Checking Brain Expertise Using Rough Set Theory

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Abstract. Most information about the external world comes from our visual brain. However, it is not clear how this information is processed. We will analyze brain responses using machine learning methods based on rough set theory. We will test the expertise of the visual area V4, which is responsible for shape classifications. Characteristic of each stimulus are treated as a set of learning attributes. We assume that bottom-up information is related to hypotheses, while top-down information is related to predictions. Therefore, neuronal responses are divided into three categories. Category 0 occurs if cell response is below 20 spikes/s (sp/s), indicating that the hypothesis is not valid. Category 1 occurs if cell activity is higher than 20 spikes, implying the hypothesis is valid. Category 2 occurs if cell response is above 40 sp/s; in this case we conclude that the hypothesis and prediction are valid. By using experimental data we make a decision table for each cell, and generate equivalence classes. We express the brains basic concepts by means of the learners basic categories. By approximating stimulus categories with concepts of different cells we determine core properties of cells, and differences between them. On this basis we have created profiles of their receptive field properties.

Keywords: V4, machine learning, bottom-up, top-down processes, neuronal activity.

1 Introduction

Most of our knowledge about function of the brain is based on electrophysiological recordings from single neurons. In the lower visual areas like the retina, LGN or V1 (primary visual cortex) it is relatively easy to find an optimal stimulus for each neuron. The receptive fields in these areas are small and simple. On the other end, in the area designated as IT (inferotemporal cortex), receptive fields are very large and optimal stimuli are generally unknown, though they could be as complex as faces. In consequence, different laboratories propose different often contradictory hypotheses on the basis of their different testing stimuli. Another part of the confusion is related to non-uniform properties of neurons in area V4 of the brain. Therefore we do not know if different experimental results and hypotheses are related to different methods and classifications or to different classes of cells.

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In order to clarify these confusions, we propose the use of rough set theory (Pawlak, [1]) to classify concepts of different cells as related to different stimuli attributes. We define an information system [1] as a pair $S = (U, A)$ where U denotes a nonempty set of objects, and A set of attributes. For each pair (a, u), $a \in A$, $u \in U$ 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 follows: $(x, y) \in IND(B)$ if and only if $a(x) = a(y)$ for every $a \in B$, where $a(x) \in V$. $IND(B)$ is the equivalence relation, and $[u]_B$ is the equivalence class of u. The concept $X \subseteq U$ is $B-definable$ if for each $u \in U$ either $[u]_B \subseteq X$ or $[u]_B \subseteq U - X$. $\underline{B}\,X = \{u \in U : [u]_B \subseteq X\}$ is a lower approximation of X. The concept $X \subseteq U$ is $B-indefinable$ if is not $B-definable$ and exists such $u \in U$ that $[u]_B \cap X \neq \emptyset$. $\bar{B}X = \{u \in U : [u]_B \cap X \neq \emptyset\}$ is an upper approximation of X.

2 Methods

Most of our analysis will be related to data from Pollen et al. [2]. As mentioned above we have divided all cell responses into three ranges. Activity below 20 sp/s is defined as a category 0 cell response. Activity above 20 sp/s is defined as category 1, and activity above 40 sp/s as category 2. The reason for choosing the minimum significant cell activity of 20 sp/s is as follows. During normal activity our eyes are constantly moving. Our fixation periods are between 100 and $300ms$, which is similar to those of monkeys (averaged fixation duration was $195 \pm 168ms(SD)$, median $144ms$ [3]).

Assuming that a single neuron, in order to give reliable information about an object, must fire a minimum of 2-3 spikes during the eye fixation period, we obtained a minimum frequency of 20 sp/s. We assume that these discharges are related to bottom-up information (hypothesis testing) and that they are related to the objects form.

