Linear Decoder Analysis Applied to Multineuronal Records of Retinal Ganglion Cells

J. H. Soletta, F. D. Farfán, A. L. Albarracín and C. J. Felice Laboratorio de Medios e Interfases, Departamento de Bioingeniería of FACET – UNT. Instituto Superior de Investigaciones Biológicas, CONICET – UNT. San Miguel de Tucumán, Argentina

Abstract— Achieving a thorough understanding about the neural code is one of the neuroscientists' greatest challenges. One way to evaluate our current knowledge about the neural code is trying to reconstruct sensorial stimuli from neuronal responses. In spite of nowadays there are several types of decoding techniques, few of them have been used and analyzed in actual multi neuronal records of retinal ganglion cells. In this work, we had employed and analyzed a linear decoder to reconstruct different visual stimulus, white noise scramble and natural image, from multi neuronal records of retinal ganglion cells. The efficiency of the reconstruction depends on two factors: one the one hand, the type of visual stimulus, if parameters used were calculated since white noise, scramble or natural image , and on the other hand, the numbers of cells employed in the reconstruction.

Keywords— Retina; Neural Reconstruction; Population Code; Mutual Information

I. INTRODUCTION

The main problem in neuroscience is to understand how neuronal groups of the sensorial system are able to encode relevant information from the outer environment [1]. Nowadays there are several researches about how the retinal ganglion cells decode light patterns [2]. Classic studies in this area consist of analyzing the responses of ganglion cells evoked by simple stimuli such as spot of light or moving grating. The aim of these studies is to measure the neuronal properties such as the receptive field and in this way predict their response through the use of arbitrary stimuli. A crucial test for the comprehension of neuronal codification focuses on the reconstruction process of the stimulus via neuronal responses.

Various authors have approached to study the reconstruction of the stimulus from the neuronal responses [3] [4], some of them suggested techniques to reconstruct the stimulus from the response of only one neuron, while others proposed to reconstruct simple stimulus from multi neuronal records [5]. Since it was demonstrated that neurons convey information through a population code and an individual code [6], the stimulus reconstruction should be carried out using multiple-neuron responses.

A type of decoder widely used is the linear decoder; this has been employed in the reconstruction of movement sensorial stimulus [3], reconstruction and predictions of movement from a light bar using retinal ganglion cells records and reconstruction of images by computational models [7] [8]. Until now, this technique has not been used to reconstruct complex visuals stimulus from retinal ganglion cells.

In this study, a linear decoder to reconstruct complex visual stimulus since multi neuronal ganglion cells records was proposed. The linear decoder's performance was evaluated measuring mutual information between the stimuli image and the reconstructed one. It was observed that, the quality of the reconstructed image depends on the type of stimuli used and the amount of neurons employed.

II. MATERIAL AND METHODS

A. Electrophysiological Records and Stimulus Generation

The analyzed data come from the published data by Simmons [9]. Briefly, the electrical activity of ganglion cells from a Hartley guinea pig was registered, using an arrangement of 30 electrodes. The extracellular signals were registered at a 10 kHz frequency. The duration of the registration lasted between 2 and 4 hours. The visual stimuli were projected through a Lucivid's monitor screen (MicroBrightField inc, Colchester, VT) at a 30 Hz frequency. The mean luminance of the retina was 9000 photons/s μ m². The stimuli used are White Noise, Natural movies and Scramble, in all cases the images have got a size of 64x64 pixels. The Natural movies consist of images of leaves and herbs and were recorded with a Prosilica GE 1050 high-speed digital camera with a 1/20 sensor (Allied Vision Technologies GmbH, Stadtroda, Germany) connected to a laptop running StreamPix software (NorPix Inc, Montreal, Canada) to grab frames at 60 fps. To produce a scrambled image, natural movies pixels were randomly shuffled in space and time to remove all correlations while preserving the intensity distribution. In all cases the images have 256 grey levels.

B. Stimulus Reconstruction

The method employed to reconstruct visual stimulus is the multi linear regression. The hypothesis of this technique is that all ganglion cells records contribute to estimate the grey levels of an image's pixel according to eq. 1.

