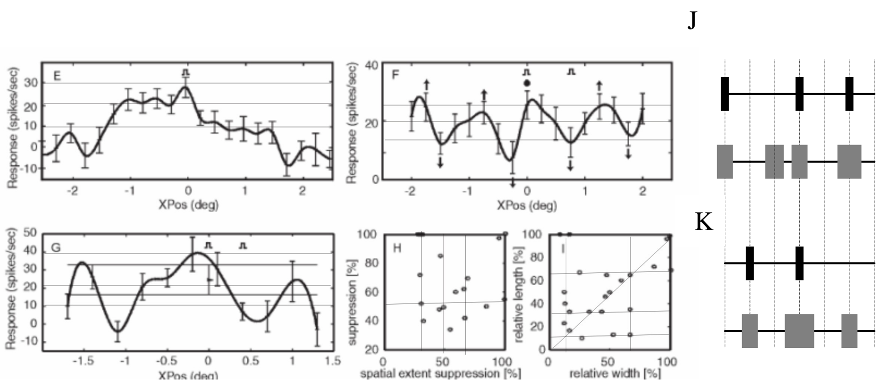

Fig. 1. Modified plots from [2]. Curves represent responses of several cells from area V4 to small single (**E**) and double (**F, G**) vertical bars. Bars change their position along x-axis (Xpos). Responses are measured in spikes/sec. Mean cell responses $\pm$ SE are marked in E, F, and G. Thick horizontal lines represent a 95% confidence interval for the response to single patch in position 0. Cell responses are divided into three ranges by thin horizontal lines. (**H**) A scatter plot showing peak percentage reduction of response to the central bar when a second bar is simultaneously presented. Assuming that the single bar give response r_2 50% suppression means that the second bar reduce cell response to r_1 (horizontal line). Cell properties can be divided into approximately three types (vertical lines): with a maximum suppression every 30, 50, or 70% of the receptive field extension. (**I**) A similar scatter plot as H but on x-axis is the ratio of optimal length and width, on y-axis is the spatial extent of the stimulus. (**J**) "Window sharpening": The schematic for the cell from part (F) and table 1 (rows 61f*) showing bar positions giving r_2 (upper part in black), and r_1 (lower part in gray) cell response. (**K**) The same as in (J) but for cell plotted in (G) and in table 1 rows 61g1 to 61g5.

Table 1. Decision table for cells from Fig. 1. Attributes *o, ob, sf, sfb* were constant and are not presented in the table. In experiments where two stimuli were used, the shape value was following**:** for two bars s=22, for two discs s=44.

Cell	xp	xpr	xs	ys	s	r
61e	-0.7	1.4	0.25	4	2	1
61f1	-1.9	0.2	0.25	4	22	2
61f2	0.1	0.2	0.25	4	22	2
61f3	1.5	0.1	0.25	4	22	2
61f4	-1.8	0.6	0.25	4	22	1
61f5	-0.8	0.8	0.25	4	22	1
61f6	0.4	0.8	0.25	4	22	1
61f7	1.2	0.8	0.25	4	22	1
62g1	-1.5	0.1	0.25	4	22	2
62g2	-0.15	0.5	0.25	4	22	2
62g3	-1.5	0.6	0.25	4	22	1
62g4	-0.25	1.3	0.25	4	22	1
62g5	1	0.6	0.25	4	22	1
63h1	-0.5	0.5	1	1	44	2
63h2	1	1	1	1	44	1
63h3	0.2	0.1	0.25	4	22	2

We assign the narrow (xpr_n), medium (xpr_m), and wide (xpr_w) x position ranges as follows: xpr_n *if* $(xpr\text{: } 0<xpr\leq 0.6)$, medium xpr_m *if* $(xpr\text{: } 0.6 <xpr\leq 1.2)$, wide xpr_w *if* $(xpr\text{: } xpr>1.2)$.

