Partial Cross-Correlation Analysis Resolves Ambiguity in the Encoding of Multiple Movement Features

Eran Stark,1 Rotem Drori,1,2 and Moshe Abeles1,2,3

1Department of Physiology, Hadassah Medical School, and 2The Interdisciplinary Center for Neural Computation, The Hebrew University of Jerusalem, Jerusalem; and 3Gonda Brain Research Center, Bar-Ilan University, Ramat-Gan, Israel

Submitted 19 September 2005; accepted in final form 23 November 2005

Stark, Eran, Rotem Drori, and Moshe Abeles. Partial cross-correlation analysis resolves ambiguity in the encoding of multiple movement features. J Neurophysiol 95: 1966–1975, 2006. First published November 30, 2005; doi:10.1152/jn.00981.2005. A classical question in neuroscience is which features of a stimulus or of an action are represented in brain activity. When several features are interdependent either at a given point in time or at distinct points in time, neural activity related to one feature appears to be correlated with other features. Thus techniques that simultaneously consider multiple features cannot account for delayed interdependencies between features. The result is an ambiguity with respect to the encoded features. Here, we resolve this ambiguity by applying a novel statistical method based on partial cross-correlations. The method yields estimates of linear correlations between neural activity and a given feature that are not affected by linear correlations with other features at multiple time delays. The method also provides a graphical output measured on a scale that allows for comparisons between different features, neurons, and experiments. We use real movement data and neural activity simulated according to a wide range of tuning models to illustrate the method. When applied to real neural activity, the procedure yields results that indicate which of the considered features the neural activity is related to and at what time delays.

INTRODUCTION

A general approach in experimental neurophysiology is to characterize single neuron activity in relation to stimulus or to action variables (Georgopoulos et al. 1982; Hubel and Wiesel 1962; Kakei et al. 1999; Merzenich and Brugge 1973; Mountcastle 1957; Scott and Kalaska 1997). A difficulty arises on attempting to relate neural activity to multiple variables that are interdependent. Neural activity may then appear to be related to one type of stimulus or action simply because it is related to another stimulus or action, which, in turn, is related to the first. For instance, during reaching movements made by a monkey (Georgopoulos et al. 1982), the firing rate of a neuron is estimated while the monkey moves its hand in various directions from a fixed initial position (Fig. 1A). Even when a clear directional response is observed, it is difficult to ascertain whether the response is related to the direction of the velocity vector, to the direction of the acceleration vector, or to both, because the two are highly correlated (Fig. 1A, bottom).

Ideally, experiments free from correlations between stimuli or between action dimensions should be constructed, but this is often impossible due to physical constraints. For instance, during continuous curved movements, correlations between directions of velocity and acceleration at zero delay are low.

Yet these features are correlated at other time delays (Fig. 1B). This is so because a change in the position of the arm is preceded by an elevation in movement velocity which, by necessity, is preceded by accelerating in the same direction.

The problem is quite general because the movement may involve either a visual stimulus such as a moving dot or a natural scene, or some output machinery such as an oculomotor apparatus or an arm. Neural activity that is related to one movement feature will appear to be related to other features that are correlated with the first at some temporal delay (Fig. 1B). Therefore inherent interdependencies between features must be controlled for statistically. Cross-correlation analysis does not account for such dependencies because it considers only two features at a time. When using other conventional techniques, such as regression analysis (Draper and Smith 1981), and considering multiple features at the same time, delayed dependencies between features are obviously not accounted for. This may bias the conclusions with respect to which features are encoded in neural activity (Todorov 2000). Despite its importance, up until now this issue was not addressed.

Here we present the partial cross-correlation matrices (PCCM) method. The method yields estimates of linear correlations between neural activity and movement features while taking into account interdependencies among features. The interdependencies are considered at various time delays. Consequently, the method renders it possible to determine to which movement features the neural activity is related and at what time delays. A graphical output, measured on a scale that can be readily compared between different features, neurons, and experiments, is also provided. The method thus provides a means of resolving ambiguity in parameter encoding.

In this paper, we present a detailed description of the method and demonstrate its use. We apply the method to two types of data: simulated neural activity with movement data from continuous movement experiments and real neural activity recorded from monkey motor cortex in conjunction with the same type of movement data.

METHODS

Experimental procedures

One monkey (Macaca fascicularis, female, 3.5 kg) was used in this study. Animal handling procedures were in accordance with the National Institutes of Health Guide for the Care and Use of Laboratory Animals (1996), complied with Israeli law, and were approved by

The costs of publication of this article were defrayed in part by the payment of page charges. The article must therefore be hereby marked “advertisement” in accordance with 18 U.S.C. Section 1734 solely to indicate this fact.
The Ethics Committee of the Hebrew University. The monkey was trained to perform a tracing task involving continuous curved movements. It was seated in a primate chair with the right hand restrained and operated a two-joint low-friction manipulandum with its left hand. A horizontal screen, mounted at chest level, blocked the view of the manipulandum and hand. A circular cursor (diameter: 0.4 cm) indicating hand endpoint was projected on the screen. The monkey traced given paths at its own pace. There were 40 different paths in each recording session, generated by cubic spline interpolation of 10 randomly placed points. This resulted in highly variable motion and modest correlations at zero delay (Fig. 1B). As soon as the monkey finished tracing a path, a juice reward was administered. Trials in which the monkey paused or deviated from the designated path for >800 ms were aborted.

