AFRL-RH-WP-TP-2017-0001

Optimal Achievable Encoding for Brain-Machine Interface

Eduardo Chichilnisky
Leland Stanford Junior University,
The Stanford University

December 2017
Final Report

AIR FORCE RESEARCH LABORATORY
711 HUMAN PERFORMANCE WING,
AIRMAN SYSTEMS DIRECTORATE,
WRIGHT-PATTERSON AIR FORCE BASE, OH 45433
AIR FORCE MATERIEL COMMAND
UNITED STATES AIR FORCE

NOTICE AND SIGNATURE PAGE

Using Government drawings, specifications, or other data included in this document for any purpose other than Government procurement does not in any way obligate the U.S. Government. The fact that the Government formulated or supplied the drawings, specifications, or other data does not license the holder or any other person or corporation; or convey any rights or permission to manufacture, use, or sell any patented invention that may relate to them.

This report was cleared for public release by the 88th Air Base Wing Public Affairs Office and is available to the general public, including foreign nationals. Copies may be obtained from the Defense Technical Information Center (DTIC) (http://www.dtic.mil).

AFRL-RH-WP-TP-2017-0001 HAS BEEN REVIEWED AND IS APPROVED FOR PUBLICATION IN ACCORDANCE WITH ASSIGNED DISTRIBUTION STATEMENT.

//signed//
PAUL HAVIG, PHD
Work Unit Manager
Battlespace Visualization Branch

//signed//
ROBERT MCKINLEY
Chief, Battlespace Visualization Branch
Warfighter Interface Division

//signed//
KRISTOFFER A. SMITH-RODRIGUEZ, LTCOL, USAF
Chief, Warfighter Interface Division
Airman Systems Directorate

This report is published in the interest of scientific and technical information exchange, and its publication does not constitute the Government's approval or disapproval of its ideas or findings.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
22 December 2017	Final	1 Oct 2016 – 30 Sep 2017

4. TITLE AND SUBTITLE

Optimal Achievable Encoding for Brain-Machine Interface

5a. CONTRACT NUMBER

5b. GRANT NUMBER
FA8650-16-1-7657

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Dr. Eduardo Chichilnisky

E-Mail: ej@stanford.edu

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER
H0RU (532911ST)

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Leland Stanford Junior University, The
Stanford University
450 Serra Mall
Stanford, CA 94305-2004

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
USAF/AFMC
AFRL Wright Research Site
2130 Eight Street, Bldg 45
Wright-Patterson AFB OH 45433-7541

10. SPONSOR/MONITOR'S ACRONYM(S)
711 HPW/RHCV

11. SPONSOR/MONITOR'S REPORT NUMBER(S) AFRL-RH-WP-TP-2017-0001

12. DISTRIBUTION / AVAILABILITY STATEMENT

DISTRIBUTION STATEMENT A. Approved for Public Release: distribution unlimited

13. SUPPLEMENTARY NOTES

88ABW Cleared 02/09/2018; 88ABW-2018-0596.

14. ABSTRACT

Our goal was to develop efficient algorithms for encoding visual stimuli using an artificial retina, in a manner that optimizes the artificial visual image delivered to the brain. We did this by focusing on three components required. First, we developed novel models of retinal encoding that improve upon the state of the art, by using machine learning methods to incorporate spatial and temporal nonlinearities. Second, we developed novel methods of decoding images from retinal responses, using artificial neural networks, and by applying linear decoding to complete recorded populations of retinal ganglion cells for the first time. Third, we developed a greedy, dictionary-based encoding approach to translate a visual image into sequential patterns of electrical stimulation in real time, in a manner that optimizes visual image transfer to the brain. Together these techniques form the algorithmic basis for the artificial retina technology being designed by the Stanford Artificial Retina

15. SUBJECT TERMS
Artificial retina, Retinal prosthesis, Brain-machine interface, Brain-computer interface, Neural interface, Vision, Artificial vision