On the basis of Fig. 1 and Tab.1 the **two-bar** horizontal interaction study for cell 61f can be presented as the following **two-bar decision rules:**

DRT1: $(o_{90} \wedge xpr_n \wedge (xp_{-1.9} \vee xp_{0.1} \vee xp_{1.5}) \wedge xs_{0.25} \wedge ys_4)_1 \wedge$
$(o_{90} \wedge xp_0 \wedge xs_{0.25} \wedge ys_4)_0 \text{->} r_2$

DRT2: $(o_{90} \wedge xpr_m \wedge (xp_{-1.8} \vee xp_{-0.8} \vee xp_{0.4} \vee xp_{1.2}) \wedge xs_{0.25} \wedge ys_4)_1 \wedge$
$(o_{90} \wedge xp_0 \wedge xs_{0.25} \wedge ys_4)_0 \text{->} r_1$

One-bar decision rules [3] can be interpreted as follows: the narrow vertical bar evokes a strong response in certain positions, medium size bars evoke medium responses in certain positions, and wide horizontal or vertical bars evoke no responses. *Two-bar decision rules* claim that: the cell responses to two bars are strong if one bar is in the middle of the receptive field (RF) (bar with index 0 in decision rules) and the second narrow bar (bar with index 1 in decision rules) is in the certain positions of the RF (DRT1). But when the second bar is in medium position range, the max cell responses became weaker (DRT2). Responses of other cells are sensitive to other bar positions (Fig. 1G, H).

The decision table (Table 2) based on Fig. 2 describes cell responses to two patches placed in different positions along x-axis in the receptive field (RF). Figure 2 shows that adding the second patch reduced single patch cell responses. We have assumed that cell response to a single patch places in the middle of the RF is r_2. The second patch suppresses cell responses stronger when is more similar to the first patch (Fig. 2D).

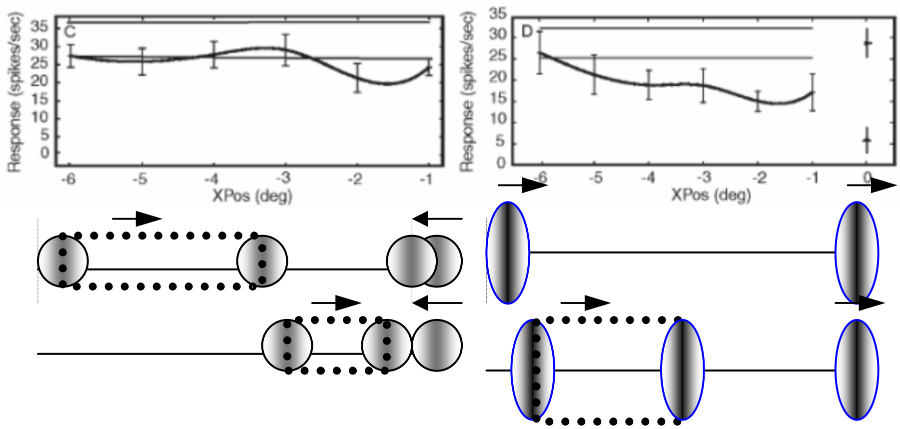

Fig. 2. Modified plots from [2]. Curves represent V4 cell responses to two 1 deg patches with gratings moving in opposite (**C**) and in the same (**D**) directions. One patch is always at *x*-axis position 0 and the second patch changes its position as it is marked in XPos coordinates. The horizontal lines represent 95% confidence intervals for the response to single patch in position 0. Below C and D schematics showing positions of the patches for *class 2* (upper parts) and *class 1* (lower parts) responses. Arrows are showing directions of moving gratings. Double dotted lines mark range of the possible positions of the second patch that give the same response.

Table 2. Decision table for one cell shown in Fig. 2. Attributes *xpr, ypr, s* = 44 are constant and are not presented in the table**.** We introduce another parameter of the stimulus, difference in the direction of drifting grating of two patches: *ddg* = 0 when drifting are in the same directions, and *ddg* = 1 if drifting in two patches are in opposite directions.

Cell	xp	xpr	xs	ys	ddg	r
64c	-4.5	3	1	1	1	2
64c1	-1.75	1.5	1	1	1	1
64c2	-0.5	1	1	1	1	2
64d	-6	0	1	8	0	2
64d1	-5.5	3	1	8	0	1

Two-patch horizontal interaction **decision rules** are as follows:

DRT3: $ddg_1 \wedge (o_0 \wedge xpr_3 \wedge xp_{-4.5} \wedge xs_1 \wedge ys_1)_1 \wedge (o_0 \wedge xp_0 \wedge xs_1 \wedge ys_1)_0 \rightarrow r_2$,
DRT4: $ddg_1 \wedge (o_0 \wedge xpr_1 \wedge xp_{-0.5} \wedge xs_1 \wedge ys_1)_1 \wedge (o_0 \wedge xp_0 \wedge xs_1 \wedge ys_1)_0 \rightarrow r_2$,
DRT5: $ddg_0 \wedge (o_0 \wedge xpr_3 \wedge xp_{-5.5} \wedge xs_1 \wedge ys_8)_1 \wedge (o_0 \wedge xp_0 \wedge xs_1 \wedge ys_1)_0 \rightarrow r_1$,

