Neural Networks 23 (2010) 733–742

Contents lists available at ScienceDirect

Neural Networks

journal homepage: www.elsevier.com/locate/neunet

2010 Special Issue

Multineuronal vectorization is more efficient than time-segmental vectorization for information extraction from neuronal activities in the inferior temporal cortex

Hidekazu Kaneko [a,*], Hiroshi Tamura [b,c], Shunta Tate [b], Takahiro Kawashima [d], Shinya S. Suzuki [a], Ichiro Fujita [b,c]

[a] *Institute for Human Science and Biomedical Engineering, National Institute of Advanced Industrial Science and Technology (AIST), AIST Tsukuba Central 6, Higashi, Tsukuba, Ibaraki 305-8566, Japan*

[b] *Laboratory for Cognitive Neuroscience, Graduate School of Frontier Biosciences, Osaka University, 1-3 Machikaneyama, Toyonaka, Osaka 560-8531, Japan*

[c] *CREST, Japan Science and Technology Agency, 4-1-8, Honcho, Kawaguchi, Saitama 332-0012, Japan*

[d] *Cooperative Research Facility Center, Toyohashi University of Technology, 1-1, Hibarigaoka, Tempaku-cho, Toyohashi, Aichi 441-8580, Japan*

ARTICLE INFO

Article history:
Received 31 October 2009
Received in revised form 3 March 2010
Accepted 8 March 2010

Keywords:
Information theory
Temporal coding
Population coding
Decoding
Single-unit recording
Vision
Inferior temporal cortex
Brain-machine interface

ABSTRACT

In order for patients with disabilities to control assistive devices with their own neural activity, multineuronal spike trains must be efficiently decoded because only limited computational resources can be used to generate prosthetic control signals in portable real-time applications. In this study, we compare the abilities of two vectorizing procedures (multineuronal and time-segmental) to extract information from spike trains during the same total neuron-seconds. In the multineuronal vectorizing procedure, we defined a response vector whose components represented the spike counts of one to five neurons. In the time-segmental vectorizing procedure, a response vector consisted of components representing a neuron's spike counts for one to five time-segment(s) of a response period of 1 s. Spike trains were recorded from neurons in the inferior temporal cortex of monkeys presented with visual stimuli. We examined whether the amount of information of the visual stimuli carried by these neurons differed between the two vectorizing procedures. The amount of information calculated with the multineuronal vectorizing procedure, but not the time-segmental vectorizing procedure, significantly increased with the dimensions of the response vector. We conclude that the multineuronal vectorizing procedure is superior to the time-segmental vectorizing procedure in efficiently extracting information from neuronal signals.

1. Introduction

Neural interface/prosthesis technology may enable amputees to voluntarily control their artificial limbs with neuronal activities and allow individuals who have sustained spinal cord injuries to remotely control assistive devices. It was recently demonstrated that electronic devices can be controlled using neuronal activities recorded from animals (Chapin, Moxon, Markowitz, & Nicolelis, 1999; Paninski, Shoham, Fellows, Hatsopoulos, & Donoghue, 2004; Schwartz, Taylor, & Tillery, 2001; Serruya, Hatsopoulos, Fellows, Paninski, & Donoghue, 2003; Wessberg et al., 2000) and tetraplegic patients (Donoghue, Nurmikko, Black, & Hochberg, 2007; Hochberg et al., 2006). These promising results obtained under laboratory conditions raise the possibility that neural interface/prosthesis technology could provide valuable therapeutic measures.

Control signals for prosthetic devices are usually derived from the neuronal activities of motor-related cortices, but signals from other cortices may also be used. For example, Felton, Wilson, Williams, and Garell (2007) recently demonstrated that a prosthetic device can be controlled using neural activity induced in the human temporal lobe by thinking about tones. Indeed, the results suggest that neuronal activities in any cortex can be used to create control signals for prosthetic devices. An important caveat, however, is the reproducibility of the neuronal activities that represent a specific motor, perceptual, or cognitive event.

This reproducibility parameter of neuronal activities can be evaluated using information theory. The amount of information shared by neuronal activities and the corresponding event is often used as a measure of the reproducibility of neuronal activities for a particular event because shared information depends on the probability that the neuronal activities and the event coincide (Cover & Thomas, 1991). When various signal processing methods

* Corresponding author. Tel.: +81 29 861 6624; fax: +81 29 861 6633.
E-mail address: kaneko.h@aist.go.jp (H. Kaneko).

0893-6080/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.neunet.2010.03.002

are compared, the methods that extract more information from the neuronal activities are generally considered superior.

The application of information theory to neuronal signals has shown that both the vectorization of spike counts across multiple neurons (multineuronal vectorization) and the vectorization of spike counts over a time period of a single neuron (time-segmental vectorization) can increase the amount of information extracted from spike trains (Aggelopoulos, Franco, & Rolls, 2005; Gochin, Colombo, Dorfman, Gerstein, & Gross, 1994; Kaneko, Tamura, Kawashima, Suzuki, & Fujita, 2007; Optican & Richmond, 1987; Reich, Mechler, & Victor, 2001a; Richmond & Optican, 1987; Rolls, Franco, Aggelopoulos, & Reece, 2003; Tovee, Rolls, Treves, & Bellis, 1993). Studies using simultaneously recorded responses from multiple neurons have indicated that a large amount of information can be obtained using the multineuronal vectorizing procedure (Aggelopoulos et al., 2005; Gochin et al., 1994; Kaneko, Tamura, Kawashima et al., 2007; Reich et al., 2001a; Rolls et al., 2003). Time-segmental vectorization was also shown to be efficient for extracting more information (Optican & Richmond, 1987; Richmond & Optican, 1987; Tovee et al., 1993). The adoption of both vectorizing procedures, however, prohibitively increases the dimensions of the response vector and may exceed the limited capacity of the data processing resources. This issue is critical for information theoretical approaches to real-time signal processing and the control of portable prosthetic devices.