During each recording session, up to eight glass-coated tungsten microelectrodes (impedance: 0.2–1.5 MΩ at 1 kHz), confined to a guide tube (internal diameter: 1.5 mm), were inserted into the contralateral primary motor or dorsal premotor area using a computer-controlled micro-drive (EFS, Alpha-Omega Engineering, Nazareth, Israel). The output signal of each electrode was amplified (10,000), band-pass filtered (0.3–6 kHz, MCP+, Alpha-Omega Eng.), and fed to a template matching device (MSD, Alpha-Omega Eng.) to isolate the activity of one to three units per electrode. Spikes and behavioral events were sampled at 1 kHz and logged on a custom data-acquisition system. Hand position was sampled at 100 Hz and was low-pass filtered (8 Hz). Velocity and acceleration were computed by taking the corresponding derivatives and converting the latter to polar coordinates. Spike trains were smoothed by convolution with a Gaussian filter (8 Hz). Velocity and acceleration were computed by taking the derivatives and converting the latter to polar coordinates.

**Simulation details**

To test whether our method could indeed correct for the mixed effect of multiple movement features, we simulated neural activity based on models of tuning to various movement features. In this manner, we know which feature the neural activity is related to and can therefore compare our expectations with the output of the method. For simulations, we used real movement profiles obtained from the Macaque continuous tracing experiments. In the first model, firing rate $R(t)$ was a function of the cosine of the direction of the acceleration vector

$$R(t) = B + G \cdot \cos[\theta_{vel}(t + \tau_{acc}) - \theta_{0}] + \epsilon(t)$$  

In the latter equation, $B$ is the baseline firing rate (spikes/s), $G$ is a dimensionless gain, $\tau_{acc}$ is the observed direction of the acceleration vector, $\theta_{0}$ is the preferred direction (PD) of the putative neuron, and $\tau_{vel}$ is the delay between the neural activity and movement (ms). Positive delays correspond to neural activity preceding movement. $\epsilon$ is a zero-mean Gaussian noise with SD $\sigma_{vel}$. To test the performance of the method on neural activity tuned to the direction of the velocity vector ($\theta_{vel}$), we used the same model. Because previous studies have shown a relationship of neural activity to amplitudes of acceleration ($A_{acc}$) (Flament and Hore 1988) or of velocity ($A_{vel}$) (Moran and Schwartz 1999a) vectors, we considered models with amplitude components. We used a linear combination of a cosine relation with $\theta_{vel}$ and a linear relation with $A_{vel}$

$$R(t) = B + G_{1} \cdot A_{vel}(t + \tau_{vel}) + G_{2} \cdot \cos[\theta_{vel}(t + \tau_{vel}) - \theta_{0}] + \epsilon(t)$$

which treats $A_{vel}$ as an additive component. We also used a cosine relation with $\theta_{vel}$ scaled by amplitude (Paninski et al. 2004)

$$R(t) = B + G \cdot \cos[\theta_{vel}(t + \tau_{vel}) - \theta_{0}] + \epsilon(t)$$

which treats $A_{vel}$ as a multiplicative factor. An additional composite model was a linear combination of two cosine relations, with $\theta_{vel}$ and with $\tau_{acc}$

$$R(t) = B + G_{1} \cdot \cos[\theta_{vel}(t + \tau_{vel}) - \theta_{0}] + G_{2} \cdot \cos[\theta_{vel}(t + \tau_{vel}) - \theta_{max}] + \epsilon(t)$$

In all models $\theta_{0} = 0^\circ$ was employed. Numerical simulations were carried out at discrete time steps of 10 ms in the following manner. First, we generated a rate profile for each trial according to one of the models but without any noise $\epsilon$. The SD of this noiseless signal, $\sigma_{vel}$, was estimated for each trial separately and averaged across trials. Noise SD was then computed according to $\sigma_{vel} = \sigma_{sig}/SNR$ (signal-to-noise ratio). We employed SNR = 1. Signal-dependent noise $\epsilon$ was then generated by random sampling from a Gaussian distribution with zero mean and SD of $\sigma_{vel}$ and added to the signal. Negative rates were clipped to zero. We verified that the mean and SD of simulation outputs matched those observed for real neurons (mean rate of 5
Innovative Methodology