These decision rules can be interpreted as follows: patches with drifting in opposite directions gratings give strong responses when positioned very near (overlapping) or 150% of their width apart one from the other (DRT3, DRT4). Interaction of patches with a similar gratings evoked small responses in large extend of the RF (DRT5). Generally, interactions between similar stimuli evoke stronger and more extended inhibition than between different stimuli. These and other examples can be generalized to other classes of objects.

We propose following classes of the Stimuli Interaction Rules

SIR1: facilitation when stimulus consists of multiple similar thin bars with small distances (about 0.5 deg) between them, and suppression when distance between bars is larger than 0.5 deg. Suppression/facilitation can be periodic along the receptive field with dominating periods of about 30, 50, or 70% of the RF width.

SIR2: inhibition when stimulus consists of multiple similar discs with distance between their edges ranging from 0 deg (touching) to 3 deg through the RF width.

SIR3: if bars or patches have different attributes like polarity or drifting directions than suppression is smaller and localized facilitation at the small distance between stimuli is present.

SIR4: center-surround interaction, described below in detail.

We will concentrate on the center-surround interaction described above as **SIR4**. We make a decision table for nine different cells tested with discs or annuli (Pollen et al. [2] Fig. 10). If the center is stimulated with a stimulus different from that in the surround then the surround inhibitory mechanism is weak (Fig. 9B in [2]). In order to compare different cells, we have normalized their optimal orientation, denoted it as 1, and removed orientation and its values from the table.

Table 3. Decision table for eight cells comparing the center-surround interaction. All stimuli were concentric discs or annuli with *xo* – outer diameter, *xi* – inner diameter. All stimuli were localized around the middle of the receptive field, so that *xp* = *yp* = *xpr* = *ypr* = 0 were constant and we did not put them in the table.

Cell	sf	sfb	xo	xi	s	r
101	0.5	0	7	0	4	0
101a	0.5	0	7	2	5	1
102	0.5	0	8	0	4	0
102a	0.5	0	8	3	5	0
103	0.5	0	6	0	4	0
103a	0.5	0	6	2	5	1
104	0.5	0	8	0	4	0
104a	0.5	0	8	3	5	2
105	0.5	0	7	0	4	0
105a	0.5	0	7	2	5	1
106	0.5	0	6	0	4	1
106a	0.5	0	6	2	5	2
107	0.5	0.25	6	0	4	2
107a	2.1	3.8	6	2	5	2
107b	2	0	4	0	4	1
108	0.5	0	6	0	4	1
108a	0.9	0.9	4	0	4	2
108b	5	9	6	2	5	2
20a	0.5	0	6	0	4	1
20b	0.5	0	6	0	4	2

We assign the spatial frequency: low (sf_l), medium (sf_m), and high (sf_h) as follows: sf_l *if (sf: 0<sf≤1)*, medium sf_m *if (sf: 1 <sf≤4)*, wide sf_h *if (sf: sf>4)*. On the basis of this definition we calculate for each row in Table 3 the spatial frequency range by taking into account the spatial frequency bandwidth (*sfb*) e. g. cell 107: sf: 0.375 – 0.657 c/deg which means sf_l, 107b: sf: 0.25 – 3.95 c/deg which means that this cell gives response *r*2 to the stimulus with frequencies sf_l and sf_m , etc. Therefore we have to split case 107a to 107al and 107am, 108a to 108al and 108am, and 108b to 108bl, 108bm, 108bh.

Stimuli used in these experiments can be placed in the following ten categories:

$Y_o = |sf_l\, xo_7\, xi_0\, s_4| = \{101, 105\};$
$Y_1 = |sf_l\, xo_7\, xi_2\, s_5| = \{101a, 105a\};$
$Y_2 = |sf_l\, xo_8\, xi_0\, s_4| = \{102, 104\};$
$Y_3 = |sf_l\, xo_8\, xi_3\, s_5| = \{102a, 104a\};$
$Y_4 = |sf_l\, xo_6\, xi_0\, s_4| = \{103, 106, 107, 108, 20a, 20b\};$
$Y_5 = |sf_l\, xo_6\, xi_2\, s_5| = \{103a, 106a, 107al, 108bl\};$
$Y_6 = |sf_l\, xo_4\, xi_0\, s_4| = \{108al\}.$
$Y_7 = |sf_m\, xo_6\, xi_2\, s_5| = \{107am, 108bm\};$
$Y_8 = |sf_m\, xo_4\, xi_0\, s_4| = \{107b, 108am\};$
$Y_9 = |sf_h\, xo_6\, xi_2\, s_5| = \{108bh\}.$

