**Proceedings of the 28th IEEE**
**EMBS Annual International Conference**
**New York City, USA, Aug 30-Sept 3, 2006**

# Improved Linear BMI Systems via Population Averaging

Jack DiGiovanna, *Student Member, IEEE*, Justin C. Sanchez, *Member, IEEE,* and Jose C. Principe, *Fellow, IEEE*

*Abstract*— **We investigate population averaging as a preprocessing stage for linear FIR BMIs. Population averaging is a biologically-inspired technique based on spatial constraints and neuronal correlation. We achieve a statistically significant improvement in accuracy while substantially (45%) reducing model parameters. Further analysis is performed to show that population averaging improves model accuracy by reducing variance in estimating the firing rate from spike bins. However, we find that population averaging provides a greater accuracy improvement than other groupings which also reduce firing rate variance. Our results suggest that appropriate spatial organization of neural signals enhances BMI performance.**

## I. INTRODUCTION

BRAIN-machine interfaces (BMI) attempt to find functional relationships between neuronal activity (collected from the cortex of the brain) and directed movements [1]-[3], which can be posed as a classic “system identification” problem. While groups have shown quite impressive results with microelectrode arrays in motor control areas of the cortex, the systems cannot perfectly reconstruct the desired signal [1]-[3]. Assuming there is sufficient data to avoid generalization problems, a logical cause for the degraded performance is input noise. If the Wiener Filter (a common benchmark) is used for BMIs, additive white Gaussian noise in the input signal will alter the autocorrelation matrix by the variance of the noise [4]. This prevents the model from achieving optimal weights.

While the precise details of how the plant (motor control system) represents movement tasks are unknown, there is experimental and neurophysiological support for the theory that the brain utilizes rate coding [5], [6]. However, in prior experiments, BMI researchers have made two strong assumptions about rate code time resolution and the input structure. First, spikes (action potentials) are “binned” at a particular window size, creating an estimate of firing rate. Second, each neuron is used individually as a filter input.

Spike “binning” provides a temporal to amplitude representation of the firing times of a spike train. Action potentials within a particular time window (bin) are summed; this reduces the sparsity of the input signal. When computing firing rates (see (1)) via binning action potentials from a single neuron there are opposing pressures of keeping the averaging time ($\Delta t$) much smaller than the behavioral response time, but large enough to not exaggerate the firing rate (i.e. a 2 ms bin with 1 spike represents a 500 Hz firing rate – theoretically the highest possible for a pyramidal cell) [6]. The variance in the rate estimate increases with shorter bin sizes. Fig. 1 illustrates this by comparing behaviorally related perievent histograms of a population using both 25 ms and 100 ms bins.

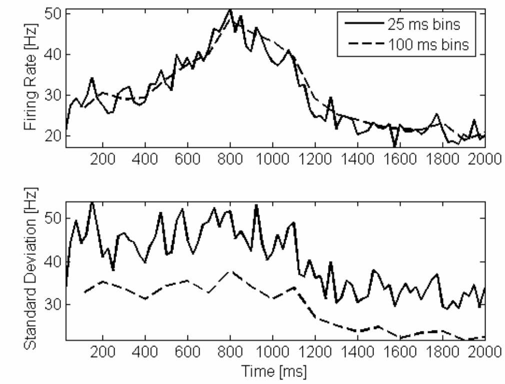

Fig.1. Population average perievent histogram. Lever is pressed at 1000 ms. The bin size affects both the rate information and input noise. Population includes four neurons.

The second assumption should be examined from first principles of neuroscience. There is cytoarchitectural and experimental evidence that neurons in the motor cortex are organized into cortical columns approximately 75 - 150 µm in radius; vertically spanning layers II – VI [7]. The firing of any particular neuron has been shown to be stochastic and noisy: neuron firing is often averaged over many behavior trials to discover behavioral relationships [5], [6]. This is not realistic for the brain, which has to make decisions based on single trials in novel circumstances where it has not developed a prior control strategy. According to the theory of population averaging, neurons in the same population (cortical column) are stochastically equivalent; therefore, the average firing rate of the entire population is representative of any neuron in that population [6]. Rather than averaging one neuron’s firing over many trials the brain can average many neurons’ firing over one trial (see fig. 2). The bin count for a population of neurons is calculated using (2), where *AP*, $\Delta t$, and *N* represent action potentials, bin size, and population size respectively. Population averaging reduces

---

This work was supported in part by the National Science Foundation under Grant #CNS-0540304, Children’s Miracle Network, Tarr Charitable Family Foundation, and the Tillie, Jennie & Harold Scwartz Foundation.

