

MATLAB/OCTAVE TOOLS FOR THE VISUAL NEUROSCIENCE CLASS I: SIMULATING PHYSIOLOGICAL EXPERIMENTS IN MOTION SENSITIVE NEURONS

Jesús Malo^{1,2}, María José Luque², Amparo Díez-Ajenjo³, María del Carmen
García-Domene^{2,4}

¹ *Image Processing Lab. Universitat de València (Spain)*

² *Dept. d'Òptica. Universitat de València (Spain)*

³ *Fundació Lluís Alcanyis. Universitat de València (Spain)*

⁴ *Fisabio Oftalmología Médica, València, Spain*

jesus.malo@uv.es, maria.j.luque@uv.es, amparo.diez@uv.es, m.carmen.garcia-domene@uv.es

Abstract

The students of Visual Neuroscience have diverse 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. 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 for the simulation of neurophysiology experiments in the V1 and MT areas of cortex. Using linear models of V1 and MT cells as unknown black-boxes, the students measure the tuning properties of such systems by recording the responses they give to moving gratings or noise.

Keywords: teaching visual neuroscience, computational models, virtual laboratory, linear response of V1 and MT cortex, motion perception.

1. INTRODUCTION: *LEARNING-BY-PLAYING* IN VISUAL NEUROSCIENCE

Even though elaboration of quantitative predictions and models is at the very heart of science, a problem in teaching Visual Neuroscience is that students (and some faculty members) with biomedicine background are still unaware of the advantages of quantitative thinking in their discipline. As a result, they have troubles with current experimental techniques and neural models heavily based on signal and information processing concepts. This is a well-known teaching problem in Vision Science [1,2]. One cannot take the analytical approach that is traditional at the physics and engineering schools: the faculty is still reluctant to include more maths in the curricula so the students simply do not have the appropriate background. One solution to this problem is *learning quantitative thinking by playing with computational models 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 use our experience in motion perception [4-8] to present tools for the simulation of neurophysiology experiments in the V1 and MT areas of cortex. In particular, we illustrate how to measure the receptive fields and tuning properties of motion sensitive cells. Using linear models of V1 and MT cells as unknown black-boxes, the students determine the tuning band of such systems by recording the responses they give to moving gratings or noise.

2. SIMULATION OF NEUROPHYSIOLOGY EXPERIMENTS: STIMULI AND RESPONSES

Experiments with neurons in the V1 and MT areas consist of (1) the presentation of stimuli -image sequences-, and (2) recording the response of the selected cell(s). In this didactic material, we take the *rate assumption* [9], so we describe the response in terms of the number of spikes per second (above or below the spontaneous activity). The proposed virtual lab consists of a set of tools to generate controlled image sequences, $\mathbf{s}(x,t)$, and a set of functions that compute the response of controlled linear neurons to moving stimuli. The V1 (or MT) neurons considered here are characterized by their receptive field, $\mathbf{g}(x,t)$, determined by their frequency (or speed) tuning respectively [10-13]. After appropriate rearranging the discrete versions of the sequence and receptive field as column vectors, the response of the p -th neuron, \mathbf{g}_p , to the stimulus, \mathbf{s} , is the scalar product:

$$r_p[\mathbf{s}] = \mathbf{g}_p^T \cdot \mathbf{s} \quad (1)$$

2.1. Measuring receptive fields with stimuli from a basis of the signal space

Given an orthonormal basis of the space of image sequence vectors, $\{\mathbf{b}_k\}_{k=1\dots n}$, (n is the dimension of the stimuli) any stimulus can be expressed in the spatio-temporal domain, \mathbf{s} , or in the transform domain, $\mathbf{S} = \mathbf{B}^T \cdot \mathbf{s}$, where the k -th column of the matrix \mathbf{B} is the vector, \mathbf{b}_k . Assuming such a transform matrix, the receptive field of a neuron can be computed in the transform domain: each component, k , of the receptive field in the transformed domain is given by the response of the neuron to the stimulus (basis function) \mathbf{b}_k :

$$\mathbf{G}_{p,k} = r_p[\mathbf{b}_k] \quad (2)$$

In text books oriented to physics students statements such as the previous one are classically preceded by an intriguing “*it is easy to see that ...*”. That is the kind of statement that has to be further illustrated to students with low interest in maths. Note that Eq. 2 is actually an idealization of a physiological experiment: we pick a stimulus (the sequence \mathbf{b}_k) and we record the response of the p -th neuron to that stimulus ($r_p[\mathbf{b}_k]$). In the proposed illustration, the students will use the neural software as a black-box: just picking stimuli and recording the responses.