These are equivalence classes for stimulus attributes, which means that in each class they are indiscernible *IND*(*B*). We have normalized orientation bandwidth to 0 in {20a, 20b} and spatial frequency bandwidth to 0 in cases {107, 107a, 108a, 108b}.

There are three ranges of responses, denoted as r_o, r_1, r_2. Therefore the expert's knowledge involves the following three classes:

$| r_o | = \{101, 102, 102a, 103, 104, 105\},$
$| r_1 | = \{101a, 103a, 105a, 106, 107b, 108, 20a\}$
$| r_2 | = \{104a, 106a, 107, 107al, 107am, 108al, 108am, 108bl, 108bm, 108bh, 20b\}$

which are denoted as $X_o, X_1, X_2.$

We want to find out whether equivalence classes of the relation *IND*{*r*} or *V4-granules* form the union of some equivalence to *B-elementary granules*, or whether $B \Rightarrow \{r\}$. We calculate the lower and upper approximation [1] of the basic concepts in terms of stimulus basic categories:

$\underline{B} X_o = Y_o \cup Y_2 = \{101, 105, 102, 104\},$

$\overline{B} X_o = Y_o \cup Y_2 \cup Y_3 \cup Y_4 = \{101, 105, 102, 104, 102a, 104a, 103, 106, 107, 108, 20a, 20b\},$

$\underline{B} X_1 = Y_1 = \{101a, 105a\},$

$\overline{B} X_1 = Y_1 \cup Y_5 \cup Y_6 \cup Y_4 = \{101a, 105a, 103a, 107al, 108b, 106a, 20b, 107b, 108a, 103, 107, 106, 108, 20a\},$

$\underline{B} X_2 = Y_7 \cup Y_9 = \{107am, 108bm, 108bh\},$

$\overline{B} X_2 = Y_7 \cup Y_9 \cup Y_8 \cup Y_3 \cup Y_4 \cup Y_5 \cup Y_6 = \{107am, 108bm, 108bh, 107b, 108am, 102a, 104a, 103a, 107a, 108bl, 106a, 20b, 103, 107, 106, 108, 20a, 108al\}$

Concepts related to response classes 0, 1, and 2 are roughly *B-definable*, which means that with some approximation we have found that the stimuli do not evoke a response, or evoke weak or strong response in the area V4 cells. Certainly a stimulus such as Y_0 or Y_2 does not evoke a response in all our examples, in cells 101, 105, 102, 104. Also stimulus Y_1 evokes a weak response in all our examples: 101a, 105a. We are interested in stimuli, which evoke strong responses because they are specific for area V4 cells. We found two such stimuli, Y_7 and Y_9. In the meantime other stimuli such as Y_3, Y_4 evoke no response, weak or strong responses in our data.

We have following decision rules:

DR10: $sf_l \wedge x_{o7} \wedge x_{i2} \wedge s_5 \longrightarrow r_1$,
DR11: $sf_l \wedge x_{o7} \wedge x_{i0} \wedge s_4 \longrightarrow r_0$,
DR12: $sf_l \wedge x_{o8} \wedge x_{i0} \wedge s_4 \longrightarrow r_0$,
DR13: $(sf_m \vee sf_l) \wedge xo_6 \wedge xi_2 \wedge s_5 \longrightarrow r_2$.

These can be interpreted as the statement that a large annulus (s5) evokes a weak response, but a large disc (s4) evokes no response when there is modulation with low spatial frequency gratings. However, somewhat smaller annulus containing medium or high spatial frequency objects evokes strong responses. It is unexpected that certain stimuli evoke inconsistent responses in different cells (Table 3):

103: $sf_l \wedge x_{o6} \wedge x_{i0} \wedge s_4 \longrightarrow r_0$,
106: $sf_l \wedge x_{o6} \wedge x_{i0} \wedge s_4 \longrightarrow r_1$,
107: $sf_l \wedge x_{o6} \wedge x_{i0} \wedge s_4 \longrightarrow r_2$,
103a: $sf_l \wedge x_{o6} \wedge x_{i2} \wedge s_5 \longrightarrow r_1$,
106a: $sf_l \wedge x_{o6} \wedge x_{i2} \wedge s_5 \longrightarrow r_2$.