The linear correlation between any two random variables $A$ and $B$ (for instance, firing rate and the cosine of $\theta_{vel}$) can be estimated by $\rho_{AB}$—the product-moment correlation coefficient (CC)

$$\rho_{AB} = \frac{(A - \langle A \rangle) \cdot (B - \langle B \rangle)}{\sigma_A \cdot \sigma_B} \tag{5}$$

where $(A)$ is the arithmetic average of $A$, and $\sigma_A$ is its SD and likewise for $B$. When an additional variable $C$ (for instance, the cosine of $\theta_{acc}$) is suspected to account for some of the correlation, its linear effect may be removed using the partial CC (Fisher 1925), defined as

$$\rho_{ABC} = \frac{\rho_{AB} - \rho_{AC} \cdot \rho_{BC}}{\sqrt{(1 - \rho_{AC}^2) \cdot (1 - \rho_{BC}^2)}} \tag{6}$$

where $\rho_{AB}$, $\rho_{AC}$, and $\rho_{BC}$ are product-moment CCs. Linear correlations—between $A$ and $C$ and between $B$ and $C$—are removed from $\rho_{AB}$ by subtraction, and the difference is normalized by the geometric average of the deviations of these correlations from one (partial CCs range from $-1$ to $1$ as do product-moment CCs). This is conceptually similar to estimating the correlation between $A$ and $B$, whereas $C$ is held constant experimentally. For instance, if $B$ and $C$ are both noisy duplicates of $A$, with SNR of 1, then the correlation between each of these and $A$ is about 0.71. It is clear however that the correlation between $A$ and $C$ is substantial as well ($\sim 0.5$). Computing partial correlations between $A$ and $B$ (or $C$) gives 0.58 instead of 0.71, but the correlation between $B$ and $C$ goes down to $\sim 0$. Thus the partial correlation clarifies which variable is related to which other variable directly and to which other variable indirectly.

If two additional variables are to be accounted for, say $C_1$ and $C_2$, the second-order partial CC can be computed by

$$\rho_{AB|C_1C_2} = \frac{\rho_{ABC} - \rho_{AC_1|C_2} \cdot \rho_{BC_1|C_2}}{\sqrt{(1 - \rho_{AC_1|C_2}^2) \cdot (1 - \rho_{BC_1|C_2}^2)}} \tag{7}$$

where $\rho_{ABC}$, and so on are partial CCs (Eq. 6). In the latter expression, we first take into account the effect of $C_1$ by estimating first-order partial CCs ($\rho_{AB|C_1}$ and $\rho_{AC|C_2}$), and then the effect of $C_2$, by actually plugging these first-order partial CCs into the expression. Note that this is not the only possible expression for obtaining an estimate of $\rho_{AB|C_1C_2}$; we can reverse the first, order taking into account the effect of $C_2$ and subsequently of $C_1$. By extension, when three additional variables are present there are six (3!) equivalent recursive expressions for estimating third-order partial correlations. In the same manner, when $n$ additional variables are to be accounted for, the $n$th-order partial correlation may be obtained by recursion. Alternatively, partial CCs of any order may be obtained from multiple linear regression (MLR) coefficients and their SDs (see appendix for more details regarding both computational procedures).

Accounting for time-dependent correlations between variables using partial cross-correlations

Applied to scalar variables, partial CCs will remove all linear correlations. When variables are time series, this application is equivalent to removal of zero delay correlations, whereas delayed correlations are not considered. Therefore if the value of variable $B$ at time $t$ is related to the value of variable $C$ at time $t + \tau$ but not at time $t$, $\rho_{ABC}$ will be about the same as $\rho_{AB}$. We want to correct for the delayed effect of variable $C$ on the correlation between variables $A$ and $B$. Because the two variables in question may themselves be correlated at nonzero delays, we write the partial cross-correlation between $A$ and $B$, given $C$, as a function of two time delays

$$\rho_{AB|C(t+\tau)} = \frac{\rho_{AB} - \rho_{AC} \cdot \rho_{BC(t+\tau)}}{\sqrt{(1 - \rho_{AC}^2) \cdot (1 - \rho_{BC(t+\tau)}^2)}} \quad \tag{8}$$

where $\tau_1$ is the delay between variables $A$ and $B$, and $\tau_2$ is the delay between variables $A$ and $C$, so $\rho_{AB|A(t+\tau_1)}$ is the cross-correlation between variables $A$ and $B$ at a time delay of $\tau_1$ and so on. Eq. 8 yields a partial cross-correlation matrix (PCCM) in which each element is $\rho_{AB|C}$ as a function of two time delays, $\tau_1$ and $\tau_2$. Single-trial partial CCs are Fisher $z$-transformed, $\hat{p}(\tau_1, \tau_2) = \frac{1}{2} \log \left( \frac{1 + |p(\tau_1, \tau_2)|}{1 - |p(\tau_1, \tau_2)|} \right)$, so they are distributed normally under the null hypothesis of no correlation between variables.