J. DiGiovanna is with the Department of Biomedical Engineering, University of Florida, 106 BME Building. Gainesville, FL 32611 USA (e-mail: digiovaj@cnel.ufl.edu)

J. C. Sanchez is with the Department of Pediatrics, Division of Neurology, University of Florida, P.O. Box 100296, JHMHC, Gainesville, FL 32610 USA (e-mail: justin@cnel.ufl.edu)

J. C. Principe is with the Department of Electrical and Computer and Biomedical Engineering, NEB 451, University of Florida, Gainesville, FL 32611 USA (e-mail: principe@cnel.ufl.edu)

the variance in estimating rate at a given bin size (or allows smaller bins with equivalent variance).

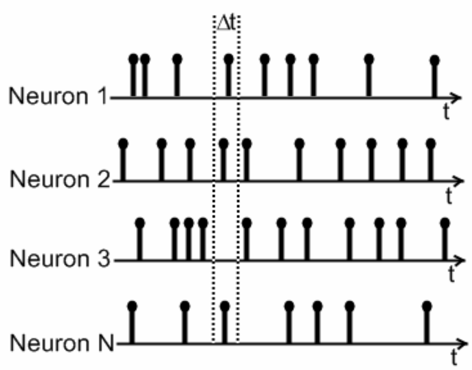

Fig. 2. Population averaging over 4 neuron's spike trains.

$$v(t) = (\text{number of } APs \text{ in } \Delta t) / \Delta t \qquad [1]$$

$$A(t) = (\text{number of } APs \text{ in a population in } \Delta t) / (N\Delta t) \qquad [2]$$

A related theory of neuron ensembles has been studied extensively in [8]. Comparing contributions of ensembles of cells vs. individual cells in the rat motor cortex, they found that the cells' contributions were generally synergistic in smaller ensembles, i.e. the information from an ensemble is greater than the sum of information from individual cells within the ensemble [8].

Prior BMI research has begun to examine the second assumption of individual neuron system inputs. They found no statistical performance loss for nonlinear filters if neurons recorded on the same electrode were summed together [9]. This is equivalent to population averaging of 250 μm (radius) columns centered at each electrode except for the scalar division by $N$ in (2), which is easily reconciled by the linear filter. [8] and [9] suggest that population averaging may provide an advantage for BMI systems.

In this paper we critically examine the assumption that the brain weights and combines individual firing rates. We use population averaging to group neurons together based on perievent histogram correlation given the spatial restrictions of cortical columns. We compare different input structures using a FIR Wiener Filter and provide a theoretical explanation of the performance results.

## II. METHODS

### A. Model Topology

We are trying to mimic the operation of the motor control system using an adaptive filter. The model is shown in fig. 3. We include two sources of noise that corrupt the input signal to the adaptive filter. The $n_r$ and $n_b$ signals represent recording noise and binning noise. We make the strong assumption that a linear FIR filter can approximate the plant and a second assumption that $n_b$ is white and additive. Signal $n_r$ is a constant error caused by recording noise, spike sorting errors, and cortical subsampling. Since we are using offline data this noise can not change and will be ignored for the remainder of this paper. Signal $n_b$ is clearly a function of bin size - the variance in estimating mean is inversely proportional to estimation time window. However, we will show that $n_b$ is also a function of input organization.

