

# MATLAB/OCTAVE TOOLS FOR THE VISUAL NEUROSCIENCE CLASS II: UNDERSTANDING THE EXCITATION PATTERNS IN V1 AND MT AREAS

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## Abstract

A problem in teaching Visual Neuroscience is that students with biomedicine background are still unaware of the advantages of quantitative thinking and usually get stuck with maths. As a result, they have troubles with current experimental techniques and neural models heavily based on signal and information processing concepts. In this series of papers devoted to the Visual Neuroscience classroom, we present a number of computational tools to help the students to *learn-by-playing*, as opposed to the classical analytical approach in physical sciences. In this work, we present tools to understand the response of V1 and MT cells to complex moving sequences. By visualizing the spectrum of natural movies and the receptive fields of the cells in the frequency domain, students understand the dynamic of the excitation-inhibition patterns in V1 and MT areas.

**Keywords:** teaching visual neuroscience, computational models, virtual laboratory, motion perception, receptive fields in V1 and MT cortex, tuning properties of V1 and MT cells.

## 1. INTRODUCTION: THE NEED OF VIRTUAL LABS IN VISUAL NEUROSCIENCE

The students (and faculty) of Visual Neuroscience have diverse academic backgrounds and are often not familiar with quantitative techniques. As a result, professors have problems to convey experimental and theoretical concepts that are mathematical in nature. Traditional (analytical) approaches used in physics or engineering are not appropriate for bio-oriented students. This is a well-known teaching problem in Vision Science [1,2]: the faculty is still reluctant to include more maths in the curricula so the students simply don't have the appropriate background. One solution to this problem is *learning quantitative thinking by playing with computational models (virtual lab) as opposed to understanding the models in the blackboard*. There are different ways to follow this general idea, e.g. providing the students with closed (stand-alone) tools that can be manipulated to illustrate the concepts [1], or the (more challenging) option of providing the students with open tools that can be combined in friendly programming environments such as Matlab/Octave [2]. This series of papers devoted to the Visual Neuroscience classroom (see the companion paper [3]) explores the second option.

In this work, we present tools to understand the response of V1 and MT cells to complex moving sequences by using our experience in motion perception and optical flow [4-8]. By visualizing the spectrum of natural movies and the receptive fields of the cells in the frequency domain, students understand the dynamic of the excitation-inhibition patterns in V1 and MT areas.

## 2. RESPONSE OF (LINEAR) MOTION SENSITIVE NEURONS

As discussed in [3,9], the response of a linear neuron to moving sequences can be computed through the scalar product of two vectors: the receptive field,  $\mathbf{g}$ , and the stimulus,  $\mathbf{s}$ . A system made of multiple linear sensors with the same impulse response (or receptive field) up to a spatial displacement, is called a *linear spatially invariant system* [10], and the response of each sensor can be computed through (i) the convolution of the input signal (the moving sequence) with the receptive field function in

relative coordinates, and (ii) the undersampling of the result at the specific locations the individual sensors are tuned to (usually a uniform grid):

$$r[s](x, t) = g \otimes s = \int g(x, t, x', t') s(x', t') dx' dt' \quad (1)$$

$$r_p[s](t) = r[s](x_p, t) \quad (2)$$

where Eq. 1 represents the convolution and Eq. 2 represents the response of the  $p$ -th sensor to the stimulus,  $s$ , at time,  $t$ , obtained by taking the value of the convolution at the location  $x_p$  where the  $p$ -th sensor is tuned to.

### 2.1. Response: overlap between stimulus and sensor sensitivity in the Fourier domain

According to the theory of linear systems [10], the convolution can be computed in the original domain (as in Eq. 1) or by a simple element-wise product in the Fourier domain (and inverting the result back):

$$r[s](x, t) = F^{-1}[G(f_x, f_t) \cdot S(f_x, f_t)](x, t) \quad (3)$$

where  $F^{-1}$  stands for the inverse of the spatio-temporal Fourier transform, and  $G$  and  $S$  are the expressions of the receptive field of the sensors and the stimulus in the Fourier domain respectively, i.e. it holds,  $G = F[g]$ ,  $g = F^{-1}[G]$ ,  $S = F[s]$ , and  $s = F^{-1}[S]$ .