By experimentally measuring n of such responses to the different basis functions (remember $k = 1\dots n$) we completely determine the vector \mathbf{G}_p , and hence, the neuron behavior. In particular, we can get the receptive field back in the spatio-temporal domain by inverting the transformed vector \mathbf{G}_p :

$$\mathbf{g}_p = \mathbf{B} \cdot \mathbf{G}_p \quad (3)$$

Eqs. 2-3 apply to any orthonormal basis. In particular, they illustrate the procedure to describe the neuron's behavior in the Fourier or the spatiotemporal domains. In the Fourier case, \mathbf{b}_k are just moving sinusoids with specific spatial and temporal frequencies (or speeds). In the spatio-temporal case, \mathbf{b}_k are just delta functions (tiny light spots) located at certain spatial position and flashing at certain time. Given the smoothness of the sensitivity of the neurons in the Fourier representation and the symmetry of this domain, experiments with sinusoidal gratings is preferred since less measurements are necessary [12,13].

2.2. Measuring speed tuning curves with uniform velocity sequences

Even though knowing the speed tuning properties of neurons does not provide a characterization of their response as general as their receptive field (note that Eq. 1 predicts the response for *any* stimulus \mathbf{s} , no matter its complexity), the determination of speed-tuning curves is a common practice in the study of motion-sensitive neurons [12,13], since it is a distinct feature of MT cells (tuned to very specific velocities) versus V1 cells (which respond to a wide set of speeds).

In fact, to make sense of speed tuning surfaces, $r_p(v)$, one has to specify the kind of stimulus used in the experiment. For example, natural images, random textures or random noise moving with the same

speed will give rise to different absolute responses because of their different *spatial* spectrum. In order to focus on speed rather than on the specific spatial structure of the moving objects, random noise or random dots sequences are preferred in the experiments because of their flat spectrum of controlled amplitude.

3. THE PROPOSED VIRTUAL LAB: CHARACTERIZATION OF VIRTUAL V1 AND MT NEURONS

Here we propose the students to take virtual neurons and stimulate them with controlled stimuli to characterize the neurons in the same way as done in the physiological experiments. In order to do so, we need (1) software to generate the stimuli, (2) software to define the neurons, and (3) software to compute the response(s) given the stimulus and the sensor(s). With these tools, the students can define a set of stimuli and record the corresponding responses to (i) measure the receptive fields of V1 and MT cells in the Fourier domain, and (ii) measure speed-tuning curves for these classes of sensors.

The general code for this virtual lab is available at 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 `tuning_experiment.m`

3.1. Software for stimulus generation: sinusoids in motion and random texture movies

Simulations in the computer require stimuli on discrete domains with certain sampling frequency and extent. Once these domains are defined, one can build analytic sequences (such as sinusoids or moving random noise) on top of them:

- **Spatio-temporal domain:** `spatio_temp_freq_domain.m` generates discrete spatio-temporal and 3d-Fourier domains of certain extent with certain spatial and temporal sampling frequencies. These domains allow generating synthetic sequences and filters in the 3d Fourier domain. The domain is arranged in the 2d format (see help of `now2then.m` or `then2now.m`).
- **Moving sinusoids:** Once the variables x , y , t , are ready, definition of spatio-temporal sinusoids with frequencies (f_x , f_y , f_t), average luminance, L , and contrast, C , is straightforward. Just type:
$$s = L * (1 + C * \sin(2 * \pi * (f_x * x + f_y * y + f_t * t)));$$
- **Random texture sequences:** `noise_sequence.m` generates a discrete sequence of colored noise that moves at certain uniform speed. Sampling frequencies, size of the sequence, spatial frequency of the colored noise and speed are controlled.
- **Random dots:** `dots_sequence.m` generates a sequence from some initial objects and a flow field. Sizes, color and location of the objects are controlled, as well as their motion through the selected field.

3.2. Software to define (or select) the sensors

Simulations in the computer require selecting certain sensor (e.g. where to put the probe in the physiological analogy). In the case of motion sensitive neurons, the sensors are defined by their spatio-temporal frequency tuning (in V1) and the speed tuning (in MT). The student selects these parameters and uses the generated filters as black boxes:

- **V1 cells:** `sens_gabor3d.m` computes the squared frequency response of 3d Gabor sensors tuned to certain spatio-temporal frequency with certain frequency widths. The Gaussian window in the Fourier domain is aligned with the frequency axes.