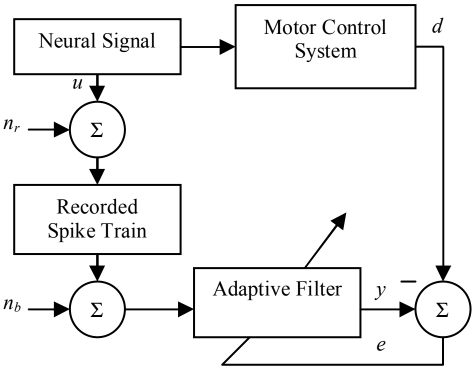

Fig. 3. System identification with an adaptive filter

The Wiener filter was used for this study because it provides a convex performance surface (no local minima) for a given input-output configuration [4]. If there is no noise, the ideal filter weights are given by the Wiener equation in (3). Using our assumption that $n_b$ is additive and white, the true filter weights are given in (4) where I is the identity matrix. Because of the discrepancy in $R$ in (4) the performance of the adaptive filter will never reach the performance of the plant. However, if we can minimize $\sigma_{n_b}^2$, the performance of the filter should improve.

$$w^* = R_u^{-1} p \qquad [3]$$

$$w = \left[R_u + I\sigma_{n_b}^2\right]^{-1} p \qquad [4]$$

The filter was trained using 1200 s of data and tested on 450 s of novel data. The WF uses a tap delay line to utilize the prior 1 s of firing from each neuron/population. Depending on the bin size (25 or 100 ms), there are either 40 or 10 parameters per input. There are sufficient training samples to theoretically achieve < 5% error [10]. The input data is normalized to be zero-mean, unit-variance.

### B. Data Collection

Neural activity from a male Sprague-Dawley rat was recorded during a go no-go behavioral task at the University of Florida McKnight Brain Institute. The rat was chronically implanted with two 16-microelectrode arrays in the forelimb regions of each hemisphere [11]. The arrays are 8 x 2 with 250 um spacing between the rows and 500 um spacing between the columns. Further experimental paradigm and recording system details are given in [9].

The neural data from each channel was spike sorted to find action potential times. The spike sorting was performed online using both thresholding and template-based techniques [12]. For this animal there were 42 neurons that could be discriminated – 24 in the left hemisphere and 18 in the right hemisphere. The firing time of each neuron was recorded; offline the data was binned within non-overlapping windows of 25 ms or 100 ms. The 100 ms bins are used to create a performance benchmark because of their frequent use in BMI models. The 25 ms bins are used to investigate filter performance with higher temporal resolution and to correlate with experimental neuroscience findings [5]. Although it is difficult to compare solutions between bin sizes (different time resolutions will change $R_u$ and $p$), using both sizes shows that our results generalize.

### C. *Behavioral Analysis*

The rat performed this task with little distraction for 1920 s. There were 93 and 45 presses for the left and right levers respectively. Based on video analysis of the experiment, we found the right lever presses were very stereotypical, while the left lever presses were more variable in their execution. To avoid behavioral anomalies affecting analysis, only right lever presses are used in BMI modeling.

### D. *Data Preprocessing*

The neural data was organized into three different preprocessing configurations that will modify the functional mapping between neural activity and behavior (number of filter inputs listed in parenthesis):

- AN – All sorted neurons (42)
- PA – Population averaging (23)
- MV – Minimum binning variance (23)

The AN configuration is the current standard for BMI system identification. The PA configuration averages individual neurons into populations if the neurons exhibit correlation in firing history before lever presses and it is spatially feasible that they are in the same cortical column. If a neuron cannot be placed in a population, that neuron's PA contribution is equal to that neuron's AN contribution. There are 12 populations and 11 single neurons in PA.

Perievent histograms are generated for each neuron's firing for one second prior to the right lever press times (in the training set) as is commonly performed in neurophysiological analysis [6]. However, we first shift the lever press times 250 ms into the past to account for the propagation time required for neural signals to reach the animal's muscles [1], [13]. These histograms are then pair-wise compared to find the correlation coefficient between the average firing histories before a lever press.

In the rat motor cortex an action potential is detectable in chronic recordings up to approximately 400 μm from the axon hillock [14]. Considering the furthest possible separation of neurons within a cortical column, signals from a population could be detectable by electrodes within a 550 μm radius cylinder of cortex. We allow these columns to be oriented arbitrarily within our recording site.