Therefore, Eq. 3 implies that high excitations are expected when the frequency content of the stimulus (the energy of  $S$ ) overlaps with the sensitivity in the Fourier domain (amplitude of the receptive field  $G$ ).

The above (Eqs. 1-3) applies to any kind of linear sensor. The key issue for the student here is having an intuition of the specific shape of (i) the spectrum of moving sequences as a function of their speed, and (ii) the frequency sensitivity of V1 and MT cells. These are the issues reviewed in the next subsections and the lesson to learn in the proposed virtual lab.

### 2.2. Motion in the Fourier domain

As reviewed elsewhere [11,12], sequences moving with uniform speed,  $\mathbf{v}$ , have slanted spectra. In other words, its frequency content is in the plane fulfilling this equation (the optical flow in the Fourier domain):

$$\mathbf{f}_x \cdot \mathbf{v} + f_t = 0 \quad (4)$$

where  $\mathbf{f}_x$  and  $\mathbf{v}$  are two-dimensional vectors, and  $\mathbf{f}_x \cdot \mathbf{v}$  is a scalar product.

Understanding Eq. 4 involves (i) a demonstration involving algebra on spatio-temporal sinusoids and some properties of 3d Fourier transform, and (ii) realizing that it describes an slanted plane whose orientation depends on  $\mathbf{v}$ . This takes a valuable time in the neuroscience class and it is better understood by playing.

### 2.3. Sensitivity of V1 and MT neurons in the Fourier domain

Following the experimental procedure that has been illustrated in another virtual lab [3], physiological experiments showed that V1 cells are narrow-band filters tuned to specific spatio-temporal frequencies [9,12], i.e. their magnitude in the frequency domain is the sum of two gaussians at  $\pm (\mathbf{f}_{x0}, f_{t0})$ :

$$G(\mathbf{f}_x, f_t) = K [ \exp(-(\mathbf{f}_x - \mathbf{f}_{x0})^2 / \sigma_x^2 - (f_t - f_{t0})^2 / \sigma_t^2) + \exp(-(\mathbf{f}_x + \mathbf{f}_{x0})^2 / \sigma_x^2 - (f_t + f_{t0})^2 / \sigma_t^2) ]^{1/2} \quad (5)$$

In the same way [3,9,12], it has been shown that MT cells aggregate responses coming from V1 cells that are tuned to *speed-coherent* spatio-temporal frequencies. Here *speed-coherent* frequencies means that the central frequency of the afferents to a single MT cell fulfil Eq. 4 for a single speed  $\mathbf{v}$ , i.e. they are aligned in a slanted plane. According to this, the receptive field of MT cells is given by the sum of receptive fields of multiple V1 cells with coherent orientation.

The visualization tools in the virtual lab proposed below help the students to easily generate and visualize such cells using different tuning parameters.

### 3. THE PROPOSED VIRTUAL LAB: *EXCITATION PATTERNS IN VIRTUAL V1 AND MT*

Here we propose the students to take characteristic sequences with controlled texture and velocity to stimulate sets of virtual neurons with specific tuning properties. This allows the simultaneous visualization of the input sequence and the dynamic pattern of responses. In order to do so, we need (i) software to generate the stimuli and the neurons, (ii) software to compute the response(s) given the stimulus and the sensor(s), and, more importantly, (iii) software to visualize the frequency content of stimulus and the bandwidth of the sensor. Note that issues (i) and (ii) were addressed in another virtual lab [3]. Here we focus on the visualization of the spatio-temporal Fourier representation, and the visualization of the dynamic response pattern. With these tools, the students analyze the spectrum of natural sequences and, as a result, select specific V1 and MT neurons that will give rise to interesting response patterns for a better understanding of their behavior.