- **MT cells:** `sens_MT.m` computes the square of the receptive field of linear MT neurons tuned to certain speed $v = [v_y \ v_x]$ by adding the receptive fields of V1 sensors with sensitivities in the appropriate frequency plane.

3.3. Software for response computation: product in the Fourier domain and integration

In these experiments, the students use the filter representation of the sensors as a black box. The relation between the filters and the response to specific stimuli is covered in other virtual lab [3]. Here, given some filter, G , computed with the above functions, and some stimulus in the Fourier domain, computed in this way: $S = \text{abs}(\text{fft3}(s,1))$, the students just derive the energy of the response by integrating the square of the product between signal, S , and sensitivity, G :

$$e = \text{sum}(\text{sum}((S.*G).^2)) \quad (4)$$

This energy measurement is the equivalent to the physiological recording. It is done in a loop for every considered stimulus s , either moving sinusoid or random noise sequence.

4. RESULTS

We select two representative neurons from the considered areas. Even though we assume the students do not know this information, the selected V1 cell is tuned to $f_x = 8$ cpd and $f_t = 4$ Hz and the selected MT cell is tuned to the speed $v = (0, -0.5)$ deg/sec. We can even give the students pre-computed filters without telling them the specific parameters. Their task in this virtual lab is finding these parameters through stimulus-response experiments.

Fig. 1 shows the (theoretical) spatio-temporal frequency sensitivities of the considered cells, as coming from the functions G (obtained by `sens_gabor3d.m` and `sens_mt.m`). Note that this selection of sensors is illustrative since, according to the orientation/speed relation in the Fourier domain [3,10,11] one could (naively) think that the V1 cell is tuned to the same speed as the MT cell.

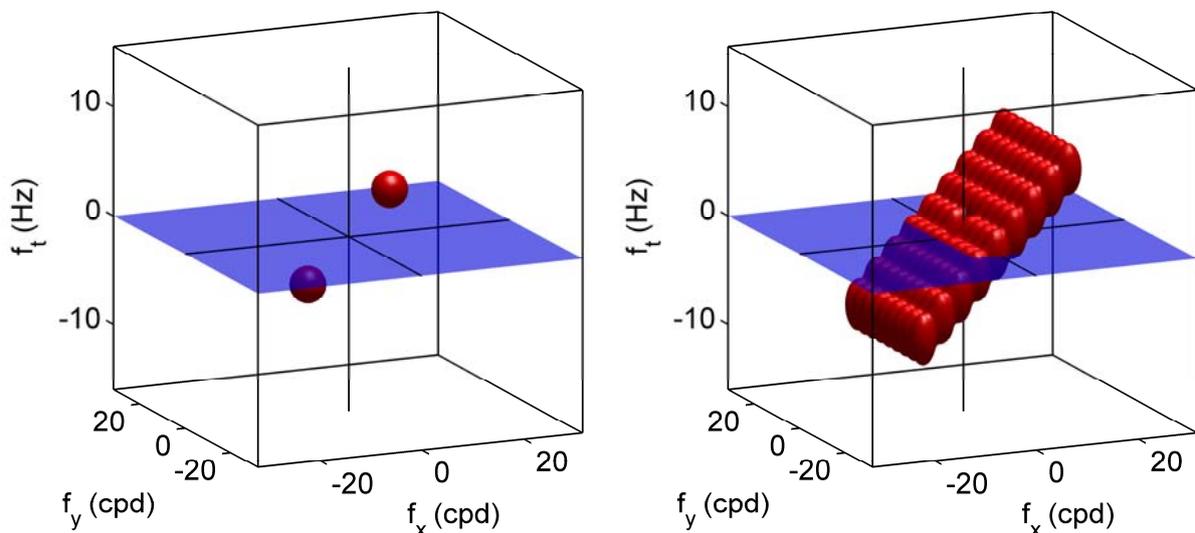


Fig. 1: Theoretical spatio-temporal frequency tuning of a V1 cell (left) and an MT cell (right) as obtained from `sens_gabor3d.m` and `sens_mt.m`.

Figs. 2 and 3 show the result of the simulated measurement of the receptive fields in the frequency domain. This experiment consists in generating moving sinusoids in a grid over the frequency domain and recording the corresponding responses. As one could expect from Fig. 1, the tuning band in the V1 cell is narrower than the equivalent result for the MT cell. This is a characteristic feature of these cells and one can figure out their location along the neural path (V1 or MT) because of this difference.