In order to reconstruct the stimulus image, each neuronal record was divided up into 30 ms intervals and for each interval the corresponding number of spikes was calculated. Being r_i the number of spikes tripped for *i* cell.

$$\mathbf{u}^{l} = \mathbf{f}_{0}^{l} + \mathbf{f}_{1}^{l}\mathbf{r}_{1} + \mathbf{f}_{2}^{l}\mathbf{r}_{2} + \dots + \mathbf{f}_{N}^{l}\mathbf{r}_{N}$$
(1)

Where u^{l} is the value of the *l* pixel, f_{i}^{l} is the value of the parameters corresponding to *i* cell to the *l* pixel, and *N* is the amount of ganglion cells considered in the reconstruction of the image. The highest values of the f_{i}^{l} parameters correspond to the parameters that minimize the mean- squared difference between the stimulus s_{i} and the reconstructed stimulus s_{i}^{*} . In

this way we obtain the parameters value corresponding to the pixel l. If repetitions of this procedure for all pixels are made it is possible to reconstruct the stimulus image.

Thereby, the group of parameters that result from calculating the mean- squared with White Noise, Natural Image and Scramble were named f^1 , f^2 and f^3 , respectively. In all cases their respective responses are used.

The neuronal records consist on the measure of the neuronal activity ahead of a 9000 stimuli response, that is to say, each record consists of 9000 trials (stimuli-response) for each type of stimuli. To avoid the high temporal correlation of visual stimulus, due to natural image result from a movie, it was decided to take a random sample of visual stimulus-response/answer group for each one of the records from the whole record to form training set and the trial set. The training set (to the f parameters calculus) consisted of take in the same record 5000 group of stimuli-response in a random way. The trial set consisted of take 2000 stimuli-response samples in a random way and use the f parameters calculated/measured with the training set to reconstruct la stimuli image.

C. Receptive fields estimate and area factor

The receptive fields of ganglion cells were estimated using the method described by Chichilnisky [10] using the responses evocated by white noise, to each receptive field was adjusted a Gaussian function of two dimensions. Whereby, each receptive field was delimitated by an ellipse and settle above an image. As in some cases the neurons have not shown a strong response in front of stimulus application, some of the receptive fields and ellipses show an extended form or atypical comparing with others papers. To valid the place/position of each receptive field it was verified that the delimited area for each ellipse belongs to the area that influences more in each ganglion cells response. We have defined as area factor the sum of delimited surfaces by the ellipse of each receptive field; hence, the area factor is measured in squares pixels and according to the amount of neurons taking into account.

D. Method Validation

To evaluate the quality of the reconstructed image, the concept of mutual information between images was used. The mutual information (MI) between two images (A and B) can be considered as the information that one image has as regards the other one, this will be the maximum if the two images are geometrically aligned [11]. This amount was estimated from the A and B histograms, $h_A(a)$ and $h_B(b)$ respectively, as well as the joint histogram $h_{AB}(a,b)$. *MI* is defined as:

$$MI(A, B) = \frac{1}{M} \sum_{a} \sum_{b} h_{A,B}(a, b) \cdot \log\left(\frac{M.h_{A,B}(a, b)}{h_{A}(a).h_{B}(b)}\right)$$
(2)

Where MI is the sum of all levels of gray in the histogram [12]. In this work the logarithm in base 2 was used; hence, the mutual information will have "bits" as units.

III. RESULTS

A. Analysis of the reconstructed images

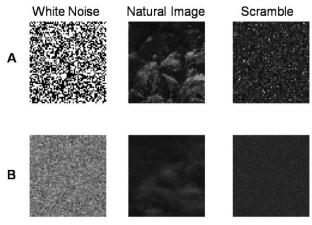
Fig.1A shows the three types of images used as stimulus and Fig. 1B their corresponding reconstruction using the proposed technique. The coefficients f^{-1} , f^{-2} and f^{-3} were used for the reconstruction of White Noise, Natural Image and Scramble, respectively. Forty five neurons were used for these reconstructions. It can be observed that in the reconstructed

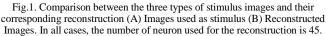
natural image (Fig. 1B, middle panel), the objects can be detected, but not the details of their shape.