The general code for this virtual lab is available at [http://isp.uv.es/soft\\_visioncolor.htm](http://isp.uv.es/soft_visioncolor.htm) in the section Toolboxes for the Visual Neuroscience Class. The specific routine with a step-by-step explanation is `response_experiment.m`

#### 3.1. Software for spatio-temporal Fourier transforms: computation and visualization

- **Computation:** `fft3.m` and `ifft3.m` direct and inverse three dimensional Fourier transform. These routines include the option of performing the shift of the discrete domain (i.e. they include the 3d version of `fftshift.m` and `ifftshift.m`). Therefore, the Fourier transform of  $s$  including the shift is:  $S = \text{fft3}(s,1)$ .
- **Visualization:** `show_fft3.m` representation of the absolute value of the Fourier transform.

#### 3.2. Software to compute dynamic response to movies

The frequency response,  $G$ , of the different cells (required to apply Eq. 3) is obtained from `sens_gabor3d.m`, that implements Eq. 5, and `sens_MT.m`. See [3] and the on-line help of the routines for details. Given the sequence,  $s$ , and the receptive field of the cells in the Fourier domain,  $G$ , the dynamic response (Eq. 3) can be obtained with the proposed toolbox as:

$$r = \text{real}(\text{ifft3}(G .* \text{fft3}(s,1), 1)); \quad (6)$$

where the discrete transform was used with the shift option. By subsampling the response sequence (array) at selected positions, we have the dynamic response of the corresponding cells tuned to those positions.

## 4. RESULTS

Figs. 1 and 2 show frames from the illustrative sequence and the spatio-temporal spectrum of the whole video clip. These results can be used to explain Eq. 4 in practice. This example is quite appropriate to explain what spatial frequency is (you can count stripes/degree) and the energy distribution in spatio-temporal spectra when specific patterns move (you can easily measure speed by dividing  $\Delta x/\Delta t$ ).

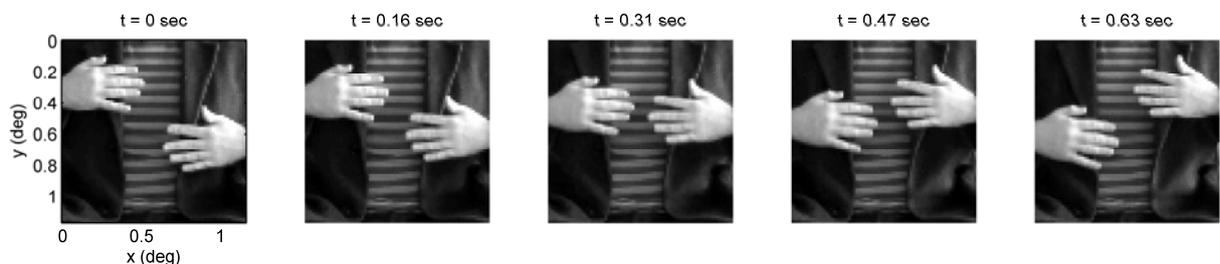


Fig. 1. Illustrative frames of the *waving hands* sequence [7]. In this sequence, the hands (about 12 cpd pattern) travel up and down at about 0.85 deg/sec: note the number of stripes/deg in the T-shirt and the displacement in the time interval shown.