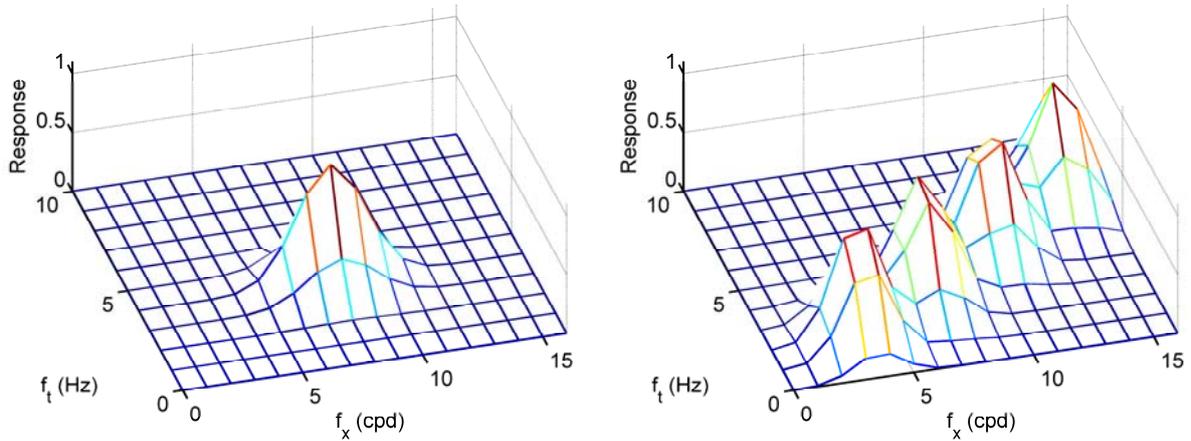


Fig. 2: Frequency tuning of a V1 cell (left) and an MT cell (right) obtained in the simulated experiment.

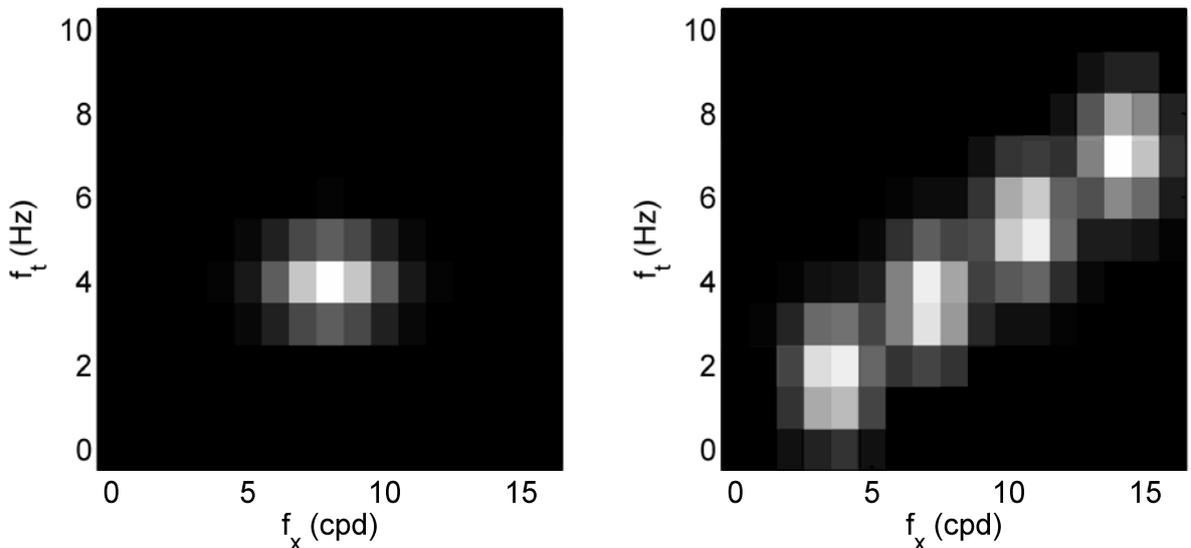


Fig. 3: Frequency tuning of a V1 cell (left) and an MT cell (right) obtained in the simulated experiment.

Fig. 4 shows the result of the simulated speed tuning experiment. This experiment was done by stimulating the cells with random noise textures of uniform speed and recording the corresponding responses. The speeds were selected from a uniform grid covering the $[-1, 1]$ deg/sec range. As opposed to the frequency result, in this case the MT cell shows an accurate speed tuning (it is highly speed selective) while the V1 cell responds to a wide range of different speeds. In fact, this comes from the aperture problem in the Fourier domain [10,11]: since the sensitivity band of the V1 cell is so narrow, a number of slanted spectra (compatible with many different speeds) elicit responses in this neuron. On the other hand, the clear plane defined by the sensitivity of the MT cell implies that it only

gives rise to high responses when the spectrum of the signal coincides with the sensitivity plane, i.e. when it has a specific 2d speed.