The MV configuration is used to show that $n_b$ is also dependant on the organization of the input signal. In the PA grouping configuration, there are 6 single-neuron, 4 two-neuron, 2 three-neuron, and 1 four neuron populations in the left hemisphere; 5 single-neuron, 2 two-neuron, and 3 three-neuron populations in the right hemisphere. In MV, neurons in each cerebral hemisphere are randomly assigned (without replacement) into populations such that the number and size of populations created is equivalent to PA

The variance of each population is divided by the average variances of that population's residents. This ratio shows the percentage reduction in rate estimation variance (REV). The reduction in REV was calculated for 10000 random groupings; the organization with the greatest reduction was selected (performed independently for both 25 and 100 ms bins, resulting in a unique MV for each size).

## III. RESULTS

The test set includes twelve consecutive right lever presses. An estimated lever position is reconstructed using the optimal MSE weights. A range of thresholds is tested to find the maximum model accuracy. Model accuracy is defined as the average value of two probabilities: the probability that the filter predicts a press during a press and the probability that the filter predicts no press when the lever is not pressed. The accuracy of the different input configurations for 100 ms and 25 ms bins is given in tables 1 and 2. A two-sample Kolmogorov-Smirnov [K-S] test (95% significance) is used to compare all filter outputs with the AN Wiener filter. If the data is drawn from the same statistical population, the result of the K-S test will be 0; if the data is statistically significantly different the result will be 1. The test is performed separately for the low (lever not pressed) and high (lever pressed) sections of the test data.

TABLE 1: PREPROCESSING PERFORMANCE COMPARISON

| Data | Inputs | Bin Size | Accuracy | 2-sample K-S test |
|---|---|---|---|---|
| AN | 42 | 100 ms | 87.12 % | Reference |
| PA | 23 | 100 ms | 88.18 % | Low = 1, High = 0 |
| AN | 42 | 25 ms | 86.80 % | Reference |
| PA | 23 | 25 ms | 88.04 % | Low = 1, High = 1 |

PA increased accuracy for both bin sizes (statistically significant). However, because of the different dimensionalities of the systems, it is difficult to attribute the increased accuracy to a single cause. In table 2 we compare reduction in REV and performance using the MV configuration. Although MV data has a larger reduction in REV, PA models provide more accurate reconstruction.

TABLE 2: BINNING VARIANCE VS. ACCURACY

| Data | Inputs | Bin Size | Reduction in REV | Accuracy |
|---|---|---|---|---|
| PA | 23 | 100 ms | 8.82% | 88.18 % |
| MV | 23 | 100 ms | 13.59 % | 76.77 % |
| PA | 23 | 25 ms | 13.95 % | 88.04 % |
| MV | 23 | 25 ms | 18.99 % | 84.79 % |

## IV. DISCUSSION

Using correlation between perievent firing rate histograms and biologically plausible cortical column specifications, we were able to achieve a slight (1%) but statistically significant improvement in model accuracy with a 45% reduction in model parameters (see Table 1). This result is consistent with prior findings that small groups of neurons act synergistically within an ensemble [8]. This technique may be very important in future BMI systems as the technology to record from additional neurons is developed. PA uses information from all recorded neurons; however, it can provide substantial reduction in the number of filter parameters. Reducing the number of parameters decreases computational complexity, storage requirements, and training time in adaptive filters (it also may decrease generalization issues).

Since PA reduces the number of input parameters (correspondingly reducing the dimensionality of the system), it is not possible to compare directly between PA and AN to make conclusions about binning noise ($n_b$) in the input signal. The higher dimensional AN system may exhibit lower accuracy due to generalization problems [4].

We remove this ambiguity by using an input configuration (MV) that is dimensionally equivalent to PA. The MV data has a lower rate estimation variance (REV) than PA. Therefore, if binning noise ($n_b$) was only a function of REV, the MV configuration should have outperformed PA because the filter weights, (4), would be closer to the optimal weights, (3), of the plant. However, Table 2 supports our hypothesis that $n_b$ is not only dependant on REV but is also a function of the organization of the input data. PA does not provide the greatest reduction in REV but achieves higher accuracy than MV; therefore, input organization is important for BMI performance. While grouping any neurons should reduce REV (there is more signal available to estimate rate), combining neurons from the same cortical column maintains (or increases) information present in the signal. Our results suggest that PA organizes the input data into a form more similar to the input to the plant (Neural Signal in fig. 3).