16. SECURITY CLASSIFICATION OF: Unclassified			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*
Unclassified	Unclassified	Unclassified	SAR	10	Paul Havig

Table of Contents

Page

1. INTRODUCTION

Our goal is to revolutionize brain-machine interfaces. Our premise is that this can be done by developing advanced software that allows devices to communicate far more efficiently with the brain than ever before, overcoming major limitations of present-day physical interfaces. Specifically, all modern brain-machine interfaces (e.g. deep brain stimulators, cochlear prostheses, motor implants) have resolution, scale, and architecture that are poorly matched to the underlying neural circuitry, a situation that is expected to persist for decades. Because of this limitation, current interfaces provide, at best, crude interactions with the neural signals that govern sensation, action, and other brain functions. We aim to make these devices far more useful by encoding signals in a way that optimizes the information transmitted from the device to the brain, within the realm of what is achievable using the device. This *optimal achievable encoding* approach is novel and unique. We tackle this problem for a particularly promising brain-machine interface, a retinal prosthesis. In this application, we leverage our understanding of retinal circuitry and function, along with modern statistical tools, in order to develop an advanced prosthesis encoding approach that most accurately mimics naturalistic retinal function. Although a retinal prosthesis is the first natural application, in principle, this approach should be generalizable to other brain-machine interfaces in the future.

2. KEYWORDS

Artificial retina, Retinal prosthesis, Brain-machine interface, Brain-computer interface, neural interface, Vision, Artificial vision

3. ACCOMPLISHMENTS

- **What were the major goals of the project?**

Task 1: Natural Encoding. Our goal was to characterize natural encoding performed by the retina by developing the most advanced models of retinal function. Natural encoding transforms the visual scene into patterns of activity in ~20 different types of retinal ganglion cells (RGCs), which send distinct information about the visual scene to distinct targets in the brain.

Task 2: Natural Decoding. Our goal was to develop a model of visual decoding from RGC spike trains that the brain uses to produce perception. Such a decoding model provides our best estimate of the visual images over time that the subject will perceive, given any particular pattern of RGC activity produced naturally or by the prosthesis. This estimate is obtained by numerical "inversion" of the encoding model to reconstruct the optimal perceived image from the pattern of RGC activity.

Task 3: Prosthesis Encoding. Our goal was to optimize an emulated prosthesis encoder, which is used to transform the incoming image into a pattern of electrical stimulation, using the experimentally measured achievable set of patterns as constraints. This optimization will select, among the set of patterns of activity that the electrodes are capable of producing in the nearby neurons, the pattern that results in the most accurate visual image possible.

- **What was accomplished under these goals?**

Task 1: Natural Encoding. We improved upon state-of-the art models of retinal encoding by developing machine learning approaches to characterize the retinal responses to naturalistic stimuli [4, 5]. We learned that certain spatial and temporal nonlinearities, not included in commonly used models, are crucial for the improved prediction of retinal responses. In addition, we developed methods to identify RGC types from their electrical signatures [7, 8]. This is used in conjunction with models of RGC response based on cell type identity, which is essential for applying our approaches to a retina blinded by loss of photoreceptors.

Task 2: Natural Decoding. We have accomplished this in two ways that will soon merge. First, we have developed linear reconstruction of images from actual recorded RGC activity, and studied its properties and how to optimize it [10, 1]. Second, we used machine learning methods to build on linear decoding with more flexible nonlinear computation. This required large data sets, so we started by doing this with simulated retinal responses using encoding models (see Task 1). This approach significantly outperformed linear decoding [3, 6]. Our next step will be to merge these by using nonlinear decoding from recorded retinal responses.

Task 3: Prosthesis Encoding. We developed a greedy dictionary-based encoding approach that efficiently and sequentially selects electrical stimuli that produce the greatest increment in image reconstruction [9]. This is the first technically viable approach to this problem, is based on the fundamental concept of producing a visual image of optimal quality, and has many extensions that we will be working on, including: expansion of the dictionary by multi-electrode patterns, nonlinear reconstruction (see Task 2), and including the statistics of retinal spiking.