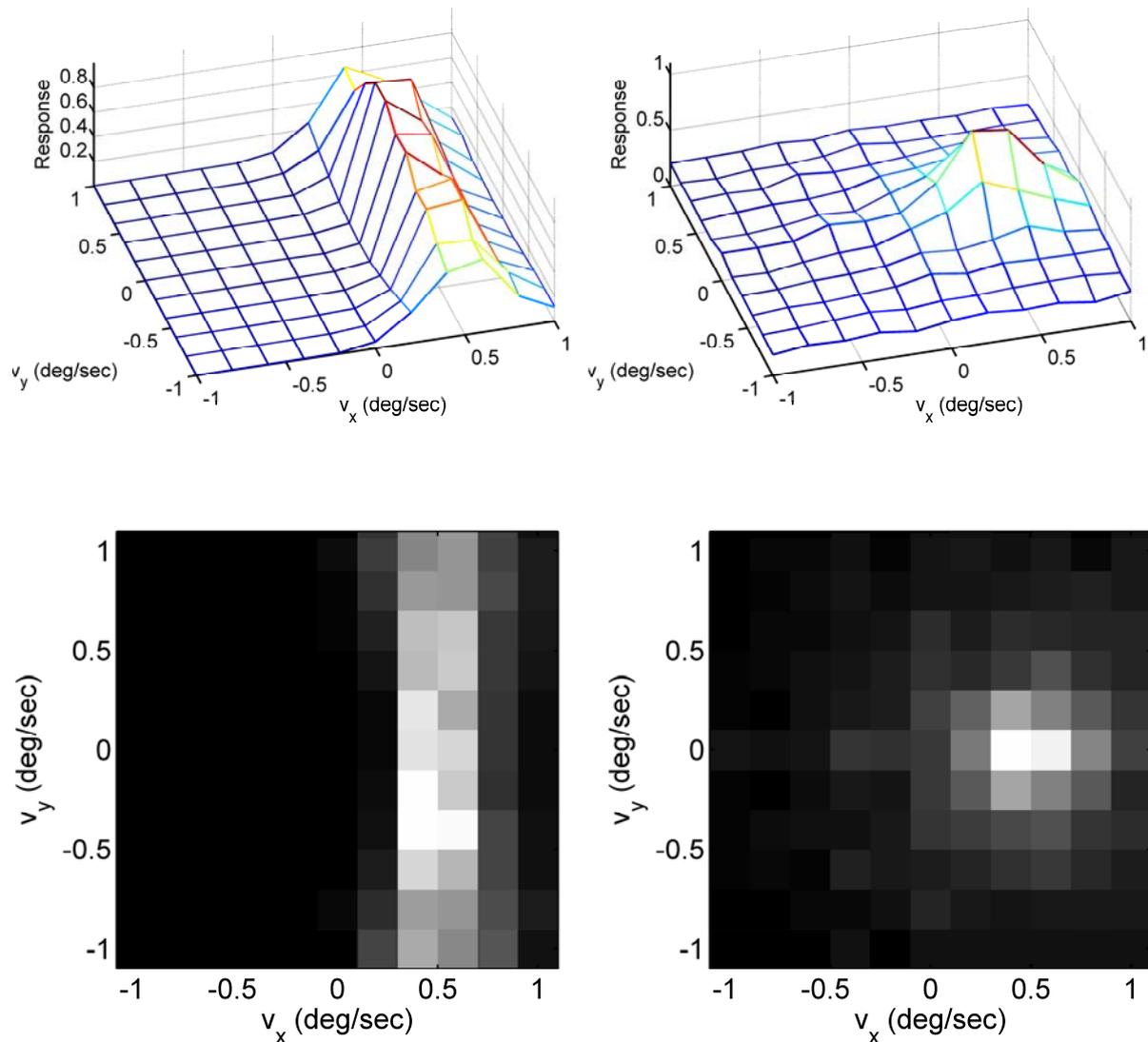


Fig. 4: Speed tuning a V1 cell (left) and an MT cell (right).

5. CONCLUSIONS

In this work we presented a virtual lab (a set of Matlab/Octave tools) to simulate physiological experiments with motion-sensitive neurons. In particular, the student can design and perform experiments to determine the receptive field of unknown sensors and their speed tuning properties. This virtual lab is appropriate for Visual Neuroscience students that may be more interested in exploring the effect of the parameters (learning-by-playing) than in analyzing the maths.

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