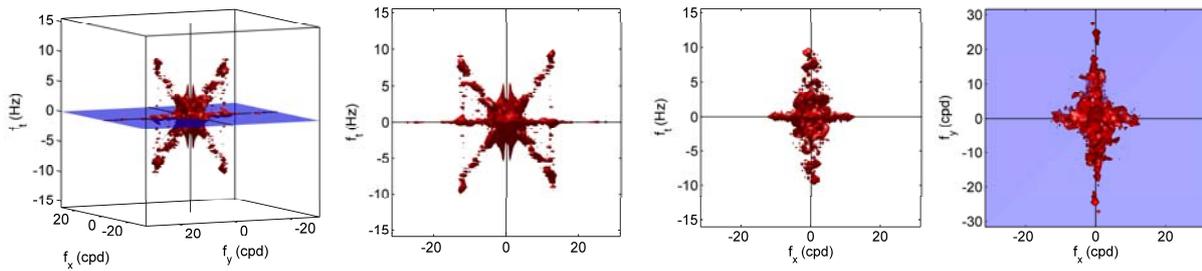


Fig. 2. Spatio-temporal Fourier spectrum of the waving hands sequence: 3d rendering (left), and different 2d projections. Note the energy of the static patterns on the blue ( $f_t = 0$ ) plane, and the energy of the moving objects leading to oriented contributions in the spectrum (for upward and downward motions).

This illustrative sequence was recorded on purpose for this kind of application [7] and it is publicly available with the basic video software toolbox together with other standard sequences [14].

Figure 3 shows the spatio-temporal frequency sensitivity of the selected V1 (top) and MT (bottom) cells sensitive to downward motion. Note that, from left to right, we considered neurons tuned to low, medium and high speeds. We considered upward sensitive neurons too (not shown in the figure). These would have receptive fields with similar inclination but oriented in the opposite direction.

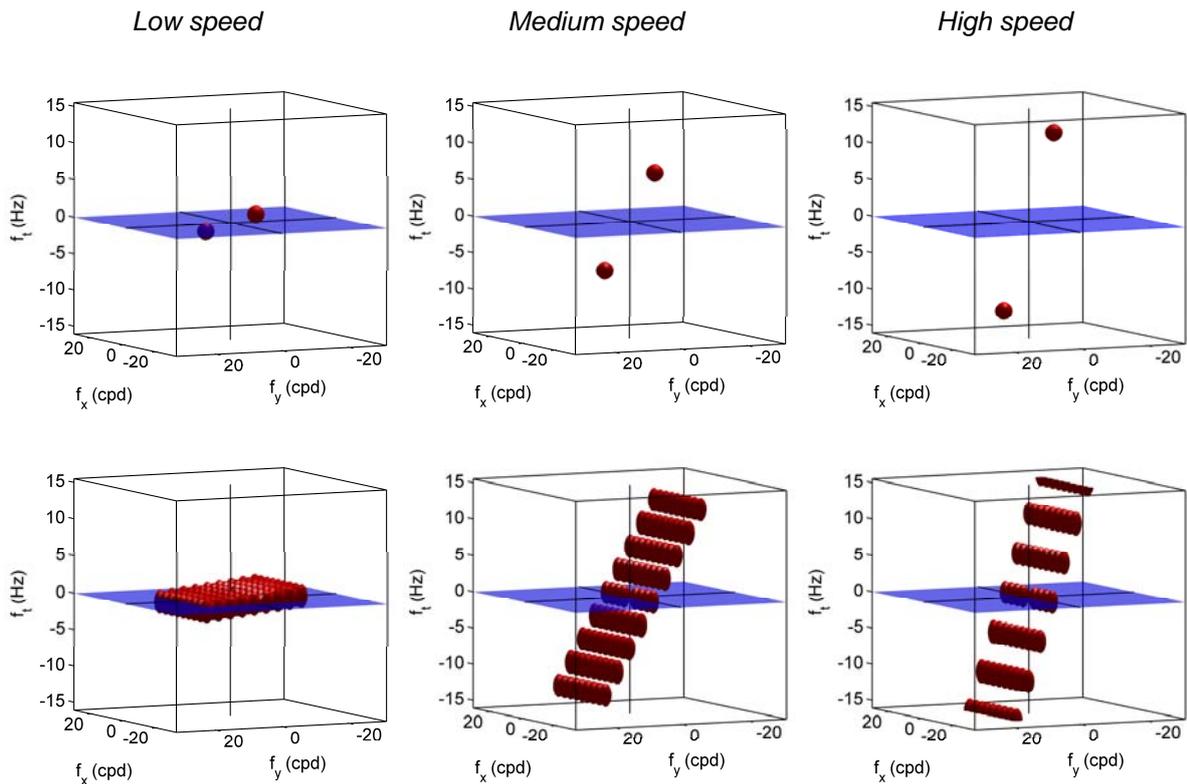


Fig. 3. Spatio-temporal frequency sensitivity of different V1 cells (top) and different MT cells (bottom).