- **What opportunities for training and professional development has the project provided?**
  Nikhil Parthasarathy continued to NYU Center for Neural Science Ph.D. program. Orren Karniol-Tambour is now applying to Ph.D. programs in neuroscience. Nishal Shah advanced to Ph.D. candidacy during the work.

- **How were the results disseminated to communities of interest?**
  So far, we have prepared a number of conference presentations (talks and posters) and conference papers (see Products). We are preparing journal articles for publication now.

- **What do you plan to do during the next reporting period to accomplish the goals?**
  Nothing to report.

4. IMPACT

- **What was the impact on the development of the principal discipline(s) of the project?**
  These developments were very well received at the major conferences in the field (NIPS, ICLR, and The Eye and the Chip), and have been submitted as conference papers, archive papers, and are being worked on for journal articles (see Products). Collectively we have substantially advanced the prospects of effective encoding in a retinal prosthesis with this approach.

- **What was the impact on other disciplines?**
  Our approach to stimulus reconstruction using artificial neural networks, well received at NIPS, provides a new way to extend machine learning methods to incorporate spike trains of visual neurons. Our method for determining cell types from electrical recordings has implications for understanding the biophysics of retinal neurons.

- **What was the impact on technology transfer?**
  None yet. We expected the techniques developed to be incorporated in the technology for the device now being designed by the Stanford Artificial Retina project.

- **What was the impact on society beyond science and technology?**
  Nothing to report.

5. CHANGES/PROBLEMS

- **Changes in approach and reasons for change**
  Nothing to report.

- **Actual or anticipated problems or delays and actions or plans to resolve them.**
  Nothing to report.

- **Changes that had a significant impact on expenditures.**
  Nothing to report.

- **Significant changes in use or care of human subjects, vertebrate animals, biohazards, and/or select agents.**
  Nothing to report.

- **Significant changes in use or care of human subjects.**
  Nothing to report.

- **Significant changes in use or care of vertebrate animals**
  Nothing to report.

- **Significant changes in use of biohazards and/or select agents.**
  Nothing to report.

6. PRODUCTS

- **Publications, conference papers, and presentations**

1. Golden JR, Erickson-Davis C, Cottaris NP, Parthasarathy N, Rieke F, Brainard DH, Wandell BA, Chichilnisky EJ. (2017) *Simulation of visual perception and learning with a retinal prosthesis*. bioRxiv doi: 10.1101/206409

2. Shah NP, Madugula S, Chichilnisky EJ, Shlens J, Singer Y. (2017) *Learning a neural response metric for retinal prosthesis*. bioRxiv doi: 10.1101/226530

3. Parthasarathy N, Batty E, Falcon W, Rutten T, Rajpal M, Chichilnisky EJ, Paninski L. (2017) *Neural Networks for Efficient Bayesian Decoding of Natural Images from Retinal Neurons.* In: Advances in Neural Information Processing Systems, pp. 6437–48. (Accepted as Spotlight Presentation)

4. Shah N, Brackbill N, Rhoades C, Tikidji-Hamburyan A, Goetz G, Litke A, Sher A, Gupta V, Singer Y, Chichilnisky EJ, Shlens J. (2017) *Learning nonlinear models for visual computation in populations of retinal ganglion cells*. Presented at: The Computational and Systems Neuroscience (Cosyne) 2017 Meeting, 2017 Feb 23-26; Salt Lake City, UT.

5. Batty E, Merel J, Brackbill N, Heitman A, Sher A, Litke A, Chichilnisky EJ, Paninski L. *Multilayer Recurrent Network Models of Primate Retinal Ganglion Cell Responses.* Presented at: The 5th International Conference on Learning Representations (ICLR), 2017 Apr 24-26; Toulon, FR.