Although there was not large accuracy degradation in AN using higher temporal resolution (see Table 1), the increasing variance may be problematic for fine motor control. We hypothesize PA will allow investigation of motor control signals at higher temporal resolution due to the reduced input variance.

It is important to note that the 250 ms neural conduction shift when creating perievent histograms (described in the Data Preprocessing section) is very important for PA. If PA is used without this shift, or if the histogram includes data after the lever press, the model accuracy decreases approximately 3-4% for both bin sizes. This suggests that although certain neurons may act in ensemble to plan a specific motion, different neural ensembles are used for other motions. Future work is needed to find the optimal shift to accommodate nerve conduction time for rats.

It is interesting to consider that PA is a necessary condition for current microelectrode array recordings to provide any useful information. Current recording techniques are capturing approximately 10 – 1000 neurons, yet this still represents a gross subsampling of the 40000 neurons per $mm^3$ in the cortex [6]. We accept this subsampling assuming that the recorded neurons are representative of populations and we do not need every member of the population. We should consider that multiple recorded neurons may be from the same population. PA is biologically inspired method that can produce more accurate, parsimonious BMI systems.

## REFERENCES

[1] J. Wessberg et al., “Real-time prediction of hand trajectory by ensembles of cortical neurons in primates,” Nature, vol. 408, pp. 361-365, 2000

[2] J. M. Carmena et al., “Learning to control a brain-machine interface for reaching and grasping by primates,” *PLoS Biology*, vol. 1, pp. 1-16, 2003

[3] J.C. Sanchez, D. Erdogmus, Y. Rao, J. C. Principe, M. Nicolelis, and J. Wessberg, “Learning the contributions of the motor, premotor, and posterior parietal cortices for hand trajectory reconstruction in a brain machine interface,” presented at *IEEE EMBS Neural Eng. Conf*, Capri, Italy, 2003

[4] S. Haykin, *Adaptive Filter Theory*, Englewood Cliffs, NJ: Prentice Hall, 1996, pp. 94-104.

[5] L. Hermer-Vazquez, R. Hermer-Vazquez, and J. Chapin, “Distinct temporal activity patterns in primary motor cortex and magnocellular red nucleus during skilled vs. unskilled limb movement,” Behavior and Brain Research, 2003 vol. 150, pp. 93-107

[6] T. Trappenberg, *Fundamentals of Computational Neuroscience*. New York, NY: Oxford Press 2002. pp. 70-78.

[7] V. B. Mountsactle, “The columnar organization of the neocortex,” Brain, vol. 120, pp. 702-722. 1997

[8] N. S. Narayanan, E. Kimchi, and M. Laubach, “Redundancy and Synergy in Neuronal Ensembles in Motor Cortex,” J Neuroscience, vol. 17, pp 4207-4216, April, 2005.

[9] J. C. Sanchez, J. C. Principe, P.R. Carney, “Is neuron discrimination necessary for linear and nonlinear brain machine interface models,” accepted to *11th Int. Conf. Human-Computer Interaction*, 2005.

[10] J. Principe, N. Euliano, et al. *Neural and adaptive systems: fundamentals through simulations*, New York, NY: John Wiley & Sons, 2000

[11] R. Hall and E. Lindholm, “Organization of the motor and somatosensory cortex in the albino rat,” *Brain Research*, vol. 66, pp. 24-38, 1973

[12] M. Nicolelis, A. Ghazanfar, B. Faggin, S. Votaw, and L. Oliveira, “Reconstructing the engram: simulataneous, multisite, many single neuron recordings,” *Neuron*, vol. 18, pp. 529-537, April 1997

[13] J. Chapin, K. Moxon, R. Markowitz, M. Nicolelis, “Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex,” Nature Neuroscience, vol. 2, pp. 664-670, July 1999

[14] G. Buzsaki and A. Kandel, “Somadendritic backpropagation of action potentials in cortical pyramidal cells of the awake rat,” J. Neurophys. vol. 79, pp. 1587-1591, 1998.