The brain is constantly making predictions which are verified by comparing them with sensory information. These tests are performed in a positive feedback loop ([4], [5]). If prediction is in agreement with the hypothesis, activity of the cell increases approximately twofold ([4]). This increased activity is related to category 2. (neuronal discharges of 40 sp/s). We will represent data from Pollen et al. [2] in the following table. In the first column there are different measurements of neurons. Neurons are classified by numbers related to various figures in [2]. Different measurements of the same cell are denoted by letters (a, b,). For example, 11a denotes the first measurement in neuron 1 Fig. 1, 11b - etc. Stimulus properties are as follows:

1. orientation in degrees appears in the column labeled o, and orientation bandwidth is labeled by ob.
2. spatial frequency is denoted as sf, 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: for grating $s = 1$, for vertical bar $s = 2$, for horizontal bar $s = 3$, for disc $s = 4$, for annulus $s = 5$

Stimulus attributes can be express as: $B = \{o, ob, sf, sfb, xp, xpr, yp, ypr, xs, ys, s\}$. Cell responses are denoted by r and divided into three ranges: r_0: activity below 20 sp/s; r_1: activity above 20sp/s; r_2: activity above 40sp/s .

3 Results

We have analyzed several neurons from [2]. Below we have shown modified figures from the above work, along with their decision tables. On this basis we have generated figures comparing the category of the stimulus with the concept of the brain cell. Fig. 1 shows tests performed on two neurons. Curves describe responses to long narrow bars which in Fig. 1A, C are oriented vertically and in Fig. 1B, D horizontally. They change their position along the x and y axis. The light intensity of bars is constantly changing these are so-called drifting gratings [2]. The cell in the left part of Fig. 1 (Fig. 1A, B) does not show strong responses. Only when a vertical (Fig. 1A) or horizontal bar (Fig. 1C) is near the middle of the receptive field the cells activity reaches 20 spikes/s. It means that this stimulus has category 1. More interesting is the second cell (on the right Fig. 1C, D). It shows several areas of strong activity where not only category 1 but

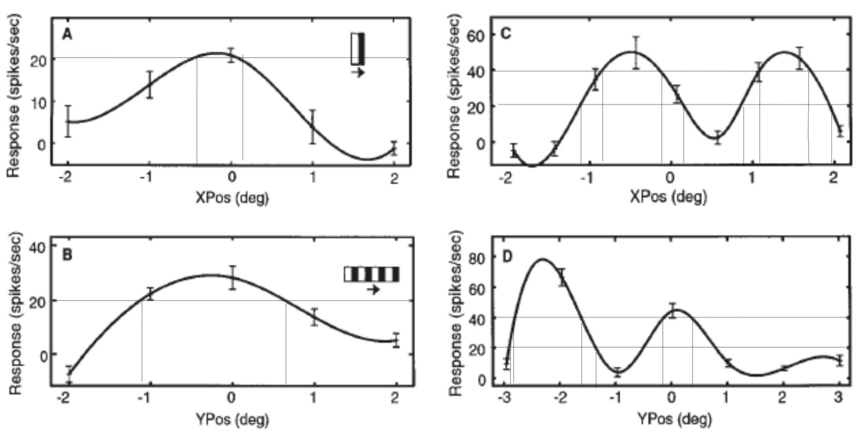

Fig. 1. Curves represent approximated responses of two cells (A,B) and (C, D) from area V4 to vertical and horizontal bars. Bars changed their position in Xpos or Ypos directions and responses of the cell was measured. Mean SE are marked in the figures. Stimulus attributes are shown in the table below. Cell responses are divided to two ranges (concepts) by horizontal lines. Plots are modified on the basis of [2].

also category 2 are realized. As one can notice, these *hot spots* are not symmetric along the middle of the receptive field, but they divide the receptive field into several smaller subfields. Such results are the basis of the idea that the receptive field of V4 neurons can be divided into several independent parts (see Fig. 3). In the next step of our analysis, we have converted these data into decision table (Table 1). In the top row of the table is a list of stimulus attributes, next two rows describe the first cell other rows describe the second cell from Fig. 1. As it was mentioned above different rows are related to different measurements. Results presented in the decision table for the second cell are shown in Fig. 2 as the preferred stimulus for this cell. Fig. 2 shows areas in the receptive field where category 1 (left side) and category 2 (right side) are fulfilled and become concept 1 and concept 2.