Figures 4 and 5 show the response pattern (for every spatial position at a certain time,  $t = 0.31$  sec) for the considered *low*, *medium* and *high* speed neurons of V1 and MT, both tuned to downward and upward motions. In the response plots, the black-white range stands for inhibition-excitation. Grey means zero response. Remember that, at that particular time, the hand at the left is moving downwards with medium speed and the other way around for the hand at the right.

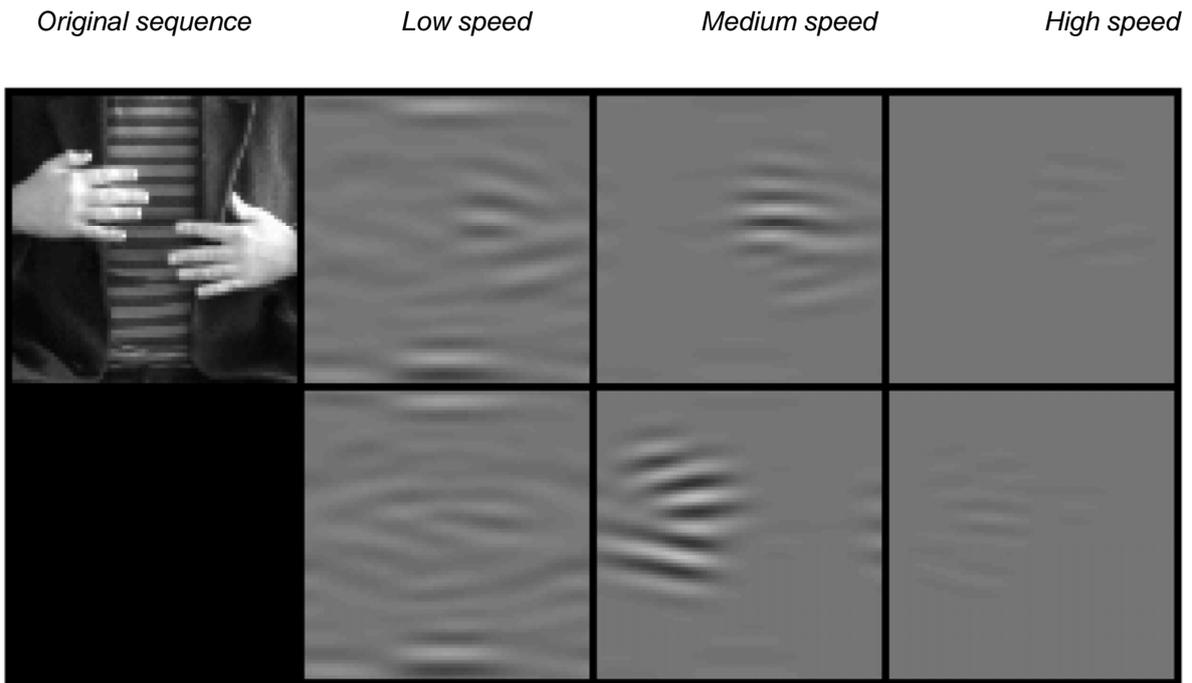


Fig. 4. Response patterns of V1 cells at the time  $t = 0.31$  sec. The top row displays the downward-sensitive neurons and the bottom row the upward-sensitive neurons.