In this paper, we estimate PCCMs for movement features within the range of $-300$ to $300$ ms, in $10$-ms increments. This range was selected on the basis of previous studies (Moran and Schwartz 1999b). Specifically, our goal is to account for effects of $\theta_{vel}$ and $\lambda_{vel}$ at the same time delay relative to the firing rate, $\tau_1$, and for the effects of $\theta_{acc}$ and of $A_{vel}$ at another time delay, $\tau_2$. Taking the sine and cosine of $\theta_{vel}$ and $\lambda_{vel}$, we obtain together with $A_{vel}$ and $A_{acc}$, a total of six movement features: $A_{vel}$, $\sin(\theta_{vel})$, $\cos(\theta_{vel})$, $A_{acc}$, $\sin(\theta_{acc})$, and $\cos(\theta_{acc})$. Denoting the firing rate profile by $R$ and using the indexing convention of Eq. 8, the fifth-order PCCMs can be written as

$$M_{A_{vel},\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{A_{vel}R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

$$M_{A_{vel},\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{A_{vel}R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

$$M_{cos(\theta_{vel}),\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{cos(\theta_{vel})R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

$$M_{cos(\theta_{vel}),\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{cos(\theta_{vel})R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

$$M_{A_{vel},\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{A_{vel}R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

$$M_{A_{vel},\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2) = \rho_{A_{vel}R|\theta_{vel},\lambda_{vel}}(\tau_1, \tau_2)$$

Note that when $\tau_1 = \tau_2 = 0$, the PCCM result is equivalent to the MLR solution (appendix) when regressing the firing rate $R$ on all six features, at zero delay. When $\tau_1 = \tau_2$, the PCCM result is equivalent to the MLR solutions obtained when regressing $R$ on all six features lagged together (Ashe and Georgopoulos 1994).

Computational specifics

Partial cross-correlations may be estimated in either the time or the frequency domains. In the time domain, this is accomplished by lagging each of several variables on all relevant delays relative to another variable, such as firing rate, and trimming to get matrices of equal sizes. For instance, to compute a doubly-lagged PCCM for three time series—vectors $A$, $B$, and $C$—vectors $B$ and $C$ are replicated, zero-padded, and lagged relative to the reference vector $A$. Resulting matrices are trimmed such that the number of data points is equal for all time delays, and the partial CC at delays of $(\tau_1, \tau_2)$ is then computed between the trimmed vector $A$ and the appropriate column of the trimmed matrix $B$, given the appropriate column of the trimmed matrix $C$.

Such estimation carries a computational burden which is proportional to $N^3 M^3$, $N$ being the length of the trimmed time series, $M$ being the maximal lag of interest, and $k$ being the number of time delays.
More efficient calculations are carried out in the frequency domain using the fast Fourier transform algorithm. When there are exactly three variables, the complex bispectrum (Nikias and Mendel 1993) can be used. The improved efficiency is due to the fact that multiplication in the frequency domain is equivalent to convolution in the temporal domain.

RESULTS

Disambiguating several variables

Interdependency between movement features may result in ambiguity with respect to the encoded features. This is illustrated by simulating neural activity with a cosine relation to the direction of the acceleration vector, \( \theta_{\text{acc}} \), at a zero delay (see Eq. 1). In this case, the activity is also highly correlated with the direction of the velocity vector, \( \theta_{\text{vel}} \). This is because \( \theta_{\text{vel}} \) and \( \theta_{\text{acc}} \) are strongly correlated with each other (Fig. 1B). The ambiguity can be resolved by estimating the partial correlation between the firing rate and \( \theta_{\text{acc}} \), while accounting for correlations between firing rate and \( \theta_{\text{vel}} \) and between \( \theta_{\text{acc}} \) and \( \theta_{\text{vel}} \) (Eq. 6). Because variables may be correlated at nonzero delays, such partial correlations change as a function of the delay between the firing rate and velocity \( \tau_1 \), and the delay between firing and acceleration \( \tau_2 \). Thus the partial correlation between firing rate and one movement feature, given another, is displayed as a function of \( \tau_1 \) and \( \tau_2 \) (Eq. 8). This is designated henceforth as a PCCM. A PCCM is obtained from the data of a single trial (such as in Fig. 1B, middle) and the resulting PCCMs are averaged across trials.

When applying the PCCM method to the simulation described above we obtain two PCCMs (Fig. 2A). The top matrix shows the partial cross-correlation between firing rate and the cosine of \( \theta_{\text{vel}} \) given the cosine of \( \theta_{\text{acc}} \), and the bottom matrix shows the partial cross-correlation between firing rate and the cosine of \( \theta_{\text{acc}} \) given the cosine of \( \theta_{\text{vel}} \). These PCCMs reveal a strong correlation between firing rate and \( \theta_{\text{acc}} \) at zero delay. This correlation is robust to the delay between the firing rate and the cosine of \( \theta_{\text{vel}} \) and is expressed as a vertical correlation stripe in the \( \theta_{\text{acc}} \) PCCM. Moreover, the correlation between firing rate and \( \theta_{\text{vel}} \) was effectively eliminated. This concurs with our expectations since the firing rate was simulated using a model of tuning to \( \theta_{\text{acc}} \). Note that some patches are seen in the \( \theta_{\text{vel}} \) PCCM, and that the vertical correlation stripe in the \( \theta_{\text{acc}} \) PCCM is not homogenous. These patterns are caused by nonlinear relations between \( \theta_{\text{vel}} \) and \( \theta_{\text{acc}} \) and result from the fact that we compute only linear correlations. They are most prominent at the time delay where linear correlations between the two features are maximal (about \( \pm 150 \) ms, green curve in Fig. 1B). Yet this does not invalidate the conclusion that the activity of this putative neuron is related to \( \theta_{\text{acc}} \) at a zero delay.