Table 1. Decision table for two cells shown in Fig. 1. Attributes ob, sf, sfb were constant and they are not presented in the table

cell	*o*	*xp*	*xpr*	*yp*	*ypr*	*xs*	*ys*	*s*	*r*
11a	90	0	0.6	0	0	0.5	1	2	1
11b	0	0	0	-0.4	1.5	2	0.5	3	1
12a	90	-0.6	1.3	0	0	0.4	4	2	1
12a1	90	-0.6	0.8	0	0	0.4	4	2	2
12a2	90	1.3	1.1	0	0	0.4	4	2	1
12a3	90	1.3	0.6	0	0	0.4	4	2	2
12b	0	0	0	-2.2	1.5	4	0.4	3	1
12b1	0	0	0	-2.2	1.2	4	0.4	3	2
12b2	0	0	0	0.15	1.4	4	0.4	3	1
12b3	0	0	0	0.15	0.5	4	0.4	3	2

Let us define $0 \leq xpr \leq 0.8$ will be sign as xpr_n (narrow bar x-range), $0 \leq ypr \leq 1.2$ will be sign as ypr_n (narrow bar y-range),

Decision rules related to the cell in Fig. 1C, D are following:

DR1: $o_{90} \wedge (xp_{-0.6} \vee xp_{1.3}) \wedge xpr_n \wedge xs_{0.4} \wedge ys_4 \rightarrow r_2$
DR2: $o_0 \wedge (yp_{-2.2} \vee yp_{0.15}) \wedge ypr_n \wedge xs_4 \wedge ys_{0.4} \rightarrow r_2$

Fig. 3 shows responses of a V4 cell tested with different stimuli. Fig. 3A shows cell responses to different orientation of grating of a large disc covering the receptive field (RF). Fig. 3B shows changes in cell response when the width of the stimulus was changed. Figs. 3C-F show cell responses when different subfields of the RF were stimulated with different stimulus orientation. Cell responses were also tested when the same subfields were stimulated with different spatial frequencies (Fig. 5 in [2]). These results are summarized in the Table 2.

Let us simplify $0 < ob < 50$ will be sign as ob_n (narrow orientation bandwidth), $ob > 100$ as ob_w (wide orientation bandwidth), $0 < sfb < 2$ as sfb_n , and $sfb > 2.5$ sfb_w.

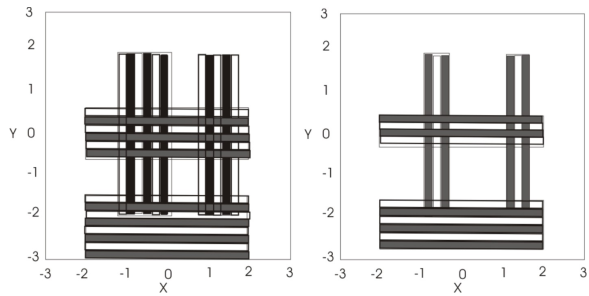

Fig. 2. Schematic representation of Table 1. Long bars have approximate concepts of the stimulus, with their positions in the receptive field related to the concept in the brain. The left schematic represents concept 1, while the right side represents concept 2.