Fig 2 shows a stimuli image (Original) and the reconstructed images with different amount of neurons. The mutual information (MI) between the original image and the reconstructed one was calculated. For this, 2000 reconstructed images for each type of stimulus and the MI were calculated. Fig. 3 shows the position of the receptive fields corresponding to the ganglion cells used in the stimulus reconstruction.

Fig. 4 illustrates the MI (in bits) between the stimulus images and the reconstructed images versus the number of cells and the area factor for the three types of stimuli used. It is observed that MI values are higher for the reconstructed white noise images (see Fig. 4A) comparing with the reconstructed natural and scramble images. In addition, it is noticed that quality of reconstructed natural images tends to increase with the amount of ganglion cells (Fig. 4B) whereas the quality of reconstructed white noise images tends to decrease (Fig. 4A).

When comparing between the MI values obtained in function of the number of cells and the area factor, it is observed that, when it is used the area factor, the curves tend to be softer or with a small number of sudden changes.





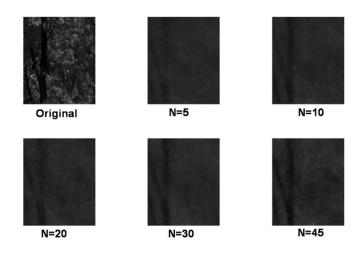


Fig2. Stimuli image and its corresponding reconstruction using different amounts of ganglion cells.

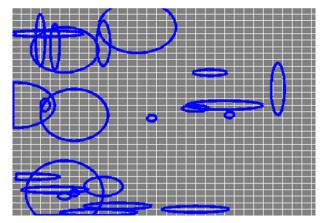


Fig 3. Receptive fields of 45 ganglion cells used in the stimulus reconstruction. The colour blue ellipses represent the Gaussian surfaces shape adjusted to each RF. The white colour grid delimits the pixels of the image.

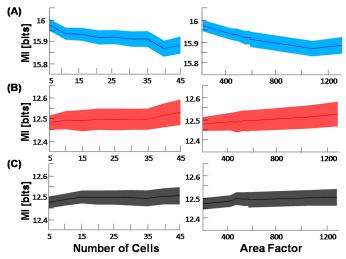


Fig 4 Mutual information between the reconstructed image and the stimuli employed according to the number of cells (first column) and the area factor (second column) (A) White Noise. (B) Natural Image (C) Scramble. For all curves the dark colour represents the mean/average and the light colour the standard deviation.

In the Fig 5 is observed that MI values are higher when f^2 parameters are used, while the values of the f^1 and f^3 are similar to each other, and they do not show great variation with the number of ganglion cells involved in the reconstruction process.

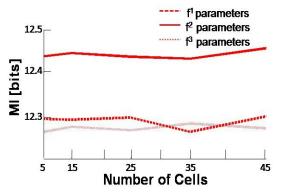


Fig 5. MI values calculated between natural images and its corresponding reconstruction using: f^{1} , f^{2} and f^{3}

IV. DISCUSSION

In this study a technique to reconstruct visual stimulus from the responses of retinal ganglion cells was analyzed. The image reconstruction through multiple linear regression shows that the retina may codify certain part of the visual information of a pixel from the linear combination of frequencies of multiple spikes coming from ganglion cells.

It was observed that the technique used allows reconstructing the stimulus but only with a certain level of similitude. The discrepancy between the reconstructed image and the original one (stimulus) can be due to different factors among which we find:

The neuronal code used, known as spike frequency, only conveys few aspects of stimulus image information, other codification schemes such as the latency among spikes could be used [8].

Although it is observed that increasing the number of neurons the MI values are higher (Fig 3), it is possible that the amount of neurons used were not enough to perform a better reconstruction of the stimuli employed.

There are no nonlinearities present in the receptive fields, it has been showed that the surround part of the ganglion cells receptive fields codify the stimulus in a nonlinearly [13].

Though some of the receptive fields shown in Fig 3 cover just a portion of the image, the technique used allow reconstructing the stimuli image in a complete way. This is due to the multi linear regression estimate an amount of 64x64 parameters, one for each pixel of the image. Therefore, when an image is reconstructed the pixels that are not cover by the receptive fields take the values of their corresponding parameters.