Having obtained several such PCCMs we wish to determine to which movement features the firing rate is related. To this end, we use a t-statistic, which is a measure of correlation that does not depend on the number of trials, and can be compared between different variables. The t-statistic is computed based on the average value across trials (Fig. 2A) and the SD across trials (Fig. 2B)

\[
t(\tau_1, \tau_2) = \frac{\hat{p}(\tau_1, \tau_2)}{\text{SD}(\hat{p}(\tau_1, \tau_2)/\sqrt{n}}
\]

where \( n \) is the number of trials, and \( \hat{p}(\tau_1, \tau_2) \) is a Fisher \( z \)-transformed CC at a pair of time delays. For CCs that are normally distributed this statistic is distributed according to the \( t \)-distribution with \( n-1 \) df, hence \( P \) values can readily be computed. As is, the statistic is a useful visualization tool (Fig. 2C).

Application to amplitude and direction of the velocity and acceleration vectors

In the preceding example, we considered two movement features: the cosine of \( \theta_{\text{vel}} \) and the cosine of \( \theta_{\text{acc}} \). We now apply the PCCM method to an extended set of features, by considering the sine components of \( \theta_{\text{vel}} \) and \( \theta_{\text{acc}} \) in addition to their cosines. Furthermore, we consider the amplitudes of these vectors, \( A_{\text{vel}} \) and \( A_{\text{acc}} \). Specifically, we consider \( \theta_{\text{vel}} \) and \( \theta_{\text{acc}} \) at one point in time relative to the firing rate, and \( \theta_{\text{acc}} \) and \( A_{\text{acc}} \) at another point in time. After taking the sine and cosine of \( \theta_{\text{vel}} \) and \( \theta_{\text{acc}} \), we obtain, together with \( A_{\text{vel}} \) and \( A_{\text{acc}} \), a total of six movement features, and estimate a PCCM for each (APPENDIX). Figure 3A shows the six PCCMs for the same movement data and simulated neural activity that were used previously (Fig. 2).
Innovative Methodology

FIG. 3. PCCMs for multiple movement features. A: movement data and simulated neural activity used here are the same as in Figs. 1 and 2. In contrast to previous figures, here the analysis covers 6 movement features: Avel, the sine of \( \theta_{vel} \), the cosine of \( \theta_{vel} \), Aacc, the sine of \( \theta_{acc} \), and the cosine of \( \theta_{acc} \). Thus each PCCM is computed between neural activity and 1 feature, given 5 other features. The name of the feature above each panel indicates that the partial correlation is between firing rate and this feature, given the other 5. Other conventions are the same as in Fig. 2. Obviously, the encoded feature is cosine of \( \theta_{vel} \) at 0 delay. B: \( \theta_{vel} \) sine and cosine PCCMs are combined (Eq. 16) yielding 1 PCCM for \( \theta_{vel} \). The same is done for acceleration, resulting in 1 PCCM for \( \theta_{acc} \).

2). Each of these PCCMs describes the correlation between firing rate and one of the six features, given the other five. To determine whether neural activity is related to \( \theta_{vel} \) (or \( \theta_{acc} \)) in general, the sine and cosine PCCMs, \( M_{\sin} \) and \( M_{\cos} \), of \( \theta_{vel} \) (or \( \theta_{acc} \)) are combined, for each pair of time delays, by taking the square root of the sum of squares

\[
M_s(\tau_1, \tau_2) = \sqrt{M_{\sin}(\tau_1, \tau_2) + M_{\cos}^2(\tau_1, \tau_2)}
\]  

(16)

To illustrate this, we apply Eq. 16 to the \( \theta_{vel} \) sine and cosine PCCMs and then to the \( \theta_{acc} \) sine and cosine PCCMs. Thus the four directional PCCMs are reduced to two (Fig. 3B). Each of these two matrices measures partial correlations between firing rate and \( \theta_{vel} \) (or \( \theta_{acc} \)), given \( A_{vel} \), \( A_{acc} \), and \( \theta_{acc} \) (or \( \theta_{vel} \)). Together with the two amplitude PCCMs (Fig. 3A, leftmost panels) we obtain a set of four matrices which gives a succinct characterization of the movement features encoded by the putative neuron.

Application of the PCCM method to neural activity simulated according to composite models

Up to this point, neural activity has been simulated according to a cosine model of directional tuning (Eq. 1). In this model, relationships between neural activity and the cosine of direction are fully captured by a product-moment CC. We now go one step further and test the capability of the method to resolve ambiguities in simulated neural activity based on real movement data and on more complex tuning models.