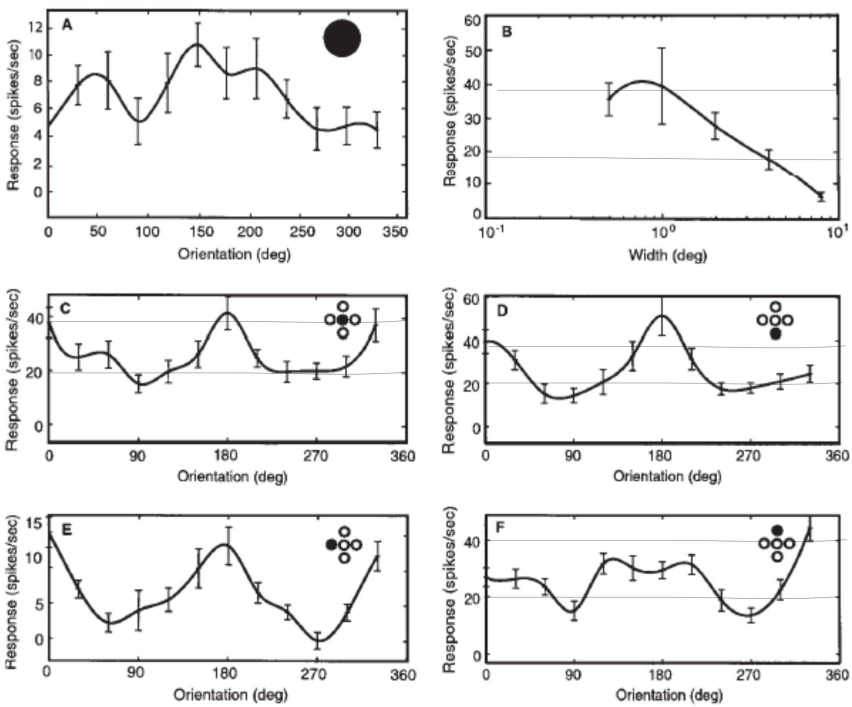

Fig. 3. Modified plots on the basis of [2]. One V4 cell tested with different stimuli. A. a large disc of grating covering the whole receptive field B. a large slit of light which changes its width. Notice the optimal width is around 1 deg. C-F Curves representing responses of the same cell when its subfields (their positions are shown in plots) are covered with a small 2 deg grating discs 2 deg apart in a 6 deg receptive field.

Table 2. Decision table for one cell responses to subfields stimulation Fig. 3C-F and Fig.5 in [2]. Attributes xpr, ypr, s are constant and they are not presented in the table.

cell	*o*	*ob*	*sf*	*sfb*	*xp*	*yp*	*r*
3c	172	105	2	0	0	0	1
3c1	10	140	2	0	0	0	1
3c2	180	20	2	0	0	0	2
3d	172	105	2	0	0	-2	1
3d1	5	100	2	0	0	-2	1
3d2	180	50	2	0	0	-2	2
3e	180	0	2	0	-2	0	0
3f	170	100	2	0	0	2	1
3f1	10	140	2	0	0	2	1
3f2	333	16	2	0	0	2	2
5a	180	0	2.3	2.6	0	-2	1
5b	180	0	2.5	3	0	2	1
5c	180	0	2.45	2.9	0	0	1
5c1	180	0	2.3	1.8	0	0	2

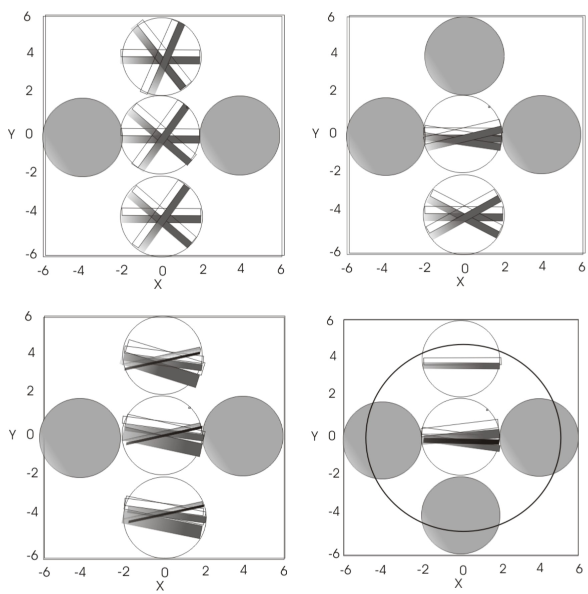

Fig. 4. Schematic representation of Table 2. Receptive field was divided into five subfields which were stimulated separately. Gray circles indicate cell response was below 20 spikes/s. The two upper plots represent subfields tuning to different orientations, whereas the two lower plots describe spatial frequency tuning. Plots on the left are related to concept 1, and plots on the right to concept 2. Notice that on the basis of the plots on the right one can imagine an optimal stimulus. It cannot be the same stimulus in all subfields because it does not give a strong response (Fig. 3A).

Table 3. Decision table for eight cells comparing the center-surround interaction. All stimuli were concentric, and therefore attributes were not xs, ys, but xo outer diameter, xi inner diameter. All stimuli were localized around middle of the receptive field so $xp = yp = xpr = ypr = 0$ and were skipped.