Fig 4 compares how the *MI* values vary according to the number of neurons and the area factor. These findings suggest that the area factor is a very important feature of the neural response and it should be considered in the reconstruction process and/or the study of the neural code of retinal ganglion cells.

The proposed technique is similar (in a mathematical sense) to that used by Stanley [14] for the reconstruction of visual stimuli through neural records in the lateral geniculate nucleus (NGL). This could indicate that the stimulus coding occurs linearly in both structures of the visual system (retina and NGL).

Additionally, it was observed that the efficiency in the reconstruction of the stimulus image depends not only on which group of parameters is used $(f^1, f^2 \text{ or } f^3)$ but also on the stimulus employed. As it is observed in Fig 5, when f^2 parameters are used to reconstruct stimulus from natural images the *MI* values are higher. This shows that the parameters are not interchangeable among them. This is because the retina is adapted to process certain types of stimulus, especially natural images. These have a higher degree of correlation in comparison to other images.

V. CONCLUSIONS

The multi linear regression technique allows to reconstruct complex visual stimulus since the response of retinal ganglion cells. The efficiency of the reconstruction depends on two factors: one the one hand, the type of visual stimulus, and on the other hand the type of the parameters used in the reconstruction (f^1, f^2, f^3) , and on the other hand, the numbers of cells employed in the reconstruction.

Funding

This work has been supported by grants from Agencia Nacional de Promoción Científica y Tecnológica (ANPCYT); Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), and Consejo de Investigaciones de la Universidad Nacional de Tucumán (CIUNT), as well as with Institutional funds from Instituto Superior de Investigaciones Biológicas (INSIBIO).

REFERENCE

- Abbott L F. 1994. Decoding Neuronal Firing and Modeling Neural Networks. Quart. Rev. Biophys. 27:291-331.
- [2] Gollisch T, Meister M. 2010. Eye Smarter than Scientists Believed: Neural Computations in Circuits of the Retina, Neuron 65, January 28.
- [3] Bialek W, Rieke F, de Ruyter Van Steveninck RR, Warland D. 1991. Reading a neural code. Science 252:1854-1857.
- [4] Rieke F, Warland D, Bialek W. 1993. Coding efficiency and information rates in sensory neurons, Europhys Lett 22:151–156.
- [5] Warland K., Reinagel P, Meister M. 1997. Decoding Visual Information From a Population of Retinal Ganglion Cells. J Neurophysiol 78:2336-2350.
- [6] Nirenberg S, Carcieri S M, Jacobs A L & Latham P E. 2001. Retinal ganglion cells act largely as independent encoders, Nature, vol 411.
- [7] Marre O et al. 2015. High Accuracy Decoding of Dynamical Motion from a Large Retinal Population. PLOS Computational Biology, DOI:10.1371/journal.pcbi.1004304.
- [8] Butt D A et al. 2007. Temporal precision in the naural code and the timescales of natural vision. Nature, 449, 992-95.
- [9] Simmons K, Prentice J, Tkacik G, Homann J, Yee H, et al. 2013. Transformation of stimulus correlations by the retina Database. Available from doi:10.5061/dryad.246qg.
- [10] Chichilnisky E J. 2001. A simple white noise analysis of neuronal light responses. Network 12 199–213.
- [11] Maes F, Collignon A, Vandermeulen D, Marchal G and Suetens P. 1997. Multimodality Image Registration by Maximization of Mutual Information. IEEE Trans. Med. Imag., vol. 16, Apr.
- [12] Cole-Rhodes A, Johnson K, LeMoigne J, Zavorin I. 2003. Multiresolution Registration of Remote Sensing Imagery by Optimization of Mutual Information Using a Stochastic Gradient. IEEE Transactions On Image Processing, vol. 12, NO. 12.
- [13] Takeshita D, Gollisch T. 2014. Nonlinear spatial Integration in the Receptive Field Surround of Retinal Ganglion Cells. The Journal of Neuroscience, 34(22):7548-7561.
- [14] Stanley G B, Li F F and Dan Y. 1999. Reconstruction of Natural Scenes from Ensemble Responses in the Lateral Geniculate Nucleus. The Journal of Neuroscience, September 15.