We use a composite model in which the firing rate is linearly related to movement features, \( A_{vel} \) and \( \theta_{vel} \), in an additive manner (Eq. 2). Based on the movement data and on the simulated firing rate profiles, we estimate four PCCMs (Fig. 4A). Indeed, these PCCMs show that the response of the putative neuron is related to \( A_{vel} \) and to \( \theta_{vel} \) at a time delay of \(-50\) ms. As in the single feature simulations, some patches are seen in the acceleration PCCMs (Fig. 4A, bottom). These may result from nonlinear relations between velocity and accelera-

FIG. 4. Application of the PCCM method to neural data simulated according to composite models. A: cosine relation with \( \theta_{vel} \) and linear relation with \( A_{vel} \) (Eq. 2; \( \tau_{vel} = 50\) ms). The 4 PCCMs are organized as follows: top: velocity, bottom: acceleration; left: amplitude; right: direction. Colors depict t-statistic values. Each PCCM shows the correlation between firing rate and 1 movement feature, given the other features. Other conventions are the same as in Fig. 3. As expected from the model, horizontal stripes are evident in the \( A_{vel} \) and \( \theta_{vel} \) PCCMs. B: cosine relation with \( \theta_{acc} \) multiplied by \( A_{vel} \) (Eq. 3; \( \tau_{vel} = 50\) ms). As expected, the amplitude relation is not noticeable in the PCCMs. The direction relation is obvious. C: cosine relation with \( \theta_{vel} \) and cosine relation with \( \theta_{acc} \) (Eq. 4). The delay between firing rate and velocity is 200 ms, and the delay between firing rate and acceleration is 50 ms. These features and delays are unmistakable in the PCCMs. All simulations in this figure were based on the same movement data (387 trials).
tion. Nonetheless, relationships of firing rate with acceleration are much smaller in magnitude than with velocity and indicate that the simulated neural activity is mostly related to $A_{vel}$ and to $\theta_{vel}$ and not to acceleration.

The model of cosine tuning used in the preceding text for direction took into account the direction of the movement vector but not its amplitude. A more realistic model incorporating $A_{vel}$ as a scaling factor for $\theta_{vel}$ (Eq. 3) is used next. In that model, rate depends on amplitude and on cosine of direction in a multiplicative manner. When directions are distributed homogeneously between 0 and 360°, their cosine is distributed symmetrically around zero. In such a setting, the linear correlation between firing rate and amplitude is zero. In contrast, amplitudes are not symmetrically distributed, so the correlation between rate and direction cosine is not zero. Therefore we expect a clear relation with the direction and not with the amplitude. Indeed, when generating simulated firing rate profiles according to this model, the PCCM method reveals an exclusive relation with $\theta_{vel}$ (Fig. 4B).

Next, we use a composite model of tuning to $\theta_{vel}$ and $\theta_{acc}$ (Eq. 4). For both components, the preferred direction (PD) is the same, but the time delays are different: the simulated neural activity precedes velocity by 200 ms and acceleration by 50 ms. As in the previous cases, the PCCM method is successful in recovering the correct features and resolving ambiguity in their encoding (Fig. 4C). A noteworthy attribute in the resulting PCCMs, not seen in previous simulations, is that the two correlation stripes thin considerably at their graphical point of intersection, at delays of about {50, 200} ms. This arises from the fact that at this point in time, the simulated neural activity is an outcome of both features. Therefore computing partial correlations removes relations of the neural activity with both of them. It is clear, however, which features are encoded and at what time delays.

We tested the capability of the method to reveal encoded features by using models that include deviation from linear relations with direction cosine. By using a von Mises tuning function instead of a cosine, the concentration of a directional tuning curve was allowed to vary; this provides a better fit with firing rates of motor cortical neurons (Amirikian and Georgopoulos 2000). In addition, we used models of a nonlinear (sigmoidal) amplitude dependency, composite models of sigmoidal amplitude dependency and von-Mises directional relation, and non-Gaussian additive noise. The PCCM method exhibited remarkable robustness to the type of tuning function: the correct movement features were apparent in the resulting PCCMs for a wide range of simulation coefficients in linear and in nonlinear models alike.

Overall, these simulations demonstrate that the method is capable of revealing tuning to specific movement features despite ambiguities caused by delayed correlations between movement features.

Application of the PCCM method to real neural data

We applied the PCCM method to the activity of neurons recorded in Macaque motor cortex during continuous tracing movements. We present two typical examples. The first example (Fig. 5A) demonstrates a case of encoding a single movement feature, namely $\theta_{vel}$. Only one matrix in the set of four PCCMs contains a high correlation stripe in striking similarity to the results obtained from the simulation of exclusive relationship to $\theta_{vel}$ (Fig. 4B). It is quite clear that this motor cortical neuron represents the direction of the velocity vector, regardless of other features.

A second example illustrates a case of simultaneous encoding of two movement features, $A_{vel}$ and $A_{acc}$ (Fig. 5B). There is a horizontal stripe in the $A_{vel}$ PCCM at a time delay of approximately $-25$ ms, and there is a vertical stripe in the $A_{acc}$ PCCM at the same time delay. This set of PCCMs resembles the two feature simulation results (Fig. 4C), the main difference being that instead of encoding directions, this neuron is related to the amplitudes of velocity and acceleration vectors.