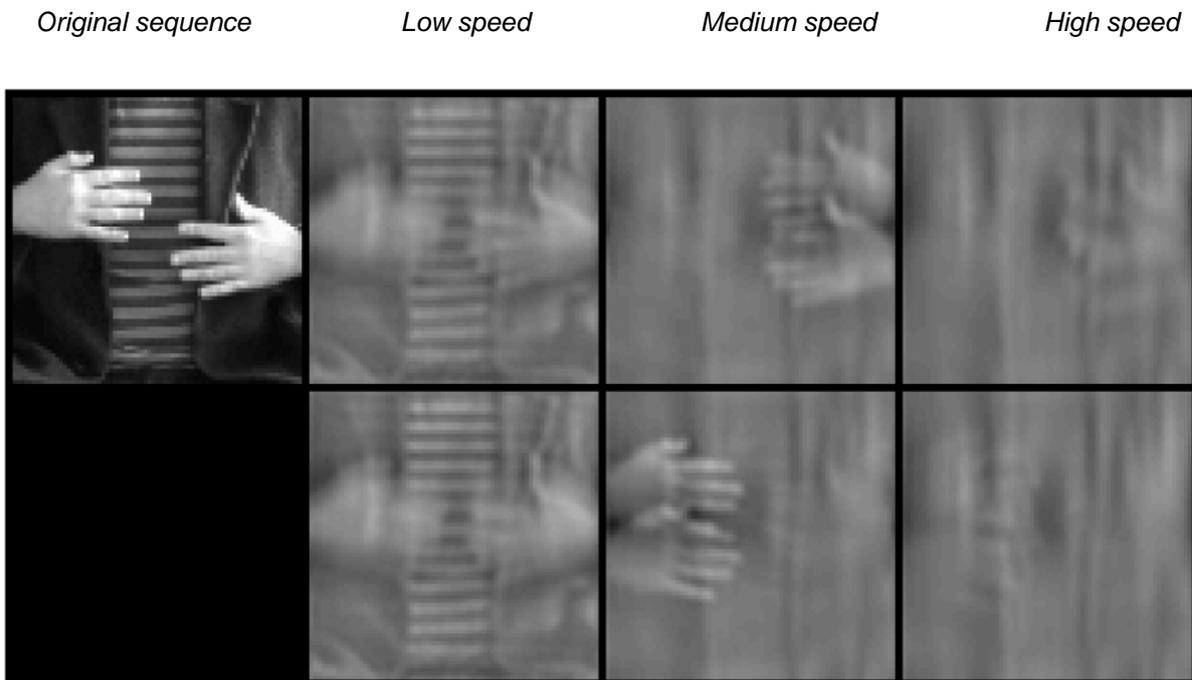


Fig. 5. Response patterns of MT cells at the time  $t = 0.31$  sec. The top row displays the downward-sensitive neurons and the bottom row the upward-sensitive neurons.

As expected from their receptive fields, the V1 neurons are focused on specific spatio-temporal frequencies and hence object information is lost. They roughly respond to patterns of the right frequency: note that maximum signals are obtained at the locations where the hands (which have the appropriate spatial frequency) wave with the right temporal frequency. On the other hand, MT cells respond to any spatial frequency, whenever it moves with the right speed. Therefore, they signal (or isolate) objects moving with

that speed: note how the neurons sensitive to low and stationary patterns signal at the strips of the T-shirt but do not see the hands, while the neurons sensitive to the medium speed isolate the hands but are blind to the static background. Finally, the neurons sensitive to high speeds are silent since there is no high speed in the sequence.

## 5. CONCLUSIONS

In this work we presented a virtual lab (a set of Matlab/Octave tools) to simulate the response to natural movies at different regions of the visual brain. The proposed tools allow a straightforward application of spatio-temporal filters that model the linear response of V1 and MT cells. Familiarity with such response patterns is essential to understanding how the optical flow can be computed at the visual brain [9,11-13]. This virtual lab is appropriate for Visual Neuroscience students that may be more interested in exploring the effect of the parameters of the models (learning-by-playing) rather than in analyzing the maths.

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