$cell$	ob	sf	sfb	xo	xi	s	r
101	0	0.5	0	7	0	4	0
101a	0	0.5	0	7	2	5	1
102	0	0.5	0	8	0	4	0
102a	0	0.5	0	8	3	5	0
103	0	0.5	0	6	0	4	0
103a	0	0.5	0	6	2	5	1
104	0	0.5	0	8	0	4	0
104a	0	0.5	0	8	3	5	2
105	0	0.5	0	7	0	4	0
105a	0	0.5	0	7	2	5	1
106	0	0.5	0	6	0	4	1
106a	0	0.5	0	6	3	5	2
107	0	0.5	0.25	6	0	4	2
107a	0	2.1	3.8	6	2	5	2
107b	0	2	0	4	0	4	1
108	0	0.5	0	6	0	4	1
108a	0	2	0	4	0	4	2
108b	0	5	9	6	2	5	2
20a	0.5	0.5	0	6	0	4	1
20b	0.3	0.5	0	6	0	4	2

Decision rules related to cell from Fig. 3 are following:

DR3: $ob_n \wedge (yp_0 \vee yp_2) \rightarrow r_2$
DR4: $ob_w \wedge xp_0 \rightarrow r_1$
DR5: $sfb_n \wedge yp_0 \rightarrow r_2$
DR6: $sfb_w \wedge xp_0 \rightarrow r_1$

Notice that Figs. 2 and 4 show possible configurations of the optimal stimuli. However, they do not take into account interactions between several stimuli, when more than one subfield is stimulated.

Therefore we propose following **Subfield Interaction Rules:**

SIR1: facilitation when stimulus consists of multiple bars with small distances ($0.5 - 1$ deg) between them, and inhibition when distance between bars is $1.5 - 2$ deg.
SIR1: inhibition when stimulus consists of multiple similar discs with distance between them ranging from 0 deg (touching) to 3 deg.
SIR1: Center-surround interaction, which is described below in detail.

We will concentrate on the center-surround interaction. We will make a decision table for nine different cells tested with the disc covering their receptive field and an annulus when the center of the receptive field is not stimulated (Pollen et al. [2] Fig. 10). If the center is stimulated with another stimulus attributes then the surround inhibitory mechanism is also weak (Fig. 9B in [2]). In order to compare different cells, we have normalized their optimal orientation which will be denoted as 1.

The experiments test receptive field with disc and annulus stimuli, which could be, described as following six categories:

$$Y_0 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_7\ xi_0\ s_4| = \{101, 105\}$$

$$Y_1 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_7\ xi_2\ s_5| = \{101a, 105a\}$$

$$Y_2 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_8\ xi_0\ s_4| = \{102, 104\}$$

$$Y_3 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_8\ xi_3\ s_5| = \{102a, 104a\}$$

$$Y_4 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_6\ xi_0\ s_4| = \{103, 106, 107, 108, 20a\}$$

$$Y_5 = |o_1\ ob_0\ sf_{0.5}\ sfb_0\ xo_6\ xi_2\ s_5| = \{103a, 106a, 107a, 108b, 20b\}$$

$$Y_6 = |o_1\ ob_0\ sf_2\ sfb_0\ xo_4\ xi_0\ s_4| = \{107b, 108a\}$$

which are equivalence classes for stimulus attributes, which means that in each class they are indiscernible $IND(B)$. For simplicity we simplify orientation bandwidth to 0 in $\{20a, 20b\}$ and spatial frequency bandwidth to 0, in cases $\{107, 107a, 108a, 108b\}$, and put values covered by the bandwidth to the spatial frequency parameters. There are three ranges of responses denoted as r_o, r_1, r_2 therefore the experts knowledge involves the following three concepts:

$$|r_o| = \{101, 102, 102a, 103, 104, 105\}$$

$$|r_1| = \{101a, 103a, 105a, 107b, 108, 20a\}$$

$$|r_2| = \{104a, 106a, 107, 107a, 108a, 108b, 20b\}$$

which will be denoted as X_o, X_1, X_2.