Derivation of a preferred direction

Until now we have concentrated on the issues of which movement feature is encoded by neural activity, and at what time delay. However, there is often a need to determine the direction of the velocity—or the acceleration—vector preferred by a neuron; namely, the neuron’s PD. Assume we have determined that a neuron is related to direction at a fixed time delay by observing a high correlation stripe. For instance, looking back at Fig. 5A we infer that the neuron is tuned to $\theta_{vel}$ due to the horizontal stripe in the $\theta_{vel}$ PCCM at a time delay of $-20$ ms. To determine the velocity PD that is associated with this delay, we return to the separate sine and cosine PCCMs.
Derivation of a preferred direction (PD) of a motor cortical neuron: A PCCM of \( \theta_{vel} \) sine and cosine averaged across 250 trials (same neuron as in Fig. 5A). Color scale indicates partial CCs. There is a negative correlation with the sine of \( \theta_{vel} \) at a time delay of \(-20\) ms. B: estimation of velocity PD from the sine and cosine PCCMs. Each pixel in the 2 PCCMs shown in A defines a planar vector: the angle of this vector is plotted for each pixel (Eq. 17). Based on the \( \theta_{vel} \) t-statistic matrix (Fig. 5A, top right), a region of high correlation with \( \theta_{vel} \) is delineated between the two black lines. The direction in this region is \( 303 \pm 4^\circ \) (mean \( \pm \) SD).

**Innovative Methodology**

E. STARK, R. DRORI, AND M. ABELES

**FIG. 6.** Derivation of a preferred direction (PD) of a motor cortical neuron. A: PCCMs of \( \theta_{vel} \) sine and cosine averaged across 250 trials (same neuron as in Fig. 5A). Color scale indicates partial CCs. There is a negative correlation with the sine of \( \theta_{vel} \) at a time delay of \(-20\) ms. B: estimation of velocity PD from the sine and cosine PCCMs. Each pixel in the 2 PCCMs shown in A defines a planar vector: the angle of this vector is plotted for each pixel (Eq. 17). Based on the \( \theta_{vel} \) t-statistic matrix (Fig. 5A, top right), a region of high correlation with \( \theta_{vel} \) is delineated between the two black lines. The direction in this region is \( 303 \pm 4^\circ \) (mean \( \pm \) SD).
of relationships. Such an approach was used to compute mutual information between position and velocity for a two-dimensional visual stimulus at zero delay (Adelman et al. 2003). This approach can be extended by estimating conditional mutual information (Cover and Thomas 1991) between neural activity and one lagged movement feature, given another lagged feature instead of partial CCs. Such an extension would potentially account for complex temporal dependencies between variables.

As shown, the above-discussed assumptions do not preclude an application of the method to experimental data. Moreover, useful insights are obtained from neural data that are inherently noisy.

Limitations of the PCCM method

There are several limitations of which we need to be aware. First, the method can only be used when the amount of data are sufficient. “Sufficiency” depends on various factors such as inter-trial variability and the SNR of the variables encoded in the neural activity, but some guidelines can be set. First, given experimental values, several dozen trials are required for the t-statistics to stabilize. The required number of trials does not increase exponentially with the number of variables used. This can be understood by considering a set of three variables: when estimating triplet-wise correlations among three variables, more data are required than when estimating first-order partial CCs because the latter depend only on three pair-wise CCs (Eq. 6). Thus instead of estimating the full three-way joint PDF, we need only estimate three marginal distributions of the full PDF, and this naturally requires less data than are required for estimating the full PDF. However, all variables must be collected at the same time as the neural data are. Second, trial length should be more than twice the maximal delay of interest to have some data left after the trimming process (METHODS).

Second, in the applications presented, we have restricted ourselves to three sets of variables: the firing rate, velocity, and acceleration. Different elements of each set, for instance, Avel, our selves to three sets of variables: the firing rate, velocity, and the sine of C, given the other, will be about zero, although the pair-wise cross-correlations are different from zero. This is largely a theoretical case since physiological data are noisy. Nonetheless, it is advisable to look at the distribution and the auto-correlation of each feature, as well as at joint distributions and pair-wise cross-correlations, together with PCCMs.

Finally, the linear version of the PCCM method, presented here, should not be used whenever a product-moment CC would not be used for characterizing pair-wise relations. Thus when the assumed generative model is nonadditive (e.g., a multiplicative relation between velocity and acceleration), when tuning is not monotonous (e.g., a Gaussian dependency on velocity amplitude), or when firing rates are highly non-Gaussian (e.g., very low), the method as is should not be used. Yet, a rank-based or an information-theoretic version of the method could be used instead as mentioned in the preceding text.

Interpretation of PCCMs

The PCCM graphs provide a rich way of visualizing partial correlations. In general, we look for graphical patterns (clusters or high valued pixels) rather than isolated high valued pixels. Several graphical patterns may be observed in a PCCM. If a single, prominent stripe is visible, then the neural activity is most likely to be related to the corresponding feature at a particular time delay, insensitive to another feature at all delays (for instance, Figs. 4 and 5). When one stripe is accompanied by another stripe, in another PCCM, then neural activity is probably related to two features, at distinct time delays (Figs. 4, A and C, and 5B). Other graphical characteristics are also possible. For instance, when neural activity is related to a specific temporal relation between two movement features, a “blob” may be observed, and when the neural activity is related to the co-occurrence of two features, at any time delay, a diagonal stripe may be seen.