In the present study, we compared these two vectorizing procedures based on their ability to efficiently extract information from extracellular spike activities from a population of neurons. For this comparison, we obtained multineuronal data from the inferior temporal (IT) cortex of monkeys with a multisite microelectrode while they were presented with a set of visual stimuli. The IT is an association area that is crucial for visual object recognition (D'Esposito et al., 1997; Miyashita, 1988; Roland & Gulyas, 1994, 1995). In our multineuronal vectorizing procedure, we defined a response vector whose components represented the spike counts of multiple neurons. In the time-segmental vectorizing procedure, a response vector consisted of components representing a neuron's spike counts for one to five time-segment(s) of the whole response period (1 s). To fairly compare these vectorizing procedures, the total neuron-seconds of the analyzed data was fixed at 1 neuron-second. We then determined which of these two strategies enabled us to obtain more information with the same number of vector dimensions.

2. Methods

2.1. Recording multiple neuronal activities

Neuronal responses to 64 visual stimuli were recorded from the IT of four anesthetized monkeys (*Macaca fuscata*; body weight: 5.2–7.5 kg; see Tamura, Kaneko, Kawasaki, and Fujita (2004) for details). All experimental procedures were based on guidelines from the National Institutes of Health of the United States (1996). Furthermore, the Osaka University animal experiment committee approved the procedures.

The general experimental procedures were similar to those described previously (Tamura et al., 2004). The monkeys were prepared for repeated recording by undergoing initial aseptic surgery under sodium pentobarbital anesthesia. For recording experiments, the monkeys were anesthetized with isoflurane. Vital signs (i.e., heart rate, body temperature, end-tidal CO_2, and arterial oxygen saturation level) were monitored throughout the experiments. The monkeys' eyes were covered with contact lenses. For multichannel recording of neuronal activity, a seven-core electrode (seven recording sites, impedance of each site: 1–2 MΩ at 1 kHz; Heptode, UWE Thomas Recording, Germany) was inserted into the IT through a craniotomy. To ensure stable recordings, we immobilized the brain surface with paraffin. After placing an electrode at each recording position we waited at least 20 min before the data acquisition was started. To prevent eye movement, the monkeys were paralyzed with pancuronium bromide.

Because the sampling radius of the seven-core electrode is approximately 150 μm, multichannel recordings were made at 300 μm intervals to avoid sampling the same neuron twice. The neuronal activity from each recording site was amplified 10,000 times, band-pass filtered (500 Hz to 3 kHz), and digitized at 20 kHz for offline spike sorting and analysis.

Multiple single-unit recording of nearby neurons was achieved by applying spike sorting to the multichannel recording data (Kaneko, Suzuki, Okada, & Akamatsu, 1999; Kaneko, Tamura, & Suzuki, 2007; McNaughton, O'Keefe, & Barnes, 1983). We employed a custom-made spike sorter consisting of three procedures: spike detection, burst detection, and spike classification (Kaneko et al., 1999; Kaneko, Tamura, & Suzuki, 2007). Multineuronal spikes were detected by matching the observed waveforms with a set of spike templates with different durations (spike detection). For each neuron spike, six waveforms were recorded simultaneously at six recording sites (i.e., the tip and five lateral sites of the seven-core electrode; one recording site was not used for technical reasons). The amplitudes of these waveforms constituted a spike-amplitude vector. A burst of spikes was identified based on short inter-spike intervals (1.5–15 ms) with an allowance for small amplitude ratio variations (burst detection). The amplitude vector of the first intraburst spike was used for spike clustering. Finally, clusters of spike-amplitude vectors were classified by bottom-up hierarchical clustering (spike classification).

2.2. Visual stimulation

We used 64 visual stimuli (see Fig. 1B in Tamura et al. (2004)), including 53 two-dimensional geometric shapes (e.g., circles, squares, triangles, bars, stars, gradation patterns, and gratings) and 11 photographs of natural objects (e.g., banana, apple, human face, monkey face, and hand). During each of the 10 presentation sessions, each of the 64 visual stimuli was presented for 1 s in random order at the center of the receptive field against a homogeneous gray background (15.7 cd/m^2). The interstimulus interval was 1 s. The onset and offset of the stimulus presentation were timed by the V-SYNC signals of the display. The entire recording period lasted 1280 s plus the sum of the V-SYNC signal delays (5.6 s). Because the response latency in the IT is approximately 80 ms, on average across neurons (Richmond, Wurtz, & Sato, 1983), we defined the response period as a 1 s period starting 80 ms after the onset of each stimulus presentation.

2.3. Response vector

For both the multineuronal and time-segmental vectorizing procedures, we expressed the responses of multiple neurons and their temporal patterns mathematically as vectors (Gochin et al., 1994; Optican & Richmond, 1987; Richmond & Optican, 1987).

When we vectorize the responses of multiple neurons, the number of spikes (i.e., spike count) generated from each neuron during the response period is assigned to a component in the response vector. Let n be the number of neurons used for the multineuronal vectorization and the spike count of the i-th neuron be equal to r_i. We represent the response vector of the multiple neurons as

$$\mathbf{r} = (r_1, r_2, \ldots, r_n). \quad (1)$$

To make the total neuron-seconds of used data equal to 1 neuron-second, the period for evaluating r_i is fixed at $(1/n)$ s.