We want to find out whether equivalence classes of the relation $IND\{r\}$ form the union of some equivalence relation $IND(B)$, or whether $B \Rightarrow \{r\}$. We will calculate the lower and upper approximation [1] of the brains basic concepts in term of stimulus basic categories:

$\underline{B}\ X_0 = Y_0 = \{101, 105\}$
$\bar{B}X_0 = Y_0 \cup Y_2 \cup Y_3 \cup Y_4 = \{101, 105, 102, 104, 102a, 104a, 103, 106, 107, 108, 20a\}$
$\underline{B}\ X_1 = Y_1 = \{101a, 105a\}$
$\bar{B}X_1 = Y_1 \cup Y_5 \cup Y_6 \cup Y_4 =$
$\{101a, 105a, 103a, 107a, 108b, 106a, 20b, 107b, 108a, 103, 107, 106, 108, 20a\}$
$\underline{B}\ X_2 = 0$
$\bar{B}X_2 = Y_3 \cup Y_4 \cup Y_5 \cup Y_6 =$
$\{102a, 104a, 103a, 107a, 108b, 106a, 20b, 103, 107, 106, 108, 20a, 107b, 108a\}$

Concept 0 and concept 1 are roughly $B-defined$, which means that only with some approximation can we say that stimulus Y_o does not evoke a response (concept 0) in cells 101, 105, but that other stimuli Y_2, Y_3 can evoke no response or weak (concept 1) or strong (concept 2) response. This is similar for concept 1. However, concept 2 is internally $B - undefinable$. Stimulus attributes related to this concept should give us information about cell characteristics, but data from the Table 3 cannot do it.

We can find quality [1] of our experiments by comparing properly classified stimuli $POSB(r) = \{101, 101a, 105, 105a\}$ to all stimuli and to all responses: $\gamma\{r\} = \frac{card\{101,101a,105,105a\}}{card\{101,101a,,20a,20b\}} = 0.2$. We can also ask what percentage of cells we fully classified. We obtain consistent responses from 2 of 9 cells, which means that $\gamma = 0.22$. This is related to the fact that for some cells we have tested more than two stimuli. What is also important from an electrophysiological point of view is there are negative cases. There are many negative instances for the concept 0, which means that in many cases this brain area responds to our stimuli; however it seems that our concepts are still only roughly defined. **Decision rules** related to cells listed in the Table 3 are following:

DR7: $xo_7 \wedge xi_2 \wedge s_5 \to r_1$
DR8: $xo_7 \wedge s_4 \to r_0$
DR9: $xo_8 \wedge s_4 \to r_0$

They can be interpreted that large annulus (s5) evokes weak response, but large disc (s4) evokes no response.

4 Discussion

The purpose of our study was to determine how different categories of stimuli and particular concepts, as related to the expertise of a single cell. We can test our theory on a set of data from David et al. [5], shown in Fig.5.

Assuming that the stimulus configuration in top two images on the left side is similar to that proposed in Fig. 2, we can apply DR2 and SIR1. This means that these images will be related to concept 2. Top-right and bottom-left images show significant differences between their center and surround, therefore these images would also give significant responses. However, in the top-right image only part of the surround is stimulated therefore DR4, DR6, and DR7 rules are applied. In the bottom-left image the object is localized in part of the center and part of the surround: DR5 but SIR3. In consequence responses to both images are related to the concept 1. In two bottom-right images there is no significant difference between 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: DR8, DR9. In most cells such a stimulus is classified as concept 0.

In summary, we have showed 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.

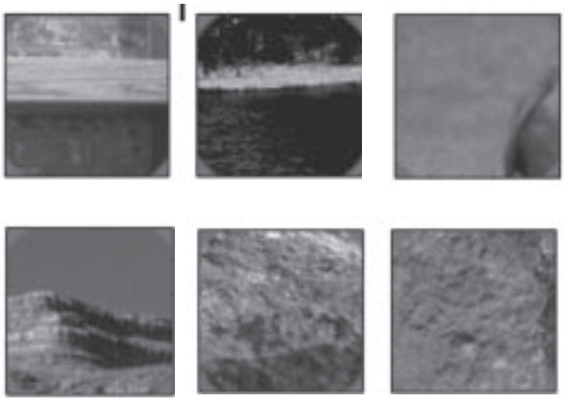

Fig. 5. In their paper David et al. [6] stimulated V4 neurons (medium size of their receptive fields was 10.2 deg) with natural images. Several examples of their images are shown above. We have divided responses of their cells into three concepts. Two left images in top gave strong responses above 40 sp/s related concept 2. Image top-right and bottom-left evoke responses above 20 sp/s related to concept 1. Two images on the right in bottom row gave very weak related to concept 0 responses.

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