6. Parthasarathy N, Batty E, Falcon W, Rutten T, Rajpal M, Chichilnisky EJ, Paninski L. *Nonlinear amortized Bayesian decoding of natural scenes from retinal responses.* Presented at: The Collaborative Research in Computational Neuroscience (CRCNS) 2017 Annual PI Meeting, 2017 Jun 14-16; Providence, RI.

7. Karniol-Tambour O*, Goetz G*, Grosberg L, Rhoades C, Brackbill N, Shah NP, Sher A, Litke AM, Chichilnisky EJ. *Using deep learning and simple encoding models to infer the neural code for a retinal prosthesis*. Presented at: The France-Stanford Center for Interdisciplinary Studies Workshop on Brain-Inspired Computation, 2017 Fall; Stanford, CA. (*equal contribution)

8. Goetz G*, Karniol-Tambour O*, Grosberg L, Rhoades C, Brackbill N, Shah NP, Sher A, Litke AM, Chichilnisky EJ. *Inferring the neural code in a blind retina.* Presented at: The Eye and The Chip, World Research Congress on Artificial Vision (TEATC), 2017 Sep 23-26; Detroit,

MI. (*equal contribution)

9. Shah N, Madugula S, Grosberg L, Mena G, Ganesan K, Bhaskhar N, Hottowy P, Dabrowski W, Sher A, Litke AM, Mitra S, Chichilnisky EJ. *Greedy dictionary-based stimulation for optimization of epiretinal prosthesis.* Presented at: The Eye and The Chip, World Research Congress on Artificial Vision (TEATC), 2017 Sep 23-26; Detroit, MI.

10. Brackbill N, Parthasarathy N, Karniol-Tambour O, Rhoades C, Shah NP, Goetz G, Tikidji-Hamburyan A, Sher A, Litke AM, Chichilnisky EJ. *Reconstruction of natural images from responses of primate retinal ganglion cells.* Presented at: The European Retina Meeting (ERM), 2017 Oct 5-7; Paris, FR.

- **Website(s) or other Internet site(s)**
  Nothing to report.

- **Technologies or techniques**
  Nothing to report.

- **Inventions, patent applications, and/or licenses**
  Nothing to report.

- **Other products**
  Nothing to report

7. PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

Name:	*Eduardo J. Chichilnisky*
Project Role:	*PI*
Researcher Identifier (e.g. ORCID ID):	0000-0002-5613-0248
Nearest person month worked:	*6*
Contribution to Project:	Conceived and directed the project, oversaw presentations and publications
Funding Support:	
Name:	*Nishal Shah*
Project Role:	*Graduate Student*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*6*
Contribution to Project:	Development of greedy dictionary-based algorithm for encoding
Funding Support:	
Name:	*Orren Karniol Tambour*
Project Role:	*Programmer*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*9*
Contribution to Project:	Development of methods to identify retinal ganglion cell types from electrical recordings and emulate responses with encoding models

Funding Support:	
Name:	*Nikhil Parthasarathy*
Project Role:	*Graduate Student*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*8*
Contribution to Project:	Development of methods to reconstruct visual images from electrical activity of retinal neurons using artificial neural networks
Funding Support:	

- **Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?**
  Nothing to report.

- **What other organizations were involved as partners?**
  Nothing to report.

8. SPECIAL REPORTING REQUIREMENTS
Nothing to report

List of Symbols, Abbreviations and Acronyms

RGC - retinal ganglion cell

NIPS - Neural Information Processing Systems Meeting

ICLR - International Conference on Learning Representations Meeting

COSYNE - The Computational and Systems Neuroscience Meeting

CRCNS - The Collaborative Research in Computational Neuroscience Meeting

TEATC - World Research Congress on Artificial Vision

ERM - The European Retina Meeting

ORCID ID - Open Researcher and Contributor Identification