In our experience, the most commonly observed graphical pattern in PCCM graphs is a horizontal or vertical stripe, which is compatible with encoding of some feature at a constant delay. It may thus be desired to reduce the dimensionality of a PCCM by searching for significant stripes. A simple procedure for doing so would be to define a stripe as a row (or column) of pixels in which most pixels have high values, both absolutely (indicating significant partial CCs) and relative to the maximal t-statistic value in a set of PCCMs (indicating a stripe of high partial CCs relative to its surroundings). A stripe corresponding to this definition would have a single time delay and indicate a relation to a single feature.

Applications and possible extensions

In this paper, we illustrated the PCCM method using movements from one type of experiments. The method is quite general and can be used in other applications. First, the procedure can be successfully applied to movements obtained from center-out experiments assuming minimal data size requirements are met (movement duration long enough to permit trimming and enough trials per direction; from our experience, 0.5 s/trial and 30 trials/direction are sufficient). Thus the method can be applied to a large corpus of existing data. Second, it is perhaps needless to point out that correlations

Innovative Methodology

PARTIAL CROSS-CORRELATION OF MULTIPLE MOVEMENT FEATURES

J Neurophysiol • VOL 95 • MARCH 2006 • www.jn.org
among any kinematical movement features (for example, position and its time derivatives), dynamical movement features (for example, muscular activity), nonmovement features (for example, visual stimuli, contrast and brightness, natural auditory sounds, natural visual scenes), or any combination thereof, can be handled in the manner presented here.

The PCCM method can be applied to other data types. For instance, the firing rate of a single neuron can be replaced with a series of spike times. This would generate a more detailed temporal relation between neural activity and movement features, akin to spike-triggered averages (De Ruyter van Steveninck and Bialek 1988). Alternatively, movement features can be replaced with local field potential signals recorded by two electrodes, whereas a third variable is the spike trains recorded by one of these electrodes (Halliday et al. 1995). As a third example, if one variable is the spike trains of one neuron and another variable is the spike trains of a second neuron, the PCCM method can be used to remove effects of multiple other variables on the functional connectivity between these two neurons (Aertsen et al. 1989; Ben-Shaul et al. 2001).

Finally, the PCCM method can be used to determine which movement features are encoded by neurons. The outcome may be used to guide selection of features for improved movement reconstruction and ultimately—for movement construction.

A P P E N D I X

Numerical evaluation of partial CC

High-order partial CCs may be evaluated directly by recursion (Dubois 1957) using the following MATLAB code

```matlab
function y = reduce(X)
    n = size(X, 1); % matrix size
    d = ones(n - 1, 1); % dummy
    b = X(2: end, 1); % before reduction
    E = X(2: end, 2: end); % before reduction
    C = X(1, 2: end); % variable to be partialed
    y = E - (b'*d') * (d'*C); % reduce
    y(2: end, 1) = y(1, 2: end)/y(1, 1); % after reduction
end
```

For example, to evaluate Eq. 9 at \( \tau_1, \tau_2 \), \( X \) would be—at the first iteration—a symmetric \( 7 \times 7 \) matrix of product-moment pair-wise CCs. The last column (row) in the correlation matrix \( X \) consists of CCs between \( R \) and each of the other variables, lagged appropriately (METHODS). The second to last column (row) consists of CCs between \( A_{def} \) and all other variables. The routine is then called recursively five times, resulting in a \( 2 \times 2 \) partial covariance matrix. From this matrix the fifth-order partial CC is computed directly.

Alternatively, partial CCs may be obtained from MLR. Denote the data matrix of \( n \) observations of \( m \) standardized features by \( X \), and the firing rate by the \( n \times 1 \) vector \( y \). The MLR solution is then an \( m \times 1 \) vector, \( b = (X^T X)^{-1} X^T y \), where \( X^T \) indicates matrix transpose and \( X^{-1} \) indicates matrix inversion (Draper and Smith 1981). The asymptotic SD of each element of \( b, \sigma_i, i = 1 \ldots m \), is obtained by multiplying the corresponding element of the variability vector [the square root of the main diagonal elements of \((X^T X)^{-1}\)] by the root-mean-square error (the \( L_2 \) norm of the prediction error, \( y - \hat{y}b \)). Next, a \( t \)-statistic is computed for each regression coefficient (element of \( b \)), \( t_i = b_i/\sigma_i \cdot \sqrt{\text{DOF}} \), where the regression degrees-of-freedom are \( \text{DOF} = n - m \). Finally, the corresponding \((m - 1)^{th}\) partial CC is obtained by \( t_i/\sqrt{t_i^2 + \text{DOF}} \). Thus partial CCs are monotonically related to the suitable MLR coefficients.

ACKNOWLEDGMENTS

We are grateful to M. Nakar for help with the construction of the experimental setup, to V. Shankovsky for technical help, and to I. Asher and Y. Ben-Shaul for help in carrying out the experiments. We thank A. Globerson and A. Stark for a critical reading of the manuscript.

GRANTS

This research was supported in part by Center of Excellence Grant 1564/04 administered by the Israel Science Foundation, the Horowitz Foundation, the Rich Center, the German-Israel Foundation, and the Deutsch-Israelische Projektkooperation.

REFERENCES