A disc with not very large dimension containing a low spatial frequency grating can evoke no response (103), a small response (106), or a strong response (107).

3.2 Application of Proposed Decision Rules to Results Obtained by Others

The purpose of our study has been to determine rules showing how different stimuli are related to neurological responses in neurons of the area V4. We have tested our theory on a set of data from David et al. [4]. Fig. 3 shows an example from [4]. We will analyze these images dividing them into rough parts and applying decision rules proposed above.

The stimulus configuration in the first image on the left is similar to that in Fig. 1. Thin lines mark orientation of the dominating stimulus with two minima like in Fig. 1G. Alternatively, this image can be classified as interaction between bars with different polarities. Their small distance interactions facilitate cell responses (SIR3). This means that this image will give class 2 responses in V4. If we divide the middle image into two parts, we notice small, but significant differences between its central and surround parts. Assuming that the center and surround are tuned to a feature of the object in the images, we believe that these images would also give significant responses.

Fig. 3. In their paper David et al. [4] stimulated V4 neurons (medium size of their receptive fields was 10.2 deg) with natural images. Several examples of their images are shown above. We have divided responses of these cells into three classes. The image on the left represents cell, which gives strong response related to stimulus concept 2. The image in the middle evokes response above 20 spikes/s; that is related to stimulus concept 1. The image on the right gives very weak response; it is related to the stimulus concept 0.

This image can be seen as a group of medium x position range bars (bars of medium width), which means using the *DR3* decision rule. Even if this image shows differences between its central and surround parts, they have also many similar features like orientation or spatial frequencies. Therefore even if the center and surround alone would give strong cell responses, their interactions will be inhibitory (rule *SIR4*). In consequence, the middle image will give class 1 responses in V4 and it is related to stimulus concept 1. In the image on the right there is no significant difference between the stimulus in the center and the surround. Therefore the response will be similar to that obtained when a single disc covers the whole receptive field: *DR11, DR12*. In most cells such stimuli class will be equivalent to a stimulus concept 0.

4 Discussion

In this work we have concentrated on the pre-attentive processes. These so-called early processes extract and integrate into many parallel channels the basic features of the environment. These processes are related to the human perceptions property of objects with unsharp boundaries of values of attributes put together by similarities [5]. These similarities may be related to synchronizations of the multi-resolution parallel computations that are difficult to simulate in the digital computer [6]. It seems that it is relatively straightforward task to classify different objects on the basis of their physical properties, which define values of their attributes. Generally problem appears when the same object in different conditions changes values of its attributes, or in other words its parts became unsharp. One solution is that the brain extracts as elementary parts so-called “basic features” [7].

Our eyes constantly perceive changes in light colors and intensities. From these sensations our brain extracts features related to different objects. The “basic features” were identified in psychophysical experiments as elementary features that can be extracted in parallel. Evidence of parallel extraction comes from the fact that their extraction time is independent of the number of objects. Other features need serial search, so that the time needed to extract them is proportional to the number of objects. The high-level serial process is associated with the integration, and consolidation of items and with a conscious report. Other, low-level parallel processes are rapid, global, related to high efficiency categorization of items and largely unconscious [7]. Our work is related to the constitution of decision rules extracting basic features from the visual stream.

We have suggested previously [3] that the brain may use the multi-valued logic in order to test learned predictions about object attributes by comparing them with actual stimulus-related hypotheses. Neurons in V4 integrate object's attributes from its parts in two ways: one is relate to local excitatory-inhibitory interactions described here as SIR (stimuli interaction rules), and another way by changing possible part properties using feedback connections tuning lower visual areas. Different neurons have different SIRs watching objects by multiple "unsharp windows" (Figs. 1, 2). If object's attributes fit to the unsharp window, neuron sends positive feedback [8] to lower areas filters which in end-effect sharpen the attribute-extracting window changing neuron response from class 1 to class 2 (Fig. 1 J and K).

In summary, we have shown that using rough set theory we can divide stimulus attributes in relationships to neuronal responses into different concepts. Even if most of our concepts were very rough, they determine rules on whose basis we can predict neural responses to new